Neuro-Fuzzy Forecasting of Tourist Arrivals

Doctor of Philosophy Thesis

Hubert Preman Fernando

Volume I

School of Applied Economics
Faculty of Business and Law
Victoria University

Abstract

This study develops a model to forecast inbound tourism to Japan, using a combination of artificial neural networks and fuzzy logic and compares the performance of this forecasting model with forecasts from other quantitative forecasting methods namely, the multi-layer perceptron neural network model, the error correction model, the basic structural model, the autoregressive integrated moving average model and the naïve model.

Japan was chosen as the country of study mainly due to the availability of reliable tourism data, and also because it is a popular travel destination for both business and pleasure. Visitor arrivals from the 10 most popular tourist source countries to Japan, and total arrivals from all countries were used to incorporate a fairly wide variety of data patterns in the testing process.

This research has established that neuro-fuzzy models can be used effectively in tourism forecasting, having made adequate comparisons with other time series and econometric models using real data. This research takes tourism forecasting a major leap forward to an entirely new approach in time series pedagogy. As previous tourism studies have not used hybrid combinations of neural and fuzzy logic in tourism forecasting this research has only touched the surface of a field that has immense potential not only in tourism forecasting but also in financial time series analysis, market research and business analysis.

Declaration

"I, Hubert Preman Fernando, declare that the PhD thesis entitled Neuro-Fuzzy Forecasting of Tourist Arrivals is no more than 100,000 words in length, exclusive of tables, figures, appendices, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work".

Signature: Date: 2 November 2005

Acknowledgements

I would like to express my sincere thanks to Professor Lindsay Turner, for his academic and intellectual guidance, advice, assistance, encouragement and support during the course of this research study, and the preparation of this thesis. I consider myself very fortunate to have had Professor Turner as my principal supervisor not only because of his excellent supervision but also because I was able to draw on his wide knowledge and expertise in tourism economics and forecasting techniques.

I would also like to thank Dr. Leon Reznik, for introducing me to fuzzy logic, Dr. Nada Kulendran for his advice on the application of the Error Correction Model and Miss. Angelina Veysi and Miss Linda Osti for their assistance with data processing.

I would also like to thank my wife Kumarie, and two daughters Nikoli and Sohani for their understanding, encouragement, support and immense patience during this period, when they were in fact, deprived of my time and attention.

I dedicate this thesis to my late parents Hubert and Etta and my only sibling the late Ramyani, who were also deprived of my time and attention during the final months of their lives.

Contents

List of Figures

List of Tables

Chapter 1
Introduction

Due to the continued growth in global tourism and the importance of overseas travel for both business and pleasure, national and international travel organisations and governments are currently placing considerable effort on generating accurate tourism forecasts. The World Tourism Organisation, the Pacific Asia Travel Association, Tourism and Travel Intelligence (UK), the Australian Tourism Forecasting Council and the Bureau of Tourism Research are involved in producing tourism forecasts for use by industry. The travel, transport and accommodation sectors are major users of these forecasts. This research plays a significant role in taking current methodology a step forward by testing a hybrid neuro-fuzzy model in forecasting tourism flows.

Traditional quantitative forecasting techniques can be broadly categorised into two main areas: time series techniques such as autoregressive and moving average methods, and econometric techniques such as regression methods. Publications on tourism demand forecasting have been mainly based on these time series and econometric models. However, more recently, artificial neural networks have been used in tourism forecasting (Law 2000). Though fuzzy logic has been used in quantitative forecasting, no work on forecasting tourism demand has yet been published using a neuro-fuzzy hybrid of fuzzy logic and artificial neural networks.

This study branches away from both the earlier econometric and time series studies to develop a new approach to tourism forecasting. The presentations made by Fernando, Turner and Reznik at the 1998 and 1999b Australian Tourism Research CAUTHE conferences established the potential for both artificial neural networks and fuzzy logic in tourism forecasting. However, the concept of a hybrid neuro-fuzzy forecasting model for tourism demand needs to be tested on a wider scale. Because this research is on the leading edge of tourism forecasting, it makes a significant contribution to the current literature.

This study uses the principles of artificial neural networks and fuzzy logic to develop forecasting models for tourism to Japan. The forecasts obtained using these models are compared with those from traditional time series and econometric models, to determine the comparative level of accuracy of these techniques in forecasting tourist arrivals. The terms travel and tourism are used synonymously as arrivals data collected at ports of entry to a country include people traveling for business, pleasure, sightseeing, visiting friends and relatives, employment, education and many other reasons. This research focuses on total inbound arrivals to Japan.

The reason for selecting Japan as the subject country of this study is three-fold. Firstly, Japan has well documented and reliable tourist data. Secondly, Japan is a significant travel destination both for business and pleasure. Thirdly, no work has been published in the literature on tourism demand forecasts for Japan that examines the comparative merits of time series, econometric, neural network and fuzzy forecasting techniques.

1.1 Overview of the Thesis

Chapter 1 introduces the research problem, states the aims and objectives of the research and provides an outline of the research methodology. Since the research uses Japanese tourism data, a brief review of Japan's tourism potential, inbound tourist flows, economy and trade policy is also included in Chapter 1. The data and information on tourism presented in Chapter 1 were obtained from the Japan National Tourism Organisation, partly from its published reports and partly during a visit to Japan in 2002. Chapter 2 is a comprehensive review of the literature on tourism forecasting, time series modeling, econometric modeling, artificial neural networks, fuzzy logic and the neuro-fuzzy hybrid.

In Chapter 3 the univariate multi-layer perceptron neural network model is used to forecast tourist arrivals to Japan. Three neural network models, a non-periodic model, a partial periodic model and a periodic model are presented. Forecasts using these models are compared with those of the naïve model.

Chapter 4 presents forecasts of tourist arrivals to Japan using the ARIMA model and the Basic Structural Model (BSM). In Chapter 5 the error correction model (ECM) is compared with the multivariate multi-layer perceptron model. The neuro-fuzzy model ANFIS is used in Chapter 6 to forecast arrivals using a combination of neural networks and fuzzy logic. Chapter 7 concludes the thesis with a summary comparison of the forecasting models and suggestions for the direction of future research.

1.2 The Research Problem

Over the past few decades, international travel has increased significantly. Tourism has become a growing industry sector in many countries. Japan is one of many countries that actively promote inbound tourism. The need for forecasts of tourist arrivals has been highlighted by the rapid growth of the travel sector. Quantitative forecasting methods have been used in the past to forecast inbound tourism and the level of sophistication of forecasting techniques has increased with the development of research interest directed at improving forecasting accuracy. A combination of fuzzy logic and artificial neural networks has not been used so far in tourism forecasting. The main research problem is to develop a hybrid neuro-fuzzy model for tourism forecasting and establish whether it is a viable alternative to contemporary tourism forecasting methods.

Fuzzy logic is a relatively new field of mathematics, which recognises the vagueness of reality. Crisp data (i.e. exact measurements) cannot always convey the true picture of reality because reality viewed in totality is vague, hazy and unclear. Since total reality is not always accurately represented by crisp data, due to inherent variability, the traditional significance attached to crisp measurements is questionable. The fuzzy approach takes forecasters away from the notion of crisp accuracy to the domain of fuzzy meaningfulness.

Quantitative forecasting techniques identify patterns in historical data by decomposing time series data into its basic components. Much effort has been expended in studying the error component in attempts to reduce forecasting errors.

However, uncertainties of the future, and the non-conformance of data series with the assumptions of forecasting theory, make accurate forecasts difficult to achieve and forecasting an inexact science. Since reality is not always accurately represented by crisp data, fuzzy thinking is introduced to forecasting in the hope of improving forecasting accuracy. This study converts crisp tourism data and national indicators into fuzzy sets and identifies, using artificial neural networks, the underlying rules that describe the data. These rules are then used to make fuzzy forecasts, which are in turn converted into crisp forecasts for comparison with actual data. Therefore, this technique combines artificial neural networks and fuzzy logic to form a neuro-fuzzy hybrid, giving forecasting a new direction.

While short term data analysis (such as in financial market forecasting) has benefited from successes in short term quantitative forecasting, other quantitative forecasting applications have had to be content with lower levels of accuracy, or be modified by expert systems. Tourism demand forecasting is an example where travel patterns vary for a variety of reasons that make it difficult to establish a consistent historical pattern within the stochastic time series movement. This study attempts to highlight the need for better forecasts using quantitative techniques that, model historical data but do not fit them into pre-designed patterns that may not reflect the true properties of the data. The fundamental time series forecasting assumption that historical data and error patterns will follow through into the future is made in this study. However, the objective of the study is not only to obtain low forecast errors, but also to acknowledge the varying characteristics of data series beyond the four basic components (trend, cycle, seasonality and irregularity) in order to identify the best forecasting method for idiosyncratic data series. In pursuing this objective the study uses a range of data series and compares empirical forecasting results from a range of techniques, to identify an alternative empirical tool for tourism forecasting.

The neural network paradigm has the capacity to hold aspects of all elements of a historical data series encapsulated within a black-box of parameters, making the model unique to that set of data. Forecasters currently have the difficult task of using relatively rigid models to predict a stochastic future and this becomes especially difficult in the long term. This use of rigid models in turn exasperates the problem of different characteristic time series for each arrival analysis. However, the neural network concept opens up possibilities for a wide variety of empirical analyses within the one methodology. The neuro-fuzzy concept is also empirical, but refines the neural network forecasting process into modelling fuzzy rather than crisp data, recognizing the vagueness rather than the preciseness of stochastic tourist arrival data.

More recently artificial neural networks have been developed as an alternative forecasting tool (Fernando, Turner and Reznik (1999a), Law and Au (1999), Law (2000), Cho (2003) and Kon and Turner (2005)) and have been shown to produce superior forecasts for certain time series data primarily using multi-layer perceptron neural network models. A second aspect of the research problem is to compare the accuracy of artificial neural network multi-layer perceptron forecasts with neuro-fuzzy forecasts to determine the effect of fuzzy analysis on forecasting accuracy.

A third aspect of the research problem is to test whether neuro-fuzzy tourism forecasts compare well with other modern univariate time series forecasts such as those from the ARIMA model and the basic structural model. Time series and econometric methods have been used in the past to forecast tourism demand, for example, Martin and Witt (1987), Morley (1996), Turner, Kulendran and Fernando (1997a), Kulendran and King (1997), Chu (1998a), Turner and Witt (2001a), Song and Witt (2003) Song, Wong and Chon (2003).

Econometric methods identify cause and effect relationships between tourism demand and variables that cause the flow of tourists. Multivariate structural causal models (Turner and Witt 2001a) and the error correction model (Kulendran, 1996) are examples of causal methods recently used in tourism demand forecasting. A fourth aspect of the research problem is to compare neuro-fuzzy forecasts with those of the error correction model, incorporating national economic indicators that have commonly been used in previous econometric studies (Kulendran and Witt (2001), Song and Witt (2000)), together with tourist arrival data. National economic indicators commonly used in tourism studies are, per capita gross domestic product, airfares, own price and trade openness. Own price and trade openness are derived from the gross domestic product, the consumer price indices, imports, exports and forward exchange rates.

Time series data of total tourist arrivals from the top ten largest source markets to Japan are used in this study to develop the forecasting models. The top ten inbound source markets to Japan are: Australia, Canada, China, France, Germany, Korea, Singapore, Taiwan, UK, and USA. This study develops forecasting models for total arrivals to Japan from these ten countries and for total arrivals to Japan from all countries. The total volume and multi-directional nature of these flows provide a data set sufficient in variety, depth and breadth, for a comparison of alternative forecasting tools.

1.3 Aims and Objectives

The aim of this study is to develop a model to forecast inbound tourism to Japan, using a combination of artificial neural networks and fuzzy logic and to compare the performance of this forecasting model with forecasts from other quantitative forecasting models namely, the multi-layer perceptron neural network model, the error correction model, the basic structural model, the autoregressive integrated moving average model and the naïve model.

The objective of the study is to determine whether a hybrid neuro-fuzzy model is a viable alternative to traditional quantitative methods of forecasting tourist arrivals. In attempting to achieve this objective the study determines whether the use of fuzzy data improves forecasting performance.

1.4 Research Methodology

This research uses the multi-layer perceptron artificial neural network model, the Box-Jenkins ARIMA model, the basic structural model, the error correction model, the hybrid neuro-fuzzy model and the naïve model to forecast inbound tourist arrivals to Japan. Quantitative forecasting methods fundamentally use historical data to forecast future values assuming historical data patterns will have systematic progression into the future.

The data used in this study are monthly time series of tourist arrivals to Japan from January 1978 to December 2003. The time series from January 1978 to December 2001 is used as the within sample data, to develop the forecasting models. The remainder of the series is used as an out of sample data set with which the forecasting performance of the models developed is then tested for forecast accuracy.

The forecasting performance is measured only by the forecasting accuracy of a model. Quantitative forecasting models are evaluated by comparing the forecasting performance of alternative models when identical data are being used. As the accuracy of a forecasting model depends on how close the forecast arrival number is to the actual arrival number, the forecasting model that has the least difference (or error) between the actual and forecast values in the out of sample test period is adjudged the best forecast model.

For the entire out of sample period the forecasting performance or accuracy is measured using two standard error measurements, the root mean squared error

(RMSE) and the mean absolute percentage error (MAPE) (Hanke and Reitsch 1992). The root mean squared error measures the square of both positive and negative errors, as the square root of the average, over the out of sample period.

$$\boldsymbol{RMSE = \sqrt{\frac{1}{N}\sum\left(Forecast_t - Actual_t\right)^2}} \quad ,$$

where, ***N*** is the number of observations and ***t*** is the time period. The mean absolute percentage error,

$$\boldsymbol{MAPE = \frac{100}{N}\sum\left|\frac{Forecast_t - Actual_t}{Actual_t}\right|} \quad ,$$

and expresses the absolute error as a percentage of the actual arrival number. When comparisons are made between models using different data series such as tourist arrivals from different countries, the mean absolute percentage error is a better measure of comparative accuracy as it provides an indication of the error, relative to the actual value and independent of the volume of arrivals. MAPE is used in this thesis as the main criterion for evaluating forecasting performance of the various models developed, and RMSE is used as a secondary indicator of forecasting performance.

In comparing the alternative forecasting models, each model is applied to each data series from each of the ten countries. The model that generates the largest number of lowest MAPE values is adjudged the best model. This measure is referred to in subsequent analysis as the "Lowest MAPE count". A second criterion for evaluating forecasting performance is where a MAPE value less than 10% is considered good, while values between 10% and 20% are considered moderately good and values more than 20% are considered poor. A third criterion is the model with the lowest mean MAPE for the forecast data series. The lowest mean MAPE is given less importance because a few very large (or small) MAPE figures could distort the overall mean MAPE. In such an analysis these large (or small) MAPE figures cannot be considered outliers, as the aim of the exercise is to compare several models that use the same input data series.

In order to improve the statistical validity of the results, total tourist arrival time series from eleven different sources to Japan are used with each forecasting method. Further, to test the effectiveness of the forecasting models over varying horizons, forecasts are made one-month-ahead, 12-months-ahead and 24-months-ahead for each forecasting method and each data series. These forecasts are made for both one-year and two-year lead periods. The focus is upon the short to medium term because this is the currently favoured approach in industry forecasting and this in turn reflects the current unstable nature of tourist arrivals due to continuing short-term shocks (terrorism, health scares and political upheaval), and also the increasingly short-term investment cycles and horizons for tourism business operators.

The forecasts are calculated for the 24-month out of sample test period from January 2002 to December 2003. However, error measures are calculated separately for the 12- month lead period from January 2002 to December 2002, and for the 24-month lead period from January 2002 to December 2003. This is to ascertain whether the forecasting accuracy varies with the length of the out of sample forecasting period. The data structure described above is summarized in Table 1.1.

Table 1.1 Data Structure

	One month ahead horizon					
Within sample period	Jan-78 to Dec-01	Jan-78 to Jan-02	--	Jan-78 to Nov-02	--	Jan-78 To Nov-03
Out of sample period	Jan-02	Feb-02	--	Dec-02	--	Dec-03
	One year lead					
	Two year lead					

	12 months ahead horizon		24 months ahead horizon	
Within sample period	Jan-78 to Dec-01	Jan-78 to Dec-02	Jan-78 to Dec-01	Jan-78 To Dec-01
Out of sample period Two year lead One year lead	Jan-02 to Dec-02	Jan-03 to : : : Dec-03	Jan-02 to Dec-02	Jan-02 To : : : Dec-03

For the one-month-ahead horizon, the within sample period is taken as January 1978 to December 2001, to forecast one-month-ahead for January 2002. The within sample period is taken as January 1978 to January 2002, to forecast one-month-ahead for February 2002 and so on. In this manner, 24 such forecasts are made to obtain forecasts for the out of sample period January 2002 to December 2003, one month at a time.

For the 12-months-ahead horizon, the within sample period is taken as January 1978 to December 2001, to forecast 12-months-ahead from January 2002 to December 2002. The within sample period is taken as January 1978 to December 2002, to forecast 12 months ahead from January 2003 to December 2003. These 2 sets of 12-month forecasts cover the 2-year out of sample period from January 2002 to December 2003, one year at a time.

For the 24 months ahead horizon, the within sample period is taken as January 1978 to December 2001, to forecast 24-months ahead from January 2002 to December 2003. This forecast covers the 2-year out of sample period from January 2002 to December 2003.

The naïve model assumes the data will remain unchanged from the previous period (or for seasonal data the corresponding period from the previous year), to the next. Therefore, the naïve forecast for the current period is the actual of the previous period (or for seasonal series the actual of the corresponding period of the previous year). Since the naïve model is the most basic of forecasting methods (essentially being representative of guessing the forecast number), it is important that any alternative model must provide better forecasting accuracy than the naïve model. This study requires naïve forecasts to be the minimum benchmark that all models in this study must meet. Basic naïve forecasts must be improved upon by a forecasting method for the method to be considered adequate for forecasting tourist arrivals. Therefore, it is expected that the MAPE and RMSE values of all forecast models will be better than the MAPE and RMSE values of the naïve model.

The above paradigm is applied first to the univariate artificial neural network model. The neural network model used is the multi-layer perceptron (MLP) with a linear input layer, two hidden layers containing sigmoid and tanh nodes and an output layer. Kon and Turner (2005) adjudge this model superior among the standard neural models. The within sample time series data are used as training data for developing the network parameters and the out of sample data are used as test data. Three different models of input data patterns are evaluated to determine the most suitable for tourism forecasting. The first model is a non-periodic model that uses the previous 12 months arrivals as input data to forecast for the next month. The previous 12 months data are used as the inputs because tourist data is seasonal and monthly data are used in this study. The second model is a partial periodic model, which uses data lagged by 12, 24 and 36 months as input data. For example, this model uses the January arrivals of the three previous years to forecast the following year's January arrivals. The third model is the periodic model, which uses data only from a specific month of each year. For example, all January arrivals data of the within sample period are used to forecast the January arrivals in the out of sample period. This process is repeated for each month separately.

To test the effect of differencing on MLP forecasts, a partial periodic model is developed for undiferrenced and first differenced data and compared with a non-periodic model with first and twelfth differences. First differenced data are used for the partial periodic model as the use of three seasonally lagged series removes the effects of seasonality, leaving trend as the predominant component in the data. In the non-periodic model both first and twelfth differences are taken to remove the effects of both trend and seasonality. All neural network forecasts are obtained using the DataEngine software.

The Box-Jenkins ARIMA model and the basic structural model (BSM) are proven modern univariate time series forecasting methods. They are applied in this research with Japanese tourist arrivals data mainly as a comparative tool in evaluating the performance of newer models. The ARIMA forecasts are obtained using the SAS software and forecasts from the basic structural model are obtained using the STAMP software.

Tourist arrival forecasts are next made using the error correction model (ECM) with national economic indicators as predictors. The independent variables used are: own price, trade openness of the source country, Japan's trade openness, per capita gross domestic product and airfares, together with the arrivals data used as the dependent measure. Firstly, all data series are checked for unit roots, and then the error term is developed, after which an ordinary least squares regression model with seasonal dummy variables is created to generate forecasts. Microfit software is used to obtain the error correction models and the regression parameters that are then used on a Microsoft Excel spreadsheet for forecasting.

Forecasts from the ECM model are compared with those of a multivariate neural network model. The neural network model chosen is a multi-layer perceptron (MLP) with a linear input layer, two hidden layers containing sigmoid and tanh nodes and an output layer. The within sample time series data are used as training data for developing the network parameters and the out of sample data are used as test data. The input layer of the network consists of partial periodic tourist arrivals data that are lagged by 12, 24 and 36 months and the five national economic indicators own price, trade openness of the source country, Japan's trade openness, per capita gross domestic product and airfares. The software used is DataEngine.

The main purpose of this research is to test whether fuzzy logic can be used to forecast time series tourism data. Traditionally econometric and time series forecasting methods use crisp historical data. The justification for using fuzzy logic is that crisp data rarely represents reality accurately, due to the inherent data variations that are often hidden and deemed insignificant. Fuzzy representation of a cluster of data seems more meaningful from a practical perspective in describing what the data really represents.

Preliminary models developed by the author for forecasting time series using simple fuzzy logic on univariate time series data did not achieve the levels of forecasting accuracy traditionally achieved by standard time series forecasting methods. However, a combination of fuzzy logic with neural networks (the neuro-fuzzy model) provided levels of forecasting accuracy that justified further testing of the model for time series forecasting of tourist arrivals.

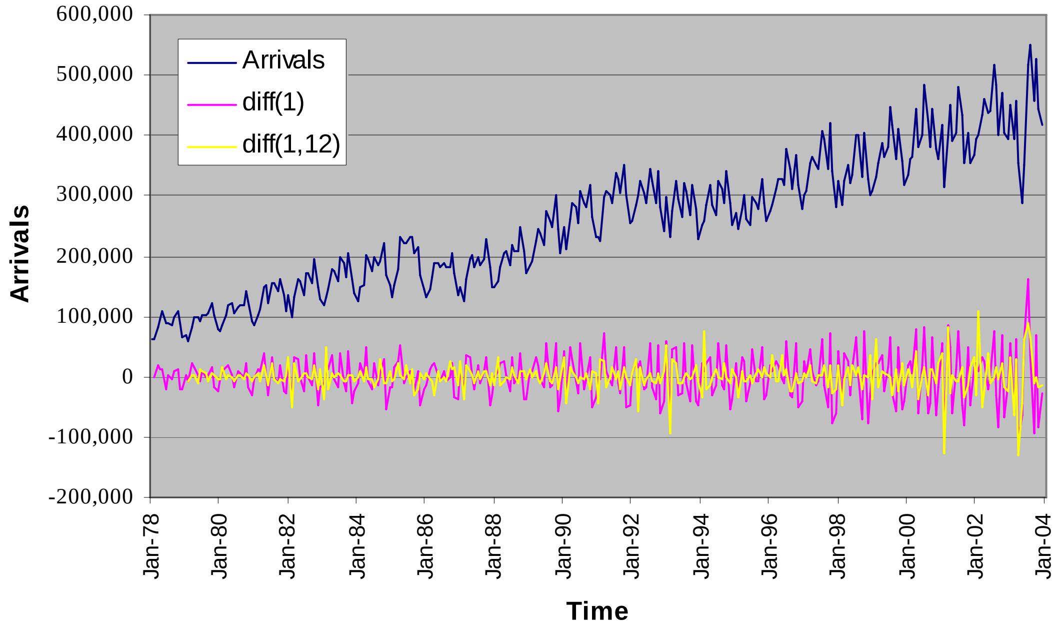
1.5 Data Content and Sources

Japan is a significant travel destination for business and pleasure travellers, has well documented reliable tourism data and has no previous work published using tourist arrivals data and the neuro-fuzzy forecasting model. Nor has a comparative study of the models used in this research been done before for Japan. In order to test the models on a sufficiently large number of time series data sets, inbound tourist arrivals to Japan from the ten most popular tourism source counties are used. Inbound tourist data studied in this research are total arrivals to Japan including all purposes of travel, (holiday, business, visiting friends and relations and other) from Australia, Canada, China, France, Germany, Korea, Singapore, Taiwan, the United Kingdom and the United States of America.

Inbound tourist arrivals into Japan were obtained from the Japan National Tourist Organisation. Monthly data from January 1978 to December 2003 are used in this study. Monthly data were collected in preference to quarterly data because a larger array of within sample data allows for greater flexibility in building artificial neural network models.

As an example of a typical arrival series, total arrivals to Japan from all countries, is shown in Figure 1.1. The series is obviously seasonal and non-stationary. The first difference makes the series stationary as shown by the plot of the first difference in Figure 1.1. The first and twelfth difference removes the effects of seasonal variation as shown by the plot of the first and twelfth difference.

Figure 1.1 Total Monthly Arrivals from all Countries to Japan, 1st difference and 1st & 12th difference



The economic indicators used in the multivariate error correction model are the source country's own price, the destination country Japan's trade openness, the source country's trade openness, the per capita gross national income of the source country and airfares from the source country to Japan. Own price and trade openness have been calculated using the consumer price index, exchange rates, gross domestic product, imports and the exports of source countries obtained from the EconData database. The airfares data were obtained from data manually collected by Dr. Sarath Divisekera of Victoria University from the National Library in Canberra.

1.6 Tourism in Japan

Japan is situated in the Pacific Ocean northeast of Asia, and has a land area of 377,873 square kilometers. Japan consists of four main islands, Hokkaido (north), Honshu (main island), Shikoku (south of main island) and Kyushu (south), surrounded by more than 4,000 very small islands. Japan's geographical features include scenic coastlines, mountains (some volcanic) and valleys. Japan's population in the year 2003 was over 128 million, the 9th largest in the world with most Japanese residing in densely populated urban areas. Japan's population density of 341 per square kilometer is the 4th highest for countries with a population of 10 million or more. Japan's capital city is Tokyo and of Japan's population 44% live in the three metropolitan zones demarcated by a 50 kilometer radius from the three metropolitan centres: Tokyo, Osaka and Nagoya. Of Japan's 47 prefectures Tokyo (12 million), Osaka (8.8 million), Kanagawa (8.5 million), Aichi (7 million) and Saitama (7 million) account for 34% of the population. The population densities of these prefectures are as high as 5,517 for Tokyo, 4,652 for Osaka, 3,515 for Kanagawa, 1,366 for Aichi and 1,827 for Saitama, per square kilometer (Statistical Handbook of Japan, 2004). Japanese is the official language in Japan but many Japanese understand basic English as it is taught as a compulsory subject at school. Japan has 4 seasons: Winter (December - February) when the temperature could drop to 0°C, Spring (March - May), Summer (June - August) with a few weeks of rain in June and Autumn (September - November).

Japan has a rich cultural heritage that is of value and interest to the global traveller. There are historic sites, places of scenic beauty and national monuments that are unique. Ancient tombs, castle ruins, ancient residences, remains and artifacts, gardens, bridges, ravines, coasts, mountains and traditional techniques in Japan are of historical as well as scientific value. Some unique environments surround and add value to the historic structures. The main cities that maintain historical environments are Kyoto, Nara and Kamakura. Asuka in the Nara prefecture has relics dating back to the 7th century, giving an insight into the life and traditions of the people at that time (Tourism in Japan, 2000-2001).

Japan also has natural resources in the form of national parks, wildlife, marine parks and hot springs. There are 391 parks in Japan of which 28 are national parks with a typical Japanese appearance and beauty, administered by the Environment Agency; 55 are quasi-national parks also of great beauty but administered by the prefectures; and the rest are natural parks and scenic areas in the prefectures (Tourism in Japan, 2002).

The waters around Japan have a variety of marine life including fish, coral gardens and underwater plants. There are 64 marine parks, within 11 national and 14 quasi-national parks. Japan also has natural hot springs with bathing in hot springs dating back to the first century. There are over 26,000 hot spring sources in Japan. Many tourist resorts feature hot springs and some still follow traditional bathing customs (Tourism in Japan, 2002).

There are two types of accommodation in Japan. Western-style hotels and Japanese style inns called ryokan. Even at the beginning of the 20th century western style hotels were used mainly by foreign visitors. The locals preferred to stay in ryokan. Ryokan are tatami guest rooms with communal hot spring baths, where guests are provided with traditional food, lifestyle and futon for sleeping. By the year 2001 Japan had over 8200 hotels and over 64,000 ryokan of which 1090 hotels and 2010 ryokan were registered with the government. Minshuku are Japanese family run guesthouses, where guests live with the family. The western style minshuku are the pensions that provide affordable western style board and lodging. The growth in availability of accommodation in Japan has been driven mainly by local travellers, who far out number overseas visitors. Therefore, the system has sufficient accommodation to cope with the steady growth in overseas visitor arrivals (Tourism in Japan, 2002).

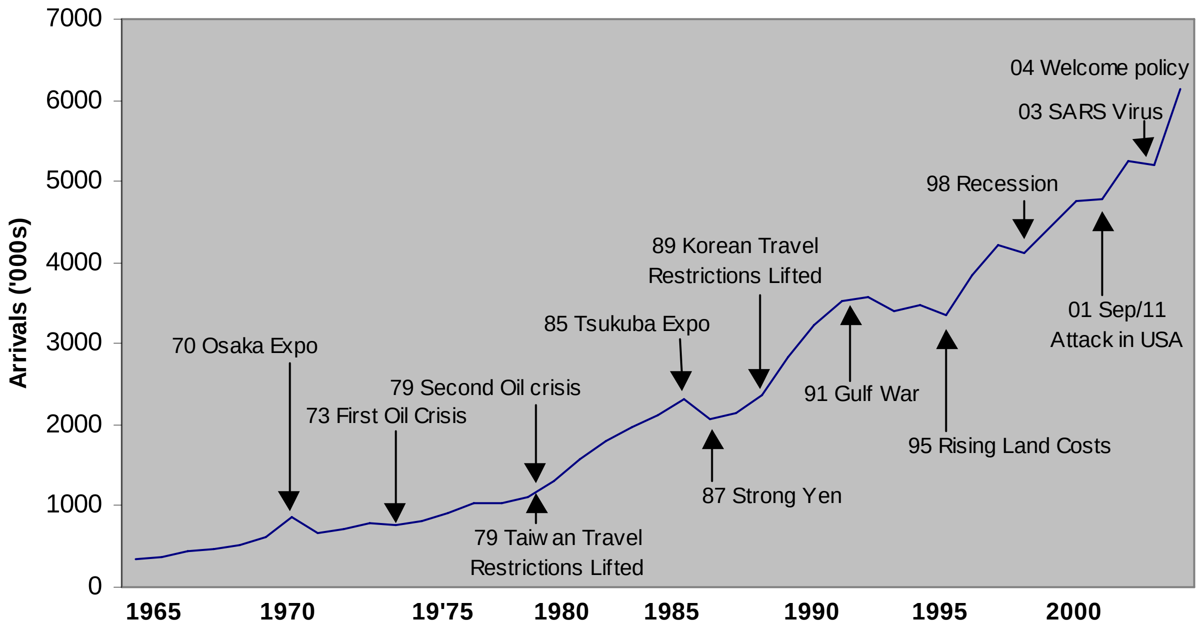
Japan has an extensive rail network that transports 22 billion passengers per year. Japan's road network, which includes expressways, accounts for over 955 billion passenger-kilometers of road travel by 65 billion passengers. Japan's 11 domestic airlines transport over 96 million passengers who travel 84 billion passenger-kilometers per year. Domestic ships transport 110 million passengers who travel 4 billion passenger-kilometers per year. There are 1860 international flights to and from Japan each week, with 580 of them operated by Japanese airlines. Japanese operators of international airlines service over 14 million passengers who travel 73 billion passenger-kilometers per year (Statistical Handbook of Japan, 2004).

1.7 Visitor Arrivals to Japan

Japan has experienced a steady growth in international visitor arrivals over the years. Tourism in Japan received a major boost in 1970 during the World EXPO, which was held in Osaka. Though Japan's tourist potential has received considerable exposure, the EXPO did not have a major impact on the long-term growth of international arrivals. Any beneficial effects that could have been expected in the 70's as a result of the EXPO were offset by the rise in airfares that resulted from the international oil crisis at that time. Although the oil crisis and the consequent rise in airfares had a detrimental effect on arrivals from western countries, the number of arrivals from Asian countries increased. This increased influx of Asian tourists can be attributed to the improving economic conditions in the Asian region generally. In 1979 Taiwan lifted travel restrictions on overseas travel and the resulting increase in Taiwanese visitors to Japan marked the start of an increased growth in total overseas arrivals to Japan that continued up to the mid 80's. Tourism received a further boost when Korea lifted restrictions on overseas travel in 1989. However, from 1992 to 1995 there was a reduction in arrivals due to the global recession that followed the Gulf war in 1991, and Japan's increased cost of living at that time resulting from a positive balance of trade that kept the yen highly valued. This trend reversed as Japan's exchange rate reduced during its 1995 recession resulting in an up turn in arrivals in 1996 and 1997. However, arrivals again dropped in 1998 due to the Southeast Asian economic crisis but this decline was countered by an increase in western travellers in 1999. Due to the fast recovery of the Southeast Asian economies post 1998 and consequent increase in arrivals to Japan from these countries, and a continued increase in arrivals from western countries; total arrivals to Japan further increased in the year 2000. A total of

5.24 million overseas visitors arrived in Japan in 2002, an increase of 9.8 percent on arrivals in 2001. This number decreased to 5.21 million in 2003, due mainly to the outbreak of SARS and the war in Iraq. However, as a result of policies inaugurated in 2003 to encourage inbound tourism and achieve 8 million arrivals in 2007, overseas arrivals in 2004 increased to 6.1 million. Total visitor arrivals to Japan from 1964 to the year 2004 are shown in Figure 1.2 with significant events indicated on the figure against the relevant time periods.

Figure 1.2 Total Visitor Arrivals to Japan from 1964 to 2004

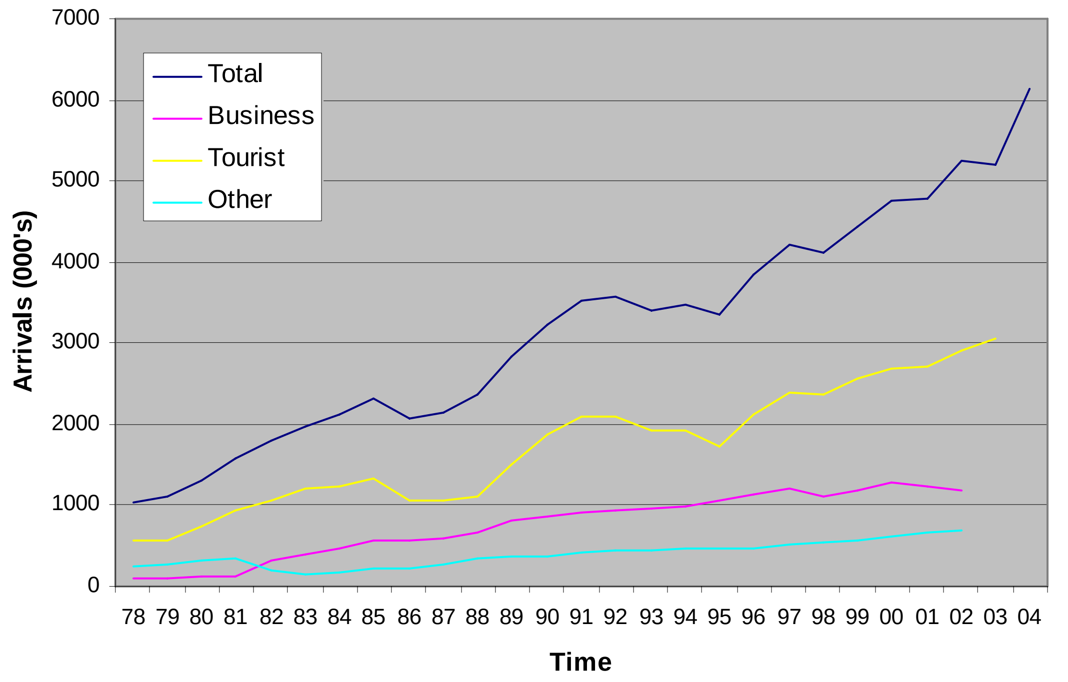


Source: Japan National Tourist Organisation.

The average length of stay of visitors is 8.5 days. In 1990 the average stay was 13.2 days but since the mid 90s this figure has been 8.5 days on average, indicating a significant change in the attitude and life style of visitors to Japan, and also the shorter distance travel growth from neighbouring countries.

Arrivals to Japan can be classified as tourists, business arrivals and others such as students from other countries arriving in Japan for studies, and Japanese residents abroad, visiting friends and relations. The total arrivals include, in addition to the above, shore excursionists who arrive without visas and are granted entry permits at the port of arrival. Figure 1.3 shows a steadily increasing trend in all three categories of overseas visitors.

Figure 1.3 Total, Tourist, Business and Other Arrivals to Japan from 1978 to 2003



Data Source: Japan National Tourist Organisation.

The age and gender breakdown for visitor arrivals in the year 2003 is shown in Table 1.2. These figures show 54.7% were male and 45.3% were female visitors. The age group with the largest number of male visitors (15.5%) was the 30 to 39 year category, the next largest (13.5%) being the 40 to 49 year category. The age group with the largest number of female visitors (12.0%) was the 20 to 29 year category, the next largest (10.9%) being the 30 to 39 year category.

Table 1.2 Visitor Arrivals to Japan in 2003 by Gender and Age

Age Category	Males	Females
0 to 9	99,519 (1.7 %)	95,918 (1.7 %)
10 to 19	153,875 (2.7 %)	172,668 (3.0 %)
20 to 29	497,958 (8.7 %)	689,969 (12.0 %)
30 to 39	886,872 (15.5 %)	626,723 (10.9 %)
40 to 49	772,150 (13.5 %)	442,288 (7.7 %)
50 to 59	438,403 (7.7 %)	307,091 (5.4 %)
60 and over	285,892 (5.0 %)	257,914 (4.5 %)
Total	2,727,240 (54.7%)	2,592,571 (45.3 %)

Source: Japan National Tourist Organisation.

The number of international conventions held in Japan from 1994 to 2003, and the number of international participants is shown in Table 1.3. Japan ranks 11th among countries worldwide that hold international conventions and meetings in terms of the number of conventions held. Year 2001 recorded the highest number of conventions held but there has been a decline since. October and November were the most popular months for these meetings. In 2003 Japan hosted 219 large international conventions, each with delegates from at least five countries (Source: Japan National Tourist Organisation).

Table 1.3 Number of International Conventions and Participants		
Year	Conventions	Participants
1994	1769	73315
1995	1820	76313
1996	1917	66045
1997	2163	77036
1998	2415	78862
1999	2475	73874
2000	2689	91340
2001	2737	99719
2002	2683	110791
2003	2554	106308

Source: Japan National Tourist Organisation

The number of Japanese traveling overseas each year is much larger than the number of overseas visitors to Japan. As a result, receipts from international visitors to Japan are much lower than the payments from Japanese overseas travellers. The number of Japanese overseas travellers in 2003 was 13.2 million, down from 16.5 million in 2002. In the year 2003 receipts from inbound visitors were US$ 8,848 million while payments from outbound Japanese travellers were US$ 28,959 million. Per traveller, in 2003 this amounted to receipts of US$ 1,701 per visitor and payments of US$ 1,755 per Japanese outbound traveller (World Tourism Organisation Travel Compendium, 2005).

The main visitor source countries, in decreasing order of total arrivals to Japan, for the years 1995 to 2003 are shown in Table 1.4. Though the rankings change marginally from year to year the countries within the top 12 have remained fairly consistent over the nine year period from 1995 to 2003 and unchanged from 1999. The rankings of the top three countries, Korea, Taiwan and USA have not changed since 1995.

Table 1.4 Top 12 Countries of Visitor Origin from 1995 to 2003

Ran	1995	1996	1997	1998	1999	2000-2003
1	Korea	Korea	Korea	Korea	Korea	Korea
2	Taiwan	Taiwan	Taiwan	Taiwan	Taiwan	Taiwan
3	USA	USA	USA	USA	USA	USA
4	China	China	Hong	Hong	China	China
5	UK	Hong	China	China	Hong	Hong Kong
6	Hong	UK	UK	UK	UK	UK
7	Australia	Australia	Australia	Australia	Australia	Australia
8	Philippines	Canada	Canada	Canada	Canada	Canada
9	Canada	Germany	Germany	Germany	Philippines	Philippines
10	Germany	Philippines	Philippines	Philippines	Germany	Germany
11	France	Thailand	France	France	France	France
12	Thailand	France	Singapore	Singapore	Singapore	Singapore

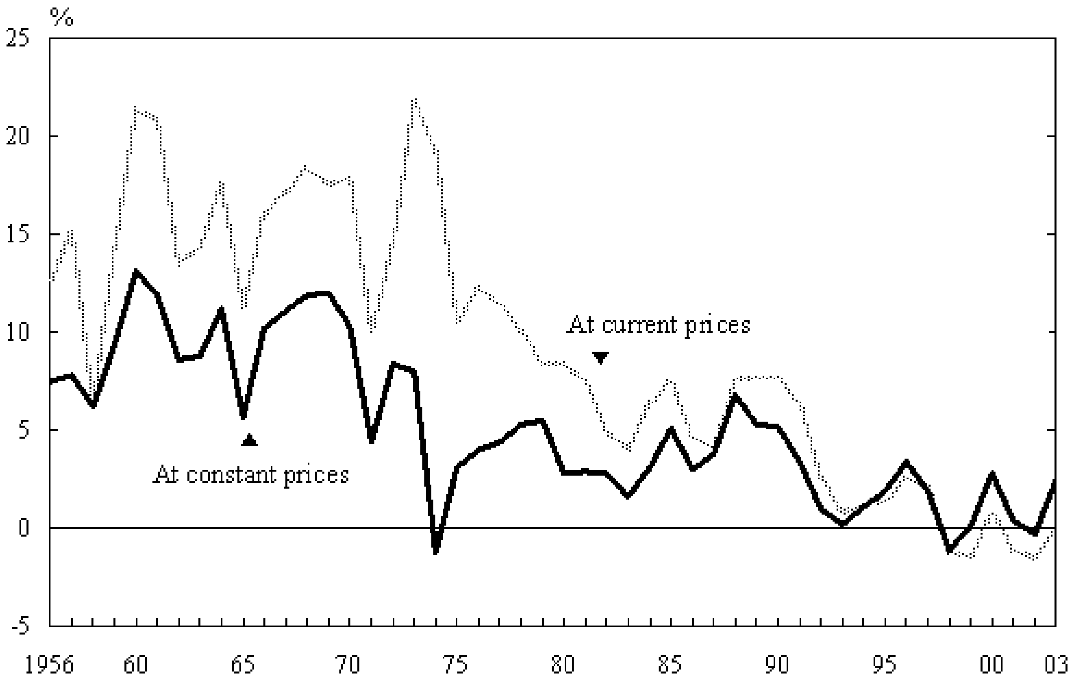
Source: Japan National Tourist Organisation.

1.8 Japan's Economy

Japan is the third largest economy after the USA and China. The reasons for Japan's economic success are its low defense budget, the achievements and strides made in high technology and commerce, the ability of industry to work closely with the government and the nationalistic approach of the workforce, which is supportive of productivity improvements. Japan's manufacturers, suppliers, and distributors have always worked together and supported each other's success. The comparatively non-unionised and non-confrontational nature of the workforce has largely been based upon the traditional assurance of lifetime employment. However, many of the traditional characteristics of the Japanese economy are changing as a result of the impact of current global trends. Japan's labor force in 2003 consisted of some 66 million workers, 40% of whom are women. Labor union membership was about 12 million. The largest sector of the Japanese economy is the service sector, which accounts for 73% of GDP. Japanese industry, accounts for 25% of GDP and stands among the world's most technologically advanced producers of motor vehicles, electronic equipment, machine tools, steel and nonferrous metals, ships, chemicals, textiles and processed foods. Robotics is one of Japan's technological strengths, with Japan possessing more than 50% of the world's 720,000 robots. However, Japanese industry is heavily dependent on imported raw materials and fuels. The agricultural sector accounts for 2% of GDP and is a protected sector. Japan imports 50% of its grain requirements. Japan's fishing industry accounts for about 15% of world production (World Trade Organisation: Japan Trade Policy Review 2000 and Wikipedia 2003).

Figure 1.4 Japan's Economic Growth Rates

(Source: Chart extracted from Japan Statistical Handbook, 2004)



1) Figures for 2003 refer to the second preliminary estimates. The data from 1956 to 1980 are based on the 1968 SNA, while those from 1981 to 2003 are based on the 1993 SNA.
Source: Cabinet Office.

Figure 1.4 shows the reducing growth rates for Japan's economy from 1956 to 2003. In the 1960s economic growth averaged over 10%. This high growth was due to high personal savings that increased investment in the private sector, the availability of quality labour, high population growth and the adoption of foreign technology. In fact during this period the USA and Europe protested about Japan's increased exports as they resulted in trade deficits with Japan. The main policy issues that were addressed during this period of growth were high pollution levels owing to increased industrial production, increased population density in urban areas and increased need for nursing facilities for the elderly.

In the 1970s economic growth slowed down and averaged 5%. In 1971 Japan revalued its fixed US dollar exchange rate of 22 years from 360 yen to 308 yen, which made exports less affordable in the US market. In 1973 Japan moved to a floating exchange rate. The 1973 Middle East war and the first oil crisis lead to high inflation and a negative growth of 1%. Japan recovered from this slump and ended the decade with a growth rate of 5%.

Economic growth slowed again at the start of the 1980s due to trade surpluses with industrial nations that resulted in appreciation of the yen. In the 1980s railway and telecommunication companies were privatised, economic policies and currency adjustments were established to control the overvaluation of the yen and economic growth was achieved through domestic demand. High-technology industries grew in the 1980's and as a result domestic demand for high-technology products increased. The domestic demand for higher standards of living, housing, healthcare and leisure activities boosted the economy. During the 1980s, the Japanese economy shifted its emphasis away from agriculture and manufacturing to telecommunications and computers. The information economy was led by highly advanced computer technology. Tokyo became a major world financial center with the Tokyo Securities and Stock Exchange becoming the world's largest stock exchange. Rapid economic growth from 1987 to 1989 helped revive the steel industry and other subsidiary manufactures that had been performing poorly in the mid 80's. In the late 1980s Japan had a sound economy with low inflation, low unemployment and high profits. The economic growth in the 1980s averaged 4%. High investments in the stock market and in real estate lead to further industrial growth and urban development.

However, in the early 1990's due to excessive speculative investments in stocks and real estate, prices commenced a corrective downward trend. This trend and low domestic consumption resulted in low economic growth. Economic growth reduced to zero in 1992. The domestic market and the US market for Japanese cars declined. The demand for Japanese electronics also declined. The main reason for the slow growth from 1992 to 1995 was excessive capitalisation in the 1980s. Due to the fall in real estate prices government intervention was necessary to support the banking sector that had obtained loans based on equity in real estate. In 1995 an earthquake hit Kobe and the increased demand for the recovery effort and the new market for mobile phones increased economic growth. Through the 1980's bad debt in financial institutions remained an obstacle to economic recovery. Economic growth increased to 4% in 1996 as a result of low rates of inflation. However, in 1997 and 1998 Japan experienced a severe recession, brought about by reduced business investment and private consumption and financial problems in the banking sector and the real estate market. In 1997 the government funded large banks to prevent them from bankruptcy, but reduced lending forced many companies to close down, resulting in a negative growth of 1.5% in 1998 making Japan the only industrialised country to be in recession. Capital, financed largely by debt, prompted firms to restrain further investment. The drop in private consumption was due to reduced household disposable income and uncertainty about the future of the social security system. Government outlays on public works were a positive growth factor in 1998 and 1999 as were net exports. In 1999 output started to increase as business confidence gradually improved. Japan's economy started to recover in 1999 due to demand for information technology and electronic components in the US and it started the new millenium with a growth of 2.5% in the year 2000 (World Trade Organisation: Japan Trade Policy Review 2000 and Statistical Handbook of Japan, 2004).

In 2000 when the IT bubble collapsed growth in Japan dropped again, resulting in negative growth in 2001. The 9/11 terrorist attack in the US also had an adverse effect on the Japanese economy with over 20,000 bankruptcies in 2001. In 2002 the world economy including Japan's slowed due to the war in Iraq and in 2003 the SARS (Severe Acute Respiratory Syndrome) epidemic affected Japan's economy as it did other Asian economies. However, in 2004 exports increased and the economy improved as a result of investments in plant and equipment (Statistical Handbook of Japan, 2004).

1.9 Japan's International Trade

Japanese government policy recognized that Japan needed to import raw materials to develop its economy, and that it needed exports to balance imports, after World War II. Japan had difficulty exporting enough to pay for its imports therefore export promotion programs and import restrictions were introduced. The tariff was Japan's principal trade policy instrument. However, more recently the government of Japan has been committed to maintaining a free and non-discriminatory multilateral trading system through the World Trade Organisation (WTO). Additionally, Japan has begun to place more emphasis than before on the possibilities of free trade agreements (FTAs) with regional and bilateral trade policies, because it regards FTAs as a way of complementing the multilateral system (World Trade Organisation: Japan Trade Policy Review, 2002).

Due to trade deficits in the years following World War II, all imported products were subject to government quotas and tariffs. Japan developed world-class industries that could export their products through competing in international markets. It also provided incentives for firms to export. By the late 50's Japan's international trade position had improved, and its favourable balance of payments indicated that import restrictions were not essential. Japan under pressure from the International Monetary Fund (IMF) and GATT, reluctantly adopted a policy of trade liberalisation, reducing import quotas and tariffs. In the 60's, export incentives took the form of tax relief but when Japan's balance of payments improved in the mid 60's, the need for export promotion incentives diminished and in 1964 Japan had to remove the tax relief on export income, to comply with requirements from the International Monetary Fund.

However, it did provide a special tax benefit to the export industry for market development and export promotion costs, but in the 70's all export tax incentives were eliminated.

In the 60's and 70's exports played a key role in Japan's economic growth. However, from the mid 80's the growth in domestic demand shifted the economy from being export oriented to being driven by domestic demand, resulting in imports growing faster than exports. By the end of the 80's, the domestic market was influencing Japan's import policy. As a result of GATT agreements, Japan had the lowest average tariff level of 2.5%, compared with 4.2% in the USA and 4.6% in the European Union. Japan's quotas also dropped from 490 items under quota in 1962, to 22 items under quota by the late 80's. Despite Japan's rather good record on tariffs and quotas, it continued to be the target of complaints and pressure from its trading partners during the 80's. Many complaints revolved around non-tariff barriers other than quotas such as technical standards, testing procedures, government procurement, and other policy that could be used to restrain imports. These barriers, by their very nature, were often difficult to document, but complaints were frequent.

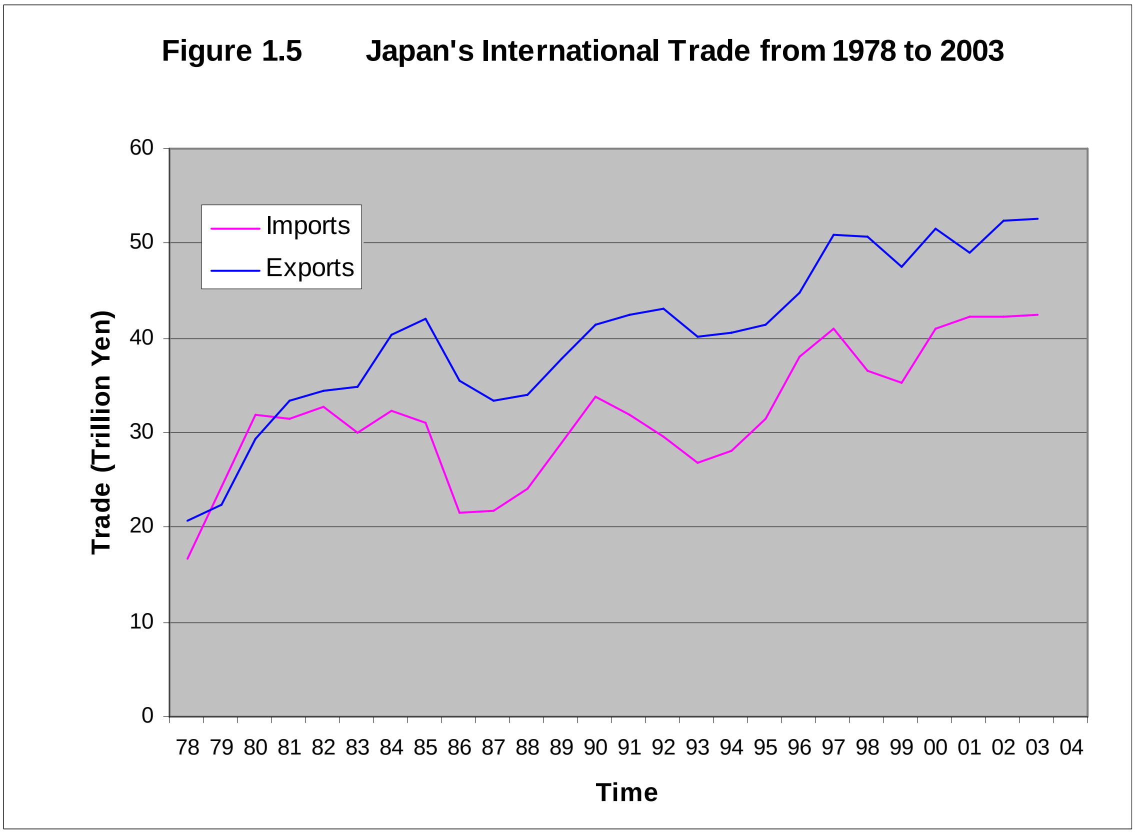
In the 1980's, voluntary export restraints were requested of Japan by many countries, which were reluctant to impose quotas on Japan in the spirit of GATT. Of the exports to the United States, steel, color televisions, and automobiles were subject to such export restraint.

The rapid appreciation of the yen after 1985, which made imports more attractive, stimulated domestic opposition to measures that restricted imports. External pressure for change also increased when the United States named Japan an unfair trading nation in 1989, and sought negotiations on forest products, supercomputers, and telecommunications satellites. Other issues raised by the USA in 1989 were, the distribution system that was able to inhibit foreign newcomers to the market, because manufacturers had strong control over wholesalers handling their products, and investment restrictions that made it very difficult for foreign firms to acquire Japanese firms. Japan was always resilient to foreign pressures but as a consequence of domestic pressure, Japan started the 90's with a more liberal import policy. Japan introduced import promotion programs that provided substantial government incentives, but they did not fully address all the relevant issues. These programs often excluded important sectors of interest to trading partners, in the agriculture and services industries, that are subject to extensive government regulation (Stern, 1994). Japan's tariff structure has not changed much since 1995 with 60% of tariff lines rated at 5% or below and high tariffs in agriculture, food manufacturing, textiles, footwear and processed items in food manufacturing and the petroleum industries. In 2000, the simple average tariff rate was 6.5% (World Trade Organisation: Japan Trade Policy Review 2000).

In the 1990's economic policy aimed at structural reform, deregulation and greater reliance on domestic, rather than export demand. The deregulation program of 1995 reduced the scope of government regulations, in financial services, telecommunications and domestic transport. However, agriculture, construction and international transport have been exempt from deregulation. Trade statistics indicate that Japan's trade surplus declined from 1992 to 1996 but the trend reversed in 1997 with the trade surplus expanding to its highest level in 1998 (World Trade Organisation: Japan Trade Policy Review, 1998).

Exports decreased in 1998 and 1999, due to the economic crisis in Southeast Asian countries. Imports decreased in 1998 and 1999, due mainly to the slump of the Japanese economy and the appreciation of the Yen. In 2001 the total value of exports from Japan decreased, mainly due to the weaker world economy. The total value of exports from Japan in 2001 was 5.2 percent less than that in 2000. In 2001, the total value of imports into Japan increased over the past two straight years, although the rate of increase had slowed down due to the domestic recession. The total value of imports in 2001 amounted to an increase of 3.6 percent from 2000. As a result, Japan's total trade surplus in 2001 decreased to create three straight years of decline.

In 2003, the total value of exports increased due to good economic conditions in Asia, Europe, and the United States. Japan's main export partners are the USA (25%), China (12%), South Korea (7%), Taiwan (7%) and Hong Kong (6%). The main export commodities are motor vehicles, semiconductors, office machinery and chemicals. Japan's main import partners are China 20%, USA 16%, South Korea 5% and Indonesia 4%. The main import commodities are fuels, foodstuffs, chemicals, textiles, raw materials, machinery and equipment (Wikipedia, 2003 and World Trade Organisation: Japan Trade Policy Review, 2000). Movements in Japan's import and export trend from 1978 to 2003 are shown in Figure 1.5.



Data Source: OECD Main Economic Indicators.

Chapter 2
Literature Review

2.1 Introduction

A forecast is a statement made in the present about expectations of the future. Forecasting could be based on speculation, intuition, surveyed opinions, expert opinion, analogies or quantitative analysis of historical patterns. Forecasts in this thesis are based on the latter, and use quantitative forecasting methods to predict future tourism flows. Quantitative forecasting methods estimate future behaviour of a system based on historical patterns or relationships in past activity. If patterns can be established for historical quantitative data series, future values of the series can be forecast (within limits), assuming the historical patterns will hold true into the future. In reality historical patterns do not flow into the future undistorted, due to random variations in the data that might occur for no known reason, variations triggered by unforeseen incidents, systemic economic and social changes in the future or due to a combination of these reasons. These uncertainties make it difficult to forecast data series to a high level of accuracy and for large horizons. However, traditional quantitative methods have been successful in providing useful forecasts to industry and government for strategy and policy formulations. The two types of models traditionally used in quantitative forecasting are, time series models and econometric models. These methods extrapolate historical patterns into the future by identifying the structure of the data and analysing the variations of the data from common data structures. There have been numerous literature reviews of tourism forecasting through to 2003, including Crouch (1994), Lim (1997), Witt and Witt (1995) and Li, Song and Witt (2005).

More recently soft computing methods such as artificial neural networks, fuzzy logic and the neuro-fuzzy hybrid have been used in forecasting and have proved to be a viable alternative to the traditional time series and econometric models. These methods do not establish traditional time series or econometric structures; instead they develop input-output relationships based on data mining.

To determine which methods provide the most accurate forecasts of tourism demand, and most definite explanations of demand fluctuations, the different quantitative forecasting procedures must be examined, tested and compared. Early studies on tourism forecasting did not evaluate the performance of different methodologies (Archer 1980, Vanhove 1980, Van Doorn 1982, Bar On 1984) but focussed upon presenting the nature of the various methodologies available. Subsequent studies have increasingly discussed performance in terms of the accuracy of the forecasts (Sheldon and Var 1985, Uysal and Crompton 1985, Calantone, Di Benedetto and Bojanic 1987, Witt and Witt 1989). In the 1990’s some studies used traditional demand modelling (Smeral et al. 1992, Syriopoulous and Sinclair 1993), while other studies showed that autoregressive integrated moving average time series models can perform better than traditional demand modelling in tourism forecasting (Witt and Witt 1992, Kulendran and King 1997). Subsequent studies have used modern econometric models (Kulendran and King 1997; Smeral and Weber 2000; Kulendran and Witt 2001; Song et al. 2003b) and the non-traditional neural network model (Law 2000). Recently, Burger et al. (2001) stated that neural networks performed best in comparison with the naïve, moving average, decomposition, single exponential smoothing, ARIMA, multiple regression and genetic regression models.

The simplest time series forecast uses the naïve method where the actual value ($\boldsymbol{A_t}$) of the current period ($\boldsymbol{t}$) is the forecast ($\boldsymbol{F_{t+1}}$) for the next period ($\boldsymbol{t+1}$). For seasonal data, the actual value ($\boldsymbol{A_{t+1-s}}$) of the corresponding period of the previous year ($\boldsymbol{t+1-s}$) is the forecast ($\boldsymbol{F_{t+1}}$) for the period ($\boldsymbol{t+1}$) where $\boldsymbol{s}$ is the number of seasons (Hanke and Reitch, 1992 and Turner and Witt, 2001b). If the data are not stationary a trend component could be introduced as follows for non-seasonal data:

$$F_{t+1} = A_t + (A_t - A_{t-1}) \, .$$

For seasonal data, the trend adjustment could be as follows:

$$F_{t+1} = A_{t+1-s} + (A_{t+1-s} - A_{t+1-2s}) \, .$$

Martin and Witt (1989a and b) and Witt and Witt (1992) suggested that econometric tourism forecasting models do not perform as well as the naïve model. However, Witt and Witt (1995) state that no single forecasting model performs consistently best across different situations, but autoregression, exponential smoothing and econometrics are worthy of consideration as alternatives to the naïve model. Kulendran and Witt (2001) found that cointegration and error correction methods performed better than least squares regression but failed to out perform the "no change" naïve model. Song et al. (2003a) confirm the findings of previous studies that the naive no change model is superior to the error correction model and the ARIMA model. Therefore, in recent publications the naïve forecasting model has become a benchmark minimum performance measure when comparing tourism forecasting models.

2.2 Univariate Time Series Models

Time series models predict the future from past values of the same series, whereby the methodology attempts to discern the historical pattern in the time series, so that the pattern can be extrapolated into the future. A relatively small amount of research has examined time series methodology (Geurts and Ibrahim 1975, Wandner and Van Erden 1980, Geurts 1982, Martin and Witt 1989a, Sheldon 1993, Turner, Kulendran and Pergat 1995, Witt, Dartus and Sykes 1992, Di Benedetto, Anthony and Bojanic 1993, Turner, Kulendran and Fernando 1997a and b, Kulendran and King 1997, Turner, Reisinger and Witt 1998, Chu 1998a). Time series models are disadvantaged by their inherent assumption that changes in particular patterns are slow rather than rapid and develop from past events rather than occur independently.

Univariate time series modeling has been receiving more attention primarily because it is based on single data series. Initially researchers used the more sophisticated Box Jenkins methodology (Geurts and Ibrahim 1975, Canadian Government Office of Tourism 1977) and decomposition methods such as Census XII (Bar On 1972, 1973, 1975). More recent research broadened the examination to include assessment of less sophisticated methods such as exponential smoothing. Moreover, comparison of performance has included assessment of forecast accuracy against naïve processes (Martin and Witt 1989b, Witt and Witt 1989a and b, Witt, Brooke and Buckley 1991, Witt 1991a,b, Witt 1992, and Witt, Dartus and Sykes 1992). These studies lead to the suggestion by Witt that within sample naïve forecasts were actually more accurate than formal forecasting methodologies.

Subsequent studies have re-examined the performance of various time series methods, including the Box Jenkins approach (Turner, Kulendran and Pergat 1995) and introduced structural models (Turner, Kulendran and Fernando 1997b) as alternatives. In so doing the need to decompose the tourism series has also been questioned (Turner, Kulendran and Fernando 1997a). Though a single method has not emerged as the most suitable forecasting technique for all situations, it is clear from these later studies that sophisticated time series forecasting methodology are at least as accurate as naïve processes.

2.2.1 Autoregressive Models

Autoregressive models were originally developed by Yule in 1926 and presented in the form of Autoregressive (AR) and Moving Average (MA) models by Slutsky in 1937 (Makridakis and Hibon, 1997). They were combined into the ARMA model by Wold in 1938 but it was Box and Jenkins (1970) who introduced the ARIMA model, which uses differencing to make a series stationary. The Box-Jenkins autoregressive integrated moving average (ARIMA) model is the most widely used univariate forecasting model. It is a combination of autoregressive component and the moving average component. The ARIMA approach is an empirical method for identifying, estimating and forecasting a time series. It does not assume any particular pattern in historical data but uses an iterative method for selecting an appropriate model by investigating the shapes of the distributions of autocorrelation coefficients and partial autocorrelation coefficients of the time series without making assumptions about the number of terms in the model or the relative weights assigned to the terms.

Makridakis and Hibon (1997) question the use of differencing in the ARIMA model to make data stationary and show that more accurate forecasts can be obtained by the ARMA(1,1) model. Turner, Kulendran and Fernando (1997a) found that the AR model with periodic data produced better forecasts than the ARIMA with non-periodic seasonal data. They also found the ARIMA forecasts superior to the naive forecast. Chu (1998b) compared a combined ARIMA and sine wave nonlinear regression model with the ARIMA model and concluded that the combined model had lower forecast errors. Lim and McAleer (2002) found that ARIMA forecast arrivals from Malaysia and Hong Kong were not as accurate as the forecasts for arrivals from Singapore to Australia. Chu (2004) compared ARIMA forecasts with a cubic polynomial model and found the ARIMA forecast had lower errors. These studies show that ARIMA may not necessarily be the most accurate forecasting method even though it might have the best fitting model. Dharmaratne (2000) obtains good forecasts using ARIMA but concludes that customised model building may be highly rewarding in terms of accurate forecasts compared to standard or simple methods. Kulendran and Witt (2003b) found that the leading indicator model does not outperform the univariate ARIMA model and that there is no advantage in moving from a univariate ARIMA model to a more complex leading indicator model. However, Turner, Kulendran and Fernando (1997b) showed that the leading indicator transfer function model with and without a composite indicator, outperforms the ARIMA model for some source countries and particularly for disaggregated business travel.

2.2.2 Basic Structural Time Series Model

The basic structural time series model introduced by Harvey and Todd (1983), deals with univariate time varying data with trend and seasonal components. The theory of structural time series modelling is explained in Harvey (1990). The model decomposes the data into its components and uses the Kalman filter in evaluating the function. Since the components of a time series are often not fixed but stochastic in nature, the basic structural model is formulated as consisting of a stochastic trend component, a seasonal component and an error term. The trend component changes from the previous period by the amount of the slope, where the slope is also stochastic and changes from period to period. The seasonal component is additive and totals to zero over the seasons in the year. Non-stationarity is handled directly without the need for explicit differencing.

In the Box-Jenkins methodology the main identification tools are the autocorrelation function and the partial auto correlation function. Harvey and Todd (1983) explain that these correlograms are not always very informative particularly with small samples. Moreover, difficulties with interpretation are compounded for a series that has been differenced. They claim the alternative is to formulate models directly in terms of trend, seasonal, and irregular components.

Turner, Reisinger, and Witt (1998) used structural modelling for tourist flows disaggregated into holiday, business and visits to friends and relatives. The study reiterates the importance of using different but appropriate explanatory variables for different destinations. Turner and Witt (2001b) found that univariate structural time series models are capable of providing reasonably accurate forecasts. While the structural model out performs naïve forecasts the Turner and Witt (2001b) study could not show improvement in the accuracy of the structural model by including explanatory variables. In fact they concluded that practitioners who are simply interested in producing accurate forecasts of international tourism demand, would be well advised to concentrate solely on univariate structural models.

2.3 Econometric Models

Econometric models search for cause and effect relationships between tourism demand and one or more variables such as price or income, with a hypothesis that these variables cause that demand. In this case tourism demand is the dependent variable and the causes are the independent variables. Causal methodology is focused upon penetrating the structure of the cause and effect relationship in order to reproduce that structure in the future to forecast tourism flows, once the independent measures have been identified.

Recent research has questioned the validity of the assumption underlying regression analysis based on ordinary least squares (OLS), (Granger and Newbould 1974, Skene 1996, Morley 1997). In particular, the suggestion has been made that the time series used in ordinary least squares regression analysis may be non-stationary, and therefore, the validity of standard statistical tests may be in doubt. In consequence, more recent analysis has been done using co-integration methodology (Kulendran 1996, Kulendran and King 1997, Song and Witt 2003). This concept introduced by

Granger and Weiss, 1983, requires economic series to converge to a common trend over time to establish a long-term relationship, which then allows for the use of the error correction model (Engle and Granger 1987) for short term deviations from the trend, which avoids the problems of spurious regression that are possible using the ordinary least squares method.

Most research has examined causal modelling: Gray 1966, Smith and Toms 1967, Artus 1970, Blackwell 1970, Oliver 1971, Artus 1972, Barry and O'Hagen 1972, Bond and Ladman 1972, Kwack 1972, Jud 1974, Jud and Joseph 1974, Cline 1975, Gapinski and Tuckman 1976, Paraskevopulos 1977, Little 1980, Witt 1980a,b, Fujii and Mak 1981, Kliman 1981, Loeb 1982, Quayson and Var 1982, Witt 1983, O'Hagen and Harrison 1984a and b, Uysal and Crompton 1985, White 1985, Papadopoulos and Witt 1985, Edwards 1985, Gunadhi and Boey 1986, Chadee and Mieczkowski 1987, Summary 1987, Witt and Martin 1987, Brady and Widdows 1988, Martin and Witt 1987 and 1988, Rosenweig 1988, Darnell, Johnson and Thomas 1990, Witt 1990, Crouch 1992, Witt, Newbould and Watkins 1992, Smeral, Witt and Witt 1992, Di Benedetto, Anthony and Bojanic 1993, Morris, Wilson and Bakalis 1995, Jorgensen and Solvoll 1996, Kulendran 1996, Kulendran and King 1997, Lim and McAleer 1999 and 2001, Preez and Witt 2003, Song and Witt. 2003, Song, Wong and Chon 2003b.

It is difficult in most cases, to use a causal model to forecast a demand figure for the future, simply because it requires the future values of the causes of travel demand (for example, price, income or advertising) to be known. The causal literature has determined that particular variables are more reliable than others, with income in the tourist's country of origin, cost of living in the destination country, travel cost, exchange rates, substitute prices for alternative destinations, special events and marketing expenditure featuring as the most used and versatile causes of tourism demand fluctuations. Although, the most recent finding by Li, Song and Witt (2005) is that no single model outperforms others for all series. This may well reflect a fundamental flaw in the current practice of assuming that all series can be forecast using the same generic independent variables, when in fact some series have different causal influences.

Song and Witt (2000) explain the demand function for tourism as a function of its determinants as follows:

$$\boldsymbol{Q_{ij} = f\,(P_i\,, P_s\,, Y_j\,, T_j\,, A_{ij}\,, \varepsilon_{ij}\,)} \quad ,$$

where, $\boldsymbol{Q_{ij}}$ is the quantity of tourism product demanded in destination $\boldsymbol{i}$ by tourists from country $\boldsymbol{j}$; $\boldsymbol{P_i}$ the price of tourism for destination $\boldsymbol{i}$; $\boldsymbol{P_s}$ the price of tourism for substitute destinations; $\boldsymbol{Y_j}$ the level of income in country of origin $\boldsymbol{j}$; $\boldsymbol{T_j}$ the consumer tastes in country of origin $\boldsymbol{j}$; $\boldsymbol{A_{ij}}$ the advertising expenditure on tourism by destination $\boldsymbol{i}$ in country of origin $\boldsymbol{j}$ and $\boldsymbol{\varepsilon_{ij}}$ the disturbance term that captures other factors which may influence $\boldsymbol{Q_{ij}}$.

Witt, Brooke, and Buckley (1991) suggest as explanatory variables per capita real income, as measured by personal disposable income; costs at the destination as measured by the consumer price index specified in real terms in the currency of the country of origin and referred to as own price; costs of transport as measured by airfares; substitute prices as measured by cost of transport and cost of living in alternative destinations; trend to represent steady changes in popularity of the destination and in tastes as measured by time; promotional activity as measured by real promotional expenditure for the destination in country of origin currency; and habit persistence as measured by lagged tourist arrivals.

Turner, Kulendran and Fernando (1997b), identified leading indicators from among national variables: income, unemployment, forward exchange rate, money supply, price ratio, industrial production, imports and exports.

Kulendran and Wilson (2000b) use openness to trade as an important determinant of business travel and show that trade openness elasticity of the four countries studied were all positive. Their previous study (2000a) identified the existence of a causal relationship between trade and international travel indicating that tourism demand in a destination country is influenced by the trade openness of that country. Kulendran and Witt (2003a) extended the research of Kulendran and Wilson (2000b) to provide a more comprehensive comparison of the accuracy of modern forecasting methods in the context of forecasting the demand for business tourism. This study which used trade openness as one of its explanatory variables found that adding explanatory variables to a univariate structural model does not improve forecasting performance. However, they found that the error correction model using the same explanatory variables generates more accurate forecasts than the causal structural model. Other explanatory variables used in this study are income, price and real gross domestic product. Airfare had not been considered an explanatory variable in this study as Kim and Song (1998) found it did not influence business travel.

Turner and Witt (2001a) considered the following as possible explanatory variables: destination living costs, airfare, retail sales, new car registrations, gross domestic product, survey of future manufacturing, survey of consumer confidence, survey of overall prospects, trade openness, exports, imports, domestic loans and number of working days lost. Lagging of independent variables was also tested though the number of lags was difficult to hypothesize, but there was little difference to the empirical results. The explanatory variables that were found to be significant in some of the tests but not necessarily all of them are: destination living costs, retail sales, new car registrations, gross domestic product, trade openness, exports, and domestic loans.

Gonzalez and Moral (1995) considered the consumer price index as a proxy for the price of tourism, and used the ratio of the consumer price index of the destination country to that of the tourist's source country adjusted by the exchange rate as the explanatory variable that represents price of tourism relative to its substitute, domestic tourism. They also used a weighted average of the industrial production index of each of the tourist source countries as a proxy for the personal disposable income of a tourist.

2.4 Artificial Neural Networks (ANNs)

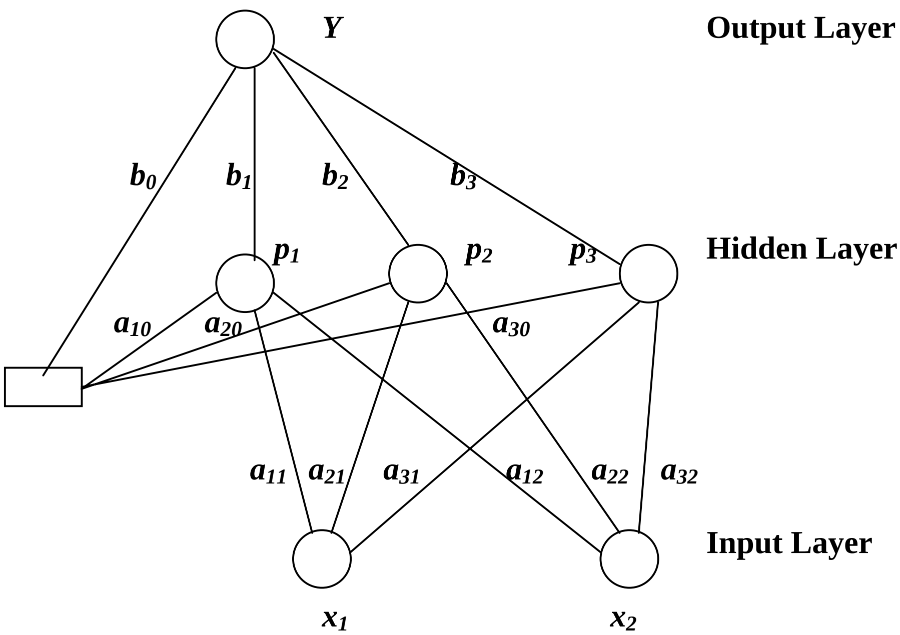
The concept of ANNs is an imitation of the structure and operation of the human brain by means of mathematical models. The ANN concept is used in forecasting, by considering historical data to be the input to a black box, which contains hidden layers of neurons. These neurons compare and structure the inputs and known outputs by non-linear weightings, which are determined by a continuous learning process (back-propagation). The learning process continues until forecast outputs are reasonably close to known actual outputs. The structure of the black box is then used for forecasting actual future outputs.

ANNs have a powerful pattern recognition capability. They learn from experience through a process of back-propagation and have been used as a forecasting technique (Sharda 1994). ANNs are data driven self-adaptive methods that capture the functional relationships within the data (Zhang, Patuwo and Hu 1998) and can be described as multivariate, non-linear and non-parametric (White 1989, Ripley 1993, Cheng and Titterington 1994). The ANN approach, which has the ability to learn from experience, is very powerful in solving practical problems if large amounts of data are available.

One type of ANN is the Multi-layer Perceptron (MLP). It has several levels of nodes, each node being called a neuron and each level being referred to as a layer. A typical MLP would have an input layer, an output layer and one or more hidden layers in between the input and the output layers. Figure 2.1 shows a neural network with an input layer with two inputs $\boldsymbol{x_1}$ and $\boldsymbol{x_2}$, one hidden layer with three hidden nodes and one output $\boldsymbol{Y}$ in the output layer.

Each node has inputs and outputs. Nodes receive a weighted sum of inputs from connected units. Nodes perform a unique function that converts the inputs into an appropriate output. This function could be to generate a 1 or a 0 depending on whether the weighted sum reached a threshold. Alternatively, a node can be programmed to perform a sigmoid, hyperbolic, or other linear or non-linear function.

Figure 2.1 Basic Structure of an Artificial Neural Network



Warner and Misra (1996), express the output $\boldsymbol{y_i}$ of neuron $\boldsymbol{i}$, at a threshold of $\boldsymbol{\mu_i}$, as,

$$y_i = 1 \qquad \text{if } \left(\Sigma a_{ij}\, x_j - \mu_i \right) \geq 0 ,$$

and $$y_i = 0 \qquad \text{if } \left(\Sigma a_{ij}\, x_j - \mu_i \right) < 0 ,$$

where $\boldsymbol{a_{ij}}$ are the weights from neuron $\boldsymbol{j}$ to neuron $\boldsymbol{i}$ and $\boldsymbol{x_j}$ are the intputs for neuron $\boldsymbol{j}$. Klimasauskas (1991) presents a hyperbolic function for the neurons of figure 2.1 as follows, where $\boldsymbol{p_i}$ are the outputs, $\boldsymbol{x_j}$ the inputs and $\boldsymbol{a_{ij}}$ the weights:

$$p_1 = \tanh \left(a_{10} + a_{11}\, x_1 + a_{12}\, x_2 \right) ,$$

$$p_2 = \tanh \left(a_{20} + a_{21}\, x_1 + a_{22}\, x_2 \right) ,$$

$$p_3 = \tanh \left(a_{30} + a_{31}\, x_1 + a_{32}\, x_2 \right) ,$$

and a sigmoid function as follows, for output ***Y*** where $\boldsymbol{p_i}$ are the inputs and $\boldsymbol{b_i}$ are the weights:

$$Y = 1 / (1 + e^{-(b0 + b1\,p1 + b2\,p2 + b3\,p3)}) .$$

Most authors use only one hidden layer (Hornik, Stinchcombe and White 1989) and a large number of hidden nodes. Some use two hidden layers (Sirinivasan, Liew and Chang 1994) to achieve a higher efficiency in the training process but this requires additional processing power.

For time series forecasting the inputs are the past observations of the data series and the output is the future value. The connectionist method presented by Gallant (1988) and Kasabov (1996a) is the most appropriate for time series forecasting where past observations are used to forecast future values. The network in Figure 2.2 illustrates how time series data ***y(t)*** are used in a univariate connectionist method.

Figure 2.2 MLP Neural Network for Univariate Forecasting

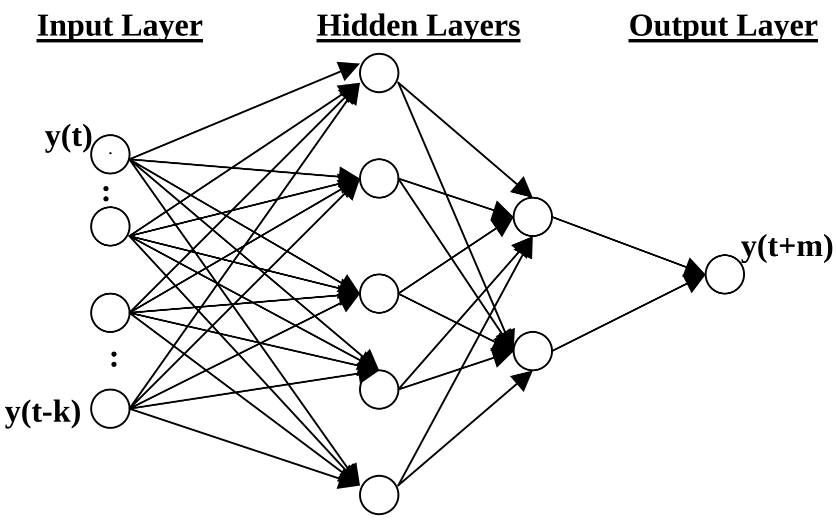
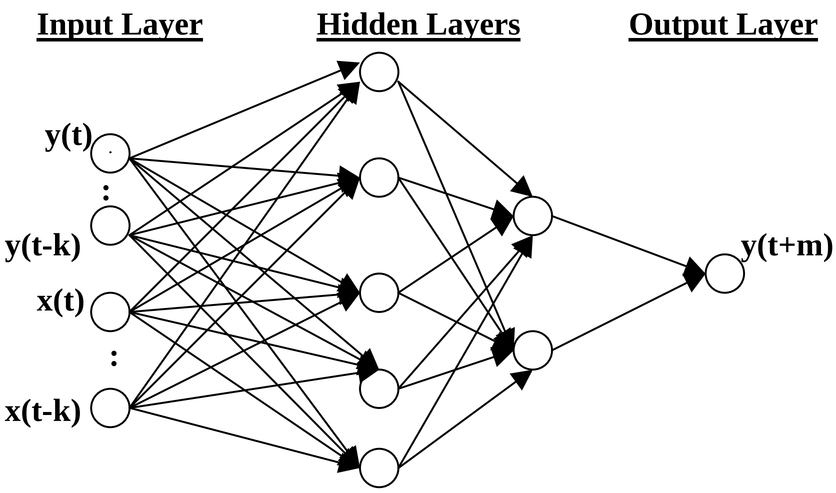


Figure 2.3 illustrates the use of ANNs for multivariate time series forecasting, where ***y(t)*** is the primary series and ***x(t)*** is a secondary series such as an economic indicator.

Figure 2.3 MLP Neural Network for Multivariate Forecasting



The concept of ANNs dates back to 1962 (Warner and Misra 1996). However, due to the non-availability of a training algorithm at that time for multi-layer networks, ANNs did not develop as a forecasting tool (Rumelhart 1986). By 1986 the back-propagation method had been developed giving ANNs a boost as a useful forecasting technique. By 1988 ANNs with back-propagation out performed regression and Box-Jenkins methods (Werbos, 1988). A further advantage of ANNs is that they do not limit the model to linearity. Lapedes and Farber (1987) concluded that ANNs can be used in forecasting non-linear time series. The traditional Box-Jenkins method assumes that the time series modeled by it are generated from linear processes (Box-Jenkins 1976, Pankratz 1983). The importance of non-linearity is recognised in the ARCH model (Engle 1982), but here too, a specific non-linear mathematical function has to be assumed at the outset without knowing whether it fits the data. ANNs on the other hand select a non-linear form by allowing the data to pass through its neurons, back-propagating until through a learning process a non-linear function is selected that fits the data. The superiority of ANNs is therefore noteworthy as they "have more general and flexible functional forms than traditional statistical methods" (Zhang, Patuwo and Hu, 1998). Zhang, Patuwo and Hu (1998) have made a comprehensive review of the ANN literature.

Several comparisons have been made of statistical and ANN methods (Hruschka 1993). ANNs can be used for modeling and forecasting non-linear time series with very high accuracy (Lapedes and Farber 1987). There are many financial applications where ANNs have been used in forecasting. Forecasting bankruptcy and business failure (Odom and Sharda 1990, Coleman, Graettinger and Lawrence 1991, Salchenkerger, Cinar and Lash 1992, Tam and Kiang 1992, Fletcher and Goss 1993, Wilson and Sharda 1994), foreign exchange rate (Weigend, Huberman and Rumelhart 1992, Refenes 1993, Borisov and Pavlov 1995, Kuan and Liu 1995, Wu 1995, Hann and Steurer 1996), stock prices (White 1988, Kimoto, Asakawa, Yoda and Takeoka 1990, Schoneburg 1990, Bergerson and Wunsch 1991, Yoon and Swales 1991, Grudnitski and Osburn 1993) and others (Dutta and Shekhar 1988, Sen, Oliver and Sen 1992, Wong, Wang, Goh and Quek 1992, Kryzanowski, Galler and Wright 1993, Chen 1994, Refenes, Zapranis and Francis 1994, Kaastra and Boyd 1995, Wong and Long 1995, Chiang, Urban and Baldridge 1996) are some of the financial applications of ANNs. Scott (2000) demonstrates that ANNs can enhance the predictive capabilities of the moving average cross-over technique employed by technical analysts when deciding on long or short trading strategy.

Other forecasting applications of ANNs include, commodity prices (Kohzadi, Boyd, Kermanshahi and Kaastra 1996), environmental temperature (Balestrino, Bini Verona and Santanche 1994), international airline passenger traffic (Nam and Schaefer 1995), macroeconomic indices (Maasoumi, Khotanzad and Abaye 1994), personnel inventory (Huntley 1991), rainfall (Chang, Rapiraju, Whiteside and Hwang 1991), student grade point averages (Gorr, Nagin and Szczypula 1994) and total industrial production (Aiken, Krosp, Vanjani and Govindarajulu 1995).

ANNs have been used in the field of tourism to classify tourist markets (Mazanec 1992), to forecast visitor behaviour (Pattie and Snyder 1996) and to forecast Japanese demand for travel to Hong Kong (Law and Au 1999). Fernando, Turner and Reznik (1999a) used ANNs successfully to forecast tourist flows to Japan from the USA. Uysal and El Roubi (1999) compared ANNs with regression analysis in tourism demand modelling. Law (2000) concluded that back-propagation ANNs out performed regression models and time series models in predicting Taiwanese demand for travel to Hong Kong. Burger et al. (2001) compared neural networks with several time series techniques to predict tourism demand from the US to Durban and concluded that the neural network method performed the best. They also found that the 12 months ahead forecast performed better than the 3 and 6 months ahead forecasts due to seasonal bias. Cho (2003) found neural network models better than ARIMA and exponential smoothing in forecasting visitor arrivals to Hong Kong from USA, Japan, Taiwan, Korea, UK and Singapore.

2.4.1 Periodic and Non-Periodic Models

In a periodic model the data of a particular season are isolated from data of other seasons to build a model for that season and forecast for that season only. While periodic models would have less data available for modeling and testing (one fourth the data for quarterly series and one 12^{th} the data for monthly series), there is a case for periodic forecasting as seasonal patterns can be isolated by a periodic model. Fernando, Reznik and Turner (1998), successfully used a periodic neuro-fuzzy model to forecast tourist arrivals to Australia. The Turner, Kulendran and Fernando (1997a) results show that the AR model with periodic data produced better forecasts than the ARIMA model with non-periodic seasonal data.

However, when models other than the AR and ARIMA were considered Turner, Kulendran and Fernando (1997a) concluded that periodic models do not increase the accuracy of forecasts. The Turner, Kulendran and Fernando (1997a) study was comparing the Holt-Winters, ARIMA and the basic structural models. It may well be that seasonal flows are not independent of the season. Consequently, this research does not use periodic models in general, however, periodic data have been used with the neural network model to test whether periodic data will make a difference to the accuracy of neural network forecasts.

2.5 Fuzzy Logic

The most recent non-traditional method that has been used in forecasting is fuzzy logic, which develops mathematical rules to deal with vagueness inherent in historical data. One way in which fuzzy logic can be applied to time series forecasting is by applying a set of fuzzy rules to describe the relationship between data clusters within and between time series. For example, one such rule could be, “If the Gross Domestic Product of Japan is high, the number of tourist departures from Japan to other countries is high”. Fuzzy rules can be derived by the study of historical time series data using data mining methods and used to forecast future values.

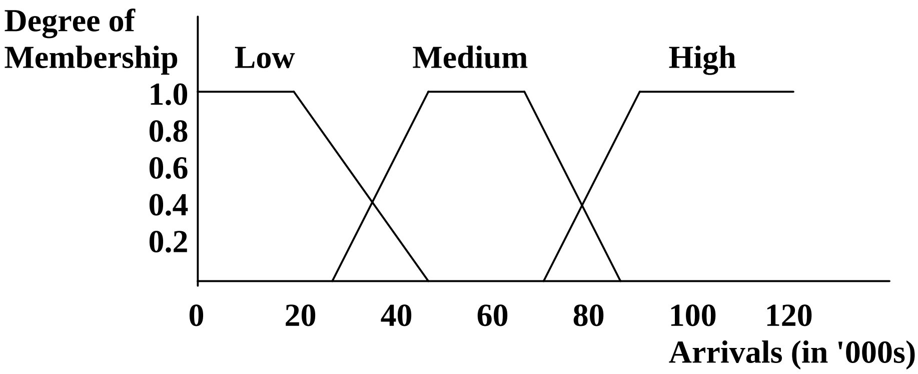
Lotfi Zadeh first developed the mathematical framework that supports fuzzy logic and fuzzy set theory in 1965. It may be regarded as a generalisation of conventional set theory (Bezdek 1993). Fuzzy sets describe the vagueness, partial truths and grayness inherent in reality. Zadeh (1973) introduced the concept of linguistic variables for the classification of values using words rather than crisp numbers. Fuzzy sets offer a more realistic classification of data by allowing partial membership of a set. In fuzzy systems, crisp measurements are converted to fuzzy membership functions, and then fuzzy logic operations are performed on these fuzzy values which are then defuzzified into crisp values again for use in real situations.

An important question that needs to be addressed is “why use fuzzy logic when crisp measurements can be used”? The answer to this question is that often, crisp precise measurements are not significant in describing reality and a precise answer does not necessarily provide the optimal solution (Zimmermann 1991). Albert Einstein's view of crisp mathematics was, "so far as the laws of mathematics refer to reality, they are not certain. And so far as they are certain, they do not refer to reality" (Reznik 1997). When the complexity of a system being analysed increases, precise and yet significant statements about its behaviour are more difficult to make. Real-world problems are so complex, the solutions are not precise, they are fuzzy (Zadeh 1973). Furthermore, in time series forecasting the factors that influence the series are so many, that it could hardly be called precise data. It is more realistic to convert the series into fuzzy clusters and use fuzzy set theory in the prediction process than to use crisp data.

In a crisp classification, for a given set ***A***, the function $\mu_A(x)$ assumes the Boolean value ***1***, if ***x*** belongs to set ***A*** or the value ***0*** if ***x*** does not belong to ***A***, for every element ***x*** in the universal set. The value ***1*** indicates that ***x*** belongs to set ***A***. In a fuzzy set, $\mu_A(x)$ can assume the value ***0.8***, a value on the scale ***0*** to ***1***, to indicate that ***x*** has a high degree of belonging to set ***A***, $\mu_B(x)$ can assume the value ***0.3*** to indicate that ***x*** has a low degree of belonging to set ***B***. This means that ***x*** can belong to both sets ***A*** and ***B*** but to a higher degree in ***A***. $\mu_A(x)$ and $\mu_B(x)$ are the membership values of ***x*** and the distributions of $\mu_A(x)$ and $\mu_B(x)$ for all values of ***x*** are the membership functions of ***x***. The value of the membership function for a given value of element ***x*** indicates whether the element belongs to the fuzzy set and to what degree. The development of a membership function is the fuzzification of crisp measurements. The membership function for tourist arrivals may be developed for example as shown in Figure 2.4.

Figure 2.4 shows that some might consider 80,000 arrivals to be high demand while others might consider it to be medium demand. Fuzzy logic recognises the inappropriateness of using the same numerical figure to describe different levels of demand for tourism perceived by different people. Therefore, a degree of vagueness or membership is assigned to linguistic clusters such as medium and high demand.

Figure 2.4 Membership Functions of a Tourist Arrival System



For example, 100,000 arrivals in the high demand category may be assigned the degree of membership 1 on the membership scale that spans from 0 to 1, where as 80,000 arrivals in the high demand category may be assigned the membership degree 0.4. On the other hand, in the medium demand category, 80,000 arrivals may be given a membership degree of 0.4 and 60,000 arrivals may be given a degree of membership 1. This means that 100,000 arrivals belong to the high demand category only, and 60,000 arrivals belong to the medium demand category only, but that 80,000 arrivals belong to both high and medium demand categories with a not very strong membership (0.4) in either. The measurement together with the degree of membership specifies the fuzziness. The distribution of the membership degrees is called the membership function. Trapezoidal membership functions of the above example are illustrated in Figure 2.4.

Once membership functions are defined for input and output data of a system, rules can be developed to establish their relationship. Rules of the form "If A then B" are the Mamdani type rules, where A could be for example "Price is high and population is low" and B could be "Arrivals are low" (Reznik 1997). Sugeno type rules (Takagi and Sugeno 1985) are of the form "If A then ***f(p,t)***", where ***f*** is a weighted function of ***p*** and ***t***, the inputs, for example price and trade.

Outputs derived using fuzzy rules and fuzzy logic operations can then be defuzzified to a crisp form to maintain commonly understood representations of the output. This process is similar to logarithmic transformation in regression analysis and the subsequent re-conversion to the original units of measure. Many different methods can be used for defuzzification. Saade (1996) uses the center of gravity method where the center of gravity of the area of the membership function, is used as the defuzzified value of the element.

Many researchers have investigated time series forecasting using fuzzy logic. Wang and Mendel (1992), and Khedkar and Keshav (1992) suggest methods of generating fuzzy rules, which are then used for forecasting. Jang and Sun (1993), present a method of predicting chaotic time series with fuzzy IF-THEN rules. Ye and Gu (1994) have developed a fuzzy system for trading at the Shanghai stock market. Benachenhou (1994) has developed a fuzzy rule extracting method for smart trading. Hybrid ANN and fuzzy systems have also been developed (McCluskey 1993, Wong and Tan 1994, Wan 1994, Bakirtzis, Theocharis, Kiartzis, and Satsios 1995, Dash, Ramakrishna, Liew, and Rahman 1995, Kim, Park, Hwang, and Kim 1995, Bataineh, Al-Anbuky, and Al-Aqtash 1996). Fiordaliso (1998) used first order Takagi_Sugeno fuzzy systems to build a nonlinear forecasting method that combined a set of individual forecasts.

2.6 Neuro-Fuzzy Models

Neuro-fuzzy models are hybrids of artificial neural networks and fuzzy logic. Fuzzy systems can be expressed in the form of an artificial neural network, and designed using the learning capability of the neural network which becomes a component of the whole neuro-fuzzy system (Reznik 1997).

The neuro-fuzzy approach combines the merits of connectionist neural networks and fuzzy approaches as a soft computing component, and rule generation from artificial neural networks has become popular due to its capability of providing some insight to the user about the symbolic knowledge embedded within the network (Mitra and Hayashi 2000). Neural networks and fuzzy systems are dynamic parallel processing systems that estimate input-output functions by a learning experience with the data, without using mathematical models. Fuzzy systems adaptively infer and modify its fuzzy associations from sample numerical data. They are advantageous in the logical field and in handling higher order processing. Neural networks can generate and refine fuzzy rules from training data and are suitable for data driven processing due to their higher flexibility. The combination of neural and fuzzy computing is an integration of the merits of neural and fuzzy approaches such as the parallel processing, robustness and learning capability of artificial neural networks and the ability of fuzzy systems to handle imprecise data (Pal and Mitra 1999). Neuro-fuzzy systems are designed to achieve the process of fuzzy reasoning, where the connection weights of the network correspond to the parameters of fuzzy reasoning (Takagi et al. 1992). Using the back-propagation learning algorithms neuro-fuzzy systems can identify fuzzy rules and learn membership functions. Neuro-fuzzy systems can be black-box type multi-layer networks used to determine input-output relations represented by a fuzzy system. According to Nauck et al. (1997) neuro-fuzzy systems should be able to learn linguistic rules and/or membership functions. Neuro-fuzzy techniques involve designing neural networks to implement fuzzy logic and fuzzy decision making, and to realise membership functions representing fuzzy sets, with an architecture that has nodes for antecedent clauses, conjunction operators and consequent clauses. Mitra and Hayashi (2000) identify five categories of neuro-fuzzy concepts:

1) Incorporating fuzziness to the neural network with fuzzy input data labels and fuzzy outputs,
2) neural networks that implement fuzzy logic and realize membership functions,
3) designing neurons to perform fuzzy operations such as unions and intersections,
4) measuring error with the degree of fuzziness, and
5) making individual input and output neurons fuzzy.

Castro, Mantas, and Benitez. (2002) developed a procedure to represent the action of an ANN in terms of fuzzy rules. They in fact extract from an ANN the fuzzy rules that express the behavior of the ANN.

There are other neuro-fuzzy hybrids where the inputs and/or outputs are fuzzy subsets with linguistic values. Here the technique would be to fuzzify the input data, assign fuzzy labels to training samples, fuzzify the learning procedure and obtain fuzzy outputs from the neural network (Mitra and Pal, 1995). In systems where the neural network has fuzzy neurons the input and output of the neurons are fuzzy sets and the activity would relate to a fuzzy process (Lee and Lee, 1975). Buckley and Hayashi (1994) classify neuro-fuzzy networks as:

1) networks with real number inputs, fuzzy outputs and fuzzy weights,
2) fuzzy inputs, fuzzy outputs and real number weights, and
3) fuzzy inputs, fuzzy outputs and fuzzy weights.

The design of neuro-fuzzy models is application specific and the literature has a wide range of successful neuro-fuzzy modelling examples. An MLP based approach to fuzzy reasoning is used by Keller and Tahani (1992), where possibility distributions of antecedent clauses are received at the input, a hidden layer is used to generate internal representations of the relationship and the resulting possibility distributions are produced at the output. Trapezoidal possibility distributions sampled at discrete points are used to represent fuzzy linguistic terms.

Ishibuchi, Tanaka, and Okada (1994) represent fuzzy input and output in an MLP with interval vectors. A back-propagation algorithm is used on a cost function defined by actual and target data. Takagi and Hayashi (1991) developed a neuro-fuzzy model that learns the membership function of the "if" statement and determines the amount of control in the "then" statement of the fuzzy rules. A systematic approach for constructing a multivariable fuzzy model from numerical data using a self organising supervised counter-propagation network, has been developed by Nie (1995). Knowledge is extracted from the data in the form of a set of rules and this rule base is then utilised by a fast learning fuzzy reasoning model with good accuracy. Cai and Kwan (1998) have also developed a fuzzy network in which the fuzzy rules and membership functions are automatically determined during training.

Jang (1993) has used the Adaptive Network-based Fuzzy Inference System (ANFIS), with a five-layer network architecture to process Sugeno type fuzzy rules of the form:

$$\text{If } \boldsymbol{x_1} \text{ is } \boldsymbol{A_1} \text{ and } \boldsymbol{x_2} \text{ is } \boldsymbol{A_2} \text{ then } \boldsymbol{y_1} = \boldsymbol{f_1(x_1,x_2)}\ ,$$

$$\text{If } \boldsymbol{x_1} \text{ is } \boldsymbol{B_1} \text{ and } \boldsymbol{x_2} \text{ is } \boldsymbol{B_2} \text{ then } \boldsymbol{y_2} = \boldsymbol{f_2(x_1,x_2)}\ .$$

The first is the membership layer. The output of the nodes of this first layer gives the membership degree of the input. The second layer is a multiplication layer where the nodes multiply the input or membership degrees from the first layer and produce the firing strength of the rule, or the degree in which the corresponding rule is fired. The third layer is the normalising layer, which calculates the ratio of the rule firing degree to the sum of all rule degrees. The fourth layer calculates the outputs $\boldsymbol{W\ f_1(x_1,x_2)}$ and $\boldsymbol{V\ f_2(x_1,x_2)}$ where $\boldsymbol{W}$ and $\boldsymbol{V}$ are the outputs from the third layer and the functions $\boldsymbol{f_1}$ and $\boldsymbol{f_2}$ are the functions of the Sugeno type fuzzy rules. The fifth layer sums up the outputs from the nodes of the fourth layer and gives the final output. Back-propagation is used to learn the antecedent membership functions, and the least mean squares algorithm determines the coefficients of the linear combinations of the resulting output from the rule. The rule base must be known in advance as ANFIS adjusts only the membership functions of the antecedent and consequent parameters.

Chak, Feng, and Ma (1998) have developed a neuro-fuzzy network that can locate its rules and optimise their membership functions by competitive learning and the use of the Kalman filter to have fewer rules. Berenji and Khedkar (1992) use a supervised learning procedure that has a soft minimum function that can be differentiated to design a neuro-fuzzy controller that is suitable for applications where interpretation is not as important as performance (Mitra and Hayashi 2000). Rutkowski and Cpalka (2003) have designed a flexible neuro-fuzzy system where the parameters or the membership function and the type of system can be identified. Azeem, Hanmandlu, and Ahmad (2000) extends the ANFIS model to a generalized ANFIS encompassing the Takagi-Sugeno model and the fuzzy rule base. Paul and Kumar (2002) have developed a fuzzy neural inference system that has the flexibility to handle both numeric and linguistic inputs.

Yupu, Xiaoming and Wengyuan (1998) use a genetic algorithm to search for optimal fuzzy rules and membership functions. The design combines prior knowledge about the system with the learning ability to obtain optimal results. Farag, Quintana and Lambert-Torres (1998) first find the initial parameters of the membership function Kohenen's classification algorithm and then extract linguistic fuzzy rules.

Knowledge-based networks that use the connectionist model first introduced by Gallant (1988), are data dependent. The number of nodes to be used depends on the amount of training data. Embedding initial knowledge in the network topology is one method of obtaining optimal results. Knowledge based networks require fewer sets of training data. In neuro-fuzzy models the fuzzy sets enhance the artificial neural networks, making knowledge-based networks more efficient. Knowledge extracted from experts in the form of membership functions and fuzzy rules can be used to pre weight the neural structure. Kasabov (1996b) used a five layered feed forward architecture with the second layer calculating fuzzy input membership functions, the third layer representing fuzzy rules, the fourth layer calculating output membership functions and the fifth layer calculating output defuzzification.

2.7 Neuro-Fuzzy Modelling of Time Series

The connectionist network presented by Gallant (1988), and Kasabov (1996b) is the most suitable artificial neural network model for forecasting time series. The connectionist model can be combined with fuzzy logic to design a neuro-fuzzy model. Time series data are always crisp values. These crisp values are first fuzzified by creating membership functions and then fed into the connectionist neural network. At the last layer of the network the fuzzy output is defuzzified. The model is similar to that used by Nie (1995) and Cai and Kwan (1998).

Abraham, Chowdhury and Petrovic-Lazarevic (2001) used a Takagi-Sugeno type ANFIS model to predict the Australian foreign exchange market. Sonja, Coghill and Abraham (2001) used ANFIS to monitor cigarette smoking by minors. Abraham (2002) used the Evolving Fuzzy Neural Network (EfuNN) to implement a Mamdani model and the Adaptive Neuro Fuzzy Inference System (ANFIS) to implement a Takagi-Sugeno model, to forecast rainfall over a 10 year test period. Based on historical data of four previous years the fifth year's monthly rainfall was forecast. Castillo and Melin (2002) use neural network, fuzzy logic and fractal theory to predict time series of exchange rates, and concluded that the method was superior to classical regression models. However, no work has yet been published on tourism demand forecasting using fuzzy logic or a hybrid system, although Fernando, Reznik and Turner (1998 and 1999b), successfully used multivariate national indicators in forecasting tourist arrivals to Australia using a neuro-fuzzy system.

Chapter 3
Neural Network Multi-layer Perceptron Models

3.1 Introduction

Artificial neural networks have been used extensively as a forecasting tool and more recently for forecasting tourism flows. Fernando, Turner and Reznik (1999a), Law and Au (1999), Law (2000), Cho (2003) and Kon and Turner (2005) used artificial neural network models to forecast tourism demand. The multi-layer perceptron is a category of neural networks that uses feed forward back propagation to establish the relationship between inputs and outputs by training the network using a supervised learning method to model linear and non linear data. Neural networks can model univariate as well as multivariate data but this study aims to explore its univariate forecasting performance. Neural networks do not have any pre-conditions or assumptions for the pattern or variations in historical data but through an iterative process develop a model that fits the data. However, too close a fit may not be desirable, as it would not allow for random variations in the future.

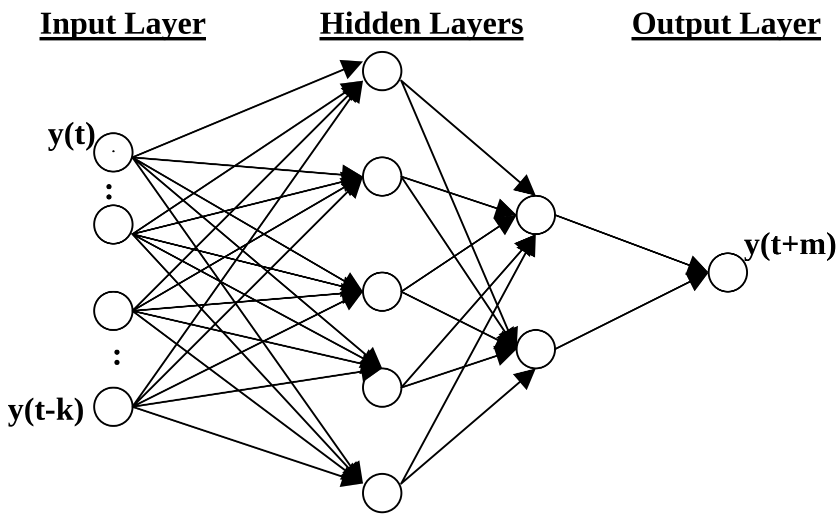
This chapter consists of a comparison of three, univariate artificial neural network (ANN) multi-layer perceptron (MLP) forecasting models. The three models compared are a non-periodic model, a partial periodic model and a periodic model. The forecasting performance of the neural network models is compared with that of the naïve model, which is considered in this study as the minimum benchmark for forecasting performance. The non-periodic model and the partial periodic model are run with differenced data and with undifferenced data, to test, which provides better forecasts using MLP networks.

The variable being forecast is tourist arrivals to Japan. Monthly tourist arrivals from Australia, China, France, Germany, Korea, Singapore, Taiwan, UK, the USA and total arrivals from all countries, from January 1978 to December 2001, to forecast arrivals for the 24 month period from January 2002 to December 2003. Forecasts are made for tourist arrivals from each of the above countries, one month ahead, 12 months ahead, and 24 months ahead, to test whether the forecasting accuracy is consistent for arrivals to Japan from different countries and for different forecasting horizons. The criterion for comparing models is the forecasting accuracy as measured by the MAPE of the 24 month out of sample period from January 2002 to December 2003, which is divided into one and two year lead periods. The aim of this study is to determine which empirical neural network model would provide the best forecast for tourist arrivals data.

3.2 The Multi-Layer Perceptron Model

In this study, the artificial neural network (ANN) multi-layer perceptron (MLP) model with two hidden layers containing sigmoid and tanh nodes is used in a connectionist neural network. Figure 3.1 shows the univariate connectionist model used to forecast **m** periods ahead using the time series **y(t**) with **k+1** periods of data. Tourist arrivals to Japan from January 1978 to December 2001 are taken as the input series. The number of input nodes represents the number of input variables in the model. In a univariate model lags of the series or differenced series can be used as variables.

Figure 3.1 Connectionist MLP Model for Univariate Forecasting



Input nodes have a linear transformation to the nodes of the next layer, as follows:

$$z_j = \Sigma w_{ij} x_j \quad ,$$

where x is the input signal for input node j, z is the output to the next node i and w is the connecting weight between node j and node i. This transformation is applied to every node of the network including the output layer.

Given limitations in data size and processing capacity a MLP network will not normally have more than two layers. Most researchers use only one hidden layer (refer to Kon and Turner, 2005). However, as monthly data of a 20-year period are used in this study, it is important to capture the linear and non-linear patterns of within sample data by providing the network with transfer functions that could transform input data to match output data patterns. Two hidden layers are used in this study with tanh functions at each node of the first layer and sigmoid functions at each node of the second layer. The tanh function is of the form:

$$f(z) = tanh(z) = (e^{z} - e^{-z})/(e^{z} + e^{-z}) \quad .$$

The sigmoid function is of the form:

$$f(z) = 1/(1 + e^{-z}) \quad .$$

The number of nodes in a hidden layer depend on the volume of input data, as the total number of node-to-node connections must be at most less than the number of within sample data points. As monthly tourist arrivals are known to be seasonal 12 nodes are used in each hidden layer as far as data numbers permit. In 12 and 24 months ahead forecast horizons, when the within sample has fewer data points, the number of nodes in the hidden layers is reduced but kept, as far as possible, to multiples of 4 nodes to facilitate capture of seasonality.

The MLP models were run using DataEngine software. The data were prepared on MS Excel and imported by DataEngine where it was scaled within the range 0.4 to 0.6 in the 0 to 1 domain and separated into training, test and recall files. The network architecture was set, specifying the number of nodes, the transfer functions, the input and output files and the initial weights and learning rates.

The MLP model used is a feed forward model, where the outputs from the nodes in the input layer are fed forward to the nodes of the first hidden layer, the outputs from the nodes of the first hidden layer are input to the nodes of the second hidden layer and the outputs from the nodes of the second hidden layer are input to the output node.

The back-propagation feature of the model is used where the difference between the output and the expected output is fed back to the nodes of the network, and the weights adjusted in an iterative process, until the difference is reduced to a preset level. Back-propagation with momentum is used to quicken the training phase while still maintaining a small learning rate, which would otherwise require a high processing time. However, a flat root mean square error curve would be an indication that the learning error has been set too low.

The network configuration used in the MLP models is as follows:
Input layer transfer function: linear
1st Hidden layer transfer function: tanh
2nd Hidden layer transfer function: sigmoid
Output layer transfer function: linear
Learning Method: Back propagation, single step
Learning parameters for all layers: Learning rate 0.1, Momentum 0.1
Weight initialization –0.1 to 0.1
Stop condition 1000 epochs.

In neural network modelling trend and seasonality in a time series can be dealt with by taking the 1st and 12th difference of the data to remove trend and seasonal effects, respectively, prior to analysis. Alternatively, the neural network could be allowed to model and capture the trend and seasonality. Nelson, Hill, Remus et al. (1999) addressed this issue by deseasonalising the data and concluded from their study that when there was seasonality in a time series, forecasts from neural networks estimated on deseasonalised data were significantly more accurate than the forecasts produced by neural networks that used data that were not deseasonalised. One possible explanation they present for their results is that neural networks that use deseasonalised time series do not have to focus on learning the seasonal components and can therefore pick-up other residual patterns.

Three MLP models are compared in this study. The first is the non-periodic model used by Fernando, Turner and Reznik (1999a) based on Freisleben (1992). The inputs to this model are the 12 previous monthly arrivals. The output is the arrivals figure of the following month for a one-month ahead forecast horizon, or of the corresponding month of the following years for 12 and 24 months ahead forecasts. The non-periodic model for a ***k*** period horizon is of the form:

$$x_{t+k} = f(x_t, x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}, x_{t-5}, x_{t-6}, x_{t-7}, x_{t-8}, x_{t-9}, x_{t-10}, x_{t-11}) \quad .$$

As long term trend and seasonality can be presumed inherent in most tourist arrivals series, the 1st and 12th differenced data are used in an alternative non-periodic model. Removing trend by taking the 1st difference and seasonal variations by taking the 12th difference would leave the network only the task of capturing some of the residual variation. The non-periodic model using first differenced **(∇_1)** and twelfth differenced **(∇_{12})** data for a ***k*** period horizon is of the form:

$$\nabla_1 \nabla_{12} x_{t+k} = f(\nabla_1 \nabla_{12} x_t, \nabla_1 \nabla_{12} x_{t-1}, \nabla_1 \nabla_{12} x_{t-2}, \ldots, \nabla_1 \nabla_{12} x_{t-11}) \quad .$$

The second MLP model used in this study is a partial periodic model that uses tourist arrivals data lagged by 12, 24 and 36 months as inputs. In this model each month's arrivals are matched against the three previous years' (lagged) arrivals of the same calendar month. Since only the three previous years' arrivals in a calendar month are taken at a time, as inputs, the model is partial periodic. No attempt was made to test for autocorrelation, as tourist arrivals are mostly seasonal. Subsequent ARIMA estimation has proved this to be the case. In an MLP partial periodic model arrivals from all calendar months may influence the output, unlike in a full periodic model where only data of a specific calendar month would be modelled at a time. However, the use of lagged series relieves the model of having to capture much of the seasonal component. The partial periodic model is as follows:

$$x_t = f(x_{t-12}, x_{t-24}, x_{t-36}) \quad .$$

An alternative partial periodic model would uses 1st differenced data. The tourist arrivals series are observed from graphical patterns to be non-stationary. Subsequent unit root testing (refer Chapter 5) confirmed the non-stationary nature of the data. The series are made stationary by taking the first difference so that the MLP model would be required to capture only some of the residual variations in the series. Further, forecasts of a stationary series will remain within the data domain of the within sample series, without crossing the domain boundaries defined at the outset, making the neural network more efficient. This model which uses the 1st difference of the tourist arrivals time series $\nabla_1 x_t$ lagged by 12, 24 and 36 months as the inputs is of the form:

$$\nabla_1 x_t = f(\nabla_1 x_{t-12}, \nabla_1 x_{t-24}, \nabla_1 x_{t-36}) \quad .$$

The third MLP model used is the periodic model. The inputs to this model are the tourist arrivals series of a specific month lagged by 12, 24 and 36 months. The output is the arrivals figure of that month in the forecast horizon, for example, $\boldsymbol{xjan_t}$ for January of year $\boldsymbol{t}$. As differenced data used in the previous MLP models produced poor forecasting results no attempt was made to difference the data for this model. The periodic model for a ***12*** period horizon is of the form:

$$xjan_t = f(xjan_{t-12}, xjan_{t-24}, xjan_{t-36}) \quad ,$$

$$xfeb_t = f(xfeb_{t-12}, xfeb_{t-24}, xfeb_{t-36}) \quad ,$$

$$\vdots$$

$$xdec_t = f(xdec_{t-12}, xdec_{t-24}, xdec_{t-36}) \quad .$$

3.3 The Naïve Model

The basic concept of the naïve model is the use of the current period's actual as the next period's forecast. This simple forecast does not involve any mathematical modelling or elaborate computations. Therefore, it forms the benchmark when testing the adequacy of forecasting models. Any forecasting model that does not perform at least as well as the naïve model should not be considered adequate.

For seasonal data, the actual value (A_{t+1-s}) of the corresponding season of the previous year ($t+1-s$) is the forecast (F_{t+1}) for the period ($t+1$) where s is the number of seasons (Hanke and Reitch 1992 and Turner and Witt 2001):

$$F_{t+1} = A_{t+1-s} \quad .$$

Since monthly data are used in this study, s = 12, naïve forecasts for the one month ahead forecasting horizon are made as follows:

$$F_{t+1} = A_{t-11} \quad .$$

Naïve forecasts for the 12 months ahead forecasting horizon are made as follows

$$F_{t+12} = A_{t.} \quad .$$

For horizons greater than 12 months, the actual value of a particular month of the penultimate year of the horizon is used as the forecast for the corresponding month. The naïve forecast for the 24 months ahead horizon is as follows:

$$F_{t+24} = A_t \quad .$$

3.4 MLP Non-Periodic Forecasts

3.4.1 Non-periodic forecast of arrivals from all countries

Table 3.4.1 shows the non-periodic forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead forecasting horizon, but is fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead forecasting horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period and the model forecasts best over the 24 months-ahead forecasting horizon.

Table 3.4.1 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	30599	5.50	38932	7.86	24071	4.43
2 year	53203	9.79	59098	11.23	55423	10.19

3.4.2 Non-periodic forecast of arrivals from Australia

Table 3.4.2 shows the non-periodic forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also good (MAPE less than 10%) for all three forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 3.4.2	ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Australia					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	895	5.06	1026	5.71	905	5.81
2 year	1184	6.62	1170	6.80	1234	6.98

3.4.3 Non-periodic forecast of arrivals from Canada

Table 3.4.3 shows the non-periodic forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead forecasting horizon, but is fair (MAPE between 10% and 20%) for the one month ahead and 24 months ahead forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.4.3	ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Canada					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	908	6.81	897	6.75	907	6.21
2 year	1308	10.02	1323	9.94	1555	10.99

3.4.4 Non-periodic forecast of arrivals from China

Table 3.4.4 shows the non-periodic forecasting performance for tourist arrivals to Japan from China. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is poor (MAPE 20% or more) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.4.4 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5905	14.58	4750	11.31	7510	17.50
2 year	9214	27.95	8749	27.45	10039	32.29

3.4.5 Non-periodic forecast of arrivals from France

Table 3.4.5 shows the non-periodic forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also good (MAPE less than 10%) for all three forecasting horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.4.5	ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	538	6.05	547	6.47	407	4.36
2 year	816	8.67	850	9.53	811	9.12

3.4.6 Non-periodic forecast of arrivals from Germany

Table 3.4.6 shows the non-periodic forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for all three forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 3.4.6	ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1021	7.08	1003	7.17	1037	9.47
2 year	1216	10.16	1174	10.48	1328	12.83

3.4.7 Non-periodic forecast of arrivals from Korea

Table 3.4.7 shows the non-periodic forecasting performance for tourist arrivals to Japan from Korea. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead forecasting horizon and fair (MAPE between 10% and 20%), for the 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and 12 months ahead forecasting horizons and poor (MAPE 20% or less) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 3.4.7 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Korea

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	16326	9.64	18874	12.73	26949	19.32
2 year	22754	12.32	24806	15.02	37127	23.02

3.4.8 Non-periodic forecast of arrivals from Singapore

Table 3.4.8 shows the non-periodic forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is poor (MAPE 20% or less), for the one month ahead and 12 months ahead forecasting horizons and fair (MAPE between 10% and 20%), for the and 24 months ahead forecasting horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period and the model forecasts are poor.

Table 3.4.8 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Singapore

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1934	22.22	1797	21.56	1323	13.08
2 year	2128	30.17	1992	28.11	2049	26.49

3.4.9 Non-periodic forecast of arrivals from Taiwan

Table 3.4.9 shows the non-periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead and 12 months ahead forecasting horizons and good (MAPE less than 10%), for the 24 months ahead forecasting horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.4.9 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	10908	10.41	11827	12.65	6325	7.52
2 year	18132	29.35	19603	33.99	19217	32.62

3.4.10 Non-periodic forecast of arrivals from the UK

Table 3.4.10 shows the non-periodic forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead and 12 months ahead horizons and poor (MAPE 20% or less), for the 24 months ahead horizon. For the two year lead period, the performance is fair (MAPE between 10% and 20%), for the one month ahead and 12 months ahead horizons and poor (MAPE 20% or less), for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.4.10 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from the UK						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	3167	13.48	3545	16.65	7675	40.78
2 year	2868	13.61	3838	19.29	6106	31.98

3.4.11 Non-periodic forecast of arrivals from the USA

Table 3.4.11 shows the non-periodic forecasting performance for tourist arrivals to Japan from the USA. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and the 24 months ahead forecasting horizons, but is fair (MAPE between 10% and 20%) for the 12 months ahead forecasting horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months-ahead forecasting horizon.

Table 3.4.11 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from the USA						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5766	6.44	6256	7.55	3184	3.75
2 year	7354	9.39	7930	10.60	7189	9.35

3.5 MLP Non-Periodic Forecast with first and twelfth differences ($\nabla_1 \nabla_{12}$)

3.5.1 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from all countries

Table 3.5.1 shows the non-periodic forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for all three forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.5.1 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	68204	13.45	50320	11.27	73072	16.14
2 year	84950	17.62	64189	13.25	72604	16.22

3.5.2 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Australia

Table 3.5.2 shows the non-periodic forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead forecasting horizon, poor (MAPE 20% or less) for the 12 months ahead horizon and good (MAPE less than 10%), for the 24 months ahead horizon. For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the one month ahead horizon, poor (MAPE 20% or less) for the 12 months ahead horizon and good (MAPE less than 10%), for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 3.5.2 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Australia

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1917	11.82	4849	34.20	1369	8.47
2 year	1982	11.56	3910	24.82	1711	9.84

3.5.3 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Canada

Table 3.5.3 shows the non-periodic forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead and 24 months ahead forecasting horizons and poor (MAPE 20% or less) for the 12 months ahead horizon. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead horizon and poor (MAPE 20% or less) for the 12 months ahead and 24 months ahead horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months-ahead forecasting horizon.

Table 3.5.3 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Canada

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	2390	17.27	3118	27.08	1773	11.00
2 year	2656	19.74	2912	24.49	2724	21.59

3.5.4 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from China

Table 3.5.4 shows the non-periodic forecasting performance for tourist arrivals to Japan from China. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead forecasting horizon and poor (MAPE 20% or less) for the 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period and the model forecasts are poor.

Table 3.5.4 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	6249	12.29	9413	20.87	16658	41.67
2 year	9468	28.98	10473	32.29	18640	46.75

3.5.5 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from France

Table 3.5.5 shows the non-periodic forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead, 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%), for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.5.5	ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1558	17.58	1167	13.51	1549	19.49
2 year	1786	19.88	1150	13.75	1382	16.28

3.5.6 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Germany

Table 3.5.6 shows the non-periodic forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead forecasting horizon and fair (MAPE between 10% and 20%), for the 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%), for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases as the lead period increases, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.5.6	ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1151	8.91	1375	11.37	1430	14.21
2 year	2223	17.88	1494	13.00	1352	13.51

3.5.7 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Korea

Table 3.5.7 shows the non-periodic forecasting performance for tourist arrivals to Japan from Korea. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead and 12 months ahead forecasting horizons and poor (MAPE 20% or less) for the 24 months ahead horizon.

For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the one month ahead and 12 months ahead forecasting horizons, and poor (MAPE 20% or less) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.5.7 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Korea

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	12082	10.23	17108	13.23	34840	29.28
2 year	21695	12.48	22791	15.12	37311	26.23

3.5.8 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Singapore

Table 3.5.8 shows the non-periodic forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead and 24 months ahead forecasting horizons and fair (MAPE between 10% and 20%) for the 12 months ahead horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period and the model forecasts are poor.

Table 3.5.8 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Singapore

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	3431	34.71	1488	13.91	2563	32.22
2 year	3441	49.53	2164	28.52	3052	36.89

3.5.9 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Taiwan

Table 3.5.9 shows the non-periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are poor.

Table 3.5.9 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	49044	38.68	11840	13.30	10510	12.06
2 year	47713	67.58	26937	43.84	22029	36.82

3.5.10 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from the UK

Table 3.5.10 shows the non-periodic forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are poor.

Table 3.5.10 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from the UK						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	8454	33.51	10209	49.57	14159	70.67
2 year	11116	37.17	17043	89.55	11367	55.75

3.5.11 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from the USA

Table 3.5.11 shows the non-periodic forecasting performance for tourist arrivals to Japan from the USA. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.5.11 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from the USA						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	6731	8.10	6124	8.69	4368	5.76
2 year	10772	13.27	12175	17.38	10308	14.60

3.6 MLP Partial Periodic Forecast

3.6.1 Partial Periodic forecast of arrivals from all countries

Table 3.6.1 shows the non-periodic forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.6.1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	24943	4.87	31537	6.46	35722	7.14
2 year	55528	10.24	55720	10.38	55688	11.38

3.6.2 Partial periodic forecast of arrivals from Australia

Table 3.6.2 shows the non-periodic forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is also good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.6.2	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Australia					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	598	3.68	465	2.98	886	5.56
2 year	992	5.38	923	4.92	1245	7.39

3.6.3 Partial Periodic forecast of arrivals from Canada

Table 3.6.3 shows the non-periodic forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is also mostly good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.6.3	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Canada					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	758	5.36	730	5.10	1047	7.79
2 year	1305	9.00	1339	8.85	1359	10.01

3.6.4 Partial Periodic forecast of arrivals from China

Table 3.6.4 shows the non-periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.6.4 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	4709	10.13	5483	11.72	9405	20.75
2 year	9099	28.34	8339	26.05	11230	32.83

3.6.5 Partial Periodic forecast of arrivals from France

Table 3.6.5 shows the non-periodic forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is also good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.6.5	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from France				
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	411	4.49	408	4.07	734	8.46
2 year	786	8.00	810	7.87	767	8.79

3.6.6 Partial Periodic forecast of arrivals from Germany

Table 3.6.6 shows the non-periodic forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is also good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.6.6	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1015	7.60	1019	7.34	1053	8.07
2 year	1076	9.73	1077	9.48	990	8.60

3.6.7 Partial Periodic forecast of arrivals from Korea

Table 3.6.7 shows the non-periodic forecasting performance for tourist arrivals to Japan from Korea. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon.

For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons, and poor (MAPE 20% or less) for and 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 3.6.7 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Korea

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	17910	11.48	18324	12.74	27127	21.60
2 year	21062	12.74	25700	15.43	35624	24.07

3.6.8 Partial Periodic forecast of arrivals from Singapore

Table 3.6.8 shows the non-periodic forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.6.8 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Singapore

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1480	16.33	1455	16.70	1319	13.92
2 year	1893	25.94	1765	25.22	1934	25.47

3.6.9 Partial Periodic forecast of arrivals from Taiwan

Table 3.6.9 shows the non-periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and the 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.6.9 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	6383	7.15	6522	7.46	8291	8.74
2 year	18696	31.55	18532	31.63	21118	35.15

3.6.10 Partial Periodic forecast of arrivals from the UK

Table 3.6.10 shows the non-periodic forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead, the 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead horizon, and poor (MAPE 20% or less) for the 12 months ahead and 24 months ahead forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error is inconsistent and the model forecasts are poor.

Table 3.6.10	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from the UK					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	3967	20.00	3969	20.96	17523	97.44
2 year	3654	17.95	3828	20.06	14564	81.55

3.6.11 Partial Periodic forecast of arrivals from the USA

Table 3.6.11 shows the non-periodic forecasting performance for tourist arrivals to Japan from the USA. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is also good (MAPE less than 10%) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.6.11	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from the USA					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	4375	5.24	4769	6.07	2926	4.13
2 year	6644	8.57	7367	9.81	7628	9.85

3.7 MLP First Differenced (∇_1) Partial Periodic Forecast

3.7.1 ∇_1 Partial Periodic forecast of arrivals from all countries

Table 3.7.1 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon. For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.7.1 ∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	71005	15.71	85400	19.38	98663	22.37
2 year	74336	16.45	87939	19.40	100756	21.65

3.7.2 ∇_1 Partial Periodic forecast of arrivals from Australia

Table 3.7.2 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon. For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.7.2 ∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Australia

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	2415	15.74	1494	10.17	3554	25.33
2 year	2480	15.45	2829	16.98	3527	23.66

3.7.3 ∇_1 Partial Periodic forecast of arrivals from Canada

Table 3.7.3 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead forecasting horizon, good (MAPE less than 10%) for the 12 months ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%), for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.7.3 ∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Canada

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	2796	20.96	1153	8.12	2156	17.26
2 year	2253	17.04	1910	14.57	1981	16.52

3.7.4 ∇_1 Partial Periodic forecast of arrivals from China

Table 3.7.4 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from China. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead, the 12 months ahead and the 24 months ahead horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the model forecasts are poor.

Table 3.7.4 ∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	14198	34.06	21044	51.62	20663	50.89
2 year	14205	38.44	20474	51.56	21828	52.61

3.7.5 ∇_1 Partial Periodic forecast of arrivals from France

Table 3.7.5 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.7.5	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1545	19.30	1154	14.67	1743	23.20
2 year	1368	15.94	1429	16.98	1496	18.46

3.7.6 ∇_1 Partial Periodic forecast of arrivals from Germany

Table 3.7.6 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead, the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.7.6	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1448	14.12	1394	11.95	1255	10.37
2 year	1365	13.49	1443	12.55	1239	10.53

3.7.7 ∇_1 Partial Periodic forecast of arrivals from Korea

Table 3.7.7 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Korea. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead, the 12 months ahead and the 24 months ahead horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the model forecasts are poor.

Table 3.7.7	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Korea					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	29241	25.42	31518	28.17	41872	37.07
2 year	33792	25.34	36208	28.08	41522	32.46

3.7.8 ∇_1 Partial Periodic forecast of arrivals from Singapore

Table 3.7.8 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead forecasting horizon and the 24 months ahead and poor (MAPE 20% or less) for and 12 months ahead horizon. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.7.8	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Singapore					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1362	14.29	1867	20.43	1616	16.35
2 year	1788	24.02	1923	26.52	2044	26.01

3.7.9 ∇_1 Partial Periodic forecast of arrivals from Taiwan

Table 3.7.9 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 24 months ahead forecasting horizons and good (MAPE less than 10%) for the 12 months ahead horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon, for a one-year lead period.

Table 3.7.9 ∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	9523	10.39	7607	8.69	13754	17.72
2 year	19992	35.48	18934	33.04	21444	35.18

3.7.10 ∇_1 Partial Periodic forecast of arrivals from the UK

Table 3.7.10 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead, the 12 months ahead and the 24 months ahead horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the model forecasts are poor.

Table 3.7.10	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from the UK					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	14745	76.71	9762	51.56	19815	108.73
2 year	14878	83.22	9157	51.32	15778	85.04

3.7.11 ∇_1 Partial Periodic forecast of arrivals from the USA

Table 3.7.11 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from the USA. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is good (MAPE less than 10%) for the one month ahead and the 12 months ahead forecasting horizons and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.7.11	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from the USA					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5597	7.58	5026	6.89	6713	9.73
2 year	7074	9.82	6151	9.05	7639	11.34

3.8 MLP Periodic Forecast

3.8.1 Periodic forecast of arrivals from all countries

Table 3.8.1 shows the periodic forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.1 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	35420	6.85	33861	7.04
2 year	n/a	n/a	57341	10.73	54170	10.87

3.8.2 Periodic forecast of arrivals from Australia

Table 3.8.2 shows the periodic forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is also good (MAPE less than 10%) for the 12 months ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.2	ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Australia					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	732	3.59	2054	11.58
2 year	n/a	n/a	2282	6.82	2325	13.38

3.8.3 Periodic forecast of arrivals from Canada

Table 3.8.3 shows the periodic forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.3	ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Canada					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	1084	7.44	970	6.61
2 year	n/a	n/a	1751	12.58	2200	14.29

3.8.4 Periodic forecast of arrivals from China

Table 3.8.4 shows the periodic forecasting performance for tourist arrivals to Japan from China. For the one year lead period the forecasting performance fair (MAPE between 10% and 20%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is poor (MAPE 20% or more) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.4 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	5419	12.32	7877	17.91
2 year	n/a	n/a	8584	26.83	10007	30.37

3.8.5 Periodic forecast of arrivals from France

Table 3.8.5 shows the periodic forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also good (MAPE less than 10%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.5	ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	338	3.32	491	5.33
2 year	n/a	n/a	990	9.46	799	8.03

3.8.6 Periodic forecast of arrivals from Germany

Table 3.8.6 shows the periodic forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.8.6	ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	1115	8.37	1218	10.20
2 year	n/a	n/a	1299	12.14	1239	11.75

3.8.7 Periodic forecast of arrivals from Korea

Table 3.8.6 shows the periodic forecasting performance for tourist arrivals to Japan from Korea. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.7 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Korea

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	11924	9.18	19900	15.58
2 year	n/a	n/a	16603	11.56	26709	17.59

3.8.8 Periodic forecast of arrivals from Singapore

Table 3.8.8 shows the periodic forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is poor (MAPE 20% or more) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.8.8 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Singapore

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	1326	15.01	1107	12.59
2 year	n/a	n/a	1646	24.18	1722	21.95

3.8.9 Periodic forecast of arrivals from Taiwan

Table 3.8.9 shows the periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one-year lead period the forecasting performance good (MAPE less than 10%) for the 12 months ahead and the 24 months-ahead forecasting horizons. For the two year lead period, the forecasting performance is poor (MAPE 20% or more) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.8.9 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	7429	9.13	8684	8.47
2 year	n/a	n/a	19077	33.65	22397	37.05

3.8.10 Periodic forecast of arrivals from the UK

Table 3.8.10 shows the periodic forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is poor (MAPE 20% or more) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or more) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the model forecasts are poor.

Table 3.8.10	ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from the UK					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	5672	22.21	11019	58.10
2 year	n/a	n/a	4844	21.47	8721	45.17

3.8.11 Periodic forecast of arrivals from the USA

Table 3.8.11 shows the periodic forecasting performance for tourist arrivals to Japan from the USA. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two-year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.8.11	ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from the USA					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	5411	7.05	3042	4.32
2 year	n/a	n/a	7960	10.72	7905	10.21

3.9 Naïve Forecasts

Forecast for the one month ahead horizon is the same as that for the 12 months ahead horizon as the data are seasonal.

3.9.1 Naïve forecast of arrivals from all countries

Table 3.9.1 shows the naive forecasting performance for tourist arrivals to Japan from all countries. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and 24 months ahead forecasting horizons. For the two-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.1 Naive Forecasting Performance for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	47084	9.92	47084	9.92	43323	9.26
2 year	59512	12.30	59512	12.30	66744	13.93

3.9.2 Naïve forecast of arrivals from Australia

Table 3.9.2 shows the naive forecasting performance for tourist arrivals to Japan from Australia. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead forecasting horizons. For the two-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.2 Naive Forecasting Performance for Tourist Arrivals to Japan from Australia

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1455	10.07	1455	10.07	1748	10.80
2 year	1351	8.62	1351	8.62	2087	13.02

3.9.3 Naïve forecast of arrivals from Canada

Table 3.9.3 shows the naive forecasting performance for tourist arrivals to Japan from Canada. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead forecasting horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.3 Naive Forecasting Performance for Tourist Arrivals to Japan from Canada

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1120	8.60	1120	8.60	1372	10.37
2 year	1280	10.19	1280	10.19	1583	12.41

3.9.4 Naïve forecast of arrivals from China

Table 3.9.4 shows the naive forecasting performance for tourist arrivals to Japan from China. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead horizon and poor (MAPE 20% or more) for the 24 months ahead horizon. For the two-year lead period the forecasting performance is poor (MAPE 20% or more) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are poor.

Table 3.9.4 Naive Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5887	14.21	5887	14.21	9318	21.00
2 year	8476	27.30	8476	27.30	10954	32.48

3.9.5 Naïve forecast of arrivals from France

Table 3.9.5 shows the naive forecasting performance for tourist arrivals to Japan from Canada. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two-year lead period, the forecasting performance is also good (MAPE less than 10%) for the 12 months ahead horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.5	Naive Forecasting Performance for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	585	6.34	585	6.34	940	11.93
2 year	852	9.40	852	9.40	889	10.65

3.9.6 Naïve forecast of arrivals from Germany

Table 3.9.6 shows the naive forecasting performance for tourist arrivals to Japan from Germany. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months-ahead horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.6	Naive Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1092	7.87	1092	7.87	1317	10.30
2 year	1247	11.20	1247	11.20	1268	10.97

3.9.7 Naïve forecast of arrivals from Korea

Table 3.9.7 shows the naive forecasting performance for tourist arrivals to Japan from Korea. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead forecasting horizons. For the two-year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.7	Naive Forecasting Performance for Tourist Arrivals to Japan from Korea					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	13113	10.51	13113	10.51	18600	15.90
2 year	17606	12.75	17606	12.75	26280	18.34

3.9.8 Naïve forecast of arrivals from Singapore

Table 3.9.8 shows the naive forecasting performance for tourist arrivals to Japan from Singapore. For the one-year lead period the forecasting performance is poor (MAPE 20% or more) for the 12 months-ahead horizon and good (MAPE less than 10%) for the 24 months ahead horizon. For the two-year lead period the forecasting performance is poor (MAPE 20% or more) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are poor.

Table 3.9.8	Naive Forecasting Performance for Tourist Arrivals to Japan from Singapore					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1644	21.34	1644	21.34	993	9.09
2 year	1794	27.70	1794	27.70	1968	25.86

3.9.9 Naïve forecast of arrivals from Taiwan

Table 3.9.9 shows the naive forecasting performance for tourist arrivals to Japan from Taiwan. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead forecasting horizons. For the two-year lead period, the forecasting performance is also poor (MAPE 20% or more) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon but poor for the 2-year lead period.

Table 3.9.9 Naive Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	12620	14.17	12620	14.17	9149	10.55
2 year	19842	35.43	19842	35.43	20045	34.39

3.9.10 Naïve forecast of arrivals from the UK

Table 3.9.10 shows the naive forecasting performance for tourist arrivals to Japan from the UK. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months-ahead horizon and poor (MAPE 20% or more) for the 24 months ahead horizon. For the two-year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the 12 months ahead horizon and poor (MAPE 20% or more) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.10	Naive Forecasting Performance for Tourist Arrivals to Japan from the UK					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	3815	12.72	3815	12.72	14877	79.46
2 year	3817	13.50	3817	13.50	10569	43.31

3.9.11 Naïve forecast of arrivals from the USA

Table 3.9.11 shows the naive forecasting performance for tourist arrivals to Japan from the USA. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and 24 months ahead forecasting horizons. For the two-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months-ahead horizon and good (MAPE less than 10%) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.9.11	Naive Forecasting Performance for Tourist Arrivals to Japan from the USA					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	6382	7.97	6382	7.97	2586	2.89
2 year	8072	10.38	8072	10.38	8352	9.88

3.10 Differenced and Undifferenced MLP Model Comparison

Table 3.10.1 shows a comparison of the one-month ahead forecasting performance of the differenced and undifferenced non-periodic MLP models and a comparison of the differenced and undifferenced partial periodic MLP models. Of the non-periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 8 (36%) of 22 forecasts while the differenced model has the lower MAPE in none (0%) of the forecasts. The 22 forecasts were obtained for 1 and 2 year lead periods using 11 data series. Of the partial periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 12 (55%) of 22 forecasts, while the differenced model has the lower MAPE in 2 (9%) of the forecasts.

The undifferenced non-periodic model also has a mean MAPE of 12.5%, the mean MAPE of the differenced non-periodic model being 22.8%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced non-periodic model and the differenced model is significant. The undifferenced partial periodic model also has a mean MAPE of 12.0%, the mean MAPE of the differenced partial periodic model being 25.0%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced partial periodic model and the differenced model is significant. On the level of accuracy achieved, the undifferenced non-periodic model has 10 (50%) forecasts with MAPE figures less than 10%, while the differenced non-periodic model has 2 (9%) forecasts with MAPE less than 10%. The undifferenced partial periodic model has 12 (55%) forecasts with MAPE figures

less than 10%, while the differenced partial periodic model has 2 (9%) forecasts with MAPE less than 10%.

Table 3.10.2 shows a comparison of the 12-months-ahead forecasting performance of the differenced and undifferenced non-periodic MLP models and a comparison of the differenced and undifferenced partial periodic MLP models. Of the non-periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 6 (27%) of 22 forecasts while the differenced model has the lower MAPE in 1 (5%) of the forecasts. Of the partial periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 14 (64%) of 22 forecasts while the differenced model has the lower MAPE in 1 (5%) of the forecasts.

The undifferenced non-periodic model also has a mean MAPE of 13.6%, the mean MAPE of the differenced non-periodic model being 24.2%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced non-periodic model and the differenced model is significant. The undifferenced partial periodic model also has a mean MAPE of 12.3%, the mean MAPE of the differenced partial periodic model being 23.3%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced partial periodic model and the differenced model is significant. On the level of accuracy achieved, the undifferenced non-periodic model has made 9 (41%) forecasts with MAPE figures less than 10%, while the differenced non-periodic model has 1 (5%) forecast with MAPE less than 10%. The undifferenced partial periodic model has 12 (55%) forecasts with MAPE figures less than 10%, while the differenced partial periodic model has 4 (18%) forecasts with MAPE less than 10%.

Table 3.10.3 shows a comparison of the 24 months ahead forecasting performance of the differenced and undifferenced non-periodic MLP models and a comparison of the differenced and undifferenced partial periodic MLP models. Of the non-periodic models the undifferenced model is better than the differenced model, as it has the lower MAPE in 16 (73%) of 22 forecasts while the differenced model has the lower MAPE in none (0%) of the forecasts. Of the partial periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 6 (27%) of 22 forecasts while the differenced model has the lower MAPE in none (0%) of the forecasts.

The undifferenced non-periodic model also has a mean MAPE of 15.4%, the mean MAPE of the differenced non-periodic model being 25.2%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced non-periodic model and the differenced model is significant. The undifferenced partial periodic model also has a mean MAPE of 20.8%, the mean MAPE of the differenced partial periodic model being 30.6%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced partial periodic model and the differenced model is significant. On the level of accuracy achieved, the undifferenced non-periodic model has 10 (45%) forecasts with MAPE figures less than 10%, while the differenced non-periodic model has 3 (14%) forecasts with MAPE less than 10%. The undifferenced partial periodic model has 11 (50%) forecasts with MAPE figures

less than 10%, while the differenced partial periodic model has 1 (5%) forecast with MAPE less than 10%.

Table 3.10.1 **Univariate one month ahead Forecasting Performance of differenced and undifferenced Neural Network models**

Country	Forecast Lead	Non-Periodic RMSE	Non-Periodic MAPE	NP Differenced RMSE	NP Differenced MAPE	Partial Periodic RMSE	Partial Periodic MAPE	PP Differenced RMSE	PP Differenced MAPE
All	1 year	30599	5.5	68204	13.4	24943	4.9	71005	15.7
	2 year	53203	9.8	84950	17.6	55528	10.2	74336	16.5
Australia	1 year	895	5.1	1917	11.8	598	3.7	2415	15.7
	2 year	1184	6.6	1982	11.6	992	5.4	2480	15.5
Canada	1 year	908	6.8	2390	17.3	758	5.4	2796	21.0
	2 year	1308	10.0	2656	19.7	1305	9.0	2253	17.0
China	1 year	5905	14.6	6249	12.3	4709	10.1	14198	34.1
	2 year	9214	28.0	9468	29.0	9099	28.3	14205	38.4
France	1 year	538	6.1	1558	17.6	411	4.5	1545	19.3
	2 year	816	8.7	1786	19.9	786	8.0	1368	15.9
Germany	1 year	1021	7.1	1151	8.9	1015	7.6	1448	14.1
	2 year	1216	10.2	2223	17.9	1076	9.7	1365	13.5
Korea	1 year	16326	9.6	12082	10.2	17910	11.5	29241	25.4
	2 year	22754	12.3	21695	12.5	21062	12.7	33792	25.3
Singapore	1 year	1934	22.2	3431	34.7	1480	16.3	1362	14.3
	2 year	2128	30.2	3441	49.5	1893	25.9	1788	24.0
Taiwan	1 year	10908	10.4	49044	38.7	6383	7.2	9523	10.4
	2 year	18132	29.3	47713	67.6	18696	31.5	19992	35.5
UK	1 year	3167	13.5	8454	33.5	3967	20.0	14745	76.7
	2 year	2868	13.6	11116	37.2	3654	17.9	14878	83.2
USA	1 year	5766	6.4	6731	8.1	4375	5.2	5597	7.6
	2 year	7354	9.4	10772	13.3	6644	8.6	7074	9.8
Summary Measures									
Mean		9007	12.5	16319	22.8	8513	12.0	14882	25.0
Standard Deviation		12829	7.8	23754	15.1	12865	8.1	20867	19.6
MAPE p-values:									
c/w Differenced NP model			-0.01						
c/w Differenced PP model							-0.01		
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	%
of 22 forecasts		8	36%	0	0%	12	55%	2	9%
MAPE <= 10%		11	50%	2	9%	12	55%	2	9%
10% <MAPE< 20%		7	32%	13	59%	7	32%	11	50%
MAPE >= 20%		4	18%	7	32%	3	14%	9	41%
MAPE <= 10%									
for 1 year lead		7	64%	2	100%	7	58%	1	50%
for 2 year lead		4	36%	0	0%	5	42%	1	50%

Table 3.10.2 **Univariate 12 months ahead Forecasting Performance of differenced and undifferenced Neural Network models**

Country	Forecast Lead	Non-Periodic RMSE	Non-Periodic MAPE	NP Differenced RMSE	NP Differenced MAPE	Partial Periodic RMSE	Partial Periodic MAPE	PP Differenced RMSE	PP Differenced MAPE
All	1 year	38932	7.9	50320	11.3	31537	6.5	85400	19.4
	2 year	59098	11.2	64189	13.3	55720	10.4	87939	19.4
Australia	1 year	1026	5.7	4849	34.2	465	3.0	1494	10.2
	2 year	1170	6.8	3910	24.8	923	4.9	2829	17.0
Canada	1 year	897	6.8	3118	27.1	730	5.1	1153	8.1
	2 year	1323	9.9	2912	24.5	1339	8.8	1910	14.6
China	1 year	4750	11.3	9413	20.9	5483	11.7	21044	51.6
	2 year	8749	27.4	10473	32.3	8339	26.1	20474	51.6
France	1 year	547	6.5	1167	13.5	408	4.1	1154	14.7
	2 year	850	9.5	1150	13.7	810	7.9	1429	17.0
Germany	1 year	1003	7.2	1375	11.4	1019	7.3	1394	11.9
	2 year	1174	10.5	1494	13.0	1077	9.5	1443	12.6
Korea	1 year	18874	12.7	17108	13.2	18324	12.7	31518	28.2
	2 year	24806	15.0	22791	15.1	25700	15.4	36208	28.1
Singapore	1 year	1797	21.6	1488	13.9	1455	16.7	1867	20.4
	2 year	1992	28.1	2164	28.5	1765	25.2	1923	26.5
Taiwan	1 year	11827	12.6	11840	13.3	6522	7.5	7607	8.7
	2 year	19603	34.0	26937	43.8	18532	31.6	18934	33.0
UK	1 year	3545	16.6	10209	49.6	3969	21.0	9762	51.6
	2 year	3838	19.3	17043	89.5	3828	20.1	9157	51.3
USA	1 year	6256	7.6	6124	8.7	4769	6.1	5026	6.9
	2 year	7930	10.6	12175	17.4	7367	9.8	6151	9.1
Summary Measures									
Mean		9999	13.6	12830	24.2	9095	12.3	16174	23.3
Standard Deviation		14717	7.9	16269	18.3	13594	7.9	25001	15.3
MAPE p-values:									
c/w NP Differenced model			-0.01						
c/w PP Differenced model							-0.01		
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	**%**
of 22 forecasts		6	27%	1	5%	14	64%	1	5%
MAPE <= 10%		9	41%	1	5%	12	55%	4	18%
10% <MAPE< 20%		9	41%	11	50%	5	23%	9	41%
MAPE >= 20%		4	18%	10	45%	5	23%	9	41%
MAPE <= 10%									
for 1 year lead		6	67%	1	100%	7	58%	3	75%
for 2 year lead		3	33%	0	0%	5	42%	1	25%

Table 3.10.3		Univariate 24 months ahead Forecasting Performance of differenced and undifferenced Neural Network models							
Country	Forecast Lead	Non-Periodic RMSE	MAPE	NP Differenced RMSE	MAPE	Partial Periodic RMSE	MAPE	PP Differenced RMSE	MAPE
All	1 year	24071	4.4	73072	16.1	35722	7.1	98663	22.4
	2 year	55423	10.2	72604	16.2	55688	11.4	100756	21.7
Australia	1 year	905	5.8	1369	8.5	886	5.6	3554	25.3
	2 year	1234	7.0	1711	9.8	1245	7.4	3527	23.7
Canada	1 year	907	6.2	1773	11.0	1047	7.8	2156	17.3
	2 year	1555	11.0	2724	21.6	1359	10.0	1981	16.5
China	1 year	7510	17.5	16658	41.7	9405	20.7	20663	50.9
	2 year	10039	32.3	18640	46.7	11230	32.8	21828	52.6
France	1 year	407	4.4	1549	19.5	734	8.5	1743	23.2
	2 year	811	9.1	1382	16.3	767	8.8	1496	18.5
Germany	1 year	1037	9.5	1430	14.2	1053	8.1	1255	10.4
	2 year	1328	12.8	1352	13.5	990	8.6	1239	10.5
Korea	1 year	26949	19.3	34840	29.3	27127	21.6	41872	37.1
	2 year	37127	23.0	37311	26.2	35624	24.1	41522	32.5
Singapore	1 year	1323	13.1	2563	32.2	1319	13.9	1616	16.4
	2 year	2049	26.5	3052	36.9	1934	25.5	2044	26.0
Taiwan	1 year	6325	7.5	10510	12.1	8291	8.7	13754	17.7
	2 year	19217	32.6	22029	36.8	21118	35.1	21444	35.2
UK	1 year	7675	40.8	14159	70.7	17523	97.4	19815	108.7
	2 year	6106	32.0	11367	55.7	14564	81.6	15778	85.0
USA	1 year	3184	3.8	4368	5.8	2926	4.1	6713	9.7
	2 year	7189	9.3	10308	14.6	7628	9.8	7639	11.3
Summary Measures									
Mean		10108	15.4	15671	25.2	11735	20.8	19594	30.6
Standard Deviation		14222	11.0	21302	16.9	14931	24.0	28672	24.7
MAPE p-values:									
c/w NP Differenced model			-0.01						
c/w PP Differenced model							-0.01		
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	**%**
of 22 forecasts		16	73%	0	0%	6	27%	0	0%
MAPE <= 10%		10	45%	3	14%	11	50%	1	5%
10% <MAPE< 20%		6	27%	9	41%	3	14%	8	36%
MAPE >= 20%		6	27%	10	45%	8	36%	13	59%
MAPE <= 10%									
for 1 year lead		7	70%	2	67%	7	64%	1	100%
for 2 year lead		3	30%	1	33%	4	36%	0	0%

Table 3.10.4	**Forecasting Performance Comparison Summary of differenced and undifferenced Neural Network models**							
	Non-Periodic		NP Differenced		Partial Periodic		PP Differenced	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Mean	9705	13.8	14940	24.1	9781	15.1	16883	26.3
Standard Deviation	13738	9.0	20414	16.6	13682	15.6	24743	20.2
MAPE p-values:								
c/w NP Differenced model		-0.01						
c/w PP Differenced model						-0.01		
Lowest MAPE Count	Count	%	Count	**%**	Count	**%**	Count	**%**
of 66 forecasts	30	45%	1	2%	32	48%	3	5%
MAPE <= 10%	30	45%	6	9%	35	53%	7	11%
10% <MAPE< 20%	22	33%	33	50%	15	23%	28	42%
MAPE >= 20%	14	21%	27	41%	16	24%	31	47%
MAPE <= 10%								
for 1 year lead	20	67%	5	83%	21	60%	5	71%
for 2 year lead	10	33%	1	17%	14	40%	2	29%

Table 3.10.4 shows a summary comparison of the forecasting performance of the differenced and undifferenced non-periodic MLP models, and a comparison of the differenced and undifferenced partial periodic MLP models. Of the non-periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 30 (45%) of 66 forecasts, while the differenced model has the lower MAPE in 1 (2%) of the forecasts. Of the partial periodic models the undifferenced model is better than the differenced model as it has a lower MAPE in 32 (48%) of 66 forecasts, while the differenced model has the lower MAPE in 3 (5%) of the forecasts.

The undifferenced non-periodic model has a mean MAPE of 13.8%, while that of the differenced model is 24.1%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced non-periodic model and the differenced model is significant. The undifferenced partial periodic model has a mean

MAPE of 15.1%, while that of the differenced model is 26.3%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced partial periodic model and the differenced model is significant. On the level of accuracy, the undifferenced non-periodic model has 30 (45%) forecasts with MAPE figures less than 10%, while the differenced model achieved only 6 (9%) such forecasts. The undifferenced partial periodic model has 35 (53%) forecasts with MAPE figures less than 10%, while the differenced model has only 7 (11%) such forecasts.

3.11 MLP Model Comparison with the Naïve model

Table 3.11.1 shows a comparison of the forecasting performance of the Non-periodic, Partial periodic, Periodic and Naïve models for the one month ahead forecasting horizon. For the one month ahead forecasting horizon, the partial periodic model is the best model as it has the lowest MAPE in 14 (64%) of 22 forecasts. Twelve (55%) partial periodic forecasts have MAPE figures less than 10%. Seven (58%) and 5 (42%) of these 12 forecasts were for the 1 and 2 year lead periods respectively, indicating the model works better for the 1 year lead period.

The partial periodic model also has the smallest mean MAPE of 12.0%. The non-periodic model has a mean MAPE of 12.5%. Both models have significant mean differences from the MAPE of the naïve model with the paired sample p-value for the mean difference being less than 0.01. The non-periodic model has the lowest MAPE figures in 5 (23%) forecasts. The naïve model has the lowest MAPE in 3 (14%) forecasts. The periodic model is not applicable to one-month ahead forecasts as it forecasts 12 months ahead.

Table 3.11.2 shows a comparison of the forecasting performance of the Non-periodic, Partial periodic, Periodic and Naïve models for the 12 months ahead forecasting horizon. Using the lowest MAPE as the forecasting performance evaluation criterion, for the 12 months ahead forecasting horizon, the partial periodic model is the best model as it has the lowest MAPE in 13 (59%) of 22 forecasts. Twelve (55%) of the 22 partial periodic forecasts have MAPE figures less than 10%. Seven (58%) and 5 (42%) of these 12 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for the 1 year lead period.

The partial periodic model has the lowest mean MAPE of 12.3%, the paired sample p-values indicating significant mean differences at the 5% level for MAPE values between the partial periodic model and the non-periodic and naïve models. The periodic model has a mean MAPE of 12.9% while the non-periodic model has a mean MAPE of 13.6. The periodic model has the lowest MAPE figures in 5 (23%) forecasts followed by the non-periodic model with the lowest MAPE figures in 2 (9%) forecasts. The naïve model also has the lowest MAPE in 2 (9%) forecasts.

Table 3.11.3 shows a comparison of the forecasting performance of the Non-periodic, Partial periodic, Periodic and Naïve models for the 24-months-ahead forecasting horizon. Using the lowest MAPE as the forecasting performance evaluation criterion, for the 24 months ahead forecasting horizon, the non-periodic model is the best model as it has the lowest MAPE in 11 (50%) of 22 forecasts. Ten (45%) of the 22 partial periodic forecasts have MAPE figures less than 10%. Seven (70%) and 3 (30%) of these 10 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for the 1 year lead period.

The non-periodic model also has the smallest mean MAPE of 15.4% while the periodic model has a mean MAPE of 17.2%. The paired sample p-values do not show significant mean differences in the MAPE values of the models at the 5% level, except between the non-periodic and naïve models. The next best model is the periodic model with the lowest MAPE figures in 5 (23%) forecasts followed by the partial periodic model with the lowest MAPE figures in 4 (18%) forecasts. The naïve model has the lowest MAPE in 2 (9%) forecasts.

Table 3.11.4 shows a comparison summary of the forecasting performance of the Non-periodic, Partial periodic, Periodic and Naïve models. The partial periodic model is the best model as it has the lowest MAPE in 31 (47%) of 66 forecasts. Thirty five (53%) of the 66 partial periodic forecasts have MAPE figures less than 10%. Twenty one (60%) and 14 (40%) of these 21 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for the 1 year lead period. The next best model is the non-periodic model with the lowest MAPE figures in 18 (27%) forecasts followed by the periodic model with the lowest MAPE figures in 10 (23%) forecasts. The naïve model has the lowest MAPE in 7 (11%) forecasts.

However, paired sample p-values of the mean differences of the MAPE figures of the partial periodic model are not significant at the 5% level. This is because the variance of the MAPE of this model is high due to the very good performance of some of the 66 forecasts and the very poor performance of others. The non-periodic model has the smallest mean MAPE of 13.8%. The partial periodic model has a mean MAPE of 15.1%, The periodic model also has a mean MAPE of 15.1%.

Table 3.11.1 **Univariate one month ahead Forecasting Performance of Neural Network and Naïve Forecasts**

Country	Forecast Lead	Non-Periodic RMSE	Non-Periodic MAPE	Partial Periodic RMSE	Partial Periodic MAPE	Periodic RMSE	Periodic MAPE	Naïve RMSE	Naïve MAPE
All	1 year	30599	5.5	24943	4.9	N/a	n/a	47084	9.9
	2 year	53203	9.8	55528	10.2	N/a	n/a	59512	12.3
Australia	1 year	895	5.1	598	3.7	N/a	n/a	1455	10.1
	2 year	1184	6.6	992	5.4	N/a	n/a	1351	8.6
Canada	1 year	908	6.8	758	5.4	N/a	n/a	1120	8.6
	2 year	1308	10.0	1305	9.0	N/a	n/a	1280	10.2
China	1 year	5905	14.6	4709	10.1	N/a	n/a	5887	14.2
	2 year	9214	28.0	9099	28.3	N/a	n/a	8476	27.3
France	1 year	538	6.1	411	4.5	N/a	n/a	585	6.3
	2 year	816	8.7	786	8.0	N/a	n/a	852	9.4
Germany	1 year	1021	7.1	1015	7.6	N/a	n/a	1092	7.9
	2 year	1216	10.2	1076	9.7	N/a	n/a	1247	11.2
Korea	1 year	16326	9.6	17910	11.5	N/a	n/a	13113	10.5
	2 year	22754	12.3	21062	12.7	N/a	n/a	17606	12.8
Singapore	1 year	1934	22.2	1480	16.3	N/a	n/a	1644	21.3
	2 year	2128	30.2	1893	25.9	N/a	n/a	1794	27.7
Taiwan	1 year	10908	10.4	6383	7.2	N/a	n/a	12620	14.2
	2 year	18132	29.3	18696	31.5	N/a	n/a	19842	35.4
UK	1 year	3167	13.5	3967	20.0	N/a	n/a	3815	12.7
	2 year	2868	13.6	3654	17.9	N/a	n/a	3817	13.5
USA	1 year	5766	6.4	4375	5.2	N/a	n/a	6382	8.0
	2 year	7354	9.4	6644	8.6	N/a	n/a	8072	10.4
Summary Measures									
Mean		9007	12.5	8513	12.0			9938	13.7
Standard Deviation		12829	7.8	12865	8.1			15242	7.5
MAPE p-values:									
c/w Naïve model			-0.01		-0.01				
c/w Periodic model									
c/w Partial Periodic model			0.19						0.01
c/w Non-Periodic model					-0.19				0.01
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	%
of 22 forecasts		5	23%	14	64%	0	0%	3	14%
MAPE <= 10%		11	50%	12	55%	0	0%	7	32%
10% <MAPE< 20%		7	32%	7	32%	0	0%	11	50%
MAPE >= 20%		4	18%	3	14%	0	0%	4	18%
MAPE <= 10%									
for 1 year lead		7	64%	7	58%	0	0%	5	71%
for 2 year lead		4	36%	5	42%	0	0%	2	29%

Table 3.11.2 **Univariate 12 months ahead Forecasting Performance of Neural Network and Naïve Forecasts**

Country	Forecast Lead	Non-Periodic RMSE	Non-Periodic MAPE	Partial Periodic RMSE	Partial Periodic MAPE	Periodic RMSE	Periodic MAPE	Naïve RMSE	Naïve MAPE
All	1 year	38932	7.9	31537	6.5	35420	6.9	47084	9.9
	2 year	59098	11.2	55720	10.4	57341	10.7	59512	12.3
Australia	1 year	1026	5.7	465	3.0	732	3.6	1455	10.1
	2 year	1170	6.8	923	4.9	2282	6.8	1351	8.6
Canada	1 year	897	6.8	730	5.1	1084	7.4	1120	8.6
	2 year	1323	9.9	1339	8.8	1751	12.6	1280	10.2
China	1 year	4750	11.3	5483	11.7	5419	12.3	5887	14.2
	2 year	8749	27.4	8339	26.1	8584	26.8	8476	27.3
France	1 year	547	6.5	408	4.1	338	3.3	585	6.3
	2 year	850	9.5	810	7.9	990	9.5	852	9.4
Germany	1 year	1003	7.2	1019	7.3	1115	8.4	1092	7.9
	2 year	1174	10.5	1077	9.5	1299	12.1	1247	11.2
Korea	1 year	18874	12.7	18324	12.7	11924	9.2	13113	10.5
	2 year	24806	15.0	25700	15.4	16603	11.6	17606	12.8
Singapore	1 year	1797	21.6	1455	16.7	1326	15.0	1644	21.3
	2 year	1992	28.1	1765	25.2	1646	24.2	1794	27.7
Taiwan	1 year	11827	12.6	6522	7.5	7429	9.1	12620	14.2
	2 year	19603	34.0	18532	31.6	19077	33.6	19842	35.4
UK	1 year	3545	16.6	3969	21.0	5672	22.2	3815	12.7
	2 year	3838	19.3	3828	20.1	4844	21.5	3817	13.5
USA	1 year	6256	7.6	4769	6.1	5411	7.0	6382	8.0
	2 year	7930	10.6	7367	9.8	7960	10.7	8072	10.4
Summary Measures									
Mean		9999	13.6	9095	12.3	9011	12.9	9938	13.7
Standard Deviation		14717	7.9	13594	7.9	13563	7.9	15242	7.5
MAPE p-values:									
c/w Naïve model			-0.37		-0.04		-0.16		
c/w Periodic model			0.14		-0.07				0.16
c/w Partial Periodic model			0.01				0.07		0.04
c/w Non-Periodic model					-0.01		-0.14		0.37
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	**%**
of 22 forecasts		2	9%	13	59%	5	23%	2	9%
MAPE <= 10%		9	41%	12	55%	10	45%	7	32%
10% <MAPE< 20%		9	41%	5	23%	7	32%	11	50%
MAPE >= 20%		4	18%	5	23%	5	23%	4	18%
MAPE <= 10%									
for 1 year lead		6	67%	7	58%	8	80%	5	71%
for 2 year lead		3	33%	5	42%	2	20%	2	29%

Table 3.11.3		Univariate 24 months ahead Forecasting Performance of Neural Network and Naïve Forecasts							
Country	Forecast Lead	Non-Periodic RMSE	MAPE	Partial Periodic RMSE	MAPE	Periodic RMSE	MAPE	Naïve RMSE	MAPE
All	1 year	24071	4.4	35722	7.1	33861	7.0	43323	9.3
	2 year	55423	10.2	55688	11.4	54170	10.9	66744	13.9
Australia	1 year	905	5.8	886	5.6	2054	11.6	1748	10.8
	2 year	1234	7.0	1245	7.4	2325	13.4	2087	13.0
Canada	1 year	907	6.2	1047	7.8	970	6.6	1372	10.4
	2 year	1555	11.0	1359	10.0	2200	14.3	1583	12.4
China	1 year	7510	17.5	9405	20.7	7877	17.9	9318	21.0
	2 year	10039	32.3	11230	32.8	10007	30.4	10954	32.5
France	1 year	407	4.4	734	8.5	491	5.3	940	11.9
	2 year	811	9.1	767	8.8	799	8.0	889	10.6
Germany	1 year	1037	9.5	1053	8.1	1218	10.2	1317	10.3
	2 year	1328	12.8	990	8.6	1239	11.8	1268	11.0
Korea	1 year	26949	19.3	27127	21.6	19900	15.6	18600	15.9
	2 year	37127	23.0	35624	24.1	26709	17.6	26280	18.3
Singapore	1 year	1323	13.1	1319	13.9	1107	12.6	993	9.1
	2 year	2049	26.5	1934	25.5	1722	22.0	1968	25.9
Taiwan	1 year	6325	7.5	8291	8.7	8684	8.5	9149	10.5
	2 year	19217	32.6	21118	35.1	22397	37.1	20045	34.4
UK	1 year	7675	40.8	17523	97.4	11019	58.1	14877	79.5
	2 year	6106	32.0	14564	81.6	8721	45.2	10569	43.3
USA	1 year	3184	3.8	2926	4.1	3042	4.3	2586	2.9
	2 year	7189	9.3	7628	9.8	7905	10.2	8352	9.9
Summary Measures									
Mean		10108	15.4	11735	20.8	10383	17.2	11589	18.9
Standard Deviation		14222	11.0	14931	24.0	13541	13.8	16238	16.7
MAPE p-values:									
c/w Naïve model			-0.03		0.18		-0.06		
c/w Periodic model			-0.06		0.08				0.06
c/w Partial Periodic model			-0.06				-0.08		-0.18
c/w Non-Periodic model					0.06		0.06		0.03
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	%
of 22 forecasts		11	50%	4	18%	5	23%	2	9%
MAPE <= 10%		10	45%	11	50%	6	27%	4	18%
10% <MAPE< 20%		6	27%	3	14%	11	50%	12	55%
MAPE >= 20%		6	27%	8	36%	5	23%	6	27%
MAPE <= 10%									
for 1 year lead		7	70%	7	64%	5	83%	3	75%
for 2 year lead		3	30%	4	36%	1	17%	1	25%

Table 3.11.4	Forecasting Performance Comparison Summary of Neural Network and Naïve Forecasts							
	Non-Periodic		Partial Periodic		Periodic		Naïve	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Mean	9705	13.8	9781	15.1	9697	15.1	10489	15.5
Standard Deviation	13738	9.0	13682	15.6	13411	11.3	15359	11.5
MAPE p-values:								
c/w Naïve model		-0.01		-0.29		-0.03		
c/w Periodic model		-0.18		0.12				0.03
c/w Partial Periodic model		-0.15				-0.12		0.29
c/w Non-Periodic model				0.15		0.18		0.01
Lowest MAPE Count	Count	%	Count	%	Count	%	Count	%
of 66 forecasts	18	27%	31	47%	10	23%	7	11%
MAPE <= 10%	30	45%	35	53%	16	36%	18	27%
10% <MAPE< 20%	22	33%	15	23%	18	41%	34	52%
MAPE >= 20%	14	21%	16	24%	10	23%	14	21%
MAPE <= 10%								
for 1 year lead	20	67%	21	60%	13	81%	13	72%
for 2 year lead	10	33%	14	40%	3	19%	5	28%

3.12 Conclusion

Overall for both the non-periodic and the partial periodic models the forecasting performance was better with data that was not differenced. Data was differenced to remove seasonality. Nelson et al. (1999) used deseasonalised data and concluded that neural networks performed better with deseasonalised data. Differencing was used in this research as the objective was not so much to remove seasonality but to help the neural process. This contradictory result may even be due to varying strengths in the irregular component rather than the difference in the methods used. Current results indicate that it is better to let neural networks model data as a whole rather than in separate components.

The partial periodic model is superior to the non-periodic model, which in turn is better than the periodic model when forecasting tourism to Japan. All three models performed better than the naïve model making them all adequate models for forecasting. The mean MAPE for the three models were not significantly different and the non-periodic model had the lowest mean MAPE making it almost as good as the partial periodic model. The partial periodic model was the best for the one-month ahead and the 12 months ahead forecasting horizons, while the non-periodic model was better for the 24 months ahead horizon.

The partial periodic model captures the seasonal trend of the past three years on a month-by-month basis, which is its strength. The model's poor performance for the 24 months-ahead horizon is due to the tourist arrivals series changing dramatically in 2003 due to the SARS crisis. The models poor performance was mainly for arrivals from the SARS affected countries. It would be reasonable to expect a network that has been modelled on the basis of the past year's data to respond better to sudden changes in a data series, than a network that had been modelled on the basis of the past three years data. This could well be the reason the non-periodic model performed better for the 24 months ahead horizon.

The performance of the periodic model, though not significantly different from the partial periodic and the non-periodic models, is not more accurate. Because of the seasonal nature of tourist arrivals, the periodic model was expected to out perform the other models, as it models the data for each season (month) separately. The poor performance of the periodic model compared to the partial periodic models shows that data for each season are not totally independent. .

Chapter 3
Neural Network Multi-layer Perceptron Models

3.1 Introduction

Artificial neural networks have been used extensively as a forecasting tool and more recently for forecasting tourism flows. Fernando, Turner and Reznik (1999a), Law and Au (1999), Law (2000), Cho (2003) and Kon and Turner (2005) used artificial neural network models to forecast tourism demand. The multi-layer perceptron is a category of neural networks that uses feed forward back propagation to establish the relationship between inputs and outputs by training the network using a supervised learning method to model linear and non linear data. Neural networks can model univariate as well as multivariate data but this study aims to explore its univariate forecasting performance. Neural networks do not have any pre-conditions or assumptions for the pattern or variations in historical data but through an iterative process develop a model that fits the data. However, too close a fit may not be desirable, as it would not allow for random variations in the future.

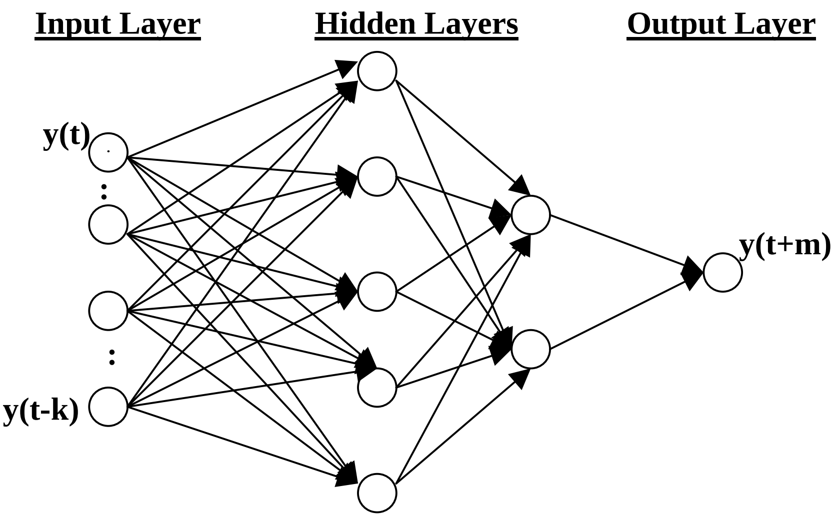
This chapter consists of a comparison of three, univariate artificial neural network (ANN) multi-layer perceptron (MLP) forecasting models. The three models compared are a non-periodic model, a partial periodic model and a periodic model. The forecasting performance of the neural network models is compared with that of the naïve model, which is considered in this study as the minimum benchmark for forecasting performance. The non-periodic model and the partial periodic model are run with differenced data and with undifferenced data, to test, which provides better forecasts using MLP networks.

The variable being forecast is tourist arrivals to Japan. Monthly tourist arrivals from Australia, China, France, Germany, Korea, Singapore, Taiwan, UK, the USA and total arrivals from all countries, from January 1978 to December 2001, to forecast arrivals for the 24 month period from January 2002 to December 2003. Forecasts are made for tourist arrivals from each of the above countries, one month ahead, 12 months ahead, and 24 months ahead, to test whether the forecasting accuracy is consistent for arrivals to Japan from different countries and for different forecasting horizons. The criterion for comparing models is the forecasting accuracy as measured by the MAPE of the 24 month out of sample period from January 2002 to December 2003, which is divided into one and two year lead periods. The aim of this study is to determine which empirical neural network model would provide the best forecast for tourist arrivals data.

3.2 The Multi-Layer Perceptron Model

In this study, the artificial neural network (ANN) multi-layer perceptron (MLP) model with two hidden layers containing sigmoid and tanh nodes is used in a connectionist neural network. Figure 3.1 shows the univariate connectionist model used to forecast **m** periods ahead using the time series **y(t**) with **k+1** periods of data. Tourist arrivals to Japan from January 1978 to December 2001 are taken as the input series. The number of input nodes represents the number of input variables in the model. In a univariate model lags of the series or differenced series can be used as variables.

Figure 3.1 Connectionist MLP Model for Univariate Forecasting



Input nodes have a linear transformation to the nodes of the next layer, as follows:

$$z_j = \Sigma w_{ij} x_j \quad ,$$

where x is the input signal for input node j, z is the output to the next node i and w is the connecting weight between node j and node i. This transformation is applied to every node of the network including the output layer.

Given limitations in data size and processing capacity a MLP network will not normally have more than two layers. Most researchers use only one hidden layer (refer to Kon and Turner, 2005). However, as monthly data of a 20-year period are used in this study, it is important to capture the linear and non-linear patterns of within sample data by providing the network with transfer functions that could transform input data to match output data patterns. Two hidden layers are used in this study with tanh functions at each node of the first layer and sigmoid functions at each node of the second layer. The tanh function is of the form:

$$f(z) = tanh(z) = (e^{z} - e^{-z})/(e^{z} + e^{-z}) \quad .$$

The sigmoid function is of the form:

$$f(z) = 1/(1 + e^{-z}) \quad .$$

The number of nodes in a hidden layer depend on the volume of input data, as the total number of node-to-node connections must be at most less than the number of within sample data points. As monthly tourist arrivals are known to be seasonal 12 nodes are used in each hidden layer as far as data numbers permit. In 12 and 24 months ahead forecast horizons, when the within sample has fewer data points, the number of nodes in the hidden layers is reduced but kept, as far as possible, to multiples of 4 nodes to facilitate capture of seasonality.

The MLP models were run using DataEngine software. The data were prepared on MS Excel and imported by DataEngine where it was scaled within the range 0.4 to 0.6 in the 0 to 1 domain and separated into training, test and recall files. The network architecture was set, specifying the number of nodes, the transfer functions, the input and output files and the initial weights and learning rates.

The MLP model used is a feed forward model, where the outputs from the nodes in the input layer are fed forward to the nodes of the first hidden layer, the outputs from the nodes of the first hidden layer are input to the nodes of the second hidden layer and the outputs from the nodes of the second hidden layer are input to the output node.

The back-propagation feature of the model is used where the difference between the output and the expected output is fed back to the nodes of the network, and the weights adjusted in an iterative process, until the difference is reduced to a preset level. Back-propagation with momentum is used to quicken the training phase while still maintaining a small learning rate, which would otherwise require a high processing time. However, a flat root mean square error curve would be an indication that the learning error has been set too low.

The network configuration used in the MLP models is as follows:
Input layer transfer function: linear
1st Hidden layer transfer function: tanh
2nd Hidden layer transfer function: sigmoid
Output layer transfer function: linear
Learning Method: Back propagation, single step
Learning parameters for all layers: Learning rate 0.1, Momentum 0.1
Weight initialization –0.1 to 0.1
Stop condition 1000 epochs.

In neural network modelling trend and seasonality in a time series can be dealt with by taking the 1st and 12th difference of the data to remove trend and seasonal effects, respectively, prior to analysis. Alternatively, the neural network could be allowed to model and capture the trend and seasonality. Nelson, Hill, Remus et al. (1999) addressed this issue by deseasonalising the data and concluded from their study that when there was seasonality in a time series, forecasts from neural networks estimated on deseasonalised data were significantly more accurate than the forecasts produced by neural networks that used data that were not deseasonalised. One possible explanation they present for their results is that neural networks that use deseasonalised time series do not have to focus on learning the seasonal components and can therefore pick-up other residual patterns.

Three MLP models are compared in this study. The first is the non-periodic model used by Fernando, Turner and Reznik (1999a) based on Freisleben (1992). The inputs to this model are the 12 previous monthly arrivals. The output is the arrivals figure of the following month for a one-month ahead forecast horizon, or of the corresponding month of the following years for 12 and 24 months ahead forecasts. The non-periodic model for a ***k*** period horizon is of the form:

$$x_{t+k} = f(x_t, x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}, x_{t-5}, x_{t-6}, x_{t-7}, x_{t-8}, x_{t-9}, x_{t-10}, x_{t-11}) \quad .$$

As long term trend and seasonality can be presumed inherent in most tourist arrivals series, the 1st and 12th differenced data are used in an alternative non-periodic model. Removing trend by taking the 1st difference and seasonal variations by taking the 12th difference would leave the network only the task of capturing some of the residual variation. The non-periodic model using first differenced **(∇_1)** and twelfth differenced **(∇_{12})** data for a ***k*** period horizon is of the form:

$$\nabla_1\nabla_{12}x_{t+k} = f(\nabla_1\nabla_{12}x_t, \nabla_1\nabla_{12}x_{t-1}, \nabla_1\nabla_{12}x_{t-2}, \ldots, \nabla_1\nabla_{12}x_{t-11}) \quad .$$

The second MLP model used in this study is a partial periodic model that uses tourist arrivals data lagged by 12, 24 and 36 months as inputs. In this model each month's arrivals are matched against the three previous years' (lagged) arrivals of the same calendar month. Since only the three previous years' arrivals in a calendar month are taken at a time, as inputs, the model is partial periodic. No attempt was made to test for autocorrelation, as tourist arrivals are mostly seasonal. Subsequent ARIMA estimation has proved this to be the case. In an MLP partial periodic model arrivals from all calendar months may influence the output, unlike in a full periodic model where only data of a specific calendar month would be modelled at a time. However, the use of lagged series relieves the model of having to capture much of the seasonal component. The partial periodic model is as follows:

$$x_t = f(x_{t-12}, x_{t-24}, x_{t-36}) \quad .$$

An alternative partial periodic model would uses 1st differenced data. The tourist arrivals series are observed from graphical patterns to be non-stationary. Subsequent unit root testing (refer Chapter 5) confirmed the non-stationary nature of the data. The series are made stationary by taking the first difference so that the MLP model would be required to capture only some of the residual variations in the series. Further, forecasts of a stationary series will remain within the data domain of the within sample series, without crossing the domain boundaries defined at the outset, making the neural network more efficient. This model which uses the 1st difference of the tourist arrivals time series $\nabla_1 x_t$ lagged by 12, 24 and 36 months as the inputs is of the form:

$$\nabla_1 x_t = f(\nabla_1 x_{t-12}, \nabla_1 x_{t-24}, \nabla_1 x_{t-36}) \quad .$$

The third MLP model used is the periodic model. The inputs to this model are the tourist arrivals series of a specific month lagged by 12, 24 and 36 months. The output is the arrivals figure of that month in the forecast horizon, for example, $\boldsymbol{xjan_t}$ for January of year ***t***. As differenced data used in the previous MLP models produced poor forecasting results no attempt was made to difference the data for this model. The periodic model for a ***12*** period horizon is of the form:

$$xjan_t = f(xjan_{t-12}, xjan_{t-24}, xjan_{t-36}) \quad ,$$

$$xfeb_t = f(xfeb_{t-12}, xfeb_{t-24}, xfeb_{t-36}) \quad ,$$

$$\vdots$$

$$xdec_t = f(xdec_{t-12}, xdec_{t-24}, xdec_{t-36}) \quad .$$

3.3 The Naïve Model

The basic concept of the naïve model is the use of the current period's actual as the next period's forecast. This simple forecast does not involve any mathematical modelling or elaborate computations. Therefore, it forms the benchmark when testing the adequacy of forecasting models. Any forecasting model that does not perform at least as well as the naïve model should not be considered adequate.

For seasonal data, the actual value (A_{t+1-s}) of the corresponding season of the previous year ($t+1-s$) is the forecast (F_{t+1}) for the period ($t+1$) where s is the number of seasons (Hanke and Reitch 1992 and Turner and Witt 2001):

$$F_{t+1} = A_{t+1-s} \ .$$

Since monthly data are used in this study, s = 12, naïve forecasts for the one month ahead forecasting horizon are made as follows:

$$F_{t+1} = A_{t-11} \ .$$

Naïve forecasts for the 12 months ahead forecasting horizon are made as follows

$$F_{t+12} = A_{t.} \ .$$

For horizons greater than 12 months, the actual value of a particular month of the penultimate year of the horizon is used as the forecast for the corresponding month. The naïve forecast for the 24 months ahead horizon is as follows:

$$F_{t+24} = A_t \ .$$

3.4 MLP Non-Periodic Forecasts

3.4.1 Non-periodic forecast of arrivals from all countries

Table 3.4.1 shows the non-periodic forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead forecasting horizon, but is fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead forecasting horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period and the model forecasts best over the 24 months-ahead forecasting horizon.

Table 3.4.1 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	30599	5.50	38932	7.86	24071	4.43
2 year	53203	9.79	59098	11.23	55423	10.19

3.4.2 Non-periodic forecast of arrivals from Australia

Table 3.4.2 shows the non-periodic forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also good (MAPE less than 10%) for all three forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 3.4.2	ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Australia					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	895	5.06	1026	5.71	905	5.81
2 year	1184	6.62	1170	6.80	1234	6.98

3.4.3 Non-periodic forecast of arrivals from Canada

Table 3.4.3 shows the non-periodic forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead forecasting horizon, but is fair (MAPE between 10% and 20%) for the one month ahead and 24 months ahead forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.4.3	ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Canada					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	908	6.81	897	6.75	907	6.21
2 year	1308	10.02	1323	9.94	1555	10.99

3.4.4 Non-periodic forecast of arrivals from China

Table 3.4.4 shows the non-periodic forecasting performance for tourist arrivals to Japan from China. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is poor (MAPE 20% or more) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.4.4 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5905	14.58	4750	11.31	7510	17.50
2 year	9214	27.95	8749	27.45	10039	32.29

3.4.5 Non-periodic forecast of arrivals from France

Table 3.4.5 shows the non-periodic forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also good (MAPE less than 10%) for all three forecasting horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.4.5	ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	538	6.05	547	6.47	407	4.36
2 year	816	8.67	850	9.53	811	9.12

3.4.6 Non-periodic forecast of arrivals from Germany

Table 3.4.6 shows the non-periodic forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for all three forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 3.4.6	ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1021	7.08	1003	7.17	1037	9.47
2 year	1216	10.16	1174	10.48	1328	12.83

3.4.7 Non-periodic forecast of arrivals from Korea

Table 3.4.7 shows the non-periodic forecasting performance for tourist arrivals to Japan from Korea. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead forecasting horizon and fair (MAPE between 10% and 20%), for the 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and 12 months ahead forecasting horizons and poor (MAPE 20% or less) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 3.4.7 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Korea

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	16326	9.64	18874	12.73	26949	19.32
2 year	22754	12.32	24806	15.02	37127	23.02

3.4.8 Non-periodic forecast of arrivals from Singapore

Table 3.4.8 shows the non-periodic forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is poor (MAPE 20% or less), for the one month ahead and 12 months ahead forecasting horizons and fair (MAPE between 10% and 20%), for the and 24 months ahead forecasting horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period and the model forecasts are poor.

Table 3.4.8 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Singapore

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1934	22.22	1797	21.56	1323	13.08
2 year	2128	30.17	1992	28.11	2049	26.49

3.4.9 Non-periodic forecast of arrivals from Taiwan

Table 3.4.9 shows the non-periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead and 12 months ahead forecasting horizons and good (MAPE less than 10%), for the 24 months ahead forecasting horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.4.9 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	10908	10.41	11827	12.65	6325	7.52
2 year	18132	29.35	19603	33.99	19217	32.62

3.4.10 Non-periodic forecast of arrivals from the UK

Table 3.4.10 shows the non-periodic forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead and 12 months ahead horizons and poor (MAPE 20% or less), for the 24 months ahead horizon. For the two year lead period, the performance is fair (MAPE between 10% and 20%), for the one month ahead and 12 months ahead horizons and poor (MAPE 20% or less), for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.4.10 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from the UK						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	3167	13.48	3545	16.65	7675	40.78
2 year	2868	13.61	3838	19.29	6106	31.98

3.4.11 Non-periodic forecast of arrivals from the USA

Table 3.4.11 shows the non-periodic forecasting performance for tourist arrivals to Japan from the USA. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and the 24 months ahead forecasting horizons, but is fair (MAPE between 10% and 20%) for the 12 months ahead forecasting horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months-ahead forecasting horizon.

Table 3.4.11 ANN Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from the USA						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5766	6.44	6256	7.55	3184	3.75
2 year	7354	9.39	7930	10.60	7189	9.35

3.5 MLP Non-Periodic Forecast with first and twelfth differences ($\nabla_1 \nabla_{12}$)

3.5.1 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from all countries

Table 3.5.1 shows the non-periodic forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for all three forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.5.1 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	68204	13.45	50320	11.27	73072	16.14
2 year	84950	17.62	64189	13.25	72604	16.22

3.5.2 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Australia

Table 3.5.2 shows the non-periodic forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead forecasting horizon, poor (MAPE 20% or less) for the 12 months ahead horizon and good (MAPE less than 10%), for the 24 months ahead horizon. For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the one month ahead horizon, poor (MAPE 20% or less) for the 12 months ahead horizon and good (MAPE less than 10%), for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 3.5.2 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Australia

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1917	11.82	4849	34.20	1369	8.47
2 year	1982	11.56	3910	24.82	1711	9.84

3.5.3 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Canada

Table 3.5.3 shows the non-periodic forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead and 24 months ahead forecasting horizons and poor (MAPE 20% or less) for the 12 months ahead horizon. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead horizon and poor (MAPE 20% or less) for the 12 months ahead and 24 months ahead horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months-ahead forecasting horizon.

Table 3.5.3 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Canada

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	2390	17.27	3118	27.08	1773	11.00
2 year	2656	19.74	2912	24.49	2724	21.59

3.5.4 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from China

Table 3.5.4 shows the non-periodic forecasting performance for tourist arrivals to Japan from China. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead forecasting horizon and poor (MAPE 20% or less) for the 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period and the model forecasts are poor.

Table 3.5.4 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	6249	12.29	9413	20.87	16658	41.67
2 year	9468	28.98	10473	32.29	18640	46.75

3.5.5 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from France

Table 3.5.5 shows the non-periodic forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead, 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%), for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.5.5	ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1558	17.58	1167	13.51	1549	19.49
2 year	1786	19.88	1150	13.75	1382	16.28

3.5.6 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Germany

Table 3.5.6 shows the non-periodic forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead forecasting horizon and fair (MAPE between 10% and 20%), for the 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%), for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases as the lead period increases, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.5.6	ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1151	8.91	1375	11.37	1430	14.21
2 year	2223	17.88	1494	13.00	1352	13.51

3.5.7 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Korea

Table 3.5.7 shows the non-periodic forecasting performance for tourist arrivals to Japan from Korea. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%), for the one month ahead and 12 months ahead forecasting horizons and poor (MAPE 20% or less) for the 24 months ahead horizon.

For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the one month ahead and 12 months ahead forecasting horizons, and poor (MAPE 20% or less) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.5.7 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Korea

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	12082	10.23	17108	13.23	34840	29.28
2 year	21695	12.48	22791	15.12	37311	26.23

3.5.8 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Singapore

Table 3.5.8 shows the non-periodic forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead and 24 months ahead forecasting horizons and fair (MAPE between 10% and 20%) for the 12 months ahead horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period and the model forecasts are poor.

Table 3.5.8 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Singapore

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	3431	34.71	1488	13.91	2563	32.22
2 year	3441	49.53	2164	28.52	3052	36.89

3.5.9 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from Taiwan

Table 3.5.9 shows the non-periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are poor.

Table 3.5.9 ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	49044	38.68	11840	13.30	10510	12.06
2 year	47713	67.58	26937	43.84	22029	36.82

3.5.10 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from the UK

Table 3.5.10 shows the non-periodic forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are poor.

Table 3.5.10	ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from the UK					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	8454	33.51	10209	49.57	14159	70.67
2 year	11116	37.17	17043	89.55	11367	55.75

3.5.11 $\nabla_1 \nabla_{12}$ Non-periodic forecast of arrivals from the USA

Table 3.5.11 shows the non-periodic forecasting performance for tourist arrivals to Japan from the USA. For the one year lead period the forecasting performance is good (MAPE less than 10%), for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.5.11	ANN Differenced Non-Periodic Forecasting Performance for Tourist Arrivals to Japan from the USA					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	6731	8.10	6124	8.69	4368	5.76
2 year	10772	13.27	12175	17.38	10308	14.60

3.6 MLP Partial Periodic Forecast

3.6.1 Partial Periodic forecast of arrivals from all countries

Table 3.6.1 shows the non-periodic forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.6.1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	24943	4.87	31537	6.46	35722	7.14
2 year	55528	10.24	55720	10.38	55688	11.38

3.6.2 Partial periodic forecast of arrivals from Australia

Table 3.6.2 shows the non-periodic forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is also good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.6.2	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Australia					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	598	3.68	465	2.98	886	5.56
2 year	992	5.38	923	4.92	1245	7.39

3.6.3 Partial Periodic forecast of arrivals from Canada

Table 3.6.3 shows the non-periodic forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is also mostly good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.6.3	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Canada					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	758	5.36	730	5.10	1047	7.79
2 year	1305	9.00	1339	8.85	1359	10.01

3.6.4 Partial Periodic forecast of arrivals from China

Table 3.6.4 shows the non-periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.6.4 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	4709	10.13	5483	11.72	9405	20.75
2 year	9099	28.34	8339	26.05	11230	32.83

3.6.5 Partial Periodic forecast of arrivals from France

Table 3.6.5 shows the non-periodic forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is also good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.6.5	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	411	4.49	408	4.07	734	8.46
2 year	786	8.00	810	7.87	767	8.79

3.6.6 Partial Periodic forecast of arrivals from Germany

Table 3.6.6 shows the non-periodic forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is also good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.6.6	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1015	7.60	1019	7.34	1053	8.07
2 year	1076	9.73	1077	9.48	990	8.60

3.6.7 Partial Periodic forecast of arrivals from Korea

Table 3.6.7 shows the non-periodic forecasting performance for tourist arrivals to Japan from Korea. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon.

For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons, and poor (MAPE 20% or less) for and 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 3.6.7 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Korea

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	17910	11.48	18324	12.74	27127	21.60
2 year	21062	12.74	25700	15.43	35624	24.07

3.6.8 Partial Periodic forecast of arrivals from Singapore

Table 3.6.8 shows the non-periodic forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.6.8 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Singapore

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1480	16.33	1455	16.70	1319	13.92
2 year	1893	25.94	1765	25.22	1934	25.47

3.6.9 Partial Periodic forecast of arrivals from Taiwan

Table 3.6.9 shows the non-periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and the 12 months ahead and 24 months ahead horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.6.9 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	6383	7.15	6522	7.46	8291	8.74
2 year	18696	31.55	18532	31.63	21118	35.15

3.6.10 Partial Periodic forecast of arrivals from the UK

Table 3.6.10 shows the non-periodic forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead, the 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead horizon, and poor (MAPE 20% or less) for the 12 months ahead and 24 months ahead forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error is inconsistent and the model forecasts are poor.

Table 3.6.10	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from the UK					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	3967	20.00	3969	20.96	17523	97.44
2 year	3654	17.95	3828	20.06	14564	81.55

3.6.11 Partial Periodic forecast of arrivals from the USA

Table 3.6.11 shows the non-periodic forecasting performance for tourist arrivals to Japan from the USA. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is also good (MAPE less than 10%) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.6.11	Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from the USA					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	4375	5.24	4769	6.07	2926	4.13
2 year	6644	8.57	7367	9.81	7628	9.85

3.7 MLP First Differenced (∇_1) Partial Periodic Forecast

3.7.1 ∇_1 Partial Periodic forecast of arrivals from all countries

Table 3.7.1 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon. For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.7.1	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from All Countries					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	71005	15.71	85400	19.38	98663	22.37
2 year	74336	16.45	87939	19.40	100756	21.65

3.7.2 ∇_1 Partial Periodic forecast of arrivals from Australia

Table 3.7.2 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon. For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for and 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.7.2	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Australia					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	2415	15.74	1494	10.17	3554	25.33
2 year	2480	15.45	2829	16.98	3527	23.66

3.7.3 ∇_1 Partial Periodic forecast of arrivals from Canada

Table 3.7.3 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead forecasting horizon, good (MAPE less than 10%) for the 12 months ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%), for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.7.3	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Canada					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	2796	20.96	1153	8.12	2156	17.26
2 year	2253	17.04	1910	14.57	1981	16.52

3.7.4 ∇_1 Partial Periodic forecast of arrivals from China

Table 3.7.4 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from China. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead, the 12 months ahead and the 24 months ahead horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the model forecasts are poor.

Table 3.7.4 ∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	14198	34.06	21044	51.62	20663	50.89
2 year	14205	38.44	20474	51.56	21828	52.61

3.7.5 ∇_1 Partial Periodic forecast of arrivals from France

Table 3.7.5 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead forecasting horizons and poor (MAPE 20% or less) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.7.5	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1545	19.30	1154	14.67	1743	23.20
2 year	1368	15.94	1429	16.98	1496	18.46

3.7.6 ∇_1 Partial Periodic forecast of arrivals from Germany

Table 3.7.6 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead, the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.7.6	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1448	14.12	1394	11.95	1255	10.37
2 year	1365	13.49	1443	12.55	1239	10.53

3.7.7 ∇_1 Partial Periodic forecast of arrivals from Korea

Table 3.7.7 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Korea. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead, the 12 months ahead and the 24 months ahead horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the model forecasts are poor.

Table 3.7.7	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Korea					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	29241	25.42	31518	28.17	41872	37.07
2 year	33792	25.34	36208	28.08	41522	32.46

3.7.8 ∇_1 Partial Periodic forecast of arrivals from Singapore

Table 3.7.8 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead forecasting horizon and the 24 months ahead and poor (MAPE 20% or less) for and 12 months ahead horizon. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 3.7.8	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Singapore					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1362	14.29	1867	20.43	1616	16.35
2 year	1788	24.02	1923	26.52	2044	26.01

3.7.9 ∇_1 Partial Periodic forecast of arrivals from Taiwan

Table 3.7.9 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 24 months ahead forecasting horizons and good (MAPE less than 10%) for the 12 months ahead horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon, for a one-year lead period.

Table 3.7.9	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from Taiwan					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	9523	10.39	7607	8.69	13754	17.72
2 year	19992	35.48	18934	33.04	21444	35.18

3.7.10 ∇_1 Partial Periodic forecast of arrivals from the UK

Table 3.7.10 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is poor (MAPE 20% or less) for the one month ahead, the 12 months ahead and the 24 months ahead horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the model forecasts are poor.

Table 3.7.10	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from the UK					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	14745	76.71	9762	51.56	19815	108.73
2 year	14878	83.22	9157	51.32	15778	85.04

3.7.11 ∇_1 Partial Periodic forecast of arrivals from the USA

Table 3.7.11 shows the differenced non-periodic forecasting performance for tourist arrivals to Japan from the USA. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is good (MAPE less than 10%) for the one month ahead and the 12 months ahead forecasting horizons and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.7.11	∇_1 Partial Periodic Model Forecasting Performance for Tourist Arrivals to Japan from the USA					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5597	7.58	5026	6.89	6713	9.73
2 year	7074	9.82	6151	9.05	7639	11.34

3.8 MLP Periodic Forecast

3.8.1 Periodic forecast of arrivals from all countries

Table 3.8.1 shows the periodic forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.1 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	35420	6.85	33861	7.04
2 year	n/a	n/a	57341	10.73	54170	10.87

3.8.2 Periodic forecast of arrivals from Australia

Table 3.8.2 shows the periodic forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is also good (MAPE less than 10%) for the 12 months ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.2	ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Australia					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	732	3.59	2054	11.58
2 year	n/a	n/a	2282	6.82	2325	13.38

3.8.3 Periodic forecast of arrivals from Canada

Table 3.8.3 shows the periodic forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.3	ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Canada					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	1084	7.44	970	6.61
2 year	n/a	n/a	1751	12.58	2200	14.29

3.8.4 Periodic forecast of arrivals from China

Table 3.8.4 shows the periodic forecasting performance for tourist arrivals to Japan from China. For the one year lead period the forecasting performance fair (MAPE between 10% and 20%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is poor (MAPE 20% or more) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.4 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	5419	12.32	7877	17.91
2 year	n/a	n/a	8584	26.83	10007	30.37

3.8.5 Periodic forecast of arrivals from France

Table 3.8.5 shows the periodic forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also good (MAPE less than 10%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.5	ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	338	3.32	491	5.33
2 year	n/a	n/a	990	9.46	799	8.03

3.8.6 Periodic forecast of arrivals from Germany

Table 3.8.6 shows the periodic forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.8.6	ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	1115	8.37	1218	10.20
2 year	n/a	n/a	1299	12.14	1239	11.75

3.8.7 Periodic forecast of arrivals from Korea

Table 3.8.6 shows the periodic forecasting performance for tourist arrivals to Japan from Korea. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.8.7 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Korea

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	11924	9.18	19900	15.58
2 year	n/a	n/a	16603	11.56	26709	17.59

3.8.8 Periodic forecast of arrivals from Singapore

Table 3.8.8 shows the periodic forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is poor (MAPE 20% or more) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.8.8 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Singapore

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	1326	15.01	1107	12.59
2 year	n/a	n/a	1646	24.18	1722	21.95

3.8.9 Periodic forecast of arrivals from Taiwan

Table 3.8.9 shows the periodic forecasting performance for tourist arrivals to Japan from Taiwan. For the one-year lead period the forecasting performance good (MAPE less than 10%) for the 12 months ahead and the 24 months-ahead forecasting horizons. For the two year lead period, the forecasting performance is poor (MAPE 20% or more) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 3.8.9 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	7429	9.13	8684	8.47
2 year	n/a	n/a	19077	33.65	22397	37.05

3.8.10 Periodic forecast of arrivals from the UK

Table 3.8.10 shows the periodic forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is poor (MAPE 20% or more) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also poor (MAPE 20% or more) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the model forecasts are poor.

Table 3.8.10 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from the UK						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	5672	22.21	11019	58.10
2 year	n/a	n/a	4844	21.47	8721	45.17

3.8.11 Periodic forecast of arrivals from the USA

Table 3.8.11 shows the periodic forecasting performance for tourist arrivals to Japan from the USA. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and the 24 months ahead forecasting horizons. For the two-year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.8.11 ANN Periodic Forecasting Performance for Tourist Arrivals to Japan from the USA						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	n/a	n/a	5411	7.05	3042	4.32
2 year	n/a	n/a	7960	10.72	7905	10.21

3.9 Naïve Forecasts

Forecast for the one month ahead horizon is the same as that for the 12 months ahead horizon as the data are seasonal.

3.9.1 Naïve forecast of arrivals from all countries

Table 3.9.1 shows the naive forecasting performance for tourist arrivals to Japan from all countries. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and 24 months ahead forecasting horizons. For the two-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.1 Naive Forecasting Performance for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	47084	9.92	47084	9.92	43323	9.26
2 year	59512	12.30	59512	12.30	66744	13.93

3.9.2 Naïve forecast of arrivals from Australia

Table 3.9.2 shows the naive forecasting performance for tourist arrivals to Japan from Australia. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead forecasting horizons. For the two-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.2	Naive Forecasting Performance for Tourist Arrivals to Japan from Australia					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1455	10.07	1455	10.07	1748	10.80
2 year	1351	8.62	1351	8.62	2087	13.02

3.9.3 Naïve forecast of arrivals from Canada

Table 3.9.3 shows the naive forecasting performance for tourist arrivals to Japan from Canada. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead forecasting horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.3	Naive Forecasting Performance for Tourist Arrivals to Japan from Canada					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1120	8.60	1120	8.60	1372	10.37
2 year	1280	10.19	1280	10.19	1583	12.41

3.9.4 Naïve forecast of arrivals from China

Table 3.9.4 shows the naive forecasting performance for tourist arrivals to Japan from China. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead horizon and poor (MAPE 20% or more) for the 24 months ahead horizon. For the two-year lead period the forecasting performance is poor (MAPE 20% or more) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are poor.

Table 3.9.4 Naive Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5887	14.21	5887	14.21	9318	21.00
2 year	8476	27.30	8476	27.30	10954	32.48

3.9.5 Naïve forecast of arrivals from France

Table 3.9.5 shows the naive forecasting performance for tourist arrivals to Japan from Canada. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two-year lead period, the forecasting performance is also good (MAPE less than 10%) for the 12 months ahead horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.5	Naive Forecasting Performance for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	585	6.34	585	6.34	940	11.93
2 year	852	9.40	852	9.40	889	10.65

3.9.6 Naïve forecast of arrivals from Germany

Table 3.9.6 shows the naive forecasting performance for tourist arrivals to Japan from Germany. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months-ahead horizon and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.6	Naive Forecasting Performance for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1092	7.87	1092	7.87	1317	10.30
2 year	1247	11.20	1247	11.20	1268	10.97

3.9.7 Naïve forecast of arrivals from Korea

Table 3.9.7 shows the naive forecasting performance for tourist arrivals to Japan from Korea. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead forecasting horizons. For the two-year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.7	Naive Forecasting Performance for Tourist Arrivals to Japan from Korea					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	13113	10.51	13113	10.51	18600	15.90
2 year	17606	12.75	17606	12.75	26280	18.34

3.9.8 Naïve forecast of arrivals from Singapore

Table 3.9.8 shows the naive forecasting performance for tourist arrivals to Japan from Singapore. For the one-year lead period the forecasting performance is poor (MAPE 20% or more) for the 12 months-ahead horizon and good (MAPE less than 10%) for the 24 months ahead horizon. For the two-year lead period the forecasting performance is poor (MAPE 20% or more) for both horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are poor.

Table 3.9.8	Naive Forecasting Performance for Tourist Arrivals to Japan from Singapore					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1644	21.34	1644	21.34	993	9.09
2 year	1794	27.70	1794	27.70	1968	25.86

3.9.9 Naïve forecast of arrivals from Taiwan

Table 3.9.9 shows the naive forecasting performance for tourist arrivals to Japan from Taiwan. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead forecasting horizons. For the two-year lead period, the forecasting performance is also poor (MAPE 20% or more) for both horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon but poor for the 2-year lead period.

Table 3.9.9 Naive Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	12620	14.17	12620	14.17	9149	10.55
2 year	19842	35.43	19842	35.43	20045	34.39

3.9.10 Naïve forecast of arrivals from the UK

Table 3.9.10 shows the naive forecasting performance for tourist arrivals to Japan from the UK. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months-ahead horizon and poor (MAPE 20% or more) for the 24 months ahead horizon. For the two-year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the 12 months ahead horizon and poor (MAPE 20% or more) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 3.9.10	Naive Forecasting Performance for Tourist Arrivals to Japan from the UK					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	3815	12.72	3815	12.72	14877	79.46
2 year	3817	13.50	3817	13.50	10569	43.31

3.9.11 Naïve forecast of arrivals from the USA

Table 3.9.11 shows the naive forecasting performance for tourist arrivals to Japan from the USA. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the 12 months ahead and 24 months ahead forecasting horizons. For the two-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the 12 months-ahead horizon and good (MAPE less than 10%) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 3.9.11	Naive Forecasting Performance for Tourist Arrivals to Japan from the USA					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	6382	7.97	6382	7.97	2586	2.89
2 year	8072	10.38	8072	10.38	8352	9.88

3.10 Differenced and Undifferenced MLP Model Comparison

Table 3.10.1 shows a comparison of the one-month ahead forecasting performance of the differenced and undifferenced non-periodic MLP models and a comparison of the differenced and undifferenced partial periodic MLP models. Of the non-periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 8 (36%) of 22 forecasts while the differenced model has the lower MAPE in none (0%) of the forecasts. The 22 forecasts were obtained for 1 and 2 year lead periods using 11 data series. Of the partial periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 12 (55%) of 22 forecasts, while the differenced model has the lower MAPE in 2 (9%) of the forecasts.

The undifferenced non-periodic model also has a mean MAPE of 12.5%, the mean MAPE of the differenced non-periodic model being 22.8%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced non-periodic model and the differenced model is significant. The undifferenced partial periodic model also has a mean MAPE of 12.0%, the mean MAPE of the differenced partial periodic model being 25.0%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced partial periodic model and the differenced model is significant. On the level of accuracy achieved, the undifferenced non-periodic model has 10 (50%) forecasts with MAPE figures less than 10%, while the differenced non-periodic model has 2 (9%) forecasts with MAPE less than 10%. The undifferenced partial periodic model has 12 (55%) forecasts with MAPE figures

less than 10%, while the differenced partial periodic model has 2 (9%) forecasts with MAPE less than 10%.

Table 3.10.2 shows a comparison of the 12-months-ahead forecasting performance of the differenced and undifferenced non-periodic MLP models and a comparison of the differenced and undifferenced partial periodic MLP models. Of the non-periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 6 (27%) of 22 forecasts while the differenced model has the lower MAPE in 1 (5%) of the forecasts. Of the partial periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 14 (64%) of 22 forecasts while the differenced model has the lower MAPE in 1 (5%) of the forecasts.

The undifferenced non-periodic model also has a mean MAPE of 13.6%, the mean MAPE of the differenced non-periodic model being 24.2%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced non-periodic model and the differenced model is significant. The undifferenced partial periodic model also has a mean MAPE of 12.3%, the mean MAPE of the differenced partial periodic model being 23.3%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced partial periodic model and the differenced model is significant. On the level of accuracy achieved, the undifferenced non-periodic model has made 9 (41%) forecasts with MAPE figures less than 10%, while the differenced non-periodic model has 1 (5%) forecast with MAPE less than 10%. The undifferenced partial periodic model has 12 (55%) forecasts with MAPE figures less than 10%, while the differenced partial periodic model has 4 (18%) forecasts with MAPE less than 10%.

Table 3.10.3 shows a comparison of the 24 months ahead forecasting performance of the differenced and undifferenced non-periodic MLP models and a comparison of the differenced and undifferenced partial periodic MLP models. Of the non-periodic models the undifferenced model is better than the differenced model, as it has the lower MAPE in 16 (73%) of 22 forecasts while the differenced model has the lower MAPE in none (0%) of the forecasts. Of the partial periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 6 (27%) of 22 forecasts while the differenced model has the lower MAPE in none (0%) of the forecasts.

The undifferenced non-periodic model also has a mean MAPE of 15.4%, the mean MAPE of the differenced non-periodic model being 25.2%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced non-periodic model and the differenced model is significant. The undifferenced partial periodic model also has a mean MAPE of 20.8%, the mean MAPE of the differenced partial periodic model being 30.6%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced partial periodic model and the differenced model is significant. On the level of accuracy achieved, the undifferenced non-periodic model has 10 (45%) forecasts with MAPE figures less than 10%, while the differenced non-periodic model has 3 (14%) forecasts with MAPE less than 10%. The undifferenced partial periodic model has 11 (50%) forecasts with MAPE figures

less than 10%, while the differenced partial periodic model has 1 (5%) forecast with MAPE less than 10%.

Table 3.10.1		**Univariate one month ahead Forecasting Performance of differenced and undifferenced Neural Network models**							
Country	Forecast Lead	Non-Periodic RMSE	MAPE	NP Differenced RMSE	MAPE	Partial Periodic RMSE	MAPE	PP Differenced RMSE	MAPE
All	1 year	30599	5.5	68204	13.4	24943	4.9	71005	15.7
	2 year	53203	9.8	84950	17.6	55528	10.2	74336	16.5
Australia	1 year	895	5.1	1917	11.8	598	3.7	2415	15.7
	2 year	1184	6.6	1982	11.6	992	5.4	2480	15.5
Canada	1 year	908	6.8	2390	17.3	758	5.4	2796	21.0
	2 year	1308	10.0	2656	19.7	1305	9.0	2253	17.0
China	1 year	5905	14.6	6249	12.3	4709	10.1	14198	34.1
	2 year	9214	28.0	9468	29.0	9099	28.3	14205	38.4
France	1 year	538	6.1	1558	17.6	411	4.5	1545	19.3
	2 year	816	8.7	1786	19.9	786	8.0	1368	15.9
Germany	1 year	1021	7.1	1151	8.9	1015	7.6	1448	14.1
	2 year	1216	10.2	2223	17.9	1076	9.7	1365	13.5
Korea	1 year	16326	9.6	12082	10.2	17910	11.5	29241	25.4
	2 year	22754	12.3	21695	12.5	21062	12.7	33792	25.3
Singapore	1 year	1934	22.2	3431	34.7	1480	16.3	1362	14.3
	2 year	2128	30.2	3441	49.5	1893	25.9	1788	24.0
Taiwan	1 year	10908	10.4	49044	38.7	6383	7.2	9523	10.4
	2 year	18132	29.3	47713	67.6	18696	31.5	19992	35.5
UK	1 year	3167	13.5	8454	33.5	3967	20.0	14745	76.7
	2 year	2868	13.6	11116	37.2	3654	17.9	14878	83.2
USA	1 year	5766	6.4	6731	8.1	4375	5.2	5597	7.6
	2 year	7354	9.4	10772	13.3	6644	8.6	7074	9.8
Summary Measures									
Mean		9007	12.5	16319	22.8	8513	12.0	14882	25.0
Standard Deviation		12829	7.8	23754	15.1	12865	8.1	20867	19.6
MAPE p-values:									
c/w Differenced NP model			-0.01						
c/w Differenced PP model							-0.01		
Lowest MAPE Count		Count	**%**	Count	%	Count	**%**	Count	**%**
of 22 forecasts		8	36%	0	0%	12	55%	2	9%
MAPE <= 10%		11	50%	2	9%	12	55%	2	9%
10% <MAPE< 20%		7	32%	13	59%	7	32%	11	50%
MAPE >= 20%		4	18%	7	32%	3	14%	9	41%
MAPE <= 10%									
for 1 year lead		7	64%	2	100%	7	58%	1	50%
for 2 year lead		4	36%	0	0%	5	42%	1	50%

Table 3.10.2 **Univariate 12 months ahead Forecasting Performance of differenced and undifferenced Neural Network models**

Country	Forecast Lead	Non-Periodic RMSE	Non-Periodic MAPE	NP Differenced RMSE	NP Differenced MAPE	Partial Periodic RMSE	Partial Periodic MAPE	PP Differenced RMSE	PP Differenced MAPE
All	1 year	38932	7.9	50320	11.3	31537	6.5	85400	19.4
	2 year	59098	11.2	64189	13.3	55720	10.4	87939	19.4
Australia	1 year	1026	5.7	4849	34.2	465	3.0	1494	10.2
	2 year	1170	6.8	3910	24.8	923	4.9	2829	17.0
Canada	1 year	897	6.8	3118	27.1	730	5.1	1153	8.1
	2 year	1323	9.9	2912	24.5	1339	8.8	1910	14.6
China	1 year	4750	11.3	9413	20.9	5483	11.7	21044	51.6
	2 year	8749	27.4	10473	32.3	8339	26.1	20474	51.6
France	1 year	547	6.5	1167	13.5	408	4.1	1154	14.7
	2 year	850	9.5	1150	13.7	810	7.9	1429	17.0
Germany	1 year	1003	7.2	1375	11.4	1019	7.3	1394	11.9
	2 year	1174	10.5	1494	13.0	1077	9.5	1443	12.6
Korea	1 year	18874	12.7	17108	13.2	18324	12.7	31518	28.2
	2 year	24806	15.0	22791	15.1	25700	15.4	36208	28.1
Singapore	1 year	1797	21.6	1488	13.9	1455	16.7	1867	20.4
	2 year	1992	28.1	2164	28.5	1765	25.2	1923	26.5
Taiwan	1 year	11827	12.6	11840	13.3	6522	7.5	7607	8.7
	2 year	19603	34.0	26937	43.8	18532	31.6	18934	33.0
UK	1 year	3545	16.6	10209	49.6	3969	21.0	9762	51.6
	2 year	3838	19.3	17043	89.5	3828	20.1	9157	51.3
USA	1 year	6256	7.6	6124	8.7	4769	6.1	5026	6.9
	2 year	7930	10.6	12175	17.4	7367	9.8	6151	9.1
Summary Measures									
Mean		9999	13.6	12830	24.2	9095	12.3	16174	23.3
Standard Deviation		14717	7.9	16269	18.3	13594	7.9	25001	15.3
MAPE p-values:									
c/w NP Differenced model			-0.01						
c/w PP Differenced model							-0.01		
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	**%**
of 22 forecasts		6	27%	1	5%	14	64%	1	5%
MAPE <= 10%		9	41%	1	5%	12	55%	4	18%
10% <MAPE< 20%		9	41%	11	50%	5	23%	9	41%
MAPE >= 20%		4	18%	10	45%	5	23%	9	41%
MAPE <= 10%									
for 1 year lead		6	67%	1	100%	7	58%	3	75%
for 2 year lead		3	33%	0	0%	5	42%	1	25%

Table 3.10.3 **Univariate 24 months ahead Forecasting Performance of differenced and undifferenced Neural Network models**

Country	Forecast Lead	Non-Periodic RMSE	Non-Periodic MAPE	NP Differenced RMSE	NP Differenced MAPE	Partial Periodic RMSE	Partial Periodic MAPE	PP Differenced RMSE	PP Differenced MAPE
All	1 year	24071	4.4	73072	16.1	35722	7.1	98663	22.4
	2 year	55423	10.2	72604	16.2	55688	11.4	100756	21.7
Australia	1 year	905	5.8	1369	8.5	886	5.6	3554	25.3
	2 year	1234	7.0	1711	9.8	1245	7.4	3527	23.7
Canada	1 year	907	6.2	1773	11.0	1047	7.8	2156	17.3
	2 year	1555	11.0	2724	21.6	1359	10.0	1981	16.5
China	1 year	7510	17.5	16658	41.7	9405	20.7	20663	50.9
	2 year	10039	32.3	18640	46.7	11230	32.8	21828	52.6
France	1 year	407	4.4	1549	19.5	734	8.5	1743	23.2
	2 year	811	9.1	1382	16.3	767	8.8	1496	18.5
Germany	1 year	1037	9.5	1430	14.2	1053	8.1	1255	10.4
	2 year	1328	12.8	1352	13.5	990	8.6	1239	10.5
Korea	1 year	26949	19.3	34840	29.3	27127	21.6	41872	37.1
	2 year	37127	23.0	37311	26.2	35624	24.1	41522	32.5
Singapore	1 year	1323	13.1	2563	32.2	1319	13.9	1616	16.4
	2 year	2049	26.5	3052	36.9	1934	25.5	2044	26.0
Taiwan	1 year	6325	7.5	10510	12.1	8291	8.7	13754	17.7
	2 year	19217	32.6	22029	36.8	21118	35.1	21444	35.2
UK	1 year	7675	40.8	14159	70.7	17523	97.4	19815	108.7
	2 year	6106	32.0	11367	55.7	14564	81.6	15778	85.0
USA	1 year	3184	3.8	4368	5.8	2926	4.1	6713	9.7
	2 year	7189	9.3	10308	14.6	7628	9.8	7639	11.3
Summary Measures									
Mean		10108	15.4	15671	25.2	11735	20.8	19594	30.6
Standard Deviation		14222	11.0	21302	16.9	14931	24.0	28672	24.7
MAPE p-values:									
c/w NP Differenced model			-0.01						
c/w PP Differenced model							-0.01		
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	**%**
of 22 forecasts		16	73%	0	0%	6	27%	0	0%
MAPE <= 10%		10	45%	3	14%	11	50%	1	5%
10% <MAPE< 20%		6	27%	9	41%	3	14%	8	36%
MAPE >= 20%		6	27%	10	45%	8	36%	13	59%
MAPE <= 10%									
for 1 year lead		7	70%	2	67%	7	64%	1	100%
for 2 year lead		3	30%	1	33%	4	36%	0	0%

Table 3.10.4	Forecasting Performance Comparison Summary of differenced and undifferenced Neural Network models							
	Non-Periodic		NP Differenced		Partial Periodic		PP Differenced	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Mean	9705	13.8	14940	24.1	9781	15.1	16883	26.3
Standard Deviation	13738	9.0	20414	16.6	13682	15.6	24743	20.2
MAPE p-values:								
c/w NP Differenced model		-0.01						
c/w PP Differenced model						-0.01		
Lowest MAPE Count	Count	%	Count	%	Count	%	Count	%
of 66 forecasts	30	45%	1	2%	32	48%	3	5%
MAPE <= 10%	30	45%	6	9%	35	53%	7	11%
10% <MAPE< 20%	22	33%	33	50%	15	23%	28	42%
MAPE >= 20%	14	21%	27	41%	16	24%	31	47%
MAPE <= 10%								
for 1 year lead	20	67%	5	83%	21	60%	5	71%
for 2 year lead	10	33%	1	17%	14	40%	2	29%

Table 3.10.4 shows a summary comparison of the forecasting performance of the differenced and undifferenced non-periodic MLP models, and a comparison of the differenced and undifferenced partial periodic MLP models. Of the non-periodic models the undifferenced model is better than the differenced model as it has the lower MAPE in 30 (45%) of 66 forecasts, while the differenced model has the lower MAPE in 1 (2%) of the forecasts. Of the partial periodic models the undifferenced model is better than the differenced model as it has a lower MAPE in 32 (48%) of 66 forecasts, while the differenced model has the lower MAPE in 3 (5%) of the forecasts.

The undifferenced non-periodic model has a mean MAPE of 13.8%, while that of the differenced model is 24.1%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced non-periodic model and the differenced model is significant. The undifferenced partial periodic model has a mean

MAPE of 15.1%, while that of the differenced model is 26.3%. The paired sample p-value of 0.01 indicates that the mean difference in MAPE of the undifferenced partial periodic model and the differenced model is significant. On the level of accuracy, the undifferenced non-periodic model has 30 (45%) forecasts with MAPE figures less than 10%, while the differenced model achieved only 6 (9%) such forecasts. The undifferenced partial periodic model has 35 (53%) forecasts with MAPE figures less than 10%, while the differenced model has only 7 (11%) such forecasts.

3.11 MLP Model Comparison with the Naïve model

Table 3.11.1 shows a comparison of the forecasting performance of the Non-periodic, Partial periodic, Periodic and Naïve models for the one month ahead forecasting horizon. For the one month ahead forecasting horizon, the partial periodic model is the best model as it has the lowest MAPE in 14 (64%) of 22 forecasts. Twelve (55%) partial periodic forecasts have MAPE figures less than 10%. Seven (58%) and 5 (42%) of these 12 forecasts were for the 1 and 2 year lead periods respectively, indicating the model works better for the 1 year lead period.

The partial periodic model also has the smallest mean MAPE of 12.0%. The non-periodic model has a mean MAPE of 12.5%. Both models have significant mean differences from the MAPE of the naïve model with the paired sample p-value for the mean difference being less than 0.01. The non-periodic model has the lowest MAPE figures in 5 (23%) forecasts. The naïve model has the lowest MAPE in 3 (14%) forecasts. The periodic model is not applicable to one-month ahead forecasts as it forecasts 12 months ahead.

Table 3.11.2 shows a comparison of the forecasting performance of the Non-periodic, Partial periodic, Periodic and Naïve models for the 12 months ahead forecasting horizon. Using the lowest MAPE as the forecasting performance evaluation criterion, for the 12 months ahead forecasting horizon, the partial periodic model is the best model as it has the lowest MAPE in 13 (59%) of 22 forecasts. Twelve (55%) of the 22 partial periodic forecasts have MAPE figures less than 10%. Seven (58%) and 5 (42%) of these 12 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for the 1 year lead period.

The partial periodic model has the lowest mean MAPE of 12.3%, the paired sample p-values indicating significant mean differences at the 5% level for MAPE values between the partial periodic model and the non-periodic and naïve models. The periodic model has a mean MAPE of 12.9% while the non-periodic model has a mean MAPE of 13.6. The periodic model has the lowest MAPE figures in 5 (23%) forecasts followed by the non-periodic model with the lowest MAPE figures in 2 (9%) forecasts. The naïve model also has the lowest MAPE in 2 (9%) forecasts.

Table 3.11.3 shows a comparison of the forecasting performance of the Non-periodic, Partial periodic, Periodic and Naïve models for the 24-months-ahead forecasting horizon. Using the lowest MAPE as the forecasting performance evaluation criterion, for the 24 months ahead forecasting horizon, the non-periodic model is the best model as it has the lowest MAPE in 11 (50%) of 22 forecasts. Ten (45%) of the 22 partial periodic forecasts have MAPE figures less than 10%. Seven (70%) and 3 (30%) of these 10 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for the 1 year lead period.

The non-periodic model also has the smallest mean MAPE of 15.4% while the periodic model has a mean MAPE of 17.2%. The paired sample p-values do not show significant mean differences in the MAPE values of the models at the 5% level, except between the non-periodic and naïve models. The next best model is the periodic model with the lowest MAPE figures in 5 (23%) forecasts followed by the partial periodic model with the lowest MAPE figures in 4 (18%) forecasts. The naïve model has the lowest MAPE in 2 (9%) forecasts.

Table 3.11.4 shows a comparison summary of the forecasting performance of the Non-periodic, Partial periodic, Periodic and Naïve models. The partial periodic model is the best model as it has the lowest MAPE in 31 (47%) of 66 forecasts. Thirty five (53%) of the 66 partial periodic forecasts have MAPE figures less than 10%. Twenty one (60%) and 14 (40%) of these 21 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for the 1 year lead period. The next best model is the non-periodic model with the lowest MAPE figures in 18 (27%) forecasts followed by the periodic model with the lowest MAPE figures in 10 (23%) forecasts. The naïve model has the lowest MAPE in 7 (11%) forecasts.

However, paired sample p-values of the mean differences of the MAPE figures of the partial periodic model are not significant at the 5% level. This is because the variance of the MAPE of this model is high due to the very good performance of some of the 66 forecasts and the very poor performance of others. The non-periodic model has the smallest mean MAPE of 13.8%. The partial periodic model has a mean MAPE of 15.1%, The periodic model also has a mean MAPE of 15.1%.

Table 3.11.1 **Univariate one month ahead Forecasting Performance of Neural Network and Naïve Forecasts**

Country	Forecast Lead	Non-Periodic RMSE	Non-Periodic MAPE	Partial Periodic RMSE	Partial Periodic MAPE	Periodic RMSE	Periodic MAPE	Naïve RMSE	Naïve MAPE
All	1 year	30599	5.5	24943	4.9	N/a	n/a	47084	9.9
	2 year	53203	9.8	55528	10.2	N/a	n/a	59512	12.3
Australia	1 year	895	5.1	598	3.7	N/a	n/a	1455	10.1
	2 year	1184	6.6	992	5.4	N/a	n/a	1351	8.6
Canada	1 year	908	6.8	758	5.4	N/a	n/a	1120	8.6
	2 year	1308	10.0	1305	9.0	N/a	n/a	1280	10.2
China	1 year	5905	14.6	4709	10.1	N/a	n/a	5887	14.2
	2 year	9214	28.0	9099	28.3	N/a	n/a	8476	27.3
France	1 year	538	6.1	411	4.5	N/a	n/a	585	6.3
	2 year	816	8.7	786	8.0	N/a	n/a	852	9.4
Germany	1 year	1021	7.1	1015	7.6	N/a	n/a	1092	7.9
	2 year	1216	10.2	1076	9.7	N/a	n/a	1247	11.2
Korea	1 year	16326	9.6	17910	11.5	N/a	n/a	13113	10.5
	2 year	22754	12.3	21062	12.7	N/a	n/a	17606	12.8
Singapore	1 year	1934	22.2	1480	16.3	N/a	n/a	1644	21.3
	2 year	2128	30.2	1893	25.9	N/a	n/a	1794	27.7
Taiwan	1 year	10908	10.4	6383	7.2	N/a	n/a	12620	14.2
	2 year	18132	29.3	18696	31.5	N/a	n/a	19842	35.4
UK	1 year	3167	13.5	3967	20.0	N/a	n/a	3815	12.7
	2 year	2868	13.6	3654	17.9	N/a	n/a	3817	13.5
USA	1 year	5766	6.4	4375	5.2	N/a	n/a	6382	8.0
	2 year	7354	9.4	6644	8.6	N/a	n/a	8072	10.4
Summary Measures									
Mean		9007	12.5	8513	12.0			9938	13.7
Standard Deviation		12829	7.8	12865	8.1			15242	7.5
MAPE p-values:									
c/w Naïve model			-0.01		-0.01				
c/w Periodic model									
c/w Partial Periodic model			0.19						0.01
c/w Non-Periodic model					-0.19				0.01
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	%
of 22 forecasts		5	23%	14	64%	0	0%	3	14%
MAPE <= 10%		11	50%	12	55%	0	0%	7	32%
10% <MAPE< 20%		7	32%	7	32%	0	0%	11	50%
MAPE >= 20%		4	18%	3	14%	0	0%	4	18%
MAPE <= 10%									
for 1 year lead		7	64%	7	58%	0	0%	5	71%
for 2 year lead		4	36%	5	42%	0	0%	2	29%

Table 3.11.2 **Univariate 12 months ahead Forecasting Performance of Neural Network and Naïve Forecasts**

Country	Forecast Lead	Non-Periodic RMSE	Non-Periodic MAPE	Partial Periodic RMSE	Partial Periodic MAPE	Periodic RMSE	Periodic MAPE	Naïve RMSE	Naïve MAPE
All	1 year	38932	7.9	31537	6.5	35420	6.9	47084	9.9
	2 year	59098	11.2	55720	10.4	57341	10.7	59512	12.3
Australia	1 year	1026	5.7	465	3.0	732	3.6	1455	10.1
	2 year	1170	6.8	923	4.9	2282	6.8	1351	8.6
Canada	1 year	897	6.8	730	5.1	1084	7.4	1120	8.6
	2 year	1323	9.9	1339	8.8	1751	12.6	1280	10.2
China	1 year	4750	11.3	5483	11.7	5419	12.3	5887	14.2
	2 year	8749	27.4	8339	26.1	8584	26.8	8476	27.3
France	1 year	547	6.5	408	4.1	338	3.3	585	6.3
	2 year	850	9.5	810	7.9	990	9.5	852	9.4
Germany	1 year	1003	7.2	1019	7.3	1115	8.4	1092	7.9
	2 year	1174	10.5	1077	9.5	1299	12.1	1247	11.2
Korea	1 year	18874	12.7	18324	12.7	11924	9.2	13113	10.5
	2 year	24806	15.0	25700	15.4	16603	11.6	17606	12.8
Singapore	1 year	1797	21.6	1455	16.7	1326	15.0	1644	21.3
	2 year	1992	28.1	1765	25.2	1646	24.2	1794	27.7
Taiwan	1 year	11827	12.6	6522	7.5	7429	9.1	12620	14.2
	2 year	19603	34.0	18532	31.6	19077	33.6	19842	35.4
UK	1 year	3545	16.6	3969	21.0	5672	22.2	3815	12.7
	2 year	3838	19.3	3828	20.1	4844	21.5	3817	13.5
USA	1 year	6256	7.6	4769	6.1	5411	7.0	6382	8.0
	2 year	7930	10.6	7367	9.8	7960	10.7	8072	10.4
Summary Measures									
Mean		9999	13.6	9095	12.3	9011	12.9	9938	13.7
Standard Deviation		14717	7.9	13594	7.9	13563	7.9	15242	7.5
MAPE p-values:									
c/w Naïve model			-0.37		-0.04		-0.16		
c/w Periodic model			0.14		-0.07				0.16
c/w Partial Periodic model			0.01				0.07		0.04
c/w Non-Periodic model					-0.01		-0.14		0.37
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	**%**
of 22 forecasts		2	9%	13	59%	5	23%	2	9%
MAPE <= 10%		9	41%	12	55%	10	45%	7	32%
10% <MAPE< 20%		9	41%	5	23%	7	32%	11	50%
MAPE >= 20%		4	18%	5	23%	5	23%	4	18%
MAPE <= 10%									
for 1 year lead		6	67%	7	58%	8	80%	5	71%
for 2 year lead		3	33%	5	42%	2	20%	2	29%

Table 3.11.3 **Univariate 24 months ahead Forecasting Performance of Neural Network and Naïve Forecasts**

Country	Forecast Lead	Non-Periodic RMSE	Non-Periodic MAPE	Partial Periodic RMSE	Partial Periodic MAPE	Periodic RMSE	Periodic MAPE	Naïve RMSE	Naïve MAPE
All	1 year	24071	4.4	35722	7.1	33861	7.0	43323	9.3
	2 year	55423	10.2	55688	11.4	54170	10.9	66744	13.9
Australia	1 year	905	5.8	886	5.6	2054	11.6	1748	10.8
	2 year	1234	7.0	1245	7.4	2325	13.4	2087	13.0
Canada	1 year	907	6.2	1047	7.8	970	6.6	1372	10.4
	2 year	1555	11.0	1359	10.0	2200	14.3	1583	12.4
China	1 year	7510	17.5	9405	20.7	7877	17.9	9318	21.0
	2 year	10039	32.3	11230	32.8	10007	30.4	10954	32.5
France	1 year	407	4.4	734	8.5	491	5.3	940	11.9
	2 year	811	9.1	767	8.8	799	8.0	889	10.6
Germany	1 year	1037	9.5	1053	8.1	1218	10.2	1317	10.3
	2 year	1328	12.8	990	8.6	1239	11.8	1268	11.0
Korea	1 year	26949	19.3	27127	21.6	19900	15.6	18600	15.9
	2 year	37127	23.0	35624	24.1	26709	17.6	26280	18.3
Singapore	1 year	1323	13.1	1319	13.9	1107	12.6	993	9.1
	2 year	2049	26.5	1934	25.5	1722	22.0	1968	25.9
Taiwan	1 year	6325	7.5	8291	8.7	8684	8.5	9149	10.5
	2 year	19217	32.6	21118	35.1	22397	37.1	20045	34.4
UK	1 year	7675	40.8	17523	97.4	11019	58.1	14877	79.5
	2 year	6106	32.0	14564	81.6	8721	45.2	10569	43.3
USA	1 year	3184	3.8	2926	4.1	3042	4.3	2586	2.9
	2 year	7189	9.3	7628	9.8	7905	10.2	8352	9.9
Summary Measures									
Mean		10108	15.4	11735	20.8	10383	17.2	11589	18.9
Standard Deviation		14222	11.0	14931	24.0	13541	13.8	16238	16.7
MAPE p-values:									
c/w Naïve model			-0.03		0.18		-0.06		
c/w Periodic model			-0.06		0.08				0.06
c/w Partial Periodic model			-0.06				-0.08		-0.18
c/w Non-Periodic model					0.06		0.06		0.03
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	**%**
of 22 forecasts		11	50%	4	18%	5	23%	2	9%
MAPE <= 10%		10	45%	11	50%	6	27%	4	18%
10% <MAPE< 20%		6	27%	3	14%	11	50%	12	55%
MAPE >= 20%		6	27%	8	36%	5	23%	6	27%
MAPE <= 10%									
for 1 year lead		7	70%	7	64%	5	83%	3	75%
for 2 year lead		3	30%	4	36%	1	17%	1	25%

Table 3.11.4	**Forecasting Performance Comparison Summary of Neural Network and Naïve Forecasts**							
	Non-Periodic		Partial Periodic		Periodic		Naïve	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Mean	9705	13.8	9781	15.1	9697	15.1	10489	15.5
Standard Deviation	13738	9.0	13682	15.6	13411	11.3	15359	11.5
MAPE p-values:								
c/w Naïve model		-0.01		-0.29		-0.03		
c/w Periodic model		-0.18		0.12				0.03
c/w Partial Periodic model		-0.15				-0.12		0.29
c/w Non-Periodic model				0.15		0.18		0.01
Lowest MAPE Count	Count	%	Count	**%**	Count	**%**	Count	**%**
of 66 forecasts	18	27%	31	47%	10	23%	7	11%
MAPE <= 10%	30	45%	35	53%	16	36%	18	27%
10% <MAPE< 20%	22	33%	15	23%	18	41%	34	52%
MAPE >= 20%	14	21%	16	24%	10	23%	14	21%
MAPE <= 10%								
for 1 year lead	20	67%	21	60%	13	81%	13	72%
for 2 year lead	10	33%	14	40%	3	19%	5	28%

3.12 Conclusion

Overall for both the non-periodic and the partial periodic models the forecasting performance was better with data that was not differenced. Data was differenced to remove seasonality. Nelson et al. (1999) used deseasonalised data and concluded that neural networks performed better with deseasonalised data. Differencing was used in this research as the objective was not so much to remove seasonality but to help the neural process. This contradictory result may even be due to varying strengths in the irregular component rather than the difference in the methods used. Current results indicate that it is better to let neural networks model data as a whole rather than in separate components.

The partial periodic model is superior to the non-periodic model, which in turn is better than the periodic model when forecasting tourism to Japan. All three models performed better than the naïve model making them all adequate models for forecasting. The mean MAPE for the three models were not significantly different and the non-periodic model had the lowest mean MAPE making it almost as good as the partial periodic model. The partial periodic model was the best for the one-month ahead and the 12 months ahead forecasting horizons, while the non-periodic model was better for the 24 months ahead horizon.

The partial periodic model captures the seasonal trend of the past three years on a month-by-month basis, which is its strength. The model's poor performance for the 24 months-ahead horizon is due to the tourist arrivals series changing dramatically in 2003 due to the SARS crisis. The models poor performance was mainly for arrivals from the SARS affected countries. It would be reasonable to expect a network that has been modelled on the basis of the past year's data to respond better to sudden changes in a data series, than a network that had been modelled on the basis of the past three years data. This could well be the reason the non-periodic model performed better for the 24 months ahead horizon.

The performance of the periodic model, though not significantly different from the partial periodic and the non-periodic models, is not more accurate. Because of the seasonal nature of tourist arrivals, the periodic model was expected to out perform the other models, as it models the data for each season (month) separately. The poor performance of the periodic model compared to the partial periodic models shows that data for each season are not totally independent. .

5.4 Results of ECM forecasts

5.4.1 ECM forecast of arrivals from all countries

Table 5.4.1 shows the ECM forecasting performance for tourist arrivals to Japan from all countries. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period the forecasting performance is good (MAPE less than 10%) for the one-month ahead horizon and is fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months-ahead horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 5.4.1 Error Correction Model Forecasting Performance for Tourist Arrivals to Japan from all countries.

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	26746	5.04	28292	5.27	28292	5.27
2 year	53172	9.32	67601	11.23	60165	10.25

The Microfit outputs of the cointegrating long-run relationships and the short run error correction model, with diagnostics, are given in Tables 5.4.1a, b and c of Appendix II for one month, 12 months and 24 months-ahead forecasts respectively.

The independent variables used in this study, namely, own price, trade openness of the tourist's country of origin, per capita gross national income of the tourist country of origin and air fare cannot be used when forecasting tourism from all countries as the values of these independent variables are specific to a single country of origin.

Therefore, in this model which deals with tourism from all countries, the independent variables used were those that related to Japan only; it's consumer price index, gross domestic product, trade openness, imports and exports. However, results show that the only significant variable was imports.

For the one-month-ahead model, there is only one cointegrating vector and the maximum likelihood long-run estimate is as follows:

$$\boldsymbol{(arr) = 1.5746 * (impjap) + u_t} \; .$$

This model shows that the relationship between total tourist arrivals from all countries and Japan's imports are elastic and that a 1% increase in imports would result in a 1.57% increase in the number of arrivals to Japan from all countries due to the travel associated with imports and trade.

The short-run, one month ahead, error correction model is as follows:

$$\boldsymbol{\nabla(arr)_t = 0.037614 - 0.059397 * m2 + 0.10881 * m3 + 0.10332 * m4 - 0.071246 * m5 - 0.10586 * m6 + 0.11529 * m7 - 0.075927 * m8 - 0.10337 * m9 + 0.11746 * m10 - 0.21747 * m11 - 0.20169 * m12 - 0.033191 * u_{t-1}} \; .$$

The error term is negative, satisfying ECM requirements and is significant at 5%. $\mathbf{R^2 = 0.71}$, indicates good fit and appropriateness of the independent terms.

For the 12 months ahead model, there is only one cointegrating vector and the maximum likelihood long-run estimate is as follows:

$$(arr) = 1.5746 * (impjap) + u_t .$$

This model shows that the relationship between total tourist arrivals from all countries and Japan's imports are elastic and that a 1% increase in imports would result in a 1.57% increase in the number of arrivals to Japan from all countries due to the travel associated with imports and trade.

The short-run, 12 months ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.037317 - 0.057647 * m2 + 0.10628 * m3 + 0.10059 * m4 - 0.071210 * m5 - 0.10248 * m6 + 0.11605 * m7 - 0.076004 * m8 - 0.10754 * m9 + 0.11802 * m10 - 0.21573 * m11 - 0.19605 * m12 - 0.034489 * u_{t-1} .$$

The error term is negative satisfying ECM requirements and is significant at 5%.
R^2 = 0.71, indicates good fit and appropriateness of the independent terms.

For the 24 months ahead model, there is only one cointegrating vector and the maximum likelihood long-run estimate is as follows:

$$(arr) = 1.5745 * (impjap) + u_t .$$

This model shows that the relationship between total tourist arrivals from all countries and Japan's imports are elastic and that a 1% increase in imports would result in a 1.57% increase in the number of arrivals to Japan from all countries due to the travel associated with imports and trade.

The short-run, 24 months ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.036429 - 0.058232 * m2 + 0.10996 * m3 + 0.10451 * m4 - 0.070017 * m5 - 0.10465 * m6 + 0.11649 * m7 - 0.074688 * m8 - 0.10215 * m9 + 0.11867 * m10 - 0.21623 * m11 - 0.20049 * m12 - 0.033426 * u_{t-1}$$

The error term is negative satisfying ECM requirements and is significant at 5%.
R^2 = 0.71, indicates good fit and appropriateness of the independent terms.

5.4.2 ECM forecast of arrivals from Australia

Table 5.4.2 shows the ECM forecasting performance for tourist arrivals to Japan from Australia. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead forecasting horizon but is poor (MAPE 20% or more) for the 12 months ahead and 24 months ahead horizons. For the two year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and the 12 months ahead horizons and poor (MAPE 20% or more) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 5.4.2 Error Correction Model Forecasting Performance for Tourist Arrivals to Japan from Australia						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1430	9.28	3602	23.49	3602	23.49
2 year	1866	11.27	3203	19.48	4415	27.63

The Microfit outputs of the cointegrating long-run relationships and the short run error correction model, with diagnostics, are given in Tables 5.4.2a, b and c of Appendix II for one month, 12 months and 24 months ahead, forecasts respectively.

For the one-month ahead model, vector 3 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -2.7571*(opr) + 6.4304*(tro) + 2.713*(jtro) + 3.1145*(gni) - 7.1520*(air) + u_t .$$

This model shows that the relationships between tourist arrivals from Australia and the variables, own price, Australia's trade openness, Japan's trade openness, the per capita GNI of Australia and the airfare from Australia to Japan are all elastic. A 1% increase in own price would result in a 2.75% decrease in arrivals from Australia. A 1% increase in Australia's trade openness would result in a 6.43% increase in arrivals. A 1% increase in Japan's trade openness would result in a 2.71% increase in arrivals. A 1% increase in Australia's per capita GNI would result in a 3.11% increase in arrivals. A 1% increase in airfare costs would result in a 7.15% decrease in arrivals.

The short-run, one month ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.0005752 - 0.57376 * \nabla(opr)_t + 1.4792 * \nabla(gni)_{t-4} + 1.3772 * \nabla(gni)_{t-9} - 1.4097 * \nabla(gni)_{t-11} - 1.0954 * \nabla(air)_{t-3} - 0.36972 * m2 + 0.40772 * m3 + 0.19569 * m4 - 0.050412 * m5 - 0.023083 * m6 - 0.017458 * m7 - 0.053385 * m8 + 0.31032 * m9 - 0.12644 * m10 - 0.24846 * m11 + 0.16375 * m12 - 0.0066844 * u_{t-1} .$$

The error term is negative satisfying ECM requirements but is not significant. $\mathbf{R^2 = 0.67}$, indicates good fit and appropriateness of the independent terms.

For the 12 months-ahead model, vector 3 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -1.8151*(opr)+9.3332*(tro)+3.0072*(jtro)+1.8096*(gni) - 8.6251*(air)+ u_t .$$

This model shows that the relationships between tourist arrivals from Australia and the variables, own price, Australia’s trade openness, Japan’s trade openness, the per capita GNI of Australia and the airfare from Australia to Japan are all elastic. A 1% increase in own price would result in a 1.81% decrease in arrivals from Australia. A 1% increase in Australia’s trade openness would result in a 9.33% increase in arrivals. A 1% increase in Japan’s trade openness would result in a 3.01% increase in arrivals. A 1% increase in Australia’s per capita GNI would result in a 1.81% increase in arrivals. A 1% increase in airfare costs would result in a 8.63% decrease in arrivals.

The short-run, 12 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.00001024 - 0.56634 * \nabla(opr)_t + 1.3741 * \nabla(gni)_{t-4} + 1.3842 * \nabla(gni)_{t-9} - 1.5165 * \nabla(gni)_{t-11} - 1.1039 * \nabla(air)_{t-3} - 0.36783 * m2 + 0.40234 * m3 + 0.19027 * m4 - 0.041651 * m5 - 0.020926 * m6 - 0.012777 * m7 - 0.056912 * m8 + 0.30818 * m9 - 0.12914 * m10 - 0.24679 * m11 + 0.17316 * m12 - 0.0044226 * u_{t-1}\ .$$

The error term is negative satisfying ECM requirements but is not significant. $\mathbf{R^2 = 0.67}$, indicates good fit and appropriateness of the independent terms.

For the 24 months ahead model, vector 3 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -2.8735*(opr)+6.1984*(tro)+2.6839*(jtro)+3.1911*(gni) - 6.9947*(air) + u_t\ .$$

This model shows that the relationships between tourist arrivals from Australia and the variables, own price, Australia's trade openness, Japan's trade openness, the per capita GNI of Australia and the airfare from Australia to Japan are all elastic. A 1% increase in own price would result in a 2.87% decrease in arrivals from Australia. A 1% increase in Australia's trade openness would result in a 6.20% increase in arrivals. A 1% increase in Japan's trade openness would result in a 2.68% increase in arrivals. A 1% increase in Australia's per capita GNI would result in a 3.19% increase in arrivals. A 1% increase in airfare costs would result in a 6.99% decrease in arrivals.

The short-run, 24 months ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.0054227 - 0.57480 * \nabla(opr)_t + 1.4878 * \nabla(gni)_{t-4} + 1.3862 * \nabla(gni)_{t-9} - 1.4004 * \nabla(gni)_{t-11} - 1.0915 * \nabla(air)_{t-3} - 0.37352 * m2 + 0.40364 * m3 + 0.19184 * m4 - 0.054425 * m5 - 0.026881 * m6 - 0.021269 * m7 - 0.057260 * m8 + 0.30640 * m9 - 0.13045 * m10 - 0.25222 * m11 + 0.15949 * m12 - 0.0072919 * u_{t-1} .$$

The error term is negative satisfying ECM requirements but is not significant. $\mathbf{R^2 = 0.67}$, indicates good fit and appropriateness of the independent terms.

5.4.3 ECM forecast of arrivals from Canada

Table 5.4.3 shows the ECM forecasting performance for tourist arrivals to Japan from Canada. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the one-month ahead forecasting horizon and fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead forecasting horizons. For the two-year lead period the forecasting performance is also fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 5.4.3 Error Correction Model Forecasting Performance for Tourist Arrivals to Japan from Canada

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1248	9.66	1797	13.58	1797	13.58
2 year	1574	12.30	2016	16.06	2171	17.42

The Microfit outputs of the cointegrating long-run relationships and the short run error correction model, with diagnostics, are given in Tables 5.4.3a, b and c of Appendix II for one month, 12 months and 24 months-ahead forecasts respectively.

For the one month ahead model, vector 1 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.1459*(opr) +1.0365*(tro)+0.3545*(jtro) +0.6925*(gni) -0.3474*(air)+ u_t .$$

This model shows that the relationships between tourist arrivals from Canada and the variables, own price, Japan's trade openness, the per capita GNI of Canada and the airfare from Canada to Japan are all inelastic but that Canada's trade openness is elastic. A 1% increase in own price would result in a 0.15% decrease in arrivals from Canada. A 1% increase in Canada's trade openness would result in a 1.04% increase in arrivals. A 1% increase in Japan's trade openness would result in a 0.35% increase in arrivals. A 1% increase in Canada's per capita GNI would result in a 0.69% increase in arrivals. A 1% increase in airfare costs would result in a 0.35% decrease in arrivals.

The short-run, one month ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.12038 - 0.33537 * \nabla(opr)_{t-12} + 0.44242 * \nabla(tro)_t + 0.32761 * \nabla(jtro)_{t-5} -$$

$$0.38353 * \nabla(jtro)_{t-11} - 1.3840 * \nabla(gni)_t - 1.7645 * \nabla(gni)_{t-7} + 1.1295 * \nabla(gni)_{t-8} -$$

$$0.36802 * m2 + 0.065435 * m3 - 0.083251 * m4 - 0.14078 * m5 - 0.32155 * m6 +$$

$$\boldsymbol{0.041483 * m7 - 0.12226 * m8 - 0.21411 * m9 + 0.11072 * m10 - 0.20449 * m11 - 0.20096 * m12 - 0.51083 * u_{t-1}}\ .$$

The error term is negative, satisfying ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.83}$, indicates good fit and appropriateness of the independent terms.

For the 12 months ahead model, vector 1 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$\boldsymbol{(arr) = -0.2106*(opr) + 1.0093*(tro) + 0.3279*(jtro) + 0.7222*(gni) - 0.3277*(air) + u_t}\ .$$

This model shows that the relationships between tourist arrivals from Canada and the variables, own price, Japan's trade openness, the per capita GNI of Canada and the airfare from Canada to Japan are all inelastic but that Canada's trade openness is elastic. A 1% increase in own price would result in a 0.21% decrease in arrivals from Canada. A 1% increase in Canada's trade openness would result in a 1.01% increase in arrivals. A 1% increase in Japan's trade openness would result in a 0.33% increase in arrivals. A 1% increase in Canada's per capita GNI would result in a 0.72% increase in arrivals. A 1% increase in airfare costs would result in a 0.33% decrease in arrivals.

The short-run, 12 months ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.12805 + 0.45801 * \nabla(tro)_t - 1.4818 * \nabla(gni)_t - 1.8192 * \nabla(gni)_{t-7} + 1.3066 * \nabla(gni)_{t-8} - 0.36559 * m2 + 0.068892 * m3 - 0.10701 * m4 - 0.14744 * m5 - 0.32245 * m6 + 0.044036 * m7 - 0.12890 * m8 - 0.24120 * m9 + 0.10479 * m10 - 0.20924 * m11 - 0.19938 * m12 - 0.48070 * u_{t-1}.$$

The error term is negative, satisfying ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.82}$, indicates good fit and appropriateness of the independent terms.

For the 24 months-ahead model, vector 1 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.1265*(opr) + 1.052*(tro) + 0.3628*(jtro) + 0.6818*(gni) - 0.3567*(air) + u_t.$$

This model shows that the relationships between tourist arrivals from Canada and the variables, own price, Japan’s trade openness, the per capita GNI of Canada and the airfare from Canada to Japan are all inelastic but that Canada’s trade openness is elastic. A 1% increase in own price would result in a 0.13% decrease in arrivals from Canada. A 1% increase in Canada’s trade openness would result in a 1.05% increase in arrivals. A 1% increase in Japan’s trade openness would result in a 0.36% increase in arrivals. A 1% increase in Canada’s per capita GNI would result in a 0.68% increase in arrivals. A 1% increase in airfare costs would result in a 0.36% decrease in arrivals.

The short-run, 24 months ahead, error correction model is as follows:

$\nabla(arr)_t = 0.11806 - 0.34228 * \nabla(opr)_{t-12} + 0.44167 * \nabla(tro)_t + 0.32718 * \nabla(jtro)_{t-5} - 0.38825 * \nabla(jtro)_{t-11} - 1.3728 * \nabla(gni)_t - 1.7727 * \nabla(gni)_{t-7} + 1.1260 * \nabla(gni)_{t-8} - 0.36552 * m2 + 0.068991 * m3 - 0.080532 * m4 - 0.13845 * m5 - 0.31901 * m6 + 0.045014 * m7 - 0.11932 * m8 - 0.21095 * m9 + 0.11369 * m10 - 0.20281 * m11 - 0.19841 * m12 - 0.50682 * u_{t-1}$.

The error term is negative, satisfying ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.83}$, indicates good fit and appropriateness of the independent terms.

5.4.4 ECM forecast of arrivals from China

Table 5.4.4 shows the ECM forecasting performance for tourist arrivals to Japan from China. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 5.4.4 Error Correction Model Forecasting Performance for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5970	14.44	6067	14.89	6067	14.89
2 year	9253	26.83	9887	31.17	12857	41.29

The Microfit outputs of the cointegrating long-run relationships and the short run error correction model, with diagnostics, are given in Tables 5.4.4a, b and c of Appendix II for one month, 12 months and 24 months ahead forecasts respectively.

For the one month ahead model, vector 3 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -2.3304 * (opr) + 1.3023 * (tro) + 8.2671 * (gni) - 2.9022 * (air) + u_t \, .$$

This model shows that the relationships between tourist arrivals from China and the variables, own price, China's trade openness, the per capita GNI of China and the airfare from China to Japan are all elastic. Japan's trade openness was found to be not significant. A 1% increase in own price would result in a 2.33% decrease in arrivals from China. A 1% increase in China's trade openness would result in a 1.30% increase in arrivals. A 1% increase in China's per capita GNI would result in a 8.27% increase in arrivals. A 1% increase in airfare costs would result in a 2.90% decrease in arrivals.

The short-run, one month ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.29412 + 1.2287 * \nabla(gni)_{t-11} - 0.50501 * m2 + 0.015701 * m3 - 0.20012 * m4 - 0.25318 * m5 - 0.42132 * m6 - 0.20771 * m7 - 0.10452 * m8 - 0.21410 * m9 - 0.23068 * m10 - 0.35617 * m11 - 0.68190 * m12 - 0.0041337 * u_{t-1} \, .$$

The error term is negative satisfying ECM requirements but is not significant. $\mathbf{R^2 = 0.64}$, indicates good fit and appropriateness of the independent terms.

For the 12 months ahead model, vector 3 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -2.2763 * (opr) + 2.1987 * (tro) + 16.9711 * (gni) - 7.9458 * (air) + u_t \ .$$

This model shows that the relationships between tourist arrivals from China and the variables, own price, China's trade openness, the per capita GNI of China and the airfare from China to Japan are all elastic. Japan's trade openness was found not to be significant. A 1% increase in own price would result in a 2.28% decrease in arrivals from China. A 1% increase in China's trade openness would result in a 2.20% increase in arrivals. A 1% increase in China's per capita GNI would result in a 16.97% increase in arrivals. A 1% increase in airfare costs would result in a 7.94% decrease in arrivals.

The short-run, 12 months ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.28815 + 1.2014 * \nabla(gni)_{t-11} - 0.49875 * m2 + 0.013022 * m3 - 0.19789 * m4 - 0.26322 * m5 - 0.43177 * m6 - 0.19228 * m7 - 0.10669 * m8 - 0.21639 * m9 - 0.23369 * m10 - 0.36544 * m11 - 0.67518 * m12 - 0.0017095 * u_{t-1} \ .$$

The error term is negative satisfying ECM requirements but is not significant. $\mathbf{R^2 = 0.63}$, indicates good fit and appropriateness of the independent terms.

For the 24 months ahead model, vector 2 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -2.4480 * (opr) + 0.40684 * (tro) + 4.0988 * (gni) + u_t \ .$$

This model shows that the relationships between tourist arrivals from China and the variables, own price and the per capita GNI of China are elastic but that China's trade openness is inelastic. Japan's trade openness and the airfare from China to Japan were found not to be significant. A 1% increase in own price would result in a 2.45% decrease in arrivals from China. A 1% increase in China's trade openness would result in a 0.41% increase in arrivals. A 1% increase in China's per capita GNI would result in a 4.10% increase in arrivals.

The short-run, 24 months ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.29761 + 1.2768 * \nabla(gni)_{t-11} - 0.49773 * m2 + 0.019688 * m3 - 0.19282 * m4 - 0.24400 * m5 - 0.41204 * m6 - 0.20090 * m7 - 0.096838 * m8 - 0.20412 * m9 - 0.22011 * m10 - 0.34473 * m11 - 0.67491 * m12 - 0.017502 * u_{t-1} \ .$$

The error term is negative satisfying ECM requirements and is significant at 10%. $\mathbf{R^2 = 0.64}$, indicates good fit and appropriateness of the independent terms.

5.4.5 ECM forecast of arrivals from France

Table 5.4.5 shows the non-periodic forecasting performance for tourist arrivals to Japan from France. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 5.4.5 Error Correction Model Forecasting Performance for Tourist Arrivals to Japan from France

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1038	10.65	1318	15.45	1318	15.45
2 year	1173	13.57	1402	16.82	1566	18.94

The Microfit outputs of the cointegrating long-run relationships and the short run error correction model, with diagnostics, are given in Tables 5.4.5a, b and c of Appendix II for one month, 12 months and 24 months-ahead forecasts respectively.

For the one-month ahead model, vector 1 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.15393 * (opr) + 0.70151 * (tro) + 0.62107 * (gni) + u_t \,.$$

This model shows that the relationships between tourist arrivals from France and the variables, own price, France’s trade openness and the per capita GNI of France are inelastic. Japan's trade openness and the airfare from France to Japan were found to be not significant. A 1% increase in own price would result in a 0.15% decrease in arrivals from France. A 1% increase in France's trade openness would result in a 0.70% increase in arrivals. A 1% increase in France's per capita GNI would result in a 0.62% increase in arrivals.

The short-run, one month ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.051453 - 0.49074 * \nabla(gni)_{t-5} - 0.12022 * m2 + 0.21746 * m3 + 0.18609 * m4 + 0.11404 * m5 - 0.12701 * m6 + 0.18408 * m7 + 0.017845 * m8 + 0.14810 * m9 + 0.34284 * m10 + 0.024944 * m11 - 0.34198 * m12 - 0.48854 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.81}$, indicates good fit and appropriateness of the independent terms.

For the 12 months ahead model, vector 1 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.13423 * (opr) + 0.74893 * (tro) + 0.57938 * (gni) + u_t .$$

This model shows that the relationships between tourist arrivals from France and the variables, own price, France's trade openness and the per capita GNI of France are inelastic. Japan's trade openness and the airfare from France to Japan were found not to be significant. A 1% increase in own price would result in a 0.13% decrease in arrivals from France. A 1% increase in France's trade openness would result in a

0.74% increase in arrivals. A 1% increase in France's per capita GNI would result in a 0.58% increase in arrivals.

The short-run, 12 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.050639 - 0.59197 * \nabla(gni)_{t-5} - 0.11320 * m2 + 0.21803 * m3 + 0.18826 * m4 + 0.10251 * m5 - 0.11364 * m6 + 0.18337 * m7 + 0.012859 * m8 + 0.14353 * m9 + 0.33613 * m10 + 0.017440 * m11 - 0.33709 * m12 - 0.47310 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.79}$, indicates good fit and appropriateness of the independent terms.

For the 24 months ahead model, vector 1 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.15581 * (opr) + 0.69499 * (tro) + 0.62656 * (gni) + u_t .$$

This model shows that the relationships between tourist arrivals from France and the variables, own price, France's trade openness and the per capita GNI of France are inelastic. Japan's trade openness and the airfare from France to Japan were found not to be significant. A 1% increase in own price would result in a 0.16% decrease in arrivals from France. A 1% increase in France's trade openness would result in a 0.69% increase in arrivals. A 1% increase in France's per capita GNI would result in a 0.63% increase in arrivals.

The short-run, 24 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.061400 - 0.48721 * \nabla(gni)_{t-5} - 0.11281 * m2 + 0.22428 * m3 + 0.19654 * m4 + 0.12609 * m5 - 0.11522 * m6 + 0.19304 * m7 + 0.029134 * m8 + 0.15856 * m9 + 0.35451 * m10 + 0.039440 * m11 - 0.32976 * m12 - 0.50023 * u_{t-1} .$$

The error term is negative, satisfying the ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.81}$, indicates good fit and appropriateness of the independent terms.

5.4.6 ECM forecast of arrivals from Germany

Table 5.4.6 shows the ECM forecasting performance for tourist arrivals to Japan from Germany. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period also, the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 5.4.6 Error Correction Model Forecasting Performance for Tourist Arrivals to Japan from Germany

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1417	12.68	1661	16.60	1661	16.60
2 year	1278	12.53	1616	16.72	1778	18.66

The Microfit outputs of the cointegrating long-run relationships and the short run error correction model, with diagnostics, are given in Tables 5.4.6a, b and c of Appendix II for one month, 12 months and 24 months-ahead forecasts respectively.

For the one month ahead model, vector 1 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.14641 * (opr) + 0.74424 * (tro) + 0.56364 * (gni) - 0.033500 * (air) + u_t .$$

This model shows that the relationships between tourist arrivals from Germany and the variables, own price, Germany's trade openness, the per capita GNI of Germany and the airfare from Germany to Japan are all inelastic. Japan's trade openness was found not to be significant. A 1% increase in own price would result in a 0.15% decrease in arrivals from Germany. A 1% increase in Germany's trade openness would result in a 0.74% increase in arrivals. A 1% increase in Germany's per capita GNI would result in a 0.56% increase in arrivals. A 1% increase in airfare costs would result in a 0.03% decrease in arrivals.

The short-run, one month ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.0075045 + 0.19938 * \nabla(opr)_{t-2} - 0.12862 * m2 + 0.31141 * m3 + 0.10933 * m4 - 0.022697 * m5 - 0.32375 * m6 + 0.089396 * m7 - 0.086688 * m8 + 0.12049 * m9 + 0.34267 * m10 - 0.095090 * m11 - 0.58568 * m12 - 0.39112 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.89}$, indicates good fit and appropriateness of the independent terms.

For the 12 months ahead model, vector 1 of the four possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.14791 * (opr) + 0.78149 * (tro) + 0.51026 * (gni) - 0.011917 * (air) + u_t .$$

This model shows that the relationships between tourist arrivals from Germany and the variables, own price, Germany's trade openness, the per capita GNI of Germany and the airfare from Germany to Japan are all inelastic. Japan's trade openness was found not to be significant. A 1% increase in own price would result in a 0.15% decrease in arrivals from Germany. A 1% increase in Germany's trade openness would result in a 0.78% increase in arrivals. A 1% increase in Germany's per capita GNI would result in a 0.51% increase in arrivals. A 1% increase in airfare costs would result in a 0.01% decrease in arrivals.

The short-run, 12 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.010816 - 0.30677 * \nabla(air)_{t-9} - 0.11675 * m2 + 0.31959 * m3 + 0.13446 * m4 - 0.0010701 * m5 - 0.27202 * m6 + 0.090949 * m7 - 0.077903 * m8 + 0.13120 * m9 + 0.36527 * m10 - 0.053299 * m11 - 0.54411 * m12 - 0.42908 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.89}$, indicates good fit and appropriateness of the independent terms.

For the 24 months ahead model, vector 1 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.14881 * (opr) + 0.73855 * (tro) + 0.57166 * (gni) – 0.035467 * (air) + u_t .$$

This model shows that the relationships between tourist arrivals from Germany and the variables, own price, Germany's trade openness, the per capita GNI of Germany and the airfare from Germany to Japan are all inelastic. Japan's trade openness was found not to be significant. A 1% increase in own price would result in a 0.15% decrease in arrivals from Germany. A 1% increase in Germany's trade openness would result in a 0.74% increase in arrivals. A 1% increase in Germany's per capita GNI would result in a 0.57% increase in arrivals. A 1% increase in airfare costs would result in a 0.04% decrease in arrivals.

The short-run, 24 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.0031311 + 0.20459 * \nabla(opr)_{t-2} - 0.12139 * m2 + 0.31894 * m3 + 0.11957 * m4 - 0.011941 * m5 - 0.31373 * m6 + 0.097283 * m7 - 0.077566 * m8 + 0.12924 * m9 + 0.35257 * m10 - 0.083126 * m11 - 0.57516 * m12 - 0.39755 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.89}$, indicates good fit and appropriateness of the independent terms.

5.4.7 ECM forecast of arrivals from Korea

Table 5.4.7 shows the ECM forecasting performance for tourist arrivals to Japan from Korea. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and the 24 months ahead. For the two-year lead period, the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 5.4.7 Error Correction Model Forecasting Performance for Tourist Arrivals to Japan from Korea

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	11880	8.55	10158	7.98	10158	7.98
2 year	16978	11.37	19611	11.70	19595	11.49

The Microfit outputs of the cointegrating long-run relationships and the short run error correction model, with diagnostics, are given in Tables 5.4.7a, b and c of Appendix II for one month, 12 months and 24 months ahead, forecasts respectively.

For the one-month ahead model, vector 1 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.5996*(opr) +0.4389*(tro) +0.979*(jtro)+1.3177*(gni) -0.36657*(air)+ u_t \; .$$

This model shows that the relationships between tourist arrivals from Korea and the variables, own price, Korea's trade openness, Japan's trade openness and the airfare from Korea to Japan are inelastic and that the per capita GNI of Korea is elastic. A 1% increase in own price would result in a 0.60% decrease in arrivals from Korea. A 1% increase in Korea's trade openness would result in a 0.44% increase in arrivals. A 1% increase in Japan's trade openness would result in a 0.98% increase in arrivals. A 1% increase in Korea's per capita GNI would result in a 1.32% increase in arrivals. A 1% increase in airfare costs would result in a 0.37% decrease in arrivals.

The short-run, one month ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.091663 - 0.18626 * \nabla(tro)_t + 0.60376 * \nabla(gni)_t + 0.28097 * \nabla(gni)_{t-8} - 0.076414 * \nabla(air)_{t-11} - 0.23773 * m2 + 0.012159 * m3 - 0.058762 * m4 - 0.067387 * m5 - 0.15605 * m6 + 0.085710 * m7 + 0.023960 * m8 - 0.33392 * m9 + 0.037099 * m10 - 0.10449 * m11 - 0.18960 * m12 - 0.051455 * u_{t-1}\ .$$

The error term is negative, satisfying ECM requirements and is significant at 5%. **R^2 = 0.75**, indicates good fit and appropriateness of the independent terms.

For the 12 months-ahead model, vector 1 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.5219*(opr) + 0.4532*(tro) + 0.9162*(jtro) + 1.283*(gni) - 0.3328*(air) + u_t\ .$$

This model shows that the relationships between tourist arrivals from Korea and the variables, own price, Korea's trade openness, Japan's trade openness and the airfare from Korea to Japan are inelastic and that the per capita GNI of Korea is elastic. A 1% increase in own price would result in a 0.52% decrease in arrivals from Korea. A 1% increase in Korea's trade openness would result in a 0.45% increase in arrivals. A 1% increase in Japan's trade openness would result in a 0.92% increase in arrivals. A 1% increase in Korea's per capita GNI would result in a 1.28% increase in arrivals. A 1% increase in airfare costs would result in a 0.33% decrease in arrivals.

The short-run, 12 months ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.091150 + 0.48958 * \nabla(gni)_t + 0.32924 * \nabla(gni)_{t-8} - 0.24349 * m2 + 0.00585 * m3 - 0.0565 * m4 - 0.07134 * m5 - 0.1573 * m6 + 0.094645 * m7 + 0.0244 * m8 - 0.3531 * m9 + 0.0388 * m10 - 0.1063 * m11 - 0.1884 * m12 - 0.061823 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.75}$, indicates good fit and appropriateness of the independent terms.

For the 24 months-ahead model, vector 1 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.5636*(opr) + 0.4428*(tro) + 0.9508*(jtro) + 1.308*(gni) - 0.3563*(air) + u_t .$$

This model shows that the relationships between tourist arrivals from Korea and the variables, own price, Korea's trade openness, Japan's trade openness and the airfare from Korea to Japan are inelastic and that the per capita GNI of Korea is elastic. A 1% increase in own price would result in a 0.56% decrease in arrivals from Korea. A 1% increase in Korea's trade openness would result in a 0.44% increase in arrivals. A 1% increase in Japan's trade openness would result in a 0.95% increase in arrivals. A 1% increase in Korea's per capita GNI would result in a 1.31% increase in arrivals. A 1% increase in airfare costs would result in a 0.36% decrease in arrivals.

The short-run, 24 months ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.0846 - 0.2096 * \nabla(tro)_t + 0.6350 * \nabla(gni)_t + 0.0687 * \nabla(air)_{t-9} - 0.0750 * \nabla(air)_{t-11} - 0.2314 * m2 + 0.0178 * m3 - 0.0529 * m4 - 0.0609 * m5 - 0.1501 * m6 + 0.0853 * m7 + 0.0308 * m8 - 0.3017 * m9 + 0.0434 * m10 - .0975 * m11 - 0.1843 * m12 - 0.0536 * u_{t-1}.$$

The error term is negative, satisfying ECM requirements and is significant at 5%. $\mathbf{R^2 = 0.75}$, indicates good fit and appropriateness of the independent terms.

5.4.8 ECM forecast of arrivals from Singapore

Table 5.4.8 shows the ECM forecasting performance for tourist arrivals to Japan from Singapore. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one-month ahead forecasting horizon and poor (MAPE 20% or less) for the 12 months ahead and the 24 months ahead horizons. For the two-year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, but the model forecasts are poor.

Table 5.4.8 Error Correction Model Forecasting Performance for Tourist Arrivals to Japan from Singapore

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1536	18.43	1649	20.76	1649	20.76
2 year	1848	24.43	2836	40.69	2289	31.69

The Microfit outputs of the cointegrating long-run relationships and the short run error correction model, with diagnostics, are given in Tables 5.4.8a, b and c of Appendix II for one month, 12 months and 24 months-ahead forecasts respectively.

For the one-month ahead model, vector 2 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = 11.7366 * (jtro) + 4.9719 * (gni) - 9.8344 * (air) + u_t \; .$$

This model shows that the relationships between tourist arrivals from Singapore and the variables, Japan’s trade openness, per capita GNI of Singapore and the airfare from Singapore to Japan are elastic. The variables, own price and Singapore 's trade openness were found not to be significant. A 1% increase in Japan’s trade openness would result in a 11.74% increase in arrivals from Singapore. A 1% increase in Singapore’s per capita GNI would result in a 4.97% increase in arrivals. A 1% increase in airfare costs would result in a 9.83% decrease in arrivals.

The short-run, one month ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.84433 - 1.4756 * \nabla(gni)_{t-11} + 1.4114 * \nabla(gni)_{t-12} + 0.97969 * m2 + 1.0602 * m3 + 1.1771 * m4 + 0.83759 * m5 + 1.1911 * m6 + 0.084492 * m7 + 0.80355 * m8 + 1.1054 * m9 + 0.95902 * m10 + 0.96240 * m11 + 1.1050 * m12 - 0.0024109 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements but not significant. $\mathbf{R^2 = 0.78}$, indicates good fit and appropriateness of the independent terms.

For the 12 months ahead model, vector 2 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = 11.657 * (jtro) + 4.9188 * (gni) – 9.7365 * (air) + u_t .$$

This model shows that the relationships between tourist arrivals from Singapore and the variables, Japan’s trade openness, per capita GNI of Singapore and the airfare from Singapore to Japan are elastic. The variables, own price and Singapore's trade openness were found not to be significant. A 1% increase in Japan’s trade openness would result in a 11.66% increase in arrivals from Singapore. A 1% increase in Singapore’s per capita GNI would result in a 4.92% increase in arrivals. A 1% increase in airfare costs would result in a 9.74% decrease in arrivals.

The short-run, 12 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.84424 - 1.4576 * \nabla(gni)_{t-11} + 1.4112 * \nabla(gni)_{t-12} + 0.99448 * m2 + 1.0604 * m3 + 1.1653 * m4 + 0.83532 * m5 + 1.1748 * m6 + 0.10114 * m7 + 0.79844 * m8 + 1.1049 * m9 + 0.96370 * m10 + 0.97650 * m11 + 1.1023 * m12 - 0.0025124 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements but not significant. $\mathbf{R^2 = 0.78}$, indicates good fit and appropriateness of the independent terms.

For the 24 months ahead model, vector 2 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = 10.3275 * (jtro) + 4.4495 * (gni) - 8.6025 * (air) + u_t .$$

This model shows that the relationships between tourist arrivals from Singapore and the variables, Japan’s trade openness, per capita GNI of Singapore and the airfare from Singapore to Japan are elastic. The variables, own price and Singapore 's trade openness were found not to be significant. A 1% increase in Japan’s trade openness would result in a 10.33% increase in arrivals from Singapore. A 1% increase in Singapore’s per capita GNI would result in a 4.45% increase in arrivals. A 1% increase in airfare costs would result in a 8.60% decrease in arrivals.

The short-run, 24 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.82589 - 1.4753 * \nabla(gni)_{t-11} + 1.2693 * \nabla(gni)_{t-12} + 0.96178 * m2 + 1.0423 * m3 + 1.1596 * m4 + 0.82044 * m5 + 1.1739 * m6 + 0.067543 * m7 + 0.78604 * m8 + 1.0878 * m9 + 0.94148 * m10 + 0.94494 * m11 + 1.0876 * m12 - 0.0031996 * u_{t-1}.$$

The error term is negative, satisfying ECM requirements but not significant. $\mathbf{R^2 = 0.78}$, indicates good fit and appropriateness of the independent terms.

5.4.9 ECM forecast of arrivals from Taiwan

Table 5.4.9 shows the ECM forecasting performance for tourist arrivals to Japan from Taiwan. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 5.4.9 Error Correction Model Forecasting Performance for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5695	5.80	4282	5.05	4282	5.05
2 year	15573	20.65	25078	41.79	18580	31.52

The Microfit outputs of the cointegrating long-run relationships and the short run error correction model, with diagnostics, are given in Tables 5.4.9a, b and c of Appendix II for one month, 12 months and 24 months-ahead forecasts respectively.

For the one-month ahead model, vector 2 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = 4.759 * (cpiTai) + 1.9949 * (jtro) - 1.9159 * (air) + u_t \,.$$

This model shows that the relationships between tourist arrivals from Taiwan and the variables, Taiwan's consumer price index, Japan’s trade openness, and airfare from Taiwan to Japan, are elastic. Data for the variables, own price and Taiwan 's trade openness were not available. A 1% increase in Taiwan’s CPI would result in a 4.76% increase in arrivals from Taiwan. A 1% increase in Japan’s trade openness would result in a 1.99% increase in arrivals. A 1% increase in airfare costs would result in a 1.92% decrease in arrivals.

The short-run, one month ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.0077217 + 3.3665 * \nabla(cpiTai)_t + 0.55430 * \nabla(jtro)_{t-1} + 0.17536 * \nabla(air)_{t-4} + 0.14714 * \nabla(air)_{t-10} - 0.11974 * \nabla(air)_{t-11} + 0.33400 * m2 - 0.12110 * m3 + 0.21430 * m4 - 0.14676 * m5 - 0.097342 * m6 + 0.44477 * m7 - 0.18390 * m8 - 0.29026 * m9 + 0.13283 * m10 - 0.24058 * m11 - 0.12449 * m12 - 0.021019 * u_{t-1} \,.$$

The error term is negative, satisfying ECM requirements and is significant at 5%. $\mathbf{R^2 = 0.67}$, indicates good fit and appropriateness of the independent terms.

For the 12 months ahead model, vector 2 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = 4.712 * (cpiTai) + 2.1791 * (jtro) - 2.0067 * (air) + u_t \, .$$

This model shows that the relationships between tourist arrivals from Taiwan and the variables, Taiwan's consumer price index, Japan’s trade openness, and airfare from Taiwan to Japan, are elastic. Data for the variables, own price and Taiwan 's trade openness were not available. A 1% increase in Taiwan’s CPI would result in a 4.71% increase in arrivals from Taiwan. A 1% increase in Japan’s trade openness would result in a 2.18% increase in arrivals. A 1% increase in airfare costs would result in a 2.01% decrease in arrivals.

The short-run, 12 months ahead, error correction model is as follows:

$$\nabla(arr)_t = 0.0013485 + 3.4372 * \nabla(cpiTai)_t + 0.64249 * \nabla(jtro)_{t-1} + 0.16464 * \nabla(air)_{t-4} - 0.11781 * \nabla(air)_{t-5} + 0.14236 * \nabla(air)_{t-10} - 0.18033 * \nabla(air)_{t-11} + 0.32362 * m2 - 0.12578 * m3 + 0.21011 * m4 - 0.15121 * m5 - 0.10307 * m6 + 0.43998 * m7 - 0.18166 * m8 - 0.29799 * m9 + 0.13519 * m10 - 0.24153 * m11 - 0.12721 * m12 - 0.0098239 * u_{t-1} \, .$$

The error term is negative, satisfying ECM requirements but not significant. **R^2 = 0.68**, indicates good fit and appropriateness of the independent terms.

For the 24 months ahead model, vector 2 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = 4.8147 * (cpiTai) + 2.015 * (jtro) - 1.9504 * (air) + u_t .$$

This model shows that the relationships between tourist arrivals from Taiwan and the variables, Taiwan's consumer price index, Japan's trade openness, and airfare from Taiwan to Japan, are elastic. Data for the variables, own price and Taiwan 's trade openness were not available. A 1% increase in Taiwan's CPI would result in a 4.82% increase in arrivals from Taiwan. A 1% increase in Japan's trade openness would result in a 2.02% increase in arrivals. A 1% increase in airfare costs would result in a 1.95% decrease in arrivals.

The short-run, 24 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.011070 + 3.3768 * \nabla(cpiTai)_t + 0.56202 * \nabla(jtro)_{t-1} + 0.17503 * \nabla(air)_{t-4} + 0.14760 * \nabla(air)_{t-10} - 0.11977 * \nabla(air)_{t-11} + 0.33767 * m2 - 0.11771 * m3 + 0.21766 * m4 - 0.14344 * m5 - 0.094090 * m6 + 0.44842 * m7 - 0.18074 * m8 - 0.28715 * m9 + 0.13635 * m10 - 0.23708 * m11 - 0.12089 * m12 - 0.020449 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements and is significant at 5%. **R^2 = 0.67**, indicates good fit and appropriateness of the independent terms.

5.4.10 ECM forecast of arrivals from the UK

Table 5.4.10 shows the ECM forecasting performance for tourist arrivals to Japan from the UK. For the one-year lead period the forecasting performance is poor (MAPE 20% or less) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period also, the forecasting performance is poor (MAPE 20% or less) for all three forecasting horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error is inconsistent and the model forecasts are poor.

Table 5.4.10 Error Correction Model Forecasting Performance for Tourist Arrivals to Japan from the UK

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5834	23.49	9927	49.55	9927	49.55
2 year	4933	21.49	9161	48.60	11525	63.58

The Microfit outputs of the cointegrating long-run relationships and the short run error correction model, with diagnostics, are given in Tables 5.4.10a, b and c of Appendix II for one month, 12 months and 24 months-ahead forecasts respectively.

For the one month ahead model, vector 1 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.0197*(opr) +0.7841*(tro) +0.5215*(jtro)+0.5517*(gni) -0.0845*(air)+ u_t \text{ .}$$

This model shows that the relationships between tourist arrivals from the UK and the variables, own price, UK trade openness, Japan’s trade openness, per capita GNI of the UK and airfare from the UK to Japan are inelastic. A 1% increase in own price would result in a 0.02% decrease in arrivals from the UK. A 1% increase in UK trade openness would result in a 0.78% increase in arrivals. A 1% increase in Japan's trade openness would result in a 0.52% increase in arrivals. A 1% increase in the UK per capita GNI would result in a 0.55% increase in arrivals. A 1% increase in airfare costs would result in a 0.09% decrease in arrivals.

The short-run, one month ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.038817 + 0.80650 * \nabla(tro)_{t-1} + 0.73924 * \nabla(jtro)_t - 0.90818 * \nabla(gni)_{t-6} + 0.14311 * m2 + 0.017073 * m3 + 0.059463 * m4 - 0.14169 * m5 - 0.022903 * m6 + 0.31617 * m7 + 0.10703 * m8 - 0.14211 * m9 + 0.11802 * m10 - 0.071547 * m11 + 0.013664 * m12 - 0.31823 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.47}$ indicates poor fit and/or inappropriateness of the independent terms.

For the 12 months ahead model, vector 1 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = 1.0563 * (tro) + 0.45139 * (jtro) + 0.38747 * (gni) - 0.11758 * (air) + u_t .$$

This model shows that the relationships between tourist arrivals from the UK and the variables, Japan's trade openness, per capita GNI of the UK and airfare from the UK to Japan are inelastic and UK trade openness is elastic. The variable own price was found not to be significant. A 1% increase in UK trade openness would result in a 1.06% increase in arrivals from the UK. A 1% increase in Japan's trade openness would result in a 0.45% increase in arrivals. A 1% increase in the UK per capita GNI would result in a 0.39% increase in arrivals. A 1% increase in airfare costs would result in a 0.12% decrease in arrivals.

The short-run, 12 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.030832 + 0.85963 * \nabla(tro)_{t-1} + 0.71194 * \nabla(jtro)_t + 0.13476 * m2 + 0.0245 * m3 + 0.0417 * m4 - 0.1274 * m5 - 0.0216 * m6 + 0.23573 * m7 + 0.09216 * m8 - 0.1494 * m9 + 0.11875 * m10 - 0.08281 * m11 + 0.00613 * m12 - 0.2874 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements and is significant at 1%. R^2 **= 0.43** indicates poor fit and/or inappropriateness of the independent terms.

For the 24 months ahead model, vector 1 of the three possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.0326*(opr) + 0.8083*(tro) + 0.5449*(jtro) + 0.5144*(gni) - 0.0727*(air) + u_t .$$

This model shows that the relationships between tourist arrivals from the UK and the variables, own price, UK trade openness, Japan's trade openness, per capita GNI of the UK and airfare from the UK to Japan are inelastic. A 1% increase in own price would result in a 0.03% decrease in arrivals from the UK. A 1% increase in UK trade openness would result in a 0.81% increase in arrivals. A 1% increase in Japan's trade openness would result in a 0.55% increase in arrivals. A 1% increase in the UK per capita GNI would result in a 0.51% increase in arrivals. A 1% increase in airfare costs would result in a 0.07% decrease in arrivals.

The short-run, 24 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.035203 + 0.79292 * \nabla(tro)_{t-1} + 0.75484 * \nabla(jtro)_t - 0.88855 * \nabla(gni)_{t-6} + 0.14109 * m2 + 0.015737 * m3 + 0.057842 * m4 - 0.14359 * m5 - 0.025508 * m6 + 0.31217 * m7 + 0.10539 * m8 - 0.14348 * m9 + 0.11571 * m10 - 0.073481 * m11 + 0.011083 * m12 - 0.32266 * u_{t-1} .$$

The error term is negative, satisfying ECM requirements and is significant at 1%.
R^2 = 0.47 indicates poor fit and/or inappropriateness of the independent terms.

5.4.11 ECM forecast of arrivals from the USA

Table 5.4.11 shows the ECM forecasting performance for tourist arrivals to Japan from the USA. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period, the forecasting performance is good (MAPE less than 10%) for the one-month ahead horizon and fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months-ahead horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 5.4.11 Error Correction Model Forecasting Performance for Tourist Arrivals to Japan from the USA						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	4337	5.84	4802	6.36	4802	6.36
2 year	6345	7.70	8596	11.10	8379	10.74

The Microfit outputs of the cointegrating long-run relationships and the short run error correction model, with diagnostics, are given in Tables 5.4.11a, b and c of Appendix II for one month, 12 months and 24 months ahead forecasts respectively. For the one month ahead model, there is only one cointegrating vector and the maximum likelihood long-run estimate is as follows:

$$(arr) = -0.19316 * (opr) + 1.4617 * (tro) + 0.85556 * (gni) - 0.19407 * (air) + u_t \ .$$

This model shows that the relationships between tourist arrivals from the USA and the variables, own price, per capita GNI of the USA and airfare from the USA to Japan are not elastic and USA trade openness is elastic. Japan's trade openness was found to be insignificant. A 1% increase in own price would result in a 0.19% decrease in arrivals. A 1% increase in USA trade openness would result in a 1.46% increase in arrivals. A 1% increase in the USA per capita GNI would result in a 0.86% increase in arrivals. A 1% increase in airfare costs would result in a 0.19% decrease in arrivals.

The short-run, one month ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.017359 + 1.6801 * \nabla(gni)_{t-8} - 1.3925 * \nabla(gni)_{t-11} - 0.19490 * m2 + 0.29803 * m3 + 0.089481 * m4 + 0.069248 * m5 + 0.017437 * m6 + 0.019466 * m7 - 0.088846 * m8 - 0.046530 * m9 + 0.25647 * m10 - 0.19218 * m11 - 0.15701 * m12 - 0.20602 * u_{t-1} \ .$$

The error term is negative, satisfying ECM requirements and is significant at 1%. $\mathbf{R^2 = 0.87}$ indicates good fit and appropriateness of the independent terms.

For the 12 months ahead model, vector 1 of the two possible long-run relationships was selected based on the expected signs of the variables. The maximum likelihood long-run estimate is as follows:

$$(arr) = -0.19390 * (opr) + 1.4614 * (tro) + 0.85507 * (gni) - 0.19323 * (air) + u_t \; .$$

This model shows that the relationships between tourist arrivals from the USA and the variables, own price, per capita GNI of the USA and airfare from the USA to Japan are inelastic and USA trade openness is elastic. Japan's trade openness was found to be not significant. A 1% increase in own price would result in a 0.19% decrease in arrivals from the USA. A 1% increase in USA trade openness would result in a 1.46% increase in arrivals. A 1% increase in the USA per capita GNI would result in a 0.86% increase in arrivals. A 1% increase in airfare costs would result in a 0.19% decrease in arrivals.

The short-run, 12 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.024392 - 0.70540 * \nabla(tro)_{t-6} + 1.7045 * \nabla(gni)_{t-8} - 1.4621 * \nabla(gni)_{t-11}$$
$$- 0.18251 * m2 + 0.30955 * m3 + 0.091118 * m4 + 0.071224 * m5 + 0.028960 * m6$$
$$+ 0.028833 * m7 - 0.088105 * m8 - 0.036586 * m9 + 0.26147 * m10 - 0.17794 * m11$$
$$- 0.13989 * m12 - 0.21355 * u_{t-1} \; .$$

The error term is negative, satisfying ECM requirements and is significant at 1%. **R^2 = 0.87** indicates good fit and appropriateness of the independent terms.

For the 24 months ahead model, there is only one cointegrating vector and the maximum likelihood long-run estimate is as follows:

$$(arr) = -0.18679 * (opr) + 1.4719 * (tro) + 0.84627 * (gni) - 0.19178 * (air) + u_t \,.$$

This model shows that the relationships between tourist arrivals from the USA and the variables, own price, per capita GNI of the USA and airfare from the USA to Japan are inelastic and USA trade openness is elastic. Japan's trade openness was found to be not significant. A 1% increase in own price would result in a 0.19% decrease in arrivals. A 1% increase in USA trade openness would result in a 1.47% increase in arrivals. A 1% increase in the USA per capita GNI would result in a 0.85% increase in arrivals. A 1% increase in airfares would result in a 0.19% decrease in arrivals.

The short-run, 24 months ahead, error correction model is as follows:

$$\nabla(arr)_t = -0.016654 + 1.6778 * \nabla(gni)_{t-8} - 1.3925 * \nabla(gni)_{t-11} - 0.19503 * m2 + 0.2981 * m3 + 0.08900 * m4 + 0.06862 * m5 + 0.01674 * m6 + 0.0188 * m7 - 0.0894 * m8 - 0.0468 * m9 + 0.2559 * m10 - 0.1931 * m11 - 0.1574 * m12 - 0.2045 * u_{t-1} \,.$$

The error term is negative, satisfying ECM requirements and is significant at 1%.
R^2 = 0.87 indicates good fit and appropriateness of the independent terms.

5.5 Results of Multivariate Multi-layer Perceptron (MMLP) Forecasts

5.5.1 MMLP forecast of arrivals from all countries

Table 5.5.1 shows the MMLP forecasting performance for tourist arrivals to Japan from all countries. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one-month-ahead forecasting horizon and good (MAPE less than 10%) for the 12 months ahead and the 24 months ahead horizons. For the two-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 5.5.1 Forecasting Performance of MLP with Indicators for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	162543	18.62	40649	8.78	36133	6.79
2 year	127917	16.71	58690	11.37	55879	10.29

5.5.2 MMLP forecast of arrivals from Australia

Table 5.5.2 shows the MMLP forecasting performance for tourist arrivals to Japan from Australia. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period also, the forecasting performance is good (MAPE less than 10%) for all three horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 5.5.2 Forecasting Performance of MLP with Indicators for Tourist Arrivals to Japan from Australia						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	746	4.51	653	3.70	855	5.54
2 year	1123	5.93	940	5.01	1201	7.42

5.5.3 MMLP forecast of arrivals from Canada

Table 5.5.3 shows the MMLP forecasting performance for tourist arrivals to Japan from Canada. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period, the forecasting performance is mostly good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 5.5.3 Forecasting Performance of MLP with Indicators for Tourist Arrivals to Japan from Canada						
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	794	5.62	767	5.32	895	5.80
2 year	1268	9.15	1212	8.54	1306	8.96

5.5.4 MMLP forecast of arrivals from China

Table 5.5.4 shows the MMLP forecasting performance for tourist arrivals to Japan from China. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 5.5.4 Forecasting Performance of MLP with Indicators for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	5248	13.18	5613	11.92	6766	13.99
2 year	10572	30.32	9308	28.81	9649	29.64

5.5.5 MMLP forecast of arrivals from France

Table 5.5.5 shows the MMLP forecasting performance for tourist arrivals to Japan from France. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period also, the forecasting performance is good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 5.5.5	Forecasting Performance of MLP with Indicators for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	445	4.84	423	3.76	486	5.09
2 year	736	8.16	694	7.10	676	7.12

5.5.6 MMLP forecast of arrivals from Germany

Table 5.5.6 shows the MMLP forecasting performance for tourist arrivals to Japan from Germany. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one-month ahead forecasting horizon and good (MAPE less than 10%) for the 12 months ahead and the 24 months ahead horizons. For the two-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one-month ahead and the 12 months ahead horizons and good (MAPE less than 10%) for the 24 months ahead horizon. The RMSE figures are not consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon.

Table 5.5.6	Forecasting Performance of MLP with Indicators for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1177	10.49	1183	9.14	1171	9.51
2 year	1196	11.35	1171	10.71	1171	9.86

5.5.7 MMLP forecast of arrivals from Korea

Table 5.5.7 shows the MMLP forecasting performance for tourist arrivals to Japan from Korea. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period also, the forecasting performance is fair (MAPE between 10% and 20%) for all three forecast horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 5.5.7 Forecasting Performance of MLP with Indicators for Tourist Arrivals to Japan from Korea

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	35163	16.75	16292	10.11	22318	13.86
2 year	31772	16.89	23767	12.48	31831	17.38

5.5.8 MMLP forecast of arrivals from Singapore

Table 5.5.8 shows the MMLP forecasting performance for tourist arrivals to Japan from Singapore. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 5.5.8	Forecasting Performance of MLP with Indicators for Tourist Arrivals to Japan from Singapore					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1231	13.95	1503	15.59	1453	14.84
2 year	1680	25.03	1935	27.28	2050	25.91

5.5.9 MMLP forecast of arrivals from Taiwan

Table 5.5.9 shows the MMLP forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and the 24 months forecasting horizons and fair (MAPE between 10% and 20%) for the 12 months ahead horizon. For the two-year lead period, the forecasting performance is poor (MAPE 20% or less) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 5.5.9	Forecasting Performance of MPL with Indicators for Tourist Arrivals to Japan from Taiwan					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	7064	7.49	11997	14.34	8232	8.84
2 year	20908	29.14	19428	34.36	18458	31.71

5.5.10 MMLP forecast of arrivals from the UK

Table 5.5.10 shows the MMLP forecasting performance for tourist arrivals to Japan from the UK. For the one-year lead period the forecasting performance is fair (MAPE between 10% and 20%), for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two-year lead period also, the forecasting performance is fair (MAPE between 10% and 20%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months ahead forecasting horizon.

Table 5.5.10 Forecasting Performance of MLP with Indicators for Tourist Arrivals to Japan from the UK

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	3261	15.04	3251	11.79	3852	13.98
2 year	2941	14.30	2848	12.46	3386	13.38

5.5.11 MMLP forecast of arrivals from the USA

Table 3.6.11 shows the MMLP forecasting performance for tourist arrivals to Japan from the USA. For the one-year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and 24 months ahead forecasting horizons and fair (MAPE between 10% and 20%) for the 12 months ahead horizon. For the two-year lead period, the forecasting performance is good (MAPE less than 10%) for the one month ahead horizon and fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 5.5.11 Forecasting Performance of MLP with Indicators for Tourist Arrivals to Japan from the USA

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	4157	5.17	9695	14.74	7443	9.43
2 year	5871	8.11	10679	16.01	7451	10.62

5.6 Model Comparison

Table 5.6.1 shows a comparison of the forecasting performance of the Error correction Model (ECM), the Multivariate Multi-layer Perceptron (MMLP), and the naïve models for the one-month ahead, forecasting horizon. Using best MAPE as the forecasting performance evaluation criterion, for the one-month ahead forecasting horizon, both ECM and MMLP perform equally well as both models have the lowest MAPE in 9 (41%) of 22 forecasts. The 22 forecasts are made up of 1 and 2 year lead forecasts for 11 data series. Eight (36%) of the 22 ECM forecasts have MAPE figures less than 10% and 6 (75%) and 2 (25%) of these 8 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for 1 year lead periods. Nine (41%) of the 22 MMLP Forecasts have MAPE figures less than 10% while 5 (56%) and 4 (44%) of these 9 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works well for both 1 and 2 year lead periods. The naïve model had the lowest MAPE in 4 (18%) forecasts.

The MMLP model has the lowest mean MAPE of 13.2%. However, at the 5% level, the mean differences in the MAPE figures of the three models are not significant.

Table 5.6.2 shows a comparison of the forecasting performance of the ECM, the MMLP, and the naïve models for the, 12 months ahead, forecasting horizon. Using lowest MAPE as the forecasting performance evaluation criterion, for the 12 months ahead, forecasting horizon, MMLP performs better than the ECM model and has the lowest MAPE in 13 (59%) of 22 forecasts. Eight (36%) of the 22 MMLP forecasts have MAPE figures less than 10% and 5 (63%) and 3 (38%) of these 8 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for 1 year lead periods. The ECM model has the lowest MAPE in 6 (27%) of the 22 forecasts while 4 (18%) of the 22 ECM forecasts have MAPE figures less than 10%. All 4 of these forecasts were for the 1 year lead period, indicating the model works better for the 1 year lead period. The naïve model had the lowest MAPE in 3 (14) forecasts.

The MMLP model has the lowest mean MAPE of 12.9%. The MMLP model is significantly better than the ECM model and the naïve model at the 5% level.

Table 5.6.3 shows a comparison of the forecasting performance of the ECM, the MMLP, and the naïve models for the, 24 months ahead, forecasting horizon. Using best MAPE as the forecasting performance evaluation criterion, for the 24 months ahead, forecasting horizon, MMLP performs better than the ECM model and has the lowest MAPE in 12 (55%) of 22 forecasts. Eleven (50%) of the 22 MMLP forecasts have MAPE figures less than 10% while 7 (64%) and 4 (36%) of these 11 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for 1 year lead periods. The ECM model has the lowest MAPE in 6 (27%) of the 22 forecasts. Four (18%) of the 22 ECM forecasts have MAPE figures less than 10%. All 4 of these forecasts were for the 1 year lead period, indicating the model works better for the 1 year lead period. The naïve model had the lowest MAPE in 4 (18%) forecasts.

The MMLP model has the lowest mean MAPE of 12.7%. The MMLP model is significantly better than the ECM model and the naïve model at the 5% level.

Table 5.6.1 **Multivariate one month ahead Forecasting Performance of ECM and MMLP**

Country	Forecast Lead	ECM RMSE	ECM MAPE	MMLP RMSE	MMLP MAPE	Naïve RMSE	Naïve MAPE
All	1 year	26746	5.0	162543	18.6	47084	9.9
	2 year	53172	9.3	127917	16.7	59512	12.3
Australia	1 year	1430	9.3	746	4.5	1455	10.1
	2 year	1866	11.3	1123	5.9	1351	8.6
Canada	1 year	1248	9.7	794	5.6	1120	8.6
	2 year	1574	12.3	1268	9.2	1280	10.2
China	1 year	5970	14.4	5248	13.2	5887	14.2
	2 year	9253	26.8	10572	30.3	8476	27.3
France	1 year	1038	10.7	445	4.8	585	6.3
	2 year	1173	13.6	736	8.2	852	9.4
Germany	1 year	1417	12.7	1177	10.5	1092	7.9
	2 year	1278	12.5	1196	11.3	1247	11.2
Korea	1 year	11880	8.6	35163	16.8	13113	10.5
	2 year	16978	11.4	31772	16.9	17606	12.8
Singapore	1 year	1536	18.4	1231	13.9	1644	21.3
	2 year	1848	24.4	1680	25.0	1794	27.7
Taiwan	1 year	5695	5.8	7064	7.5	12620	14.2
	2 year	15573	20.6	20908	29.1	19842	35.4
UK	1 year	5834	23.5	3261	15.0	3815	12.7
	2 year	4933	21.5	2941	14.3	3817	13.5
USA	1 year	4337	5.8	4157	5.2	6382	8.0
	2 year	6345	7.7	5871	8.1	8072	10.4
Summary Measures							
Mean		8233	13.4	19446	13.2	9938	13.7
Standard Deviation		11984	6.4	42212	7.5	15242	7.5
MAPE p-values:							
c/w Naïve			-0.39		-0.28		
c/w MMLP			0.43				0.28
c/w ECM					-0.43		0.39
Lowest MAPE Count		Count	**%**	Count	%	Count	**%**
of 22 forecasts		9	41%	9	41%	4	18%
MAPE <= 10%		8	36%	9	41%	7	32%
10% <MAPE< 20%		9	41%	10	45%	11	50%
MAPE >= 20%		5	23%	3	14%	4	18%
MAPE <= 10%							
for 1 year lead		6	75%	5	56%	5	71%
for 2 year lead		2	25%	4	44%	2	29%

Table 5.6.2 Multivariate 12 months ahead Forecasting Performance of ECM and MMLP

Country	Forecast Lead	ECM RMSE	ECM MAPE	MMLP RMSE	MMLP MAPE	Naïve RMSE	Naïve MAPE
All	1 year	28292	5.3	40649	8.8	47084	9.9
	2 year	67601	11.2	58690	11.4	59512	12.3
Australia	1 year	3602	23.5	653	3.7	1455	10.1
	2 year	3203	19.5	940	5.0	1351	8.6
Canada	1 year	1797	13.6	767	5.3	1120	8.6
	2 year	2016	16.1	1212	8.5	1280	10.2
China	1 year	6067	14.9	5613	11.9	5887	14.2
	2 year	9887	31.2	9308	28.8	8476	27.3
France	1 year	1318	15.4	423	3.8	585	6.3
	2 year	1402	16.8	694	7.1	852	9.4
Germany	1 year	1661	16.6	1183	9.1	1092	7.9
	2 year	1616	16.7	1171	10.7	1247	11.2
Korea	1 year	10158	8.0	16292	10.1	13113	10.5
	2 year	19611	11.7	23767	12.5	17606	12.8
Singapore	1 year	1649	20.8	1503	15.6	1644	21.3
	2 year	2836	40.7	1935	27.3	1794	27.7
Taiwan	1 year	4282	5.0	11997	14.3	12620	14.2
	2 year	25078	41.8	19428	34.4	19842	35.4
UK	1 year	9927	49.5	3251	11.8	3815	12.7
	2 year	9161	48.6	2848	12.5	3817	13.5
USA	1 year	4802	6.4	9695	14.7	6382	8.0
	2 year	8596	11.1	10679	16.0	8072	10.4
Summary Measures							
Mean		10207	20.2	10123	12.9	9938	13.7
Standard Deviation		14924	13.6	14723	8.0	15242	7.5
MAPE p-values:							
c/w Naïve			0.01		-0.09		
c/w MMLP			0.01				0.09
c/w ECM					-0.01		-0.01
Lowest MAPE Count		Count	%	Count	%	Count	**%**
of 22 forecasts		6	27%	13	59%	3	14%
MAPE <= 10%		4	18%	8	36%	7	32%
10% <MAPE< 20%		11	50%	11	50%	11	50%
MAPE >= 20%		7	32%	3	14%	4	18%
MAPE <= 10%							
for 1 year lead		4	100%	5	63%	5	71%
for 2 year lead		0	0%	3	38%	2	29%

Table 5.6.3 **Multivariate 24 months ahead Forecasting Performance of ECM and MMLP**

Country	Forecast Lead	ECM RMSE	ECM MAPE	MMLP RMSE	MMLP MAPE	Naïve RMSE	Naïve MAPE
All	1 year	28292	5.3	36133	6.8	43323	9.3
	2 year	60165	10.3	55879	10.3	66744	13.9
Australia	1 year	3602	23.5	855	5.5	1748	10.8
	2 year	4415	27.6	1201	7.4	2087	13.0
Canada	1 year	1797	13.6	895	5.8	1372	10.4
	2 year	2171	17.4	1306	9.0	1583	12.4
China	1 year	6067	14.9	6766	14.0	9318	21.0
	2 year	12857	41.3	9649	29.6	10954	32.5
France	1 year	1318	15.4	486	5.1	940	11.9
	2 year	1566	18.9	676	7.1	889	10.6
Germany	1 year	1661	16.6	1171	9.5	1317	10.3
	2 year	1778	18.7	1171	9.9	1268	11.0
Korea	1 year	10158	8.0	22318	13.9	18600	15.9
	2 year	19595	11.5	31831	17.4	26280	18.3
Singapore	1 year	1649	20.8	1453	14.8	993	9.1
	2 year	2289	31.7	2050	25.9	1968	25.9
Taiwan	1 year	4282	5.0	8232	8.8	9149	10.5
	2 year	18580	31.5	18458	31.7	20045	34.4
UK	1 year	9927	49.5	3852	14.0	14877	79.5
	2 year	11525	63.6	3386	13.4	10569	43.3
USA	1 year	4802	6.4	7443	9.4	2586	2.9
	2 year	8379	10.7	7451	10.6	8352	9.9
Summary Measures							
Mean		9858	21.0	10121	12.7	11589	18.9
Standard Deviation		13306	14.9	14450	7.5	16238	16.7
MAPE p-values:							
c/w Naïve			0.18		-0.03		
c/w MMLP			0.00				0.03
c/w ECM					-0.00		-0.18
Lowest MAPE Count		Count	%	Count	%	Count	**%**
of 22 forecasts		6	27%	12	55%	4	18%
MAPE <= 10%		4	18%	11	50%	4	18%
10% <MAPE< 20%		10	45%	8	36%	12	55%
MAPE >= 20%		8	36%	3	14%	6	27%
MAPE <= 10%							
for 1 year lead		4	100%	7	64%	3	75%
for 2 year lead		0	0%	4	36%	1	25%

Table 5.6.4 **Forecasting Performance Comparison Summary of ECM and MMLP**

	ECM		MMLP		Naïve	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Mean	9433	18.2	13230	12.9	10489	15.5
Standard Deviation	13278	12.5	27070	7.5	15359	11.5
MAPE p-values:						
c/w Naïve		0.01		-0.02		
c/w MMLP		0.01				0.02
c/w ECM				-0.01		-0.01
Lowest MAPE Count	Count	%	Count	%	Count	%
of 66 forecasts	21	32%	34	52%	11	17%
MAPE <= 10%	16	24%	28	42%	18	27%
10% <MAPE< 20%	30	45%	29	44%	34	52%
MAPE >= 20%	20	30%	9	14%	14	21%
MAPE <= 10%						
for 1 year lead	14	88%	17	61%	13	72%
for 2 year lead	2	13%	11	39%	5	28%

Table 5.6.4 shows a comparison summary of the forecasting performance of the ECM, the MMLP, and the naïve models for all three, forecasting horizons. Using lowest MAPE as the forecasting performance evaluation criterion, overall, MMLP performs better than the ECM model and has the lowest MAPE in 34 (52%) of 66 forecasts while 28 (42%) of the 66 MMLP forecasts have MAPE figures less than 10%. Of these 28 forecasts, 17 (61%) and 11 (39%) were for the 1 year and 2 year lead periods respectively, indicating the model works better for 1 year lead periods. The ECM model has the lowest MAPE in 21 (32%) of the 66 forecasts while 16 (24%) of the 66 ECM forecasts have MAPE figures less than 10%. Of these 16 ECM forecasts, 14 (88%) and 2 (13%) were for the 1 year and 2 year lead periods respectively, indicating the model works better for the 1 year lead period. The naïve model had the lowest MAPE in 11 (17%) forecasts.

The MMLP model has the lowest mean MAPE of 12.9%. The MMLP model is significantly better than the ECM model and the naïve model at the 5% level. The naïve model is in turn significantly better than the ECM model at 5%.

5.7 Conclusion

Overall, the MMLP model performs better than the ECM and the naïve models with the lowest MAPE in 52% of 66 forecasts. The accuracy of the MMLP model was also high with 42% of 66 forecasts having MAPE figures less than 10%. The MMLP model also has the lowest mean MAPE of 12.9% which is significantly different from the ECM mean MAPE of 18.2% at the 5% level of significance. However, the ECM model performs as well as the MMLP model in the one month ahead forecasting horizon.

The better forecasting performance of the MMLP model is consistent with the findings of Burger, Dohnal, Kathrada et al. (2001) that neural networks performs better than regression models. However, ECM models are useful in explaining the elasticities in relation to the independent variables.

The same explanatory variables were used for both models and the result is in keeping with the findings of other studies that found neural network models outperform econometric models. However, the benefit of using the ECM model over the MLP model is that it produces elasticities for each explanatory variable, which is very useful supplementary information.

Chapter 6
Adaptive Neuro-Fuzzy Forecasting

6.1 Introduction

This chapter consists of the application of a hybrid combination of fuzzy logic and neural networks using ANFIS, an Adaptive Neuro-Fuzzy Inference System to forecast tourist arrivals to Japan. The ANFIS model is used to make univariate and multivariate tourist arrival forecasts. The forecasting performances of the univariate and multivariate ANFIS models are compared with those of the Multi-Layer Perceptron (MLP) neural network models.

Historical monthly tourist arrivals from Australia, Canada, China, France, Germany, Korea, Singapore, Taiwan, UK, the USA and from all countries, to Japan, from January 1978 to December 2001 are used to forecast arrivals for the 24 month period from January 2002 to December 2003. Forecasts are made for each of the above series, one month ahead, 12 months ahead, and 24 months ahead, to test whether the accuracy of the forecasts varies significantly. The criterion for comparison of the models is the forecasting accuracy as measured by the MAPE and RMSE, during the 24 month out of sample period from January 2001 to December 2003. The objective of this study is to evaluate the forecasting performance of the newly developed ANFIS models for identical tourism time series.

6.2 The ANFIS Model

The univariate ANFIS model used here is that developed by Jang (1993) which is a connectionist neural network MLP model that uses the Sugeno type fuzzy inference system. In the ANFIS model crisp input series are converted to fuzzy inputs by developing membership functions for each input series. The membership function pattern used for the input series is the general bell shape. The fuzzy inputs with their associated membership functions form the inputs to the neural network. These fuzzy inputs are processed through a network of transfer functions at the nodes of the different layers of the network to obtain fuzzy outputs with linear membership functions that are combined to obtain a single crisp output, as the ANFIS method permits only one output in the model. Being restricted to having one output only is not a limitation as modelling throughout this study has been for a single output, the tourist arrivals in a single period. Data from January 1978 to December 2001 are used to train the network using a combination of the least squares method and the backpropagation gradient descent method, during which membership functions and parameters keep changing until the tourist arrivals forecast error is minimised. Then the resulting model is applied to the test data from January 2002 to December 2003. The use of natural logarithmic transformations of the data has been maintained for consistency with other forecasting models used in previous chapters.

In this model each month's tourist arrivals (output) are matched against the three previous years' (lagged) arrivals (inputs) of the same calendar month. The justification for using arrivals lagged by multiples of 12 is the fact that tourist arrivals are seasonal.

The tourist arrivals series is defined as $\boldsymbol{x_t}$, and its fuzzy set as $\boldsymbol{A_i}$, where the number of membership functions is $\boldsymbol{i}$:

$$A_i = \{ x_t , \mu_i (x_t)\} \quad ,$$

where, $\boldsymbol{\mu_i}$ are the membership functions of $\boldsymbol{A_i}$. If the fuzzy sets of the lagged series are $\boldsymbol{A_{i,j}}$, where $\boldsymbol{i}$ represents the number of membership functions of the lagged series, and $\boldsymbol{j}$ = 1, 2, and 3, for the lagged arrivals series with 12, 24 and 36 month lags respectively and the corresponding membership functions are $\boldsymbol{\mu_{i,j}}$, then, the input fuzzy sets $\boldsymbol{A_{i,j}}$ would be:

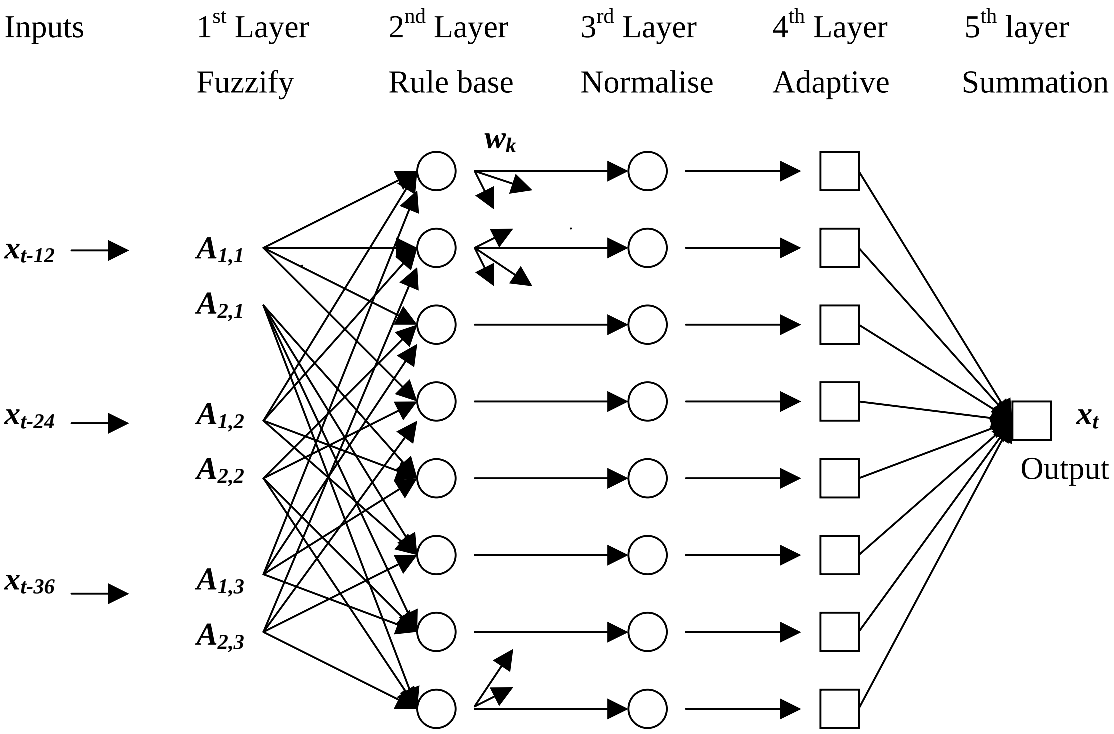
$$A_{i,1} = \{ x_{t-12} , \mu_{i,1} (x_{t-12})\} \quad ,$$

$$A_{i,2} = \{ x_{t-24} , \mu_{i,2} (x_{t-24})\} \quad ,$$

$$A_{i,3} = \{ x_{t-36} , \mu_{i,3} (x_{t-36})\} \quad .$$

To keep the computation within technical limits, the number of membership functions used for each variable are limited to two. As there are three lagged series used as inputs and two membership functions for each input series, the number of input fuzzy sets created in the first layer of the ANFIS architecture of this study is six, as shown in the architecture of Figure 6.1.

Figure 6.1 Connectionist ANFIS Model



The generalised bell membership function used in this study is defined as follows:

$$gbell(x_t;a,b,c) = \frac{1}{1+\left|\frac{x_t - c}{a}\right|^{2b}} \quad ,$$

where, $\boldsymbol{x_t}$ is the tourist arrivals series and ***a, b*** and ***c*** are parameters and ***b*** is positive. The ***gbell*** type membership function is used for the input variables.

The number of nodes of the second layer represents the number of fuzzy rules. Every node of this layer calculates the product of all incoming signals. At two membership functions per variable the number of rules and therefore, the number of nodes in this study is 8. The outputs, $\boldsymbol{w_k}$, from the second layer nodes are the firing strengths of the rules, where $\boldsymbol{k}$ is the number of rules. The firing strength from each node is the product of the input membership functions to that node, as shown below:

$$w_1 = \mu_{1,1}(x_{t-12})\mu_{1,2}(x_{t-24})\mu_{1,3}(x_{t-36}) \;,$$

$$w_2 = \mu_{1,1}(x_{t-12})\mu_{1,2}(x_{t-24})\mu_{2,3}(x_{t-36}) \;,$$

$$w_3 = \mu_{1,1}(x_{t-12})\mu_{2,2}(x_{t-24})\mu_{1,3}(x_{t-36}) \;,$$

$$w_4 = \mu_{1,1}(x_{t-12})\mu_{2,2}(x_{t-24})\mu_{2,3}(x_{t-36}) \;,$$

$$w_5 = \mu_{2,1}(x_{t-12})\mu_{1,2}(x_{t-24})\mu_{1,3}(x_{t-36}) \;,$$

$$w_6 = \mu_{2,1}(x_{t-12})\mu_{1,2}(x_{t-24})\mu_{2,3}(x_{t-36}) \;,$$

$$w_7 = \mu_{2,1}(x_{t-12})\mu_{2,2}(x_{t-24})\mu_{1,3}(x_{t-36}) \;,$$

$$w_8 = \mu_{2,1}(x_{t-12})\mu_{2,2}(x_{t-24})\mu_{2,3}(x_{t-36}) \;.$$

The third layer calculates the ratio of the firing strength of each node to the total strength as follows:

$$\overline{w}_k = \frac{w_k}{\Sigma w_k} \;.$$

The fourth layer has a linear transfer function and each of the $\boldsymbol{k}$ nodes has the following output with 4 linear parameters, p_k, q_k, r_k and s_k in each:

$$\overline{w}_k(p_k x_{t-12} + q_k x_{t-24} + r_k x_{t-36} + s_k) \;.$$

The fifth layer has a single summation node, which sums the outputs from the fourth layer for all $\boldsymbol{k}$:

$$\sum_{k=1}^{8} \overline{w}_k \, (\, p_k \, x_{t-12} + q_k \, x_{t-24} + r_k \, x_{t-36} + s_k \,) \quad .$$

The parameters of the membership functions will change during the learning process. The parameters are adjusted to reduce the sum of squared differences between the actual and forecast output. ANFIS uses a combination of least squares estimation and backpropagation for parameter estimation.

6.3 The Multivariate ANFIS Model

The multivariate ANFIS model is exactly the same as the ANFIS model explained in 6.2 above and the architecture is the same as that shown in Figure 6.1, except that additional independent variables are used as inputs along with the lagged variables. The economic indicators used as independent variables in the multivariate MLP and ECM models of Chapter 5 are the source country's own price, the trade openness of the tourist's country of origin, Japan's trade openness, per capita gross national income of the tourist's country of origin and airfares from the tourist's country of origin to Japan. Preliminary studies with the ANFIS model using these variables and the three lagged arrivals series, showed system limitations because there are too many variables and consequent membership functions. Experimental runs were then made using reduced numbers of all combinations of variables using arrivals data from USA only. In these runs the model worked better and produced the best performance when one lagged arrivals series, the per capita gross national income of the tourist's country of origin, and the airfares from the tourist's country of origin to Japan, were used as inputs.

6.4 Results of ANFIS forecasts

6.4.1 ANFIS forecast of arrivals from all countries

When tourist arrivals from all countries are modelled, some of the variables used for modelling arrivals from individual countries are not relevant. Hence, for arrivals from all countries the input variables used were, one lagged arrivals series, Japan's per capita gross domestic product and Japan's trade openness.

Table 6.4.1 shows the ANFIS forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all forecast horizons, one month ahead, the 12 months ahead and the 24 months ahead. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead, forecasting horizon.

Table 6.4.1 Forecasting Performance of a Partial Periodic ANFIS for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	25079	4.64	29549	6.08	26574	5.32
2 year	58703	10.62	57292	10.76	54401	10.80

6.4.2 ANFIS forecast of arrivals from Australia

Table 6.4.2 shows the ANFIS forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and the 12 months ahead horizons and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 6.4.2 Forecasting Performance of a Partial Periodic ANFIS for Tourist Arrivals to Japan from Australia

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	626	3.55	640	3.49	1681	8.79
2 year	1049	5.81	1011	5.72	2400	11.67

6.4.3 ANFIS forecast of arrivals from Canada

Table 6.4.3 shows the ANFIS forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and the 12 months ahead horizons and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 6.4.3	Forecasting Performance of a Partial Periodic ANFIS for Tourist Arrivals to Japan from Canada					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	885	6.65	868	6.52	1360	8.92
2 year	1313	9.64	1344	9.86	1426	10.09

6.4.4 ANFIS forecast of arrivals from China

Table 6.4.4 shows the ANFIS forecasting performance for tourist arrivals to Japan from China. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and 12 months ahead forecasting horizons and poor (MAPE 20% or more) for the 24 months ahead horizon. For the two year lead period the forecasting performance is poor (MAPE 20% or more) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one month ahead forecasting horizon, however forecasts are poor for the 2 year lead period.

Table 6.4.4	Forecasting Performance of a Partial Periodic ANFIS for Tourist Arrivals to Japan from China					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	2865	6.08	3232	7.59	9726	21.23
2 year	8736	25.78	8983	27.10	11303	33.17

6.4.5 ANFIS forecast of arrivals from France

Table 6.4.5 shows the ANFIS forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period, the forecasting performance is also good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 6.4.5 Forecasting Performance of a Partial Periodic ANFIS for Tourist Arrivals to Japan from France

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	458	3.94	448	3.91	723	9.11
2 year	864	8.38	868	8.52	799	9.50

6.4.6 ANFIS forecast of arrivals from Germany

Table 6.4.6 shows the ANFIS forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two year lead period, the forecasting performance is also good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 6.4.6	Forecasting Performance of a Partial Periodic ANFIS for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1012	6.94	1019	7.21	1185	9.42
2 year	1037	9.09	1009	8.93	1130	10.00

6.4.7 ANFIS forecast of arrivals from Korea

Table 6.4.7 shows the ANFIS forecasting performance for tourist arrivals to Japan from Korea. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and 12 months ahead forecasting horizons and poor (MAPE 20% or more) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is also fair (MAPE between 10% and 20%) for the one month ahead and 12 months ahead forecasting horizons and poor (MAPE 20% or more) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 6.4.7	Forecasting Performance of a Partial Periodic ANFIS for Tourist Arrivals to Japan from Korea					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	18976	15.07	22834	18.11	41568	33.49
2 year	18296	13.97	22342	16.66	47045	33.96

6.4.8 ANFIS forecast of arrivals from Singapore

Table 6.4.8 shows the ANFIS forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and 12 months ahead forecasting horizons, and good (MAPE less than 10%) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or more) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months-ahead forecasting horizon.

Table 6.4.8 Forecasting Performance of a Partial Periodic ANFIS for Tourist Arrivals to Japan from Singapore

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1547	17.31	1500	17.34	1035	9.51
2 year	1883	26.57	1839	26.37	1931	24.94

6.4.9 ANFIS forecast of arrivals from Taiwan

Table 6.4.9 shows the ANFIS forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and 12 months ahead forecasting horizons and good (MAPE less than 10%) for the 24 months ahead horizon. For the two year lead period, the forecasting performance is poor (MAPE 20% or more) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead forecasting horizon but poor for the 2-year lead period.

Table 6.4.9	Forecasting Performance of a Partial Periodic ANFIS for Tourist Arrivals to Japan from Taiwan					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	9735	10.34	10333	10.85	9299	9.51
2 year	18916	32.00	19102	32.79	19263	32.59

6.4.10 ANFIS forecast of arrivals from the UK

Table 6.4.10 shows the ANFIS forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is poor (MAPE 20% or more) for all forecast horizons, one month ahead and 12 months ahead and 24 months ahead. For the two year lead period, the forecasting performance is also poor (MAPE 20% or more) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall the model forecasts are poor.

Table 6.4.10	Forecasting Performance of a Partial Periodic ANFIS for Tourist Arrivals to Japan from the UK					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	11093	39.90	53674	246.97	18887	96.00
2 year	7990	25.86	37979	129.18	31433	154.86

6.4.11 ANFIS forecast of arrivals from the USA

Table 6.4.11 shows the ANFIS forecasting performance for tourist arrivals to Japan from the USA. For the one year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead horizon and fair (MAPE between 10% and 20%) for the 12 months ahead and the 24 months ahead forecasting horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months-ahead forecasting horizon.

Table 6.4.11 Forecasting Performance of a Partial Periodic ANFIS for Tourist Arrivals to Japan from the USA

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	6245	7.17	6806	7.39	3260	3.97
2 year	7558	9.37	8024	10.11	8903	10.27

6.5 Results of Multivariate ANFIS Forecasts

6.5.1 Multivariate ANFIS forecast of arrivals from all countries

Table 6.5.1 shows the ANFIS forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and 24 months ahead forecasting horizons and fair (MAPE between 10% and 20%) for the 12 months ahead horizon. For the two year lead period the forecasting performance is fair (MAPE between 10% and 20%) for all three forecasting horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead-forecasting horizon.

Table 6.5.1 Forecasting Performance of ANN Model with Indicators for Tourist Arrivals to Japan from All Countries

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	41028	8.16	51718	11.01	36973	7.56
2 year	60599	12.06	61772	12.70	66202	12.93

6.5.2 Multivariate ANFIS forecast of arrivals from Australia

Table 6.5.2 shows the ANFIS forecasting performance for tourist arrivals to Japan from Australia. For the one year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and 12 months ahead horizons, and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 6.5.2 Forecasting Performance of ANN Model with Indicators for Tourist Arrivals to Japan from Australia

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1008	6.40	1519	9.56	1593	9.74
2 year	1137	6.51	1378	8.05	2419	14.44

6.5.3 Multivariate ANFIS forecast of arrivals from Canada

Table 6.5.3 shows the ANFIS forecasting performance for tourist arrivals to Japan from Canada. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and 12 months ahead horizons and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months-ahead forecasting horizon.

Table 6.5.3 Forecasting Performance of ANN Model with Indicators for Tourist Arrivals to Japan from Canada

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1021	7.39	991	6.99	877	6.00
2 year	1283	9.93	1287	9.47	1452	10.24

6.5.4 Multivariate ANFIS forecast of arrivals from China

Table 6.5.4 shows the ANFIS forecasting performance for tourist arrivals to Japan from China. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and 12 months ahead forecasting horizons and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two year lead period the forecasting performance is poor (MAPE 20% or more) for all three forecasting horizons. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 12 months-ahead forecasting horizon.

Table 6.5.4 Forecasting Performance of ANN with Indicators for Tourist Arrivals to Japan from China

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	3194	7.62	3057	7.50	4687	11.36
2 year	8737	26.34	8589	25.80	10356	32.29

6.5.5 Multivariate ANFIS forecast of arrivals from France

Table 6.5.5 shows the ANFIS forecasting performance for tourist arrivals to Japan from France. For the one year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two year lead period, the forecasting performance is also good (MAPE less than 10%) for all three horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month-ahead forecasting horizon.

Table 6.5.5	Forecasting Performance of ANN Model with Indicators for Tourist Arrivals to Japan from France					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	533	5.34	560	6.01	720	8.88
2 year	866	9.29	861	9.35	805	9.30

6.5.6 Multivariate ANFIS forecast of arrivals from Germany

Table 6.5.6 shows the ANFIS forecasting performance for tourist arrivals to Japan from Germany. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead, 12 months ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and 12 months ahead horizons and good (MAPE less than 10%) for the 24 months ahead horizon. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months-ahead forecasting horizon.

Table 6.5.6	Forecasting Performance of ANN Model with Indicators for Tourist Arrivals to Japan from Germany					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1056	7.94	1132	8.92	1109	8.41
2 year	1322	11.69	1286	11.97	1235	9.66

6.5.7 Multivariate ANFIS forecast of arrivals from Korea

Table 6.5.7 shows the ANFIS forecasting performance for tourist arrivals to Japan from all countries. For the one year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and 24 months ahead forecasting horizons and fair (MAPE between 10% and 20%) for the 12 months ahead horizon. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead horizon and fair (MAPE between 10% and 20%) for the 12 months ahead and 24 months ahead horizons. The RMSE figures are consistent with the MAPE figures. The forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the one-month ahead forecasting horizon.

Table 6.5.7 Forecasting Performance of ANN Model with Indicators for Tourist Arrivals to Japan from Korea

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	10760	8.01	16081	14.16	8420	7.39
2 year	11686	8.72	14303	11.98	17039	11.75

6.5.8 Multivariate ANFIS forecast of arrivals from Singapore

Table 6.5.8 shows the ANFIS forecasting performance for tourist arrivals to Japan from Singapore. For the one year lead period the forecasting performance is poor (MAPE 20% or more) for the one month ahead and 12 months ahead forecasting horizons and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two year lead period the forecasting performance is poor (MAPE 20% or more) for all three forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, but the model forecasts are poor.

Table 6.5.8 Forecasting Performance of ANN Model with Indicators for Tourist Arrivals to Japan from Singapore

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	1876	23.18	1964	23.82	1233	15.62
2 year	1914	27.73	1911	27.19	1852	27.04

6.5.9 Multivariate ANFIS forecast of arrivals from Taiwan

Table 6.5.9 shows the ANFIS forecasting performance for tourist arrivals to Japan from Taiwan. For the one year lead period the forecasting performance is fair (MAPE between 10% and 20%) for the one month ahead and 12 months-ahead and 24 months ahead forecasting horizons. For the two year lead period the forecasting performance is poor (MAPE 20% or more) for all three forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, but the model forecasts are poor for the 2-year lead period.

Table 6.5.9 Forecasting Performance of ANN Model with Indicators for Tourist Arrivals to Japan from Taiwan

Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	10757	11.44	11298	12.27	13221	13.50
2 year	18298	31.75	18358	32.73	19231	30.49

6.5.10 Multivariate ANFIS forecast of arrivals from the UK

Table 6.5.10 shows the ANFIS forecasting performance for tourist arrivals to Japan from the UK. For the one year lead period the forecasting performance is poor (MAPE 20% or more) for the one month ahead and 12 months ahead forecasting horizons and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. For the two year lead period the forecasting performance is poor (MAPE 20% or more) for all three forecasting horizons. The RMSE figures are fairly consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, but the model forecasts are poor.

Table 6.5.10	Forecasting Performance for Tourist Arrivals to Japan from the UK					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	8738	34.29	32756	137.95	3062	11.67
2 year	6492	24.22	23250	76.11	24810	93.79

6.5.11 Multivariate ANFIS forecast of arrivals from the USA

Table 6.5.11 shows the ANFIS forecasting performance for tourist arrivals to Japan from the USA. For the one year lead period the forecasting performance is good (MAPE less than 10%) for all forecast horizons, one month ahead, 12 months ahead and 24 months ahead. For the two year lead period the forecasting performance is good (MAPE less than 10%) for the one month ahead and 12 months ahead horizons and fair (MAPE between 10% and 20%) for the 24 months ahead horizon. The RMSE figures are consistent with the MAPE figures. Overall, the forecasting error increases with an increase in the lead period, and the model forecasts are most accurate over the 24 months ahead, forecasting horizon.

Table 6.5.11	Forecasting Performance of ANN Model with Indicators for Tourist Arrivals to Japan from the USA					
Horizon	One month ahead		12 months ahead		24 months ahead	
Lead	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1 year	6231	7.51	6554	8.17	2899	3.18
2 year	6872	9.30	7351	9.61	8257	10.02

6.6 Univariate and Multivariate ANFIS Model Comparison

Tables 6.6.1, 6.6.2 and 6.6.3 show, for the one month ahead, 12 months ahead and 24 months ahead, forecasting horizons respectively, a comparison of the forecasting performances of the univariate ANFIS (UANFIS) and the multivariate ANFIS (MANFIS) models. For the purpose of comparison, the performances of the partial periodic MLP model and the multivariate MLP (MMLP) model are also included in these tables.

Using lowest MAPE as the forecasting performance evaluation criterion, for the one month ahead forecasting horizon (refer Table 6.6.1), both UANFIS and MMLP perform equally well as both models have the lowest MAPE in 7 (32%) of 22 forecasts. The 22 forecasts are made up of 1 and 2 year lead forecasts for 11 data series. Twelve (55%) of the 22 UANFIS forecasts have MAPE figures less than 10% while 7 (58%) and 5 (42%) of these 12 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for 1 year lead periods. Nine (41%) of the 22 MMLP forecasts have MAPE figures less than 10% while 5 (56%) and 4 (44%) of these 9 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works well for both 1 and 2 year lead periods. The partial periodic MLP model had the lowest MAPE in 6 (27%) forecasts and had 12 (55%) MAPE figures less than 10%, while the MANFIS model had the lowest MAPE in 2 (9%) forecasts and had 13 (59%) MAPE figures less than 10%.

The partial periodic MLP model has the lowest mean MAPE of 12.0%, followed by the MMLP model with 13.2%, the UANFIS model with 13.6% and the MANFIS with 13.9%. However, the mean differences in the MAPE figures of the four models are not significant at the 5% level, except that the partial periodic MLP model is significantly better than the MANFIS model.

For the 12 months ahead, forecasting horizon, (refer Table 6.6.2) partial periodic MLP has the lowest MAPE in 8 (36%) of 22 forecasts. Twelve (55%) of the 22 partial periodic MLP forecasts have MAPE figures less than 10% while 7 (58%) and 5 (42%) of these 12 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for 1 year lead periods. The MMLP model has the lowest MAPE in 7 (32%) of the 22 forecasts. Eight (36%) of the 22 MMLP forecasts have MAPE figures less than 10% while 5 (63%) and 3 (37%) of these 8 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for 1 year lead periods. The UANFIS model has the lowest MAPE in 3 (14%) forecasts and has 10 (45%) MAPE figures less than 10%, while the MANFIS had the lowest MAPE in 4 (18%) forecasts and has 10 (45%) MAPE figures less than 10%.

The partial periodic MLP model has the lowest mean MAPE of 12.3%, followed by the MMLP model with 12.9%, the MANFIS model with 21.9% and the UANFIS with 29.1%. However, the mean differences in the MAPE figures of the four models are not significant at the 5% level due to high variances, except that the partial periodic MLP model is significantly better than the MANFIS model.

For the 24 months ahead forecasting horizon, (refer Table 6.6.3) the MMLP model has the lowest MAPE in 7 (32%) of 22 forecasts. Eleven (50%) of the 22 MMLP forecasts have MAPE figures less than 10% while 7 (64%) and 4 (36%) of these 11 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for

1 year lead periods. The UANFIS model has the next lowest MAPE in 6 (27%) of the 22 forecasts. Eight (36%) of the 22 UANFIS forecasts have MAPE figures less than 10% while 7 (88%) and 1 (13%) of these 8 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for 1 year lead periods. The MANFIS model had the lowest MAPE in 5 (23%) forecasts and has 9 (41%) MAPE figures less than 10%, while the partial periodic MLP has the lowest MAPE in 4 (18%) forecasts and has 11 (50%) MAPE figures less than 10%.

The MMLP model has the lowest mean MAPE of 12.7%, followed by the MANFIS model with 16.6%, the UANFIS model with 20.6% and the partial periodic MLP model with 20.8%. However, the mean differences in the MAPE figures of the four models are not significant at the 5% level due to high variances, except that the MMLP model is significantly better than the partial periodic MLP model.

Table 6.6.4, shows a comparison summary of the forecasting performance of the partial periodic MLP, the MMLP, the UANFIS and the MANFIS models for all three, forecasting horizons. Using lowest MAPE as the forecasting performance evaluation criterion, MMLP performs best and has the lowest MAPE in 21 (32%) of 66 forecasts. Of the MMLP forecasts 28 (42%) of the 66 forecasts have MAPE figures less than 10% while 17 (61%) and 11 (39%) of these 28 forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for 1 year lead periods. The partial periodic MLP model has the lowest MAPE in 18 (27%) of the 66 forecasts. Thirty five (53%) of the 66 partial periodic MLP forecasts have MAPE figures less than 10% while 21 (60%) and 14 (40%) of these 35 partial periodic MLP forecasts were for the 1 year and 2 year lead periods respectively, indicating the model works better for 1 year lead periods. The UANFIS model has the lowest MAPE in 16 (24%) forecasts and has 30 (45%) MAPE figures less than 10%, while the MANFIS has the lowest MAPE in 11 (17%) forecasts and has 32 (48%) MAPE figures less than 10%.

The MMLP model has the lowest mean MAPE of 12.9%, followed by the partial periodic MLP model with 15.1%, the MANFIS model with 17.4% and the UANFIS model with 21.1%. The mean differences in the MAPE figures of the four models show that the MMLP model is significantly better than the MANFIS and UANFIS models and the MANFIS model is significantly better than the UANFIS model at 5%.

Table 6.6.1 **One month ahead Forecasting Performance Comparison of ANFIS and MLP Models**

Country	Forecast Lead	MLP Partial Periodic RMSE	MAPE	MMLP RMSE	MAPE	UANFIS RMSE	MAPE	MANFIS RMSE	MAPE
All	1 year	24943	4.9	162543	18.6	25079	4.6	41028	8.2
	2 year	55528	10.2	127917	16.7	58703	10.6	60599	12.1
Australia	1 year	598	3.7	746	4.5	626	3.6	1008	6.4
	2 year	992	5.4	1123	5.9	1049	5.8	1137	6.5
Canada	1 year	758	5.4	794	5.6	885	6.6	1021	7.4
	2 year	1305	9.0	1268	9.2	1313	9.6	1283	9.9
China	1 year	4709	10.1	5248	13.2	2865	6.1	3194	7.6
	2 year	9099	28.3	10572	30.3	8736	25.8	8737	26.3
France	1 year	411	4.5	445	4.8	458	3.9	533	5.3
	2 year	786	8.0	736	8.2	864	8.4	866	9.3
Germany	1 year	1015	7.6	1177	10.5	1012	6.9	1056	7.9
	2 year	1076	9.7	1196	11.3	1037	9.1	1322	11.7
Korea	1 year	17910	11.5	35163	16.8	18976	15.1	10760	8.0
	2 year	21062	12.7	31772	16.9	18296	14.0	11686	8.7
Singapore	1 year	1480	16.3	1231	13.9	1547	17.3	1876	23.2
	2 year	1893	25.9	1680	25.0	1883	26.6	1914	27.7
Taiwan	1 year	6383	7.2	7064	7.5	9735	10.3	10757	11.4
	2 year	18696	31.5	20908	29.1	18916	32.0	18298	31.8
UK	1 year	3967	20.0	3261	15.0	11093	39.9	8738	34.3
	2 year	3654	17.9	2941	14.3	7990	25.9	6492	24.2
USA	1 year	4375	5.2	4157	5.2	6245	7.2	6231	7.5
	2 year	6644	8.6	5871	8.1	7558	9.4	6872	9.3
Summary Measures									
Mean		8513	12.0	19446	13.2	9312	13.6	9337	13.9
Standard Deviation		12865	8.1	42212	7.5	13265	10.1	14553	9.2
MAPE p-values:									
c/w MANFIS			-0.02		-0.33		-0.33		
c/w UANFIS			-0.06		-0.41				0.33
c/w MMLP			-0.08				0.41		0.33
c/w UMLP					0.08		0.06		0.02
Lowest MAPE Count		Count	**%**	Count	%	Count	**%**	Count	**%**
of 22 forecasts		6	27%	7	32%	7	32%	2	9%
MAPE <= 10%		12	55%	9	41%	12	55%	13	59%
10% <MAPE< 20%		7	32%	10	45%	5	23%	3	14%
MAPE >= 20%		3	14%	3	14%	5	23%	6	27%
MAPE <= 10%									
for 1 year lead		7	58%	5	56%	7	58%	8	62%
for 2 year lead		5	42%	4	44%	5	42%	5	38%

Table 6.6.2 12 months ahead Forecasting Performance Comparison of ANFIS and MLP Models

Country	Forecast Lead	MLP Partial Periodic RMSE	MAPE	MMLP RMSE	MAPE	UANFIS RMSE	MAPE	MANFIS RMSE	MAPE
All	1 year	31537	6.5	40649	8.8	29549	6.1	51718	11.0
	2 year	55720	10.4	58690	11.4	57292	10.8	61772	12.7
Australia	1 year	465	3.0	653	3.7	640	3.5	1519	9.6
	2 year	923	4.9	940	5.0	1011	5.7	1378	8.0
Canada	1 year	730	5.1	767	5.3	868	6.5	991	7.0
	2 year	1339	8.8	1212	8.5	1344	9.9	1287	9.5
China	1 year	5483	11.7	5613	11.9	3232	7.6	3057	7.5
	2 year	8339	26.1	9308	28.8	8983	27.1	8589	25.8
France	1 year	408	4.1	423	3.8	3232	7.6	560	6.0
	2 year	810	7.9	694	7.1	8983	27.1	861	9.3
Germany	1 year	1019	7.3	1183	9.1	448	3.9	1132	8.9
	2 year	1077	9.5	1171	10.7	868	8.5	1286	12.0
Korea	1 year	18324	12.7	16292	10.1	22834	18.1	16081	14.2
	2 year	25700	15.4	23767	12.5	22342	16.7	14303	12.0
Singapore	1 year	1455	16.7	1503	15.6	1500	17.3	1964	23.8
	2 year	1765	25.2	1935	27.3	1839	26.4	1911	27.2
Taiwan	1 year	6522	7.5	11997	14.3	10333	10.9	11298	12.3
	2 year	18532	31.6	19428	34.4	19102	32.8	18358	32.7
UK	1 year	3969	21.0	3251	11.8	53674	247.0	32756	137.9
	2 year	3828	20.1	2848	12.5	37979	129.2	23250	76.1
USA	1 year	4769	6.1	9695	14.7	6806	7.4	6554	8.2
	2 year	7367	9.8	10679	16.0	8024	10.1	7351	9.6
Summary Measures									
Mean		9095	12.3	10123	12.9	13676	29.1	12181	21.9
Standard Deviation		13594	7.9	14723	8.0	17126	55.2	16855	30.1
MAPE p-values:									
c/w MANFIS			-0.05		-0.08		0.10		
c/w UANFIS			-0.07		-0.09				0.10
c/w MMLP			-0.27				0.09		0.08
c/w UMLP					0.27		0.07		0.05
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	**%**
of 22 forecasts		8	36%	7	32%	3	14%	4	18%
MAPE <= 10%		12	55%	8	36%	10	45%	10	45%
10% <MAPE< 20%		5	23%	11	50%	6	27%	6	27%
MAPE >= 20%		5	23%	3	14%	6	27%	6	27%
MAPE <= 10%									
for 1 year lead		7	58%	5	63%	7	70%	6	60%
for 2 year lead		5	42%	3	38%	3	30%	4	40%

Table 6.6.3 **24 months ahead Forecasting Performance Comparison of ANFIS and MLP Models**

Country	Forecast Lead	MLP Partial Periodic RMSE	MAPE	MMLP RMSE	MAPE	UANFIS RMSE	MAPE	MANFIS RMSE	MAPE
All	1 year	35722	7.1	36133	6.8	26573	5.3	36973	7.6
	2 year	55688	11.4	55879	10.3	54399	10.8	66202	12.9
Australia	1 year	886	5.6	855	5.5	1681	8.8	1593	9.7
	2 year	1245	7.4	1201	7.4	2400	11.7	2419	14.4
Canada	1 year	1047	7.8	895	5.8	1668	11.7	877	6.0
	2 year	1359	10.0	1306	9.0	1862	14.5	1452	10.2
China	1 year	9405	20.7	6766	14.0	5633	11.5	4687	11.4
	2 year	11230	32.8	9649	29.6	9005	27.6	10356	32.3
France	1 year	734	8.5	486	5.1	614	7.3	720	8.9
	2 year	767	8.8	676	7.1	779	8.5	805	9.3
Germany	1 year	1053	8.1	1171	9.5	1132	8.8	1109	8.4
	2 year	990	8.6	1171	9.9	1327	10.7	1235	9.7
Korea	1 year	27127	21.6	22318	13.9	32402	26.4	8420	7.4
	2 year	35624	24.1	31831	17.4	38375	27.3	17039	11.7
Singapore	1 year	1319	13.9	1453	14.8	986	9.5	1233	15.6
	2 year	1934	25.5	2050	25.9	1964	23.7	1852	27.0
Taiwan	1 year	8291	8.7	8232	8.8	7374	8.4	13221	13.5
	2 year	21118	35.1	18458	31.7	20194	34.0	19231	30.5
UK	1 year	17523	97.4	3852	14.0	6147	29.9	3062	11.7
	2 year	14564	81.6	3386	13.4	42370	143.2	24810	93.8
USA	1 year	2926	4.1	7443	9.4	3202	3.0	2899	3.2
	2 year	7628	9.8	7451	10.6	9167	10.4	8257	10.0
Summary Measures									
Mean		11735	20.8	10121	12.7	12239	20.6	10384	16.6
Standard Deviation		14931	24.0	14450	7.5	16063	28.8	15636	18.8
MAPE p-values:									
c/w MANFIS			0.15		-0.15		0.07		
c/w UANFIS			0.48		-0.10				-0.07
c/w MMLP			0.05				0.10		0.15
c/w UMLP					-0.50		-0.48		-0.15
Lowest MAPE Count		Count	%	Count	%	Count	%	Count	**%**
of 22 forecasts		4	18%	7	32%	6	27%	5	23%
MAPE <= 10%		11	50%	11	50%	8	36%	9	41%
10% <MAPE< 20%		3	14%	8	36%	7	32%	9	41%
MAPE >= 20%		8	36%	3	14%	7	32%	4	18%
MAPE <= 10%									
for 1 year lead		7	64%	7	64%	7	88%	7	78%
for 2 year lead		4	36%	4	36%	1	13%	2	22%

Table 6.6.4	**Forecasting Performance Comparison Summary of ANFIS and MLP Models**							
	MLP Partial Periodic		MMLP		UANFIS		MANFIS	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Mean	9781	15.1	13230	12.9	11742	21.1	10634	17.4
Standard Deviation	13682	15.6	27070	7.5	15438	36.4	15511	21.1
MAPE p-values:								
c/w MANFIS		-0.16		-0.04		0.04		
c/w UANFIS		-0.07		-0.04				-0.04
c/w MMLP		0.12				0.04		0.04
c/w UMLP				-0.12		0.07		0.16
Lowest MAPE Count	Count	%	Count	**%**	Count	**%**	Count	**%**
of 66 forecasts	18	27%	21	32%	16	24%	11	17%
MAPE <= 10%	35	53%	28	42%	30	45%	32	48%
10% <MAPE< 20%	15	23%	29	44%	18	27%	18	27%
MAPE >= 20%	16	24%	9	14%	18	27%	16	24%
MAPE <= 10%								
for 1 year lead	21	60%	17	61%	21	70%	21	66%
for 2 year lead	14	40%	11	39%	9	30%	11	34%

6.7 Conclusion

The univariate and multivariate ANFIS models together had the lowest MAPE figures in 27 (41%) of 66 forecasts. While the MLP models are superior, with 39 (59%) of the lowest MAPE figures, the ANFIS models have demonstrated sufficient credibility to justify further research. The univariate ANFIS model on its own has performed better than the multivariate ANFIS model, with the lowest MAPE in 16 (59%) of the 27 best ANFIS forecasts. The performance of the multivariate ANFIS model was constrained by technical requirements that restricted the number of economic indicators used to only two independent variables and one lagged variable, in contrast to the multivariate MLP model, that used five independent variables, plus three lagged variables.

As far as the accuracy of the forecasts are concerned, the combined ANFIS models had MAPE figures less than 10% in 62 of 132 forecasts, which compare well with the MLP models that had MAPE figures less than 10% in 63 of 132 forecasts. This result is in spite of the out of sample period including 2003, the year of the SARS crisis. In fact 42 of the 62 combined ANFIS forecasts with less than 10% MAPE were for the year 2002 which was before SARS affected tourism.

The forecasting accuracy achieved by the ANFIS models gives credence to fuzzy logic and its application in tourism forecasting. Since the ANFIS models performed better in 41% of forecasts, it is possible to further the argument that fuzzy measurements of reality are a viable alternative method of collecting and presenting data. However, further research is necessary to refine the model and obtain improved tourism forecasts with ANFIS.

Chapter 7
Conclusion

7.1 Introduction

Most studies in tourism forecasting have used time series or econometric methods. While there have been major improvements and refinements to these methods over the past 20 years, the basic concept used is that of regression. More recently soft computing methods have been tested for tourism forecasting but these studies have been mainly limited to the use of artificial neural networks. The purpose of this research was to explore tourism time series from a totally new perspective and view the variability of stochastic data as being fuzzy rather than crisp.

From a practical point of view the use of Mamdami type labels to describe levels of tourism demand as very high, high, medium, low or very low relative to a recent historical mean. While further subdivisions such as very high 1, 2 or 3, might be more acceptable to a practitioner, who could plan the availability of hotel rooms or travel facilities based on forecast levels of tourist demand, rather than a forecast of a specific number of arrivals. The concern with a traditional forecast is that by aiming to achieve crisp accuracy the forecaster may be compromising the process of extracting valid information from the data series. The fuzzy approach accepts the inherent fuzziness of the data and forecasts tourism demand as an accurate fuzzy level of demand. However, since time series data are crisp to begin with, and as the requirement is still for crisp forecasts, the current state of art in fuzzy time series forecasting is to use Sugeno type models where crisp data are converted into fuzzy membership functions using neural networks, and defuzzified forecasts in contemporary crisp form are presented for industry use. One such application is the ANFIS (Adaptive Neuro-Fuzzy Inference System) model developed by Jang (1993). Since neuro-fuzzy models have never been applied in tourism forecasting, except by Fernando, Turner and Reznik (1998 and 1999b), this research tests the viability of fuzzy logic in tourism forecasting, and whether it is an alternative to time series and econometric tourism forecasting methods.

Japan was chosen as the country of study mainly due to the availability of reliable tourism data, and also because it is a popular travel destination for both business and pleasure. Visitor arrivals from the 10 most popular tourist source countries to Japan, and total arrivals from all countries were used to incorporate a fairly wide variety of data patterns in the testing process.

Therefore, the aim of this study is to develop a model to forecast inbound tourism to Japan, using a combination of artificial neural networks and fuzzy logic and to compare the performance of this forecasting model with forecasts from other quantitative forecasting models namely, the multi-layer perceptron neural network model, the error correction model, the basic structural model, the autoregressive integrated moving average model and the naïve model.

Monthly data from January 1978 to December 2001 is used as within sample data for model development, and data from January 2002 to December 2003 is used as out of sample data, for testing the forecasting accuracy of the models. For each data series forecasts are made for one-month-ahead, 12-months-ahead and 24-months-ahead horizons, and for one-year and two-year lead periods.

The forecasting accuracy of the models is measured mainly using MAPE and RMSE. In almost all forecasts in this study the RMSE has been consistent with the MAPE. Therefore, when comparing alternative forecasting methods, the model that has demonstrated the lowest MAPE in most forecasts is adjudged the best model. Other criteria used for measuring forecasting performance are the number of forecasts with less than 10% MAPE, and the mean MAPE for all forecasts. Though the mean MAPE is different for each model, t-tests do not always indicate significant differences, because the variances of the MAPE values are high. These high variances in the MAPE values are due to the differences in the data structures of the different source countries responding differently to the parameters of the different forecasting models. Therefore, to test the significance of the differences in MAPE values, paired sample t-tests are carried-out separately for each country.

This study uses 11 sets of data and forecasts with each of them for three time horizons and two lead periods making a total of 22 forecasts for each time horizon and 66 forecasts in total using each model. The sample size 66 is considered a sufficiently large sample to compare the forecasting performance of the models on the basis of the number of forecasts with the lowest MAPE.

Since the SARS epidemic took place in 2003 and caused a sharp one off down turn in arrivals to Japan, during the latter part of the out of sample test period, error levels are expected to be high. Two other significant occurrences that affected tourist flows to Japan were the 2001 September 11th terrorist attack in the United States and the Asian economic crisis of 1998. This study does not model these events into the forecasting method as it is difficult to envisage how long their effect would last, but allows the forecasting methods to track the change. Though forecasting errors are expected to be high, all models compete against each other on level ground as they all use identical data.

Forecasts from the naïve model are used as the benchmark for determining the adequacy of the models tested in this research. If a model cannot outperform naïve forecasts in at least a majority of test runs, then that model would not be considered adequate for tourism forecasting.

7.2 Comparison of all models with the Naïve model

The forecasting models used in this study are the Autoregressive Integrated Moving Average model using first differences ($ARIMA^{(1)}$), the Basic Structural Model (BSM), the non-periodic Multilayer-Layer Perceptron model (MLP Non-P), the partial periodic Multilayer-Layer Perceptron model (MLP PP), the periodic Multilayer-Layer Perceptron model (MLP P), the Error Correction Model (ECM), the Multivariate Multilayer-Layer Perceptron model (MMLP), the Multivariate Adaptive Neuro-Fuzzy Inference System (MANFIS) and the univariate Adaptive Neuro-Fuzzy Inference System (ANFIS).

Tables 7.2.1, 7.2.2 and 7.2.3 show for the one-month-ahead, 12-months-ahead and 24-months-ahead, forecasting horizons respectively, a comparison of the forecasting performances of all the above models with those of the naïve model. For each model, the MAPE of the tourist arrival forecast from each source country is compared against the

MAPE of the corresponding naïve model. The best MAPE count (**X**) reflects the number of forecasts where the MAPE of a particular model outperforms that of the naïve model. Therefore, the number of forecasts where the naïve model outperforms that forecasting model is (**22 - X**) as 22 forecasts are made using each model for a particular forecasting time horizon.

Table 7.2.1 shows that for the one-month-ahead forecasting horizon, the ARIMA$^{(1)}$ model outperforms the naïve model in almost all forecasts (20 out of 22), while the BSM is the second best with 19 forecasts better than the naïve, and the MLP partial periodic and the univariate ANFIS are equal third with 18 better forecasts.

The multivariate ANFIS model and the MLP non-periodic model outperform the naïve in 16 and 15 forecasts respectively. Though all models outperform the naïve in more than 50% of forecasts, the multivariate MLP and the ECM are better than the naïve in only 12 and 13 instances respectively.

For the paired t-tests, at a significance level of 5%, models with p-values less than 5% are considered significant. In the following tables the sign of the t-value is indicated against the p-value, a negative sign indicating a better forecasting model with a mean MAPE less than that of the model it is being compared with. Paired sample t-tests show that for the one month ahead forecasting horizon, the mean difference between the MAPE of each model and that of the naïve model is significant for the ARIMA$^{(1)}$, BSM, non-periodic and partial periodic MLP and ECM models. The mean difference is not significant for the multivariate MLP and the ANFIS models.

Table 7.2.1 One month ahead Forecasting Performance (MAPE) Comparison of all models against the naïve model

Country	Forecast Lead	ARIMA	BSM	MLP Non-Periodic	MLP Partial Periodic	MLP Periodic	ECM	MMLP	MANFIS	ANFIS	Naïve
All	1 year	3.0	3.2	5.5	4.9		5.0	18.6	8.2	4.6	9.9
	2 year	8.0	8.1	9.8	10.2		9.3	16.7	12.1	10.6	12.3
Australia	1 year	4.6	4.8	5.1	3.7		9.3	4.5	6.4	3.6	10.1
	2 year	6.3	6.4	6.6	5.4		11.3	5.9	6.5	5.8	8.6
Canada	1 year	6.4	7.5	6.8	5.4		9.7	5.6	7.4	6.6	8.6
	2 year	8.3	9.8	10.0	9.0		12.3	9.2	9.9	9.6	10.2
China	1 year	12.2	11.2	14.6	10.1		14.4	13.2	7.6	6.1	14.2
	2 year	27.0	26.3	28.0	28.3		26.8	30.3	26.3	25.8	27.3
France	1 year	4.6	4.6	6.1	4.5		10.7	4.8	5.3	3.9	6.3
	2 year	8.1	7.9	8.7	8.0		13.6	8.2	9.3	8.4	9.4
Germany	1 year	8.8	10.0	7.1	7.6		12.7	10.5	7.9	6.9	7.9
	2 year	9.6	11.1	10.2	9.7		12.5	11.3	11.7	9.1	11.2
Korea	1 year	6.6	6.1	9.6	11.5		8.6	16.8	8.0	15.1	10.5
	2 year	9.3	8.8	12.3	12.7		11.4	16.9	8.7	14.0	12.8
Singapore	1 year	14.0	14.4	22.2	16.3		18.4	13.9	23.2	17.3	21.3
	2 year	25.1	26.6	30.2	25.9		24.4	25.0	27.7	26.6	27.7
Taiwan	1 year	5.8	6.9	10.4	7.2		5.8	7.5	11.4	10.3	14.2
	2 year	26.8	28.6	29.3	31.5		20.6	29.1	31.8	32.0	35.4
UK	1 year	15.8	18.0	13.5	20.0		23.5	15.0	34.3	39.9	12.7
	2 year	12.9	14.0	13.6	17.9		21.5	14.3	24.2	25.9	13.5
USA	1 year	4.6	6.0	6.4	5.2		5.8	5.2	7.5	7.2	8.0
	2 year	6.1	8.0	9.4	8.6		7.7	8.1	9.3	9.4	10.4
Mean		10.6	11.3	12.5	12.0		13.4	13.2	13.9	13.6	13.7
t-test: p-value		-0.01	-0.01	-0.01	-0.01		-0.01	-0.28	0.46	-0.46	
Count of: MAPE <= 10%		**15**	**14**	**11**	**12**	**0**	**8**	**9**	**13**	**12**	**7**
Best MAPE Count of 22 forecasts (x)		**20**	**19**	**15**	**18**	**0**	**12**	**13**	**16**	**18**	**(22-x)**

Table 7.2.2 shows that for the 12-months-ahead forecasting horizon, the MLP partial periodic model outperforms the naïve model in most forecasts (18), while the multivariate MLP is the second best with 17 forecasts better than the naïve. The ARIMA(1), BSM and the univariate ANFIS are equal third with 16 better forecasts.

The MLP periodic model and the multivariate ANFIS model outperform the naïve in 15 and 13 forecasts respectively. However, the MLP non-periodic model and the ECM are better than the naïve in only 11 and 7 instances respectively.

Table 7.2.2	**12 months ahead Forecasting Performance (MAPE) Comparison of all models against the naïve model**										
Country	Forecast Lead	ARIMA	BSM	MLP Non-Periodic	MLP Partial Periodic	MLP Periodic	ECM	MMLP	MANFIS	ANFIS	Naïve
All	1 year	7.6	6.8	7.9	6.5	6.9	5.3	8.8	11.0	6.1	9.9
	2 year	10.7	10.2	11.2	10.4	10.7	11.2	11.4	12.7	10.8	12.3
Australia	1 year	4.2	4.6	5.7	3.0	3.6	23.5	3.7	9.6	3.5	10.1
	2 year	5.8	5.9	6.8	4.9	6.8	19.5	5.0	8.0	5.7	8.6
Canada	1 year	6.2	6.3	6.8	5.1	7.4	13.6	5.3	7.0	6.5	8.6
	2 year	10.3	9.5	9.9	8.8	12.6	16.1	8.5	9.5	9.9	10.2
China	1 year	13.8	13.3	11.3	11.7	12.3	14.9	11.9	7.5	7.6	14.2
	2 year	28.7	27.9	27.4	26.1	26.8	31.2	28.8	25.8	27.1	27.3
France	1 year	4.6	4.2	6.5	4.1	3.3	15.4	3.8	6.0	7.6	6.3
	2 year	7.6	7.5	9.5	7.9	9.5	16.8	7.1	9.3	27.1	9.4
Germany	1 year	8.3	8.3	7.2	7.3	8.4	16.6	9.1	8.9	3.9	7.9
	2 year	9.0	8.8	10.5	9.5	12.1	16.7	10.7	12.0	8.5	11.2
Korea	1 year	5.6	5.7	12.7	12.7	9.2	8.0	10.1	14.2	18.1	10.5
	2 year	10.1	9.5	15.0	15.4	11.6	11.7	12.5	12.0	16.7	12.8
Singapore	1 year	15.7	19.1	21.6	16.7	15.0	20.8	15.6	23.8	17.3	21.3
	2 year	26.3	27.5	28.1	25.2	24.2	40.7	27.3	27.2	26.4	27.7
Taiwan	1 year	9.1	11.5	12.6	7.5	9.1	5.0	14.3	12.3	10.9	14.2
	2 year	34.4	34.8	34.0	31.6	33.6	41.8	34.4	32.7	32.8	35.4
UK	1 year	13.1	29.1	16.6	21.0	22.2	49.5	11.8	137.9	247.0	12.7
	2 year	11.0	19.6	19.3	20.1	21.5	48.6	12.5	76.1	129.2	13.5
USA	1 year	8.8	8.3	7.6	6.1	7.0	6.4	14.7	8.2	7.4	8.0
	2 year	12.5	12.5	10.6	9.8	10.7	11.1	16.0	9.6	10.1	10.4
Mean		12.0	13.2	13.6	12.3	12.9	20.2	12.9	21.9	29.1	13.7
t-test: p-value		-0.01	-0.29	-0.36	-0.04	-0.16	0.01	-0.09	0.10	0.10	
Count of: MAPE <= 10%		**11**	**12**	**9**	**12**	**10**	**4**	**8**	**10**	**10**	**7**
Best MAPE Count of 22 forecasts (x)		**16**	**16**	**11**	**18**	**15**	**7**	**17**	**13**	**16**	**(22-x)**

Paired sample t-tests show that for the 12-months ahead forecasting horizon, the mean difference between the MAPE of each model and that of the naïve model is significant only for the ARIMA(1) and the partial periodic MLP models.

Table 7.2.3 shows that for the 24-months-ahead forecasting horizon, the ARIMA(1) model outperforms the naïve model in most forecasts (19), while the multivariate MLP is the second best with 18 forecasts better than the naïve and the BSM is third with 17 better forecasts.

Table 7.2.3 **24 months ahead Forecasting Performance (MAPE) Comparison of all models against the naïve model**

Country	Forecast Lead	ARIMA	BSM	MLP Non-Periodic	MLP Partial Periodic	MLP Periodic	ECM	MMLP	MANFIS	ANFIS	Naïve
All	1 year	7.6	6.8	4.4	7.1	7.0	5.3	6.8	7.6	5.3	9.3
	2 year	11.8	11.0	10.2	11.4	10.9	10.3	10.3	12.9	10.8	13.9
Australia	1 year	4.2	4.6	5.8	5.6	11.6	23.5	5.5	9.7	8.8	10.8
	2 year	6.1	6.1	7.0	7.4	13.4	27.6	7.4	14.4	11.7	13.0
Canada	1 year	6.2	6.3	6.2	7.8	6.6	13.6	5.8	6.0	11.7	10.4
	2 year	11.6	9.8	11.0	10.0	14.3	17.4	9.0	10.2	14.5	12.4
China	1 year	13.8	13.3	17.5	20.7	17.9	14.9	14.0	11.4	11.5	21.00
	2 year	29.4	28.9	32.3	32.8	30.4	41.3	29.6	32.3	27.6	32.48
France	1 year	4.6	4.2	4.4	8.5	5.3	15.4	5.1	8.9	7.3	11.9
	2 year	8.8	7.8	9.1	8.8	8.0	18.9	7.1	9.3	8.5	10.6
Germany	1 year	8.3	8.3	9.5	8.1	10.2	16.6	9.5	8.4	8.8	10.3
	2 year	8.1	7.9	12.8	8.6	11.8	18.7	9.9	9.7	10.7	11.0
Korea	1 year	5.6	5.7	19.3	21.6	15.6	8.0	13.9	7.4	26.4	15.9
	2 year	9.4	8.5	23.0	24.1	17.6	11.5	17.4	11.7	27.3	18.3
Singapore	1 year	15.7	19.1	13.1	13.9	12.6	20.8	14.8	15.6	9.5	9.1
	2 year	25.5	28.4	26.5	25.5	22.0	31.7	25.9	27.0	23.7	25.9
Taiwan	1 year	9.1	11.5	7.5	8.7	8.5	5.0	8.8	13.5	8.4	10.5
	2 year	31.3	31.1	32.6	35.1	37.1	31.5	31.7	30.5	34.0	34.4
UK	1 year	13.1	29.1	40.8	97.4	58.1	49.5	14.0	11.7	29.9	79.5
	2 year	10.9	36.3	32.0	81.6	45.2	63.6	13.4	93.8	143.2	43.3
USA	1 year	8.8	8.3	3.8	4.1	4.3	6.4	9.4	3.2	3.0	2.9
	2 year	11.4	10.9	9.3	9.8	10.2	10.7	10.6	10.0	10.4	9.9
Mean		11.9	13.8	15.4	20.8	17.2	21.0	12.7	16.6	20.6	18.9
t-test: p-value		-0.02	-0.02	-0.03	0.18	-0.06	0.18	-0.03	-0.28	0.38	
Count of: MAPE <= 10%		**12**	**12**	**10**	**11**	**6**	**4**	**11**	**9**	**8**	**4**
Best MAPE Count of 22 forecasts (x)		**19**	**17**	**16**	**14**	**13**	**8**	**18**	**15**	**14**	**(22-x)**

The MLP non-periodic model and the multivariate ANFIS model outperform the naïve in 16 and 15 forecasts respectively. However, the MLP partial periodic model, the MLP periodic model and the ECM are better than the naïve in only 14, 14 and 8 instances respectively.

Paired sample t-tests show that for the 24-months ahead forecasting horizon, the mean difference between the MAPE of each model and that of the naïve model is significant for the ARIMA(1), BSM, non-periodic MLP and the multivariate MLP models.

Table 7.2.4 **Forecasting Performance Comparison Summary of all models against the naïve model**

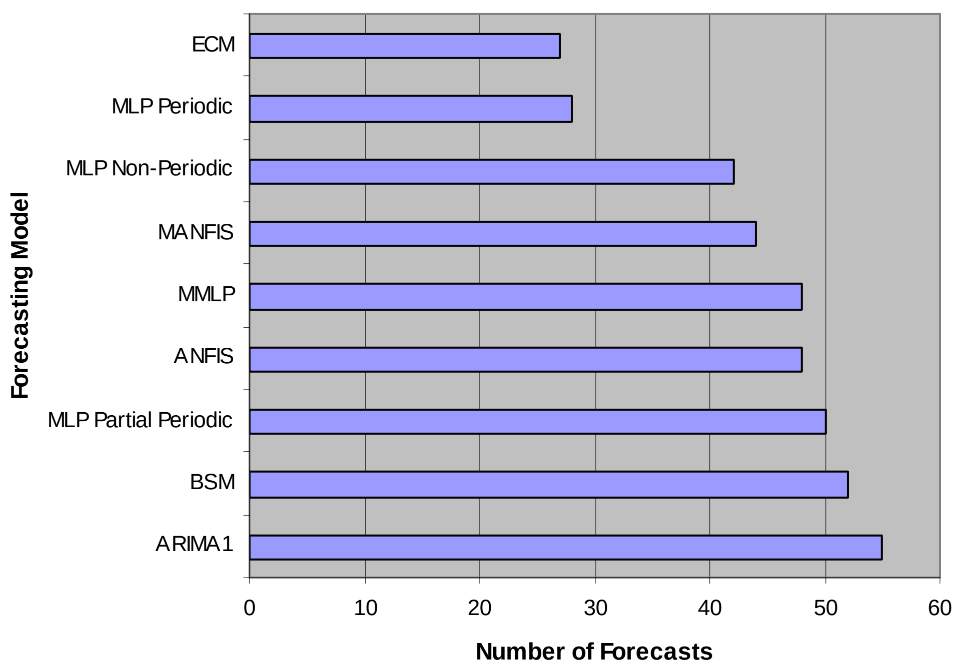
	ARIMA	BSM	MLP Non-Periodic	MLP Partial Periodic	MLP Periodic	ECM	MMLP	MANFIS	ANFIS	Naïve
Mean MAPE	11.5	12.8	13.8	15.1	15.1	18.2	12.9	17.4	21.1	15.5
Standard Deviation	7.4	8.8	9.0	15.6	11.3	12.5	7.5	21.1	36.4	11.5
t-test: p-value	-0.01	-0.01	-0.01	-0.29	-0.03	0.01	-0.02	0.22	0.18	
Count of : MAPE <= 10%	**38**	**38**	**30**	**35**	**16**	**16**	**28**	**32**	**30**	**18**
Best MAPE Count of 66 forecasts (x)	**55**	**52**	**42**	**50**	**28**	**27**	**48**	**44**	**48**	**(66-x)**

Table 7.2.4 shows that in summary, for all three forecasting horizons, the ARIMA1 model outperforms the naïve model in most forecasts (55 out of the total 66), while the BSM is the second best with 52 of 66 forecasts better than the naïve. The MLP partial periodic is third with 50 better forecasts.

The univariate ANFIS model and the multivariate MLP model outperform the naïve in 48 out of 66 forecasts each. The multivariate ANFIS mode and the MLP non-periodic model are better than the naïve in 44 and 42 instances respectively. However, the MLP periodic and the ECM are better than the naïve model in only 28 and 27 forecasts (which is less than half the total number of 66 forecasts made) and because of this they are not considered adequate for forecasting tourist arrivals to Japan. This is despite the p-value of the periodic MLP model indicating a significantly better mean difference in MAPE values compared with the naïve model. These findings are shown graphically in Figure 7.1.

Paired sample t-tests show that for all three forecasting horizons, the mean difference between the MAPE of each model and that of the naïve model is significant for the ARIMA(1), BSM, non-periodic MLP, periodic MLP and multivariate MLP models.

Figure 7.1 The total number of forecasts with MAPE lower than in the naïve model



Most of the other models do not show a significantly lower MAPE from that of the naïve even though they out-perform the naïve with lower MAPE values in a large number of forecasts. This is due to the high variances of the MAPE values, which are in turn due to differences in the arrival data structures of different countries. For example the MAPE values for USA are consistently low for all models while those for the UK are high for all models. This high MAPE variance causes t values to be low despite the MAPE in most forecasts being less than that of the naïve model.

The relatively poor performance of the regression model is supportive of previous findings by Martin and Witt (1989a) that the naïve model is significantly accurate relative to the regression methods. The findings are also supportive of Turner and Witt (2001b) in that the results tend to confirm the superiority of the ARIMA and BSM time series models over both regression and the naïve models. The neural network with and without fuzzy logic outperforms regression and the naïve model but falls short of the ARIMA and BSM time series methods. The in between position of the neural approach requires further investigation.

There is no significant difference from the naïve comparison over all time horizons to the individual findings over each time frame. The sophisticated time series methods, ARIMA and BSM, are the more accurate forecasting models in all horizons, the regression model the least accurate and the neural models fall in between or in the shorter time horizons perform alongside the sophisticated time series models.

7.3 Comparison of all models against each other

Section 7.2 shows the extent to which the models out perform the naïve method. The model comparisons in section 7.2 were based on the number of forecasts where the MAPE value of a model was less than that of the naïve model. When comparing all models against each other, though some models had many forecasts with lower MAPE values than others, the corresponding mean MAPE of these models were not always significantly lower. This section shows, using paired sample t-tests, the number of forecasts in which each model significantly out performs each of the other models and identifies the better models. Paired sample significance tests are made for each country based on 6 forecasts using identical arrivals data in all six forecasts. As each model is compared with 9 other models, for the 11 arrival data sets, 99 paired comparisons are made for each model. As there are 10 models, 90 paired comparisons are made for each country. For the paired t-tests, at a significance level of 5%, models with p-values less than 5% are considered significant. In the following tables the sign of the t-value is indicated against the p-value, a negative sign indicating a better forecasting model, with a mean MAPE less than that of the model it is being compared with.

Tables 7.3.1 to 7.3.11 show the MAPE of 6 forecasts from each of the 10 models and p-values of a paired sample t-test of all 90 pairs of models for arrivals from all countries to Japan and each of the 10 source countries, respectively. The 6 forecasts represented in each of the 11 tables are the forecasts for each arrival data source for each of the two lead periods and each of the three time horizons. Each table represents the analysis of 6 MAPE values from one arrival data set against those from 9 other models. This method of analysis using data from one country at a time is undertaken because the magnitude of the MAPE values associated with certain countries of origin, differ widely from those for some other countries making statistical analysis difficult due to high MAPE variances.

In Tables 7.3.1 to 7.3.11 each model represented by a column is compared against the models represented by the rows. The p-values indicate whether the difference in the MAPE values of the two models is significant. A negative sign assigned to the p-value indicates a negative t-value and therefore that the former model (represented in a column) has a lower mean MAPE than the latter (models represented in rows). The last row of the table shows the number of paired model comparisons where the mean difference in

MAPE values was significant for the model represented in each column. The total number of these significant mean differences in MAPE for each forecasting model is presented graphically in Figure 7.2.

Table 7.3.1	**Paired comparison of all models, to identify significant MAPE differences for arrivals from *all countries***										
MAPE values											
Horizon	Lead	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
1	1 yr	3.0	3.2	5.5	4.9		5.0	18.6	8.2	4.6	9.9
1	2 yr	8.0	8.1	9.8	10.2		9.3	16.7	12.1	10.6	12.3
12	1 yr	7.6	6.8	7.9	6.5	6.9	5.3	8.8	11.0	6.1	9.9
12	2 yr	10.7	10.2	11.2	10.4	10.7	11.2	11.4	12.7	10.8	12.3
24	1 yr	7.6	6.8	4.4	7.1	7.0	5.3	6.8	7.6	5.3	9.3
24	2 yr	11.8	11.0	10.2	11.4	10.9	10.3	10.3	12.9	10.8	13.9
p-values											
		ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
ARIMA1			**-0.04**	0.47	0.30	**-0.04**	-0.33	0.10	0.01	0.47	0.01
BSM		0.04		0.26	0.06	0.06	0.46	0.07	0.01	0.29	0.01
MLP Non-P		-0.47	-0.26		0.35	0.31	-0.20	0.06	0.01	-0.39	0.01
MLP Partial P		-0.30	-0.06	-0.35		0.45	-0.08	0.08	0.01	-0.15	0.01
MLP Periodic		0.04	-0.06	-0.31	-0.45		-0.10	0.25	0.03	-0.11	0.01
ECM		0.33	-0.46	0.20	0.08	0.10		0.05	0.01	0.17	0.01
MMLP		-0.10	-0.07	-0.06	-0.08	-0.25	**-0.05**		-0.27	-0.06	-0.34
MANFIS		**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.03**	**-0.01**	0.27		**-0.01**	0.16
ANFIS		0.47	-0.29	0.39	0.15	0.11	-0.17	0.06	0.01		0.01
Naïve		**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**	0.34	-0.16	**-0.01**	
Significant comparisons		2	3	2	2	3	3	0	0	2	0

Table 7.3.2 Paired comparison of all models, to identify significant MAPE differences for arrivals from *__Australia__*

MAPE values

Horizon	Lead	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
1	1 yr	4.6	4.8	5.1	3.7		9.3	4.5	6.4	3.6	10.1
1	2 yr	6.3	6.4	6.6	5.4		11.3	5.9	6.5	5.8	8.6
12	1 yr	4.2	4.6	5.7	3.0	3.6	23.5	3.7	9.6	3.5	10.1
12	2 yr	5.8	5.9	6.8	4.9	6.8	19.5	5.0	8.0	5.7	8.6
24	1 yr	4.2	4.6	5.8	5.6	11.6	23.5	5.5	9.7	8.8	10.8
24	2 yr	6.1	6.1	7.0	7.4	13.4	27.6	7.4	14.4	11.7	13.0

p-values

	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
ARIMA1		0.02	0.01	-0.34	0.08	0.01	0.35	0.01	0.17	0.01
BSM	**-0.02**		0.01	-0.23	0.09	0.01	-0.47	0.01	0.20	0.01
MLP Non-P	**-0.01**	**-0.01**		**-0.03**	0.16	0.01	**-0.04**	0.02	0.39	0.01
MLP Partial P	0.34	0.23	0.03		0.04	0.01	0.03	0.01	0.05	0.01
MLP Periodic	-0.08	-0.09	-0.16	**-0.04**		0.01	-0.06	0.20	**-0.04**	0.18
ECM	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**		**-0.01**	**-0.01**	**-0.01**	**-0.01**
MMLP	-0.35	0.47	0.04	**-0.03**	0.06	0.01		0.01	0.12	0.01
MANFIS	**-0.01**	**-0.01**	**-0.02**	**-0.01**	-0.20	0.01	**-0.01**		**-0.01**	0.09
ANFIS	-0.17	-0.20	-0.39	**-0.05**	0.04	0.01	-0.12	0.01		0.01
Naïve	**-0.01**	**-0.01**	**-0.01**	**-0.01**	-0.18	0.01	**-0.01**	-0.09	**-0.01**	
Significant comparisons	5	4	3	7	1	0	4	1	4	1

Table 7.3.3 Paired comparison of all models, to identify significant MAPE differences for arrivals from *__Canada__*

MAPE values

Horizon	Lead	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
1	1 yr	6.4	7.5	6.8	5.4		9.7	5.6	7.4	6.6	8.6
1	2 yr	8.3	9.8	10.0	9.0		12.3	9.2	9.9	9.6	10.2
12	1 yr	6.2	6.3	6.8	5.1	7.4	13.6	5.3	7.0	6.5	8.6
12	2 yr	10.3	9.5	9.9	8.8	12.6	16.1	8.5	9.5	9.9	10.2
24	1 yr	6.2	6.3	6.2	7.8	6.6	13.6	5.8	6.0	11.7	10.4
24	2 yr	11.6	9.8	11.0	10.0	14.3	17.4	9.0	10.2	14.5	12.4

p-values

	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
ARIMA1		0.48	0.22	-0.20	0.03	0.01	**-0.05**	0.37	0.06	0.01
BSM	-0.48		0.18	-0.18	0.05	0.01	**-0.01**	0.19	0.10	0.01
MLP Non-P	-0.22	-0.18		-0.08	0.05	0.01	**-0.01**	-0.29	0.12	0.02
MLP Partial P	0.20	0.18	0.08		0.08	0.01	-0.14	0.15	0.01	0.01
MLP Periodic	**-0.03**	**-0.05**	**-0.05**	-0.08		0.01	**-0.03**	**-0.05**	0.41	0.46
ECM	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**		**-0.01**	**-0.01**	**-0.01**	**-0.01**
MMLP	0.05	0.01	0.01	0.14	0.03	0.01		0.01	0.02	0.01
MANFIS	-0.37	-0.19	0.29	-0.15	0.05	0.01	**-0.01**		0.13	0.02
ANFIS	-0.06	-0.10	-0.12	**-0.01**	-0.41	0.01	**-0.02**	-0.13		0.36
Naïve	**-0.01**	**-0.01**	**-0.02**	**-0.01**	-0.46	0.01	**-0.01**	**-0.02**	-0.36	
Significant comparisons	3	3	3	3	1	0	8	3	1	1

Table 7.3.4 Paired comparison of all models, to identify significant MAPE differences for arrivals from *China*

MAPE values											
Horizon	Lead	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
1	1 yr	12.2	11.2	14.6	10.1		14.4	13.2	7.6	6.1	14.2
1	2 yr	27.0	26.3	28.0	28.3		26.8	30.3	26.3	25.8	27.3
12	1 yr	13.8	13.3	11.3	11.7	12.3	14.9	11.9	7.5	7.6	14.2
12	2 yr	28.7	27.9	27.4	26.1	26.8	31.2	28.8	25.8	27.1	27.3
24	1 yr	13.8	13.3	17.5	20.7	17.9	14.9	14.0	11.4	11.5	21.0
24	2 yr	29.4	28.9	32.3	32.8	30.4	41.3	29.6	32.3	27.6	32.5

p-values	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
ARIMA1		**-0.01**	0.17	0.31	0.38	0.07	0.25	-0.07	**-0.01**	0.09
BSM	0.01		0.07	0.18	0.25	0.04	0.08	-0.13	**-0.02**	0.04
MLP Non-P	-0.17	-0.07		-0.42	-0.35	0.14	-0.30	**-0.02**	**-0.01**	0.14
MLP Partial P	-0.31	-0.18	0.42		-0.19	0.16	-0.42	**-0.04**	**-0.02**	0.11
MLP Periodic	-0.38	-0.25	0.35	0.19		0.14	-0.29	-0.13	**-0.05**	0.02
ECM	-0.07	**-0.04**	-0.14	-0.16	-0.14		-0.13	**-0.01**	**-0.01**	-0.29
MMLP	-0.25	-0.08	0.30	0.42	0.29	0.13		**-0.03**	**-0.01**	0.18
MANFIS	0.07	0.13	0.02	0.04	0.13	0.01	0.03		-0.17	0.02
ANFIS	0.01	0.02	0.01	0.02	0.05	0.01	0.01	0.17		0.01
Naïve	-0.09	**-0.04**	-0.14	-0.11	**-0.02**	0.29	-0.18	**-0.02**	**-0.01**	
Significant comparisons	0	3	0	0	1	0	0	5	8	0

Table 7.3.5 Paired comparison of all models, to identify significant MAPE differences for arrivals from *France*

MAPE values											
Horizon	Lead	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
1	1 yr	4.6	4.6	6.1	4.5		10.7	4.8	5.3	3.9	6.3
1	2 yr	8.1	7.9	8.7	8.0		13.6	8.2	9.3	8.4	9.4
12	1 yr	4.6	4.2	6.5	4.1	3.3	15.4	3.8	6.0	7.6	6.3
12	2 yr	7.6	7.5	9.5	7.9	9.5	16.8	7.1	9.3	27.1	9.4
24	1 yr	4.6	4.2	4.4	8.5	5.3	15.4	5.1	8.9	7.3	11.9
24	2 yr	8.8	7.8	9.1	8.8	8.0	18.9	7.1	9.3	8.5	10.6

p-values	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
ARIMA1		**-0.02**	0.02	0.22	0.44	0.01	-0.15	0.02	0.13	0.02
BSM	0.02		0.01	0.12	0.21	0.01	-0.45	0.01	0.11	0.01
MLP Non-P	**-0.02**	**-0.01**		-0.34	-0.21	0.01	**-0.03**	0.22	0.17	0.12
MLP Partial P	-0.22	-0.12	0.34		-0.24	0.01	-0.08	0.01	0.16	0.01
MLP Periodic	-0.44	-0.21	0.21	0.24		0.01	-0.15	0.05	0.11	0.05
ECM	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**		**-0.01**	**-0.01**	-0.09	**-0.01**
MMLP	0.15	0.45	0.03	0.08	0.15	0.01		0.01	0.11	0.01
MANFIS	**-0.02**	**-0.01**	-0.22	**-0.01**	**-0.05**	0.01	**-0.01**		0.23	0.04
ANFIS	-0.13	-0.11	-0.17	-0.16	-0.11	0.09	-0.11	-0.23		-0.34
Naïve	**-0.02**	**-0.01**	-0.12	**-0.01**	**-0.05**	0.01	**-0.01**	**-0.04**	0.34	
Significant comparisons	4	5	1	3	3	0	4	2	0	1

Table 7.3.6 Paired comparison of all models, to identify significant MAPE differences for arrivals from *<u>Germany</u>*

MAPE values

Horizon	Lead	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
1	1 yr	8.8	10.0	7.1	7.6		12.7	10.5	7.9	6.9	7.9
1	2 yr	9.6	11.1	10.2	9.7		12.5	11.3	11.7	9.1	11.2
12	1 yr	8.3	8.3	7.2	7.3	8.4	16.6	9.1	8.9	3.9	7.9
12	2 yr	9.0	8.8	10.5	9.5	12.1	16.7	10.7	12.0	8.5	11.2
24	1 yr	8.3	8.3	9.5	8.1	10.2	16.6	9.5	8.4	8.8	10.3
24	2 yr	8.1	7.9	12.8	8.6	11.8	18.7	9.9	9.7	10.7	11.0

p-values

	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
ARIMA1		0.13	0.20	-0.28	0.04	0.01	0.01	0.05	-0.26	0.05
BSM	-0.13		0.34	-0.14	0.04	0.01	0.01	0.18	-0.18	0.17
MLP Non-P	-0.20	-0.34		-0.09	0.18	0.01	0.25	0.39	**-0.01**	0.22
MLP Partial P	0.28	0.14	0.09		0.01	0.01	0.01	0.01	-0.28	0.01
MLP Periodic	**-0.04**	**-0.04**	-0.18	**-0.01**		0.01	-0.13	-0.13	**-0.03**	-0.05
ECM	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**		**-0.01**	**-0.01**	**-0.01**	**-0.01**
MMLP	**-0.01**	**-0.01**	-0.25	**-0.01**	0.13	0.01		-0.24	**-0.03**	-0.33
MANFIS	**-0.05**	-0.18	-0.39	**-0.01**	0.13	0.01	0.24		-0.06	0.40
ANFIS	0.26	0.18	0.01	0.28	0.03	0.01	0.03	0.06		0.01
Naïve	**-0.05**	-0.17	-0.22	**-0.01**	0.05	0.01	0.33	-0.40	**-0.01**	
Significant comparisons	5	3	1	5	1	0	1	1	5	1

Table 7.3.7 Paired comparison of all models, to identify significant MAPE differences for arrivals from *<u>Korea</u>*

MAPE values

Horizon	Lead	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
1	1 yr	6.6	6.1	9.6	11.5		8.6	16.8	8.0	15.1	10.5
1	2 yr	9.3	8.8	12.3	12.7		11.4	16.9	8.7	14.0	12.8
12	1 yr	5.6	5.7	12.7	12.7	9.2	8.0	10.1	14.2	18.1	10.5
12	2 yr	10.1	9.5	15.0	15.4	11.6	11.7	12.5	12.0	16.7	12.8
24	1 yr	5.6	5.7	19.3	21.6	15.6	8.0	13.9	7.4	26.4	15.9
24	2 yr	9.4	8.5	23.0	24.1	17.6	11.5	17.4	11.7	27.3	18.3

p-values

	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
ARIMA1		**-0.03**	0.01	0.01	0.03	0.01	0.05	0.05	0.01	0.01
BSM	0.03		0.01	0.01	0.03	0.01	0.01	0.03	0.01	0.01
MLP Non-P	**-0.01**	**-0.01**		0.02	**-0.01**	**-0.02**	-0.37	**-0.04**	0.01	**-0.04**
MLP Partial P	**-0.01**	**-0.01**	**-0.02**		**-0.01**	**-0.01**	-0.23	**-0.03**	0.01	**-0.01**
MLP Periodic	**-0.03**	**-0.03**	0.01	0.01		-0.07	-0.49	-0.26	0.01	0.01
ECM	**-0.01**	**-0.01**	0.02	0.01	0.07		0.01	0.35	0.01	0.02
MMLP	**-0.05**	**-0.01**	0.37	0.23	0.49	**-0.01**		**-0.05**	0.05	-0.22
MANFIS	**-0.05**	**-0.03**	0.04	0.03	0.26	-0.35	0.05		0.08	0.07
ANFIS	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.05**	-0.08		**-0.01**
Naïve	**-0.01**	**-0.01**	0.04	0.01	**-0.01**	**-0.02**	0.22	-0.07	0.01	
Significant comparisons	8	9	2	1	4	5	1	3	0	3

Table 7.3.8 Paired comparison of all models, to identify significant MAPE differences for arrivals from *__Singapore__*

MAPE values

Horizon	Lead	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
1	1 yr	14.0	14.4	22.2	16.3		18.4	13.9	23.2	17.3	21.3
1	2 yr	25.1	26.6	30.2	25.9		24.4	25.0	27.7	26.6	27.7
12	1 yr	15.7	19.1	21.6	16.7	15.0	20.8	15.6	23.8	17.3	21.3
12	2 yr	26.3	27.5	28.1	25.2	24.2	40.7	27.3	27.2	26.4	27.7
24	1 yr	15.7	19.1	13.1	13.9	12.6	20.8	14.8	15.6	9.5	9.1
24	2 yr	25.5	28.4	26.5	25.5	22.0	31.7	25.9	27.0	23.7	25.9

p-values

	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
ARIMA1		0.01	0.05	0.37	**-0.02**	0.02	0.45	0.03	-0.42	0.21
BSM	**-0.01**		0.30	**-0.05**	**-0.01**	0.07	**-0.01**	0.21	-0.12	-0.44
MLP Non-P	**-0.05**	-0.30		**-0.02**	**-0.03**	0.21	**-0.05**	0.28	**-0.01**	**-0.03**
MLP Partial P	-0.37	0.05	0.02		**-0.02**	0.03	-0.40	0.01	-0.31	0.17
MLP Periodic	0.02	0.01	0.03	0.02		0.01	0.02	0.02	0.29	0.16
ECM	**-0.02**	-0.07	-0.21	**-0.03**	**-0.01**		**-0.01**	-0.26	**-0.03**	-0.12
MMLP	-0.45	0.01	0.05	0.40	**-0.02**	0.01		0.04	-0.41	0.20
MANFIS	**-0.03**	-0.21	-0.28	**-0.01**	**-0.02**	0.26	**-0.04**		**-0.01**	-0.06
ANFIS	0.42	0.12	0.01	0.31	-0.29	0.03	0.41	0.01		0.02
Naïve	-0.21	0.44	0.03	-0.17	-0.16	0.12	-0.20	0.06	**-0.02**	0.00
Significant comparisons	4	0	0	4	7	0	4	0	4	1

Table 7.3.9 Paired comparison of all models, to identify significant MAPE differences for arrivals from *__Taiwan__*

MAPE values

Horizon	Lead	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
1	1 yr	5.8	6.9	10.4	7.2		5.8	7.5	11.4	10.3	14.2
1	2 yr	26.8	28.6	29.3	31.5		20.6	29.1	31.8	32.0	35.4
12	1 yr	9.1	11.5	12.6	7.5	9.1	5.0	14.3	12.3	10.9	14.2
12	2 yr	34.4	34.8	34.0	31.6	33.6	41.8	34.4	32.7	32.8	35.4
24	1 yr	9.1	11.5	7.5	8.7	8.5	5.0	8.8	13.5	8.4	10.5
24	2 yr	31.3	31.1	32.6	35.1	37.1	31.5	31.7	30.5	34.0	34.4

p-values

	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
ARIMA1		0.02	0.07	0.26	0.26	-0.30	0.06	0.05	0.07	0.01
BSM	**-0.02**		0.37	-0.38	-0.47	-0.17	0.37	0.12	0.30	0.03
MLP Non-P	-0.07	-0.37		-0.28	0.42	-0.15	-0.44	0.23	0.33	0.01
MLP Partial P	-0.26	0.38	0.28		0.04	-0.26	0.33	0.15	0.10	0.01
MLP Periodic	-0.26	0.47	-0.42	**-0.04**		-0.36	0.46	0.47	-0.30	0.20
ECM	0.30	0.17	0.15	0.26	0.36		0.17	0.14	0.16	0.05
MMLP	-0.06	-0.37	0.44	-0.33	-0.46	-0.17		0.22	0.36	0.02
MANFIS	**-0.05**	-0.12	-0.23	-0.15	-0.47	-0.14	-0.22		-0.30	0.06
ANFIS	-0.07	-0.30	-0.33	-0.10	0.30	-0.16	-0.36	0.30		0.01
Naïve	**-0.01**	**-0.03**	**-0.01**	**-0.01**	-0.20	**-0.05**	**-0.02**	-0.06	**-0.01**	
Significant comparisons	3	1	1	2	0	1	1	0	1	0

Table 7.3.10 Paired comparison of all models, to identify significant MAPE differences for arrivals from *UK*

MAPE values											
Horizon	Lead	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
1	1 yr	15.8	18.0	13.5	20.0		23.5	15.0	34.3	39.9	12.7
1	2 yr	12.9	14.0	13.6	17.9		21.5	14.3	24.2	25.9	13.5
12	1 yr	13.1	29.1	16.6	21.0	22.2	49.5	11.8	137.9	247.0	12.7
12	2 yr	11.0	19.6	19.3	20.1	21.5	48.6	12.5	76.1	129.2	13.5
24	1 yr	13.1	29.1	40.8	97.4	58.1	49.5	14.0	11.7	29.9	79.5
24	2 yr	10.9	36.3	32.0	81.6	45.2	63.6	13.4	93.8	143.2	43.3
p-values											
		ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
ARIMA1			0.01	0.05	0.05	0.03	0.01	0.14	0.03	0.03	0.10
BSM		**-0.01**		-0.31	0.10	0.18	0.01	**-0.02**	0.04	0.04	0.32
MLP Non-P		**-0.05**	0.31		0.05	0.04	0.01	**-0.05**	0.05	0.04	0.19
MLP Partial P		**-0.05**	-0.10	**-0.05**		-0.10	-0.49	**-0.05**	0.25	0.10	**-0.02**
MLP Periodic		**-0.03**	-0.18	**-0.04**	0.10		0.07	**-0.03**	0.14	0.07	0.47
ECM		**-0.01**	**-0.01**	**-0.01**	0.49	-0.07		**-0.01**	0.14	0.06	-0.11
MMLP		-0.14	0.02	0.05	0.05	0.03	0.01		0.03	0.03	0.11
MANFIS		**-0.03**	**-0.04**	**-0.05**	-0.25	-0.14	-0.14	**-0.03**		0.03	-0.13
ANFIS		**-0.03**	**-0.04**	**-0.04**	-0.10	-0.07	-0.06	**-0.03**	**-0.03**		-0.06
Naïve		-0.10	-0.32	-0.19	0.02	-0.47	0.11	-0.11	0.13	0.06	
Significant comparisons		7	3	5	0	0	0	7	1	0	1

Table 7.3.11 Paired comparison of all models, to identify significant MAPE differences for arrivals from *USA*

MAPE values											
Horizon	Lead	ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naïve
1	1 yr	4.6	6.0	6.4	5.2		5.8	5.2	7.5	7.2	8.0
1	2 yr	6.1	8.0	9.4	8.6		7.7	8.1	9.3	9.4	10.4
12	1 yr	8.8	8.3	7.6	6.1	7.0	6.4	14.7	8.2	7.4	8.0
12	2 yr	12.5	12.5	10.6	9.8	10.7	11.1	16.0	9.6	10.1	10.4
24	1 yr	8.8	8.3	3.8	4.1	4.3	6.4	9.4	3.2	3.0	2.9
24	2 yr	11.4	10.9	9.3	9.8	10.2	10.7	10.6	10.0	10.4	9.9
p-values											
		ARIMA1	BSM	MLP Non-P	MLP P P	MLP P	ECM	MMLP	MANFIS	ANFIS	Naive
ARIMA1			0.27	-0.26	-0.12	**-0.03**	-0.19	0.05	-0.31	-0.29	-0.39
BSM		-0.27		-0.12	**-0.03**	**-0.04**	**-0.02**	0.10	-0.19	-0.17	-0.28
MLP Non-P		0.26	0.12		-0.08	0.22	0.40	0.06	0.36	0.41	0.15
MLP Partial P		0.12	0.03	0.08		0.03	0.07	0.04	0.12	0.10	0.08
MLP Periodic		0.03	0.04	-0.22	**-0.03**		0.19	0.03	-0.29	-0.22	-0.29
ECM		0.19	0.02	-0.40	-0.07	-0.19		0.06	-0.47	-0.49	-0.41
MMLP		**-0.05**	-0.10	-0.06	**-0.04**	**-0.03**	-0.06		-0.08	-0.09	-0.11
MANFIS		0.31	0.19	-0.36	-0.12	0.29	0.47	0.08		-0.40	0.14
ANFIS		0.29	0.17	-0.41	-0.10	0.22	0.49	0.09	0.40		0.10
Naïve		0.39	0.28	-0.15	-0.08	0.29	-0.41	0.11	-0.14	-0.10	
Significant comparisons		1	0	0	3	3	1	0	0	0	0

Figure 7.2 The number of paired model comparisons with a significantly lower MAPE

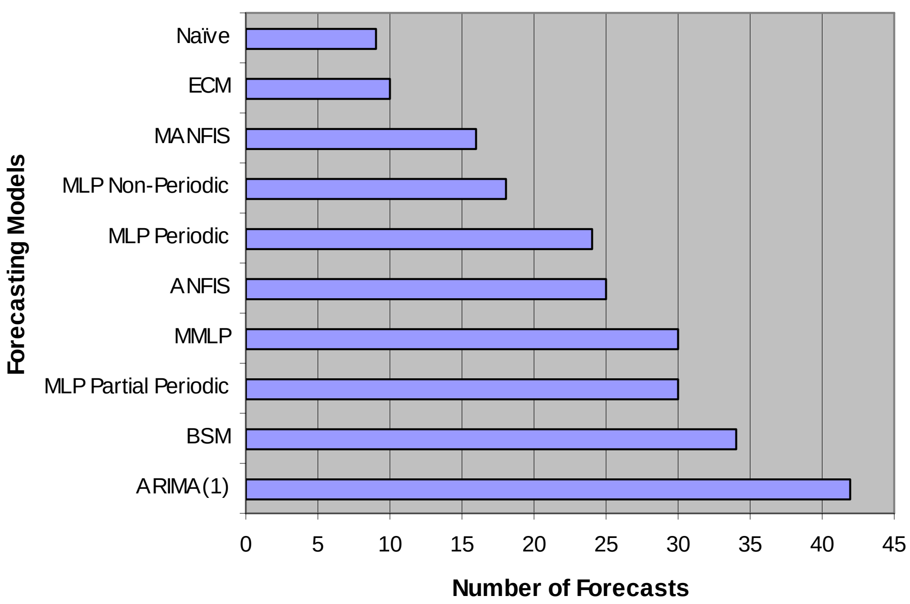


Figure 7.2 shows for all time horizons and all countries, the number of paired comparisons amongst all models with significant mean differences in MAPE values at the 5% significance level. This is an indication of the number of instances when a model significantly out-performs other models. ARIMA$^{(1)}$ performs best with 42 significant mean differences in MAPE out of 99 comparisons, BSM next with 34, MLP partial periodic and MLP multivariate with 30 each, MLP periodic with 24 and non-periodic with 18, ANFIS with 25, MANFIS with 16, ECM with 10 and naïve with 9, out of 99 comparisons each. Broadly, sophisticated time series models perform best, MLP and ANFIS models next while the ECM and the naïve perform poorly. The fact that no one model consistently out-performed all other models in all arrival source data sets indicates that each model has its own strengths within specific data structures.

Figure 7.3 shows for all time horizons, the number of forecasts (out of 66 for each model) with MAPE less than 10%. This is an indication of the degree of precision achieved by each of the forecasting models. Figure 7.3 is based on data extracted from Table 7.2.4. A comparison of the models for precision shows that ARIMA$^{(1)}$ and BSM perform best, each with MAPE less than 10% in 38 out of 66 forecasts. The MLP (except the periodic) and ANFIS models each have MAPE less than 10% in over 25 out of 66 forecasts. The MLP periodic model and the ECM model do not demonstrate good precision, with only 16 out of 66 forecasts having MAPE less than 10% and performing worse than the naïve model.

Figure 7.3 Number of forecasts with MAPE less than 10%

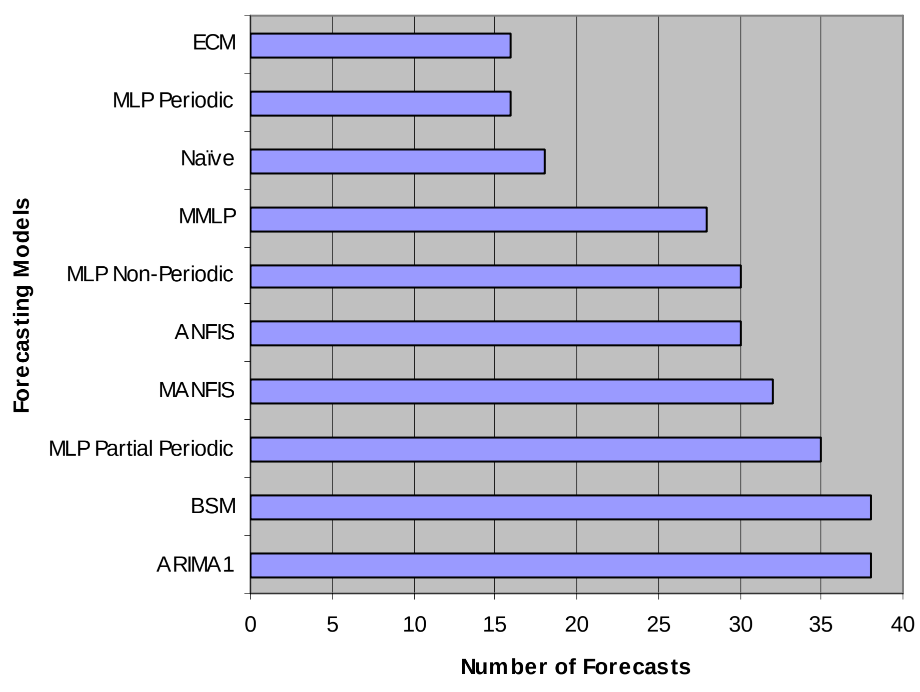


Table 7.3.12 shows the most suitable forecasting model for each country, based on the analysis of Tables 7.3.1 to 7.3.11.

Table 7.3.12 The most suitable forecasting models for tourist arrivals to Japan from each source country

Source Country	Forecasting models: 1	2	3
Australia	MLP Partial Periodic		
Canada	MMLP		
China	ANFIS		
France	BSM		
Germany	ARIMA	MLP Partial Periodic	ANFIS
Korea	BSM		
Singapore	MLP Periodic		
Taiwan	ARIMA		
UK	ARIMA	MMLP	
USA	MLP Partial Periodic	MLP Periodic	
ALL	BSM	MLP Periodic	ECM

7.4 Summary of conclusions

7.4.1 Differenced and Undifferenced MLP Model Comparison

Nelson, Hill, Remus et al. (1999) were of the view that deseasonalising the input data would improve the performance of MPL models as the neural process would then be able to focus better on variations other than those typically seasonal. This research focused on differencing the data rather than deseasonalising, as the objective was not to remove seasonality but to assist the neural process in modelling variations other than seasonal and trend. The MLP model was tested using raw data in the non-periodic model and seasonally lagged data in the partial periodic model for 1, 12 and 24-month horizons but in all cases found that differencing did not improve the forecasts (Refer 3.10).

This means that neural network parameters forecast more accurately when data are not differenced. This shows that when the neural model passes undifferenced data through nodes of the hidden layers with the aim of matching the input data to the output without filtering the inputs to identifiable decomposition or segmentation the neural method concentrates on the numeric value of the data as a whole and does not loose any information. However, when differenced data are used, trend and/or seasonality are removed and the model is mainly trying to find idiosyncratic structures within the random variations of the data. This method produces poor forecasting results indicating that variations in tourist arrival data are not totally independent of trend and seasonality. Therefore, neural network MLP forecasting methods must not separate time series components prior to applying the model but instead allow the model to deal with the data as a whole.

7.4.2 Comparison of MLP models

The partial periodic model is superior to the non-periodic model and the periodic model when forecasting tourism to Japan. The partial periodic and the non-periodic models perform better than the naïve model making them adequate models for forecasting. The partial periodic model is the best for the one-month ahead and the 12 months ahead forecasting horizons, while the non-periodic model is better for the 24 months-ahead horizon (Refer 3.11).

The partial periodic model captures the seasonal trend of the past three years on a month-by-month basis, which is its strength. The model's poor performance for the 24 months-ahead horizon is due to the tourist arrivals series changing dramatically in 2003 due to the SARS crisis.

Because the results of the Turner, Kulendran and Fernando (1997a) study, showed that the AR model with periodic data produced better forecasts than the ARIMA model with seasonal data, periodic data were tested on the MLP model to determine whether using periodic non-seasonal data would improve the performance of the MLP model. The performance of the periodic MLP model, though not better than the partial periodic model, was better for country specific data where the variance in MAPE values was not high. The comparatively poor performance of the periodic model compared to the partial periodic model could well be because data for each season are not totally independent.

The superior performance of the MLP partial periodic model in tourist arrival forecasting means that the use of lagged series as inputs helps in modeling seasonal variations and recent trend. This method combines the advantages of using periodic data with non-periodic data by having the most recent periodic data in one iteration and the most recent data from a different period in the next iteration. Therefore, the superior performance of the partial periodic model over the non-periodic and periodic models was to be expected and has explored an alternative perspective in periodic forecasting.

7.4.3 Comparison of ARIMA$^{(1)}$ and ARIMA$^{(1)(12)}$ models

The ARIMA$^{(1)}$ model is superior to the ARIMA$^{(1)(12)}$ model for forecasting tourism arrivals to Japan (Refer 4.7). This is contrary to expectations, as tourism data are generally seasonal. However, ARIMA$^{(1)(12)}$ performs better when a series has stochastic seasonality (Kulendran and Wong, 2005). The better performance of the ARIMA$^{(1)}$ model is an indication of the absence of stochastic seasonality in tourist arrivals from source countries to Japan. It is possible for tourism data not to have stochastic seasonal variations when there are regular deterministic tourism flows from source countries to a destination such as Japan. The superior performance of the ARIMA$^{(1)}$ model shows that tourist arrivals to Japan does not have much stochastic seasonality and is more deterministic. This means for major tourist destinations tourist flows are deterministic due to steady regular flows each season, and are best modeled using ARIMA$^{(1)}$.

7.4.4 Comparison of ARIMA$^{(1)}$ and BSM models

Comparing the ARIMA$^{(1)}$ model with the BSM model, they both outperformed the naïve model and performed fairly well against each other. The ARIMA$^{(1)}$ model is adjudged the better of the two overall. ARIMA$^{(1)}$ is also the better model for a one month ahead forecasting horizon but both models perform well for the 12 months ahead horizon while the BSM model is the better model for the 24 months ahead horizon (Refer 4.8). Both ARIMA and BSM are powerful forecasting tools that are difficult to outperform, as autoregression and basic structure are the fundamentals that precede any stochastic variation.

Reference in the literature to naïve forecasts as the implied minimum standard for a model's forecasting adequacy is based on its simplicity and reiterates the fact that a model that cannot be at least as accurate as the naïve model should not be considered for time series forecasting. However, due to the strong performance of the ARIMA model it should in fact be considered the minimum standard for model adequacy at least for tourism forecasting.

7.4.5 Comparison of Univariate and Multivariate ANFIS models

The main aim of this research was to test the viability of neuro-fuzzy logic in time series forecasting of tourism arrivals. Both univariate and multivariate ANFIS models performed better than the naïve model meeting the benchmark requirement for adequacy. However, comparison with equivalent MLP models showed that the MLP models performed better than the ANFIS models (Refer 6.6).

Between the univariate and multivariate models, the univariate ANFIS performed better than the multivariate ANFIS for all forecasting horizons, the one-month, 12-months and 24-months ahead. The performance of the multivariate ANFIS model was constrained by technical requirements that restricted the number of economic indicators. However, the good performance of the ANFIS models justifies further research in neuro-fuzzy forecasting.

The power of the neural network MLP model has been demonstrated in this study and others. The combination of neural networks and fuzzy logic provides a platform with potential for movement away from crisp forecasts to fuzzy forecasts, which will better represent tourist arrivals in a manner more useful to industry. This study has demonstrated the capability of the neuro-fuzzy forecasting model with comparable forecasting accuracies and precision. Refinement of this model will result in further improvement in accuracy.

7.4.6 Comparison of all models with the Naïve

All models tested in this research performed better than the naïve except, the ECM model and the MLP periodic model, which fell short of outperforming the naïve. The relatively poor performance of the regression model is supportive of previous findings by Martin and Witt (1989a), Witt and Witt (1992), Kulendran and Witt (2001) and Song and Witt (2000) who observed that that the naïve model is significantly accurate relative to the regression methods, and those of Turner and Witt (2001b) who showed that results confirm the superiority of the ARIMA and BSM time series models over both regression and the naïve models. (Refer 7.2). The relatively good performance of the MLP models that did not use periodic data shows that the poor performance of the MLP periodic model is due to the use of periodic data rather than poor characteristics of the MLP model. Each of the neural and fuzzy neural models (with the exception of the periodic MLP model) outperformed the naïve in more than 60% of forecasts. These results indicate that neural networks and the fuzzy neural combination are suitable tools that should be explored further for time series forecasting. However, these models must aim to at least perform as well as the ARIMA model if they are to be considered as a viable alternative forecasting tool.

7.4.7 Identifying the best models

Three main methods are used in this study to compare the performance of forecasting models. The first is the number of forecasts with a lower MAPE value, a measure of the lower error. This method is used to compare model performances against the naïve model. The second method is the number of forecasts with MAPE values less than 10%, a measure of precision. The third method is the number of paired comparisons with significant mean differences in MAPE values, a measure of significance. The results of these measures given earlier for all models for all three forecasting horizons in Figures 7.1, 7.2 and 7.3 are summarised below.

Table 7.4.1 Ranking the models for forecasting tourist arrivals to Japan

Rank	Performance measure:		
	Lower MAPE than in Naïve model	**MAPE less than 10%**	**Significant mean difference in MAPE**
1	ARIMA(1)	ARIMA(1)	ARIMA(1)
2	BSM	BSM	BSM
3	MLP Partial Periodic	MLP Partial Periodic	MLP Partial Periodic
4	ANFIS	MANFIS	MMLP
5	MMLP	ANFIS	ANFIS
6	MANFIS	MLP Non Periodic	MLP Periodic
7	MLP Non Periodic	MMLP	MLP Non Periodic
8	MLP Periodic	Naïve	MANFIS
9	ECM	MLP Periodic	ECM
10		ECM	Naïve

Overall, the sophisticated univariate time series models ARIMA and BSM perform best, followed by neural network models with and without fuzzy logic. The performance of the ECM model is poor being not much better than the naïve model.

The above findings are partly in keeping with the conclusions of Burger, Dohnal, Kathrada et al. (2001) who stated that neural networks performed best in comparison with the naïve, moving average, decomposition, single exponential smoothing, ARIMA, multiple regression and genetic regression models and those of Kon and Turner (2005) which adjudged MLP models to be superior.

While ARIMA(1) clearly outperforms the other models, the ECM model is shown to be significantly worse than most other models. This finding is in agreement with Witt and Witt (1992) who observed that ARIMA performs better than traditional demand modelling. The poor performance of the ECM model may be partly because the values of certain independent variables such as the gross national income were taken as a third of the quarterly figure because monthly data were not available. However, other multivariate models such as the multivariate MLP model performed better than the ECM using the same data. The better performance of the time series models from an industry point of view is a significant finding as, the use of time series models such as ARIMA would be less costly, quicker and requiring comparatively less technical skill. Whether ECM is more suitable for particular data structures needs to be further investigated. However, using an ECM just to obtain elasticities when accuracy is low is questionable.

One of the limitations of this research is that it deals only with the ECM model while econometric modeling covers a broad spectrum of methodologies such as vector autoregressive (VAR) models, autoregressive distributed Lag models (VDLM) and time varying parameter (TVP) models. The scope of this study did not warrant the inclusion of these models. Event dummies were not specified in the ECM model, to be consistent with the neural network model, which did not specify event dummies.

The ANFIS and the MLP partial periodic models have justified their suitability as time series forecasting tools by performing well for each forecasting horizon and lead period. The MLP partial periodic model ranks 3rd while ANFIS ranks 4th and 5th out of the 10 models in Table 7.4.1, a significant achievement for relatively new forecasting tools.

7.5 Recommendations for future research

The objective of this research has been achieved in establishing that neuro-fuzzy models can be used effectively in tourism forecasting with adequate comparisons with other time series and econometric models using real data. This research takes tourism forecasting a major leap forward to an entirely new approach in time series pedagogy. As previous tourism studies have not used hybrid combinations of neural and fuzzy logic in tourism forecasting this research has only touched the surface of a field that has immense potential not only in tourism forecasting but also in financial time series analysis, market research and business analysis. Fuzzy logic has so far been used extensively only in engineering design. Non-engineering applications are very recent. The scope for fuzzy applications in management is wide with clustering and segmentation being the most viable.

A new approach to measuring tourism demand flows in levels of demand, relative to a mean is a possible future research project. The use of labels to describe levels of tourism demand as very high, high, medium, low or very low, relative to a recent historical mean, with further subdivisions such as very high 1, 2 or 3, might be more acceptable to a practitioner, who would plan the availability of hotel rooms or travel facilities based on reliable forecast levels of tourist demand, rather than an average forecast of a specific number of arrivals. The fuzzy approach can forecast tourism demand as an accurate and useful fuzzy level of demand.

Fuzzy classification is another area in which fuzzy logic can improve on crisp measurements. In the field of tourism, market segmentation according to income levels, alternative destinations, facilities and so forth would be another useful future research project.

The potential of neural networks in adaptive learning where ANFIS, or similar models, can be designed to operate systems that make decisions is not fully utilised in business. Such systems can have expert opinion as an input, so that the decisions are not totally computer driven. A typical project would be to develop a sustainable regional tourism model for say Southeast Asia.

References

Abraham, A., 2002, "Cerebral Quotient of neuro Fuzzy Tehniques - Hype or hallelujah?", Working paper, Monash University (Gippsland Campus), School of Computing and Information Technology.

Abraham, A., Chowdhury, M. and Petrovic-Lazarevic, S., 2001, "Neuro-Fuzzy Technique for Australian Forex Market Analysis", Working paper 87/01 Monash University, Department of Management.

Aiken, M., Krosp, J., Vanjani, M., Govindrajulu, C. and Sexton, R., 1995, “A neural network for predicting total industrial production”, *Journal of End User Computing*, 7 (2), pp. 19-23.

Archer, B.H., 1980, “Forecasting demand: quantitative and intuitive techniques”, *International Journal of Tourism Management,* 1 (1), pp. 5-12.

Artus, J.R., 1970, “The effect of revaluation on the foreign travel balance of Germany”, *IMF Staff Papers,* 17, pp. 602-617.

Artus, J.R., 1972, “An econometric analysis of international travel”, *IMF Staff Papers, 19*, pp. 579-614.

Azeem , M. F., Hanmandlu, M. and Ahmad, N., 2000, "Generalization of adaptive neuro-fuzzy inference systems", *IEEE Transactions on Neural Networks*, 11 (6), pp. 1332-1346.

Bakirtzis, A.G., Theocharis, J.B., Kiartzis, S.J. and Satsios, K.J., 1995, “Short term load forecasting using fuzzy neural networks”, *IEEE Transactions on Power Systems*, 10 (3), pp. 1518-1524.

Balestrino, A., Bini Verona, F. and Santanche, M., 1994, “Time series analysis by neural networks: Environmental temperature forecasting”, *Automazione e Strumentazione*, 42 (12), pp. 81-87.

Bar On, R.R.V., 1972, “Seasonality in tourism - Part 1”, *International Tourism Quarterly*, Special Article No.6.

Bar On, R.R.V., 1973, “Seasonality in tourism - Part 2”, *International Tourism Quarterly*, Special Article No.6.

Bar On, R.R.V., 1975, “Seasonality in tourism”, *Technical Series No.2*, Economist Intelligence Unit, London.

Bar On, R.R.V., 1984, “Forecasting tourism and travel series”, *Problems of Tourism,*3, pp. 34-39.

Barry, K., and J. O'Hagen, 1972, “An econometric study of British tourist expenditure in Ireland”, *Economic and Social Review*, 3 (2), pp. 143-161.

Bataineh, S., Al-Anbuky, A. and Al-Aqtash, S., 1996, “An expert system for unit commitment and power demand prediction using fuzzy logic and neural networks”, *Expert Systems*, 13 (1), pp. 29-40.

Benachenhou, D., 1994, “Smart trading with (FRET)”, In: Deboeck, G. J., (Ed.), Trading on the Edge, Neural, Genetic, and Fuzzy Systems for Chaotic Financial Markets, New York: Wiley, pp. 215-242.

Berenji, H.R. and Khedkar, P., 1992, "Learning and tuning fuzzy logic controllers through reinforcements," *IEEE Trans. Neural Networks*, 3, pp. 724-740.

Bergerson, K. and Wunsch, D.C., 1991, “A commodity trading model based on neural network-expert system hybrid”, *Proceedings of the IEEE International Conference on Neural Networks*, Seattle, WA, pp. 1289-1293.

Bezdek, J., 1993, “Fuzzy models – what are they and why?”, *IEEE Transactions on Fuzzy Systems*, 1 (1), pp. 1-5.

Blackwell, J., 1970, “Tourist traffic and the demand for accommodation: some projections”, *Economic and Social Review*, 1 (3), pp.323-343.

Bond, M.E. and Ladman, J.R., 1972, “International tourism and economic development: a special case for Latin America”, *Mississippi Valley Journal of Business and Economics*, 8(1), pp. 43-55.

Borisov, A.N. and Pavlov, V.A., 1995, “Prediction of a continuous function with the aid of neural networks”, *Automatic Control and Computer sciences*, 29 (5), pp. 39-50.

Box, G.E.P., and Jenkins, G.M., 1976, Time series analysis: Forecasting and control, Holden-Day, San Francisco, CA.

Brady, J. and Widdows, R., 1988, “The impact of world events on travel to Europe during the Summer of 1986”, *Journal of Travel Research*, 26 (3), pp. 8-10.

Buckley, J.J. and Hayashi, Y., 1994, "Fuzzy neural networks: A survey", *Fuzzy Sets Syst.*, 66, pp. 1-13.

Burger, C.J.S.C., Dohnal, M., Kathrada, M. and Law, R., 2001, "A practitioners guide to time-series methods for tourism demand forecasting - a case study of Durban, South Africa", *Tourism Management*, 22 (4), pp. 403-409.

Cai, L.Y. and Kwan, H.K., 1998, "fuzzy classifications using fuzzy inference networks," *IEEE Trans. Syst., Man, Cyber.*, 28, pp. 334-347.

Calantone, R.J., Di Benedetto, C.A. and Bojanic, D., 1987, “A comprehensive review of the tourism forecasting literature”, *Journal of Travel Research*, 26 (2), pp. 28-39.

Canadian Government Office of Tourism, 1977, Methodology for Short-term Forecasts of Tourism Flows, Research Report No.4, Canadian Government, Office of Tourism, Ottawa, Canada.

Castro, J.L., Mantas, C.J. and Benitez, J.M., 2002, "Interpretation of artificial neural networks by means of fuzzy rules", *IEEE Transactions on neural networks*, 13 (1) pp. 101-116.

Castillo, O. and Melin, P., 2002, "Hybrid intelligent systems for time series prediction using neural networks, fuzzy logic and fractal theory", *IEEE Transactions on neural networks*, 13 (6) pp. 1395-1408.

Chadee, D. and Mieczkowski, Z., 1987, “An empirical analysis of the effects of the exchange rate on Canadian tourism”, *Journal of Travel Research*,26 (1), pp.13- 17.

Chak, C.K., Feng, G.and Ma, J., 1998, "An adaptive fuzzy neural network for MIMO system model approximation in high dimensional spaces," *IEEE Trans. Syst., Man, Cybern.*, 28, pp. 436-446.

Chang, I., Rapiraju, S., Whiteside, M. and Hwang, G., 1991, “A neural network to time series forecasting”, *Proceedings of the Decision Science Institute*, 3, pp. 1716-1718.

Chen, C.H., 1994, “Neural networks for financial market prediction”, *Proceedings of the IEEE International Conference on Neural Networks*, 2, pp. 1199-1202.

Cheng, B. and Titterington, D.M., 1994, “Neural networks: A review from a statistical perspective”, *Statistical Science*, 9 (1), pp. 2-54.

Chiang, W.C., Urban, T.L. and Baldridge G,W., 1996, “A neural network approach to mutual fund net asset value forecasting”, *Omega*, 24, pp. 205-215.

Cho, V., 2003, "A comparison of three different approaches to tourist arrival forecasting", Tourism Management, 24 pp. 323-330.

Chu, F.L., 1998a, “Forecasting Tourism Demand in Asian-Pacific Countries”, *Annals of Tourism Research,* 25 (3), pp. 597-615.

Chu, F.L., 1998b, “Forecasting Tourism: a combined approach”, *Tourism Mangement*, 19 (6), pp. 515-520.

Chu, F. L., 2004, "Forecasting tourism demand: A cubic polynomial approach", *Tourism Management*, 25, pp.209-218.

Cline, R.S., 1975, “Measuring travel volumes and itineraries and forecasting future travel growth to individual Pacific destinations”, In: S.P. Ladany, (ed.), Management Science Applications to Leisure-time Operations, North-Holland, New York, pp. 134-145.

Coleman, K.G., Graettinger, T.J. and Lawrence, W.F., 1991, “Neural networks for bankruptcy prediction: The power to solve financial problems”, *AI Review,* 5, pp. 48-50.

Crouch, G.I., 1992, “Effect of income and price on international tourism”, *Annals of Tourism Research*, 19, pp. 643-664.

Crouch, G.I., 1994, “The study of international tourism demand: A review of findings”, Journal *of Travel Research,* 33, pp.12-23.

Darnell, A., Johnson, P. and Thomas, B., 1990, “Beamish Museum - modelling visitor flows”, *Tourism Management,* 11 (3), pp. 251-257.

Dash, P.K., Ramakrishna, G., Liew, A.C. and Rahman, S., 1995, “Fuzzy neural networks for time series forecasting of electric load”, *IEE Proceedings – Generation, Transmission and Distribution*, 142 (5), pp. 535-544.

DataEngine, 1997, MIT-Management Intelligenter Technologien Gmbh, Germany.

Dharmaratne, G.S., 2000, "Forecasting tourist arrivals in Barbados", Annals of Tourism Research, 22, (4), pp.804-818.

Di Benedetto, C., Anthony, C. and Bojanic, D.C., 1993, “Tourism area life cycle extensions”, *Annals of Tourism Research,* 20, pp. 557-570.

Dutta, S. and Shekhar, S., 1988, “Bond rating: A non-conservative application of neural networks”, *Proceedings of the IEEE International Conference on Neural Networks,* San Diego, California, 2, pp. 443-450.

Edwards, A., 1985, “International Tourism Forecasts to 1995: EIU Special Report No. 188”, Economist Publications, London.

Engle, R.F., 1982 “Autoregressive conditional heteroscedasticity with estimates of the variance of UK inflation”, *Econometrica,* 50, pp. 987-1008.

Engle, R.F. and Granger, C.W.J., 1987, “Co-integration and error correction: representation, estimation and testing”, *Econometrica,* 55, pp. 251-276.

Farag, W.A., Quintana, V.H. and Lambert-Torres, G., 1998, "A genetic based neuro-fuzzy approach for modelling and control of dynamical systems," *IEEE Trans. Neural Networks*, 9, pp. 756-767.

Fernando, H.P., Reznik, L. and Turner, L., 1998, “The use of fuzzy national indicators for tourism forecasting”, Working paper presented at the CAUTHE Australian Tourism and Hospitality Research Conference, Gold Coast, Australia.

Fernando, H., Turner, L. and Reznik, L., 1999a, “Neural networks to forecast tourist arrivals to Japan from USA”, *3rd International Data Analysis Symposium*, Aachen, Germany.

Fernando, H., Turner, L. and Reznik, L., 1999b, “Neuro-fuzzy forecasting of tourism to Japan”, Working paper presented at the CAUTHE Australian Tourism and Hospitality Research Conference, Adelaide, Australia.

Fiordaliso, A., 1998, "A nonlinear forecasts combination method based on Takagi-Sugeno fuzzy systems", *International Journal of Forecasting*, 14 pp. 367-379.

Fletcher, D. and Goss, E., 1993, “Forecasting with neural networks – An application using bankruptcy data”, *Information and Management* 24, pp. 159-167.

Freisleben, B., 1992, "Stock market prediction with backpropagation networks", Proceedings of the 5th International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems, Springer Verlag, Berlin, pp. 451-460.

Fujii, E. and Mak, J., 1981, “Forecasting tourism demand: some methodological issues”, *Annals of Regional Science,* 15, pp. 72-83.

Gallant, S., 1988, "Connectionist expert systems," Commun. ACM, 31, pp.152-169.

Gapinski, J.H. and Tuckman, H.P., 1976, “Travel demand functions for Florida bound tourists”, *Transportation Research,* 10, pp. 267-274.

Geurts, M.D., 1982, “Forecasting the Hawaiian tourist market”, *Journal of Travel Research,* 21 (1), pp. 18-21.

Geurts, M.D. and Ibrahim, I.B., 1975, “Comparing the Box-Jenkins approach with the exponentially smoothed forecasting model: application to Hawaii tourists”, *Journal of Marketing Research,* 12, pp. 182-188.

Gonzales, P. and Moral, P., 1995, "An analysis of the tourism demand in Spain", *International Journal of Forecasting*, 11, pp. 233-251.

Gorr, W.L., Nagin, D. and Szczypula, J., 1994, “Comparative study of artificial neural network and statistical models for predicting student grade point averages”, *International Journal of Forecasting*, 10, pp. 17-34.

Granger, C.W.J. and Newbold, P., 1974, “Spurious regressions in econometrics”, *Journal of Econometrics*, 2, pp. 111-120.

Gray, H.P., 1966, “The demand for international travel by the United States and Canada”, *International Economic Review*, 7 (1), pp. 83-92.

Grudnitski, G. and Osburn, L., 1993, “Forecasting S and P and gold futures prices: An application of neural networks”, *The Journal of Futures Markets*, 13 (6), pp. 631-643.

Gunadhi, H. and Boey C.K., 1986, “Demand elasticities of tourism in Singapore”, *Tourism Management*, 7 (4), pp. 239-253.

Hanke J.E. and Reitsch A.G., 1992, Business Forecasting, Allyn and Bacon, Boston.

Hann, T.H. and Steurer, E., 1996, “Much a do about nothing? Exchange rate forecasting: Neural networks vs linear models using monthly and weekly data”, *Neurocomputing*, 10, pp. 323-339.

Harvey, A.C. and Todd, P.H.J. (1983), “Forecasting Economic Time-series with Structural and Box-Jenkins models: A case study,” *Journal of Business and Economic Statistics*, 299-315

Harvey, A. C., 1990, Forecasting, Structural Time Series Models and the Kalman Filter, Cambridge University Press, Cambridge.

Hornik, K., Stinchcombe, M. and White, H., 1989, "Multilayer feed forward networks are universal approximators", *Neural Networks*, 2, pp.359-366.

Hruschka, H., 1993, “Determining market response functions by neural network modelling: A comparison to econometric techniques”, *European Journal of Operational Research*, 66, pp.27-35.

Huntley, D. G., 1991, “Neural nets: An approach to the forecasting of time series”, *Social Science Computer Review*, 9 (1), pp. 27-38.

Ishibuchi, H., Tanaka, H. and Okada, H., 1994, "Interpolation of fuzzy if-then rules by neural networks," *Int. J. Approx. Reas*., 10, pp. 3-27.

Jang, J.S.R., 1993, "ANFIS: Adaptive network-based fuzzy inference system" IEEE Trans. Syst., Man, Cybern., 23 (3), pp. 665-685.

Jang, J.R. and Sun, C., 1993, “Predicting chaotic time series with fuzzy IF-THEN rules”, *2nd IEEE International Conference on Fuzzy Systems*, San Francisco CA, 2, pp. 1079-1084.

Jorgensen, F. and Solvoll, G., 1996, “Demand models for inclusive tour charter: the Norwegian case”, *Tourism Management*, 17 (1), pp. 17-24.

Jud, G.D., 1974, “Tourism and economic growth in Mexico since 1950”, *Inter-American Economic Affairs,* 28 (1), pp. 19-43.

Jud, G.D. and Joseph, H., 1974, “International demand for Latin American tourism”, *Growth and Change*, January, pp. 24-31.

Kaastra, I. and Boyd, M.S., 1995, “Forecasting futures trading volume using neural networks”, *The Journal of Futures Markets*, 15 (8), pp. 953-970.

Kasabov, N.K., 1996a, Foundations of neural networks, fuzzy systems and knowledge engineering, The MIT Press, CA.

Kasabov, N.K., 1996b, "Learning fuzzy rules and approximate reasoning in fuzzy neural networks and hybrid systems," Fuzzy Sets Syst., 82, pp. 135-149.

Kellar, J.M. and Tahani, H., 1992, " Implementation of conjunctive and disjunctive fuzzy logic rules with neural networks", *Int. J. Approx. Reas*., 6, pp. 221-240.

Khedkar, P.S. and Keshav, S., 1992, "Fuzzy prediction of time series", IEEE International Conference on Fuzzy Systems, California.

Kim, K.H., Park, J.K., Hwang, K.J. and Kim, S.H., 1995, “Implementation of hybrid short term load forecasting system using artificial neural networks and fuzzy expert systems”, *IEEE Transactions on Power Systems*, 10 (3), pp. 1534-1539.

Kim, S. and Song, H., 1998, "An empirical analysis of demand for Korean tourism: a cointegration and error correction approach", *Tourism Analysis*, 3, pp. 25-41.

Kimoto, T., Asakawa, K., Yoda, M. and Takeoka, M., 1990, “Stock market prediction system with modular neural networks” *Proceedings of the IEEE International Joint Conference on Neural Networks*, San Diego, California, 2, pp. 11-16.

Kliman, M.L., 1981, “A quantitative analysis of Canadian overseas tourism”, *Transportation Research*, 15A (6), pp. 487-497.

Klimasauskas, C.C., 1991, “Applying neural networks: Part 3 – Training a neural network”, *PC-AI*, May/June, pp. 20-24.

Kohzadi, N., Boyd, M.S., Kermanshahi, B. and Kaastra, I., 1996, "A comparison of artificial neural network and time series models for forecasting commodity prices", *Neurocomputing*, 10, pp.169-181.

Kon, S.C. and Turner, L.W., 2005, "Neural Network Forecasting of Tourism Demand", *Tourism Economics*, 11 (3), (Forthcoming).

Kryzanowski, L., Galler, M. and Wright, D.W., 1993, “Using artificial neural networks to pick stocks”, *Financial Analysts Journal*, July/August, pp. 21-27.

Kuan, C.M. and Liu, T., 1995, “Forecasting exchange rates using feedforward and recurrent neural networks”, *Journal of Applied Economics*, 10, pp. 347-364.

Kulendran, N., 1996, “Modelling quarterly tourist flows to Australia using cointegration analysis”, *Tourism Economics*, 2 (3), pp. 203-222.

Kulendran, N. and King, M.L., 1997, “Forecasting international quarterly tourist flows using error-correction models and time-series models”, *International Journal of Forecasting*, 13, pp. 319-327.

Kulendran, N. and Wilson, K., 2000a, "Is there a relationship between international trade and international travel?", *Applied Economics*, January 2000.

Kulendran, N. and Wilson, K., 2000b, "Modelling business Travel", *Tourism Economics*, 6 (1), pp47-59.

Kulendran, N. and Witt, S.F., 2001, "Cointegration versus least squares regression", *Annals of Tourism Research*, Volume 28, Issue 2, pp. 291-311.

Kulendran, N. and Witt, S.F., 2003a, "Forecasting the demand for international business tourism", *Journal of Travel Research*, Volume 41, pp. 265-271.

Kulendran, N. and Witt, S.F., 2003b, "Leading indicator tourism forecasts", *Tourism Management*, Volume 24, Issue 5, pp. 503-510.

Kulendran, N. and Wong, K.K.F., 2005, "Modeling Seasonality in Tourism Forecasting", *Journal of travel Research*, Volume 44, pp. 1-9.

Kwack, S.Y., 1972, "Effects of income and prices on travel spending abroad 1960 III - 1967 IV", *International Economic Review*, 13 (2), pp. 245-256.

Lapedes, A. and Farber, R., 1987, "Nonlinear signal processing using neural networks: prediction and system modeling", Technical report LA-UR-87-2662, Los Almos National Laboratory, Los Almos, NM.

Law, R., 2000, "Back-propagation learning in improving the accuracy of neural network based tourism demand forecasting", Tourism Management, 21 (4), pp. 331-340.

Law, R. and Au, N., 1999, "A neural network model to forecast Japanese demand for travel to Hong Kong", *Tourism Management*, 20 (1), pp. 89-97.

Lee, S.C. and Lee, E.T., 1975, "Fuzzy neural networks", Math. Biosci., 23, pp. 151-177.

Li, G., Song, H. and Witt S.F., 2005, "Recent Developments in Econometric Modeling and Forecasting", *Journal of Travel Research*, 44, pp. 82-99.

Lim, C., 1997, "Review of international tourism demand models", *Annals of Tourism Research,* 24, pp.835-849.

Lim, C. and McAleer, M., 1999, "A seasonal analysis of Malaysian tourist arrivals to Australia", *Mathematics and Computer Simulation,* 48, pp. 573-583.

Lim, C. and McAleer, M., 2001, "Cointegration annlysis of quarterly tourism demand by Hong Kong and Singapore for Australia", *Applied Economics*, 33, pp. 1599-1619.

Lim, C. and McAleer, M., 2002, "Time series forecasts of international travel demand for Australia", *Tourism Management,* Volume 23, Issue 4, pp. 389-396.

Little, J. S., 1980, “International travel in the US balance of payments”, *New England Economic Review*, May/June, pp. 42-55.

Loeb, P., 1982, “International travel to the United States: an economic evaluation”, *Annals of Tourism Research,* 9 (1), pp. 5-20.

Makridakis, S. and Hibon, M., 1997, "ARMA Models and the Box-Jenkins methodology", *Journal of Forecasting*, 16, pp.147-163.

Martin, C.A. and Witt, S.F., 1987, "Tourism demand forecasting models: Choice of appropriate variable to represent tourists' cost of living", *Tourism Management*, 8, pp. 233-246.

Martin, C.A. and Witt, S.F., 1988, “Substitute prices in models of tourism demand”, *Annals of Tourism Research*, 15 (2), pp. 255-268.

Martin, C.A. and Witt, S.F., 1989a, “Forecasting Tourism Demand: A Comparison of the Accuracy of Several Quantitative Methods”, *International Journal of Forecasting,* 5, pp. 7-19.

Martin, C.A. and Witt, S.F., 1989b, Accuracy of econometric forecasts of tourism, *Annals of Tourism Research*, Volume 16, Issue 3, pp. 407-428.

Maasoumi, E., Khotanzad, A. and Abaye, A., 1994, “Artificial neural networks for some microeconomic series: A first report”, *Econometric Reviews*, 13 (1), pp. 105-122.

Matlab, 1984-2004, ver.7, rel.14, The MathWorks, Inc., USA.

Mazanec, J. A., 1992, “Classifying tourists into market segments: A neural network approach”, *Journal of Travel and Tourism Marketing*, 1 (1), pp. 39-59.

McCluskey, P.C., 1993, “Feedforward and recurrent neural networks and genetic programming for stock market and time series forecasting”, Brown Univ., Providence, RI, Technical Report, CS-93-36.

Microfit, 1997, ver. 4.0, Oxford University Press, Oxford, UK.

Mitra, S. and Hayashi, Y., 2000, "Neuro-Fuzzy Rule Generation: Survey in Soft Computing Framework", *IEEE Trans. Neural Networks* 11 (3), pp. 748-768.

Mitra , S. and Pal, S.K., 1995, "Fuzzy multilayer perceptron , inferencing and rule generation*", IEEE Trans. Neural Networks,* 6, pp. 51-63.

Morley, C.L., 1997, "An evaluation of the use of ordinary least squares for estimating tourism demand models", *Journal of Travel Research,* 36 (4) pp.185-200.

Morris, A., Wilson, K., Bakalis, S., 1995 "Modelling tourism flows from Europe to Australia", *Tourism Economics*, 2, pp. 147-167.

Nam, K. and Schaefer, T., 1995, "Forecasting international airline passenger traffic using neural networks", *Logistics and Transportation*, 31 (3), pp. 239-251.

Nauck, D., Klawonn, F. and Kruse, R., 1997, "Foundations of neuro-fuzzy systems", Wiley, Chichester, UK.

Nelson, M., Hill, T., Remus, W. and O'Connor, M., 1999, "Time series forecasting using neural networks: Should the data be deseasonalized first?", Journal of Forecasting, 18 pp. 359-367.

Nie, J., 1995, "Constructing fuzzy model by self-organizing counter-propagation network," *IEEE Trans. Syst., Man, Cyber.*, 25, pp. 963-970.

Odom, M. D., and Sharda, R., 1990, “A neural network model for bankruptcy prediction”, *Proceedings of the IEEE International Joint Conference on Neural Networks*, San Diego, CA, 2, pp. 163-168.

O'Hagen, J.W. and Harrison M.J., 1984a, “Market shares of US tourist expenditure in Europe: an econometric analysis”, *Applied Economics,* 16 (6), pp. 919-931.

O'Hagen, J.W. and Harrison, M.J., 1984b, “UK and US Visitor Expenditure in Ireland: some economic findings”, *The Economic and Social Review*, 15, pp. 195-207.

Oliver, F.R., 1971, “The effectiveness of the UK travel allowance”, *Applied Economics,* 3, pp. 219-226.

Pal, S.K. and Mitra, S., 1999, "Neuro-fuzzy Pattern Recognition: Methods in Soft Computing ", Wiley, New York.

Pankratz, A., 1983, Forecasting with univariate Box-Jenkins models: Concepts and cases, John Wiley, NY.

Papadopoulos, S.I. and Witt, S.F., 1985, “A marketing analysis of foreign tourism in Greece”, In: Shaw, S., Sparks, L. and Kaynak, E., (Eds.), Proceedings of Second World Marketing Congress, University of Stirling, pp. 682-693.

Paraskevopoulos, G., 1977, “An Econometric Analysis of International Tourism”, Center of Planning and Economic Research, Lecture Series 31, Athens.

Pattie, D.C. and Snyder, J., 1996, “Using a neural network to forecast visitor behaviour”, *Annals of Tourism Research*, 23 (1), pp. 151-164.

Paul, S. and Kumar, S., 2002, "Subsethood-product fuzzy neural inference system", *IEEE Transactions on Neural Networks*, 13 (3), pp. 578-599.

Preez, J. du and Witt, S.F., 2003, "Univariate versus multivariate time series forecasting: an application to international tourism demand", *International Journal of Forecasting*, Volume 19, Issue 3, pp. 435-451.

Quayson, J. and Var, T., 1982, “A tourism demand function for the Okanagan, BC”, *Tourism Management,* 3 (2), pp. 108-115.

Refenes, A.N., 1993, “Constructive learning and its application to currency exchange rate forecasting”, In: Trippi, R.R. and Turban, E., (Eds.), Neural Networks in Finance and Investing: Using artificial intelligence to improve real-world performance, Probus Publishing, Chicago.

Refenes, A.N., Zapranis, A. and Francis G., 1994, “Stock performance modelling using neural networks: A comparative study with regression models”, *Neural Networks,* 7 (2), pp. 375-388.

Reznik, L. 1997, Fuzzy Controllers, Newnes, Oxford.

Ripley, B.D., 1993, “ Statistical aspects of neural networks”, In: Barndoeff-Nielsen, O.E., Jensen, J.L., Kendall, W.S., (Eds). Networks and Chaos - Statistical and Probabilistic Aspects, Chapman and Hall, London, pp. 44-123.

Rosenweig, J.A., 1988, “Elasticities of substitution in Caribbean tourism”, *Journal of Development Economics,* 29 (1), pp. 89-100.

Rumelhart, D.E., Hinton, G.E. and Williams, R.J., 1986, “Learning representations by backpropergating errors”, *Nature*, 323, (6188), pp. 533-536.

Rutkowski, L. and Cpalka, K., 2003, "Flexible neuro-fuzzy systems", *IEEE Transactions on Neural Networks*, 14 (3), pp. 554-574.

Saade, J., 1996, “A unifying approach to defuzzification and comparison of the outputs of fuzzy controllers”, *IEEE Transactions on Fuzzy Systems*, 4 (3), pp. 227-237.

Salchenkerger, L.M., Cinar, E.M. and Lash, N.A., 1992, “Neural Networks: A new tool for predicting thrift failures”, *Decision Science,* 23 (4), pp. 899-916.

SAS, 2004, ver.8, SAS Australia and NewZealand.

Schoneburg, E., 1990, “Stock price prediction using neural networks: A project report”, *Neurocomputing*, 2, pp. 17-27.

Scott, C., 2000, "Forecasting moving average cross-overs: an application of artificial neural networks", Melbourne University, Centre of Financial Studies, Paper 00-02.

Sen, T.K., Oliver, R.J. and Sen, N., 1992, “Predicting corporate mergers using backpropagating neural networks: A comparative study with logistic models”, Working paper, The R.B. Pamplin College of Business, Virginia Tech, Blacksburg, VA.

Sharda, R., 1994, “Neural networks for the MS/OR analyst: An application bibliography”, *Interfaces*, 24, (2), pp. 116-130.

Sheldon, P.J. and Var, T., 1985, “Tourism forecasting: a review of empirical research”, *Journal of Forecasting*, 4 (2), pp. 183-195.

Sheldon, P., 1993, “Forecasting tourism: Expenditures versus arrivals”, *Journal of Travel Research*, 22 (1), pp. 13-20.

Skene, J. 1996, “Estimating Tourism’s Economic Contribution”, presented at the CAUTHE Australian Tourism and Hospitality Research Conference, Coffs Harbour, Australia.

Smeral, E. and Weber A., 2000, "Forecasting international tourism trends to 2010", *Annals of Tourism Research*, Volume 27, (4), pp. 982-1006. .

Smeral, E., Witt, S.F. and Witt, C.A., 1992, "Econometric forecasts: tourism trends to 2000", *Annals of Tourism Research,* 19 (3), pp. 450-466.

Smith, A.B. and Toms, J.N., 1967, "Factors Affecting Demand for International Travel to and from Australia", Bureau of Transport Economics, Occasional Paper 11, Canberra.

Song, H. and Witt S.F., 2000, Tourism Demand Modelling and Forecasting: Modern Econometric Approaches, Oxford: Pergamon.

Song, H. and Witt S.F., 2003, "Tourism Forecasting: The general to Specific Approach", *Journal of Travel Research*, 42, pp. 65-74.

Song, H., Witt, S.F., Thomas C. and Jensen, T.C., 2003a, "Tourism forecasting: accuracy of alternative econometric models", *International Journal of Forecasting*, Volume 19,(1) pp. 123-141.

Song, H., Wong, K.K.F. and Chon, K.K.S., 2003b, "Modelling and forecasting the demand for Hong Kong tourism", *International Journal of Hospitality Management,* 22, pp.435-451.

Sonja, P., Coghill, K. and Abraham, A.,2001, "Neuro-Fuzzy support of knowledge management in social regulation", Proceedings of 5th International Conference on Computing Anticipatory Systems, Belgium.

Srinivasan, D., Liew, A.C., Chang, C.S., 1994, "A neural network short-term load forecaster", *Electric power Systems Research*, 28, pp.227-234.

STAMP, 2000, Timberlake Consultants, Ltd., UK.

Statistical Handbook of Japan, 2004, Ministry of Internal Affairs and Communications, Statistics Bureau, www.stat.go.jp/english/

Summary, R., 1987, "Estimation of tourism demand by multivariable regression analysis: evidence from Kenya", *Tourism Management*, 8 (4), pp. 317-322.

Syriopoulous, T.C. and Sinclair, M.T. 1993, "An Econometric Study of Tourism Demand: the AIDS Model of US and European Tourism in Mediterranean Countries", *Applied Economics*, 25, pp. 1541-52.

Takagi, H., and Hayashi, I., 1991, "Artificial neural network driven fuzzy reasoning," *Int. J. Approx. Reas*., 5, pp. 191-212.

Takagi, T. and Sugeno, M., 1985, "Fuzzy identification of systems and its application to modelling and control," *IEEE Trans. Syst., Man. Cyber.*, 15, pp. 116-132.

Takagi, H., Suzuki, N., Koda, T. and Kojima, Y., 1992, "Neural networks designed on approximate reasoning architecture and their applications", *IEEE Trans. Neural Networks*, 3, pp. 752-760.

Tam, K.Y., and Kiang, M.Y., 1992, “Managerial applications of neural networks: The case of bank failure predictions”, *Management Science*, 38 (7), pp. 926-947.

Tourism in Japan 2000-2001, Japan National Tourist Organization, Ministry of Transport

Tourism in Japan 2002, Japan National Tourist Organization, Ministry of Land, Infrastructure and Transport

Turner, L.W., Kulendran, N. and Fernando. H., 1997a, “Univariate modelling using periodic and non-periodic inbound tourism to Japan, Australia and New Zealand compared”, *Tourism Economics*, 3 (1), pp. 39-56.

Turner, L., Kulendran, N. and Fernando. H., 1997b, “The use of composite national indicators for tourism forecasting”, *Tourism Economics*, 3 (4), pp. 309-317.

Turner, L.W., Kulendran, N., and Pergat, V., 1995, “Forecasting New Zealand tourism demand with disaggregated data”, *Tourism Economics*, 1 (1), pp.51-69.

Turner, L.W., Reisinger, Y. and Witt, S.F., 1998, “Tourism demand analysis using structural equation modelling”, *Tourism Economics*, 4 (4), pp. 301-323.

Turner, L.W. and Witt, S.F., 2001a, “Factors influencing demand for international tourism: tourism demand analysis using structural equation modelling, revisited,” *Tourism Economics*, 7 (1), 21 -38.

Turner, L.W. and Witt, S.F., 2001b, “Forecasting tourism using univariate and multivariate structural time series models,” *Tourism Economics*, 7 (2), 135 -147.

Uysal, M. and Crompton, J.L., 1985, “An overview of approaches used to forecast tourism demand”, *Journal of Travel Research,* 23 (4), pp. 7-15.

Uysal, M. and El Roubi, M.S., 1999, "Artificial Neural Networks versus multiple regression in tourism demand analysis", *Journal of Travel Research*, 38 pp.111-118.

Van Doorn, J.W.M., 1982, “Can futures research contribute to tourism policy?”, *Tourism Management,* 3 (3), pp. 149-166.

Vanhove, N., 1980, “Forecasting in tourism”, *Tourist Review,* 35 (3), pp. 2-7.

Wandner, S.A. and Van Erden, J.D., 1980, “Estimating the demand for international tourism using time series analysis”, In: Hawkins, D.E., Shafer, E.L. and Rovelstad, J.M., (Eds.), Tourism Planning and Development Issues, George Washington Univ., Washington DC, pp. 381-392.

Wan, E. A., 1994, "Time series prediction by using a connectionist network with internal delay lines", In: Weigend, A.S. and Gershenfeld (Eds), Time series prediction, forecasting the future and understanding the past, Reading, MA: Addison Wesley, pp. 175-195.

Wang, L.X. and Mendel, J.M., 1992, "Generating fuzzy rules by learning from examples", *IEEE Transactions on Systems Man and Cybernetics*, 22, pp. 1414-1427.

Warner, B. and Misra, M., 1996, "Understanding neural networks as statistical tools", *The American Statistician*, 50 (4), pp. 284-293.

Weigend, A.S., Huberman, B.A. and Rumelhart, D.E., 1992, "Predicting sunspots and exchange rates with connectionist networks", In: Casdagli, M. and Eubank, S., (Eds.), Nonlinear modelling and forecasting, Addison-Wesley, Redwood city, CA, pp. 395-432.

Werbos, P.J., 1988, "Generalization of backpropagation with application to a recurrent gas market model", *Neural Networks*, 1, pp. 339-356.

White, K.J., 1985, "An international travel demand model: US travel to Western Europe", *Annals of Tourism Research*, 12 (4), pp. 529-546.

White, H., 1988, "Economic prediction using neural networks: The case of IBM daily stock returns", *Proceedings of the IEEE International Conference on Neural Networks*, 2, pp. 451-458.

White, H., 1989, “Learning in artificial neural networks: A statistical perspective”, *Neural Computation*, 1, pp. 425-464.

Wikipedia 2003, http://en.wikipedia.org/Japan/Economy.

Wilson, R. and Sharda, R., 1994, “Bankruptcy prediction using neural networks”, *Decision Support Systems*, 11, pp. 545-557.

Witt, S.F., 1980a, “An abstract mode-abstract (destination) node model of foreign holiday demand”, *Applied economics*, 12 (2), pp. 163-180.

Witt, S.F., 1980b, “An econometric comparison of UK and German foreign holiday behaviour”, *Managerial and Decision Economics*, 1 (3), pp. 123-131.

Witt, S.F., 1983, “A binary choice model of foreign holiday demand”, *Journal of Economic Studies*, 10 (1), pp. 46-59.

Witt, S.F., 1990, “Cash flow forecasting in the international tourism industry”, In: Aggarawal, R. and Lee, C.F., (Eds.), Advances in Financial Planning and Forecasting, 4, Pt. B: International Dimensions of Financial Management, JAI Press, Greenwich, USA, pp. 229-244.

Witt, S.F., l991a, “How successful are commercial tourism forecasting models”, *Proceedings of European Marketing Academy 20th Annual Conference*, Dublin, pp. 1573-1588.

Witt, S.F., l991b, “Assessing the accuracy of published econometric forecasts of international tourism demand”, *Proceedings of the Travel and Tourism Research Association (TTRA) 22nd Annual Conference,* Long Beach, pp. 473-483.

Witt, S.F., 1992, “Tourism forecasting: how well do private and public sector organizations perform?”, *Tourism Management*, 13 (1), pp. 79-84.

Witt, S.F., Brooke, M.Z. and Buckley, P.J., 1991, The Management of International Tourism, Unwin Hyman, London.

Witt, S.F., Dartus, M. and Sykes, A.M., 1992, “Modeling Conference Tourism”, *Proceedings of Travel and Tourism Research Association (TTRA), 23rd Annual Conference,* Minneapolis, pp.116-124.

Witt, S.F. and Martin, C.A., 1987, “Econometric models for forecasting international tourism demand”, *Journal of Travel Research*, 25 (3), pp. 23-30.

Witt, S.F., Newbould, G.D. and Watkins, A.J., 1992, “Forecasting domestic tourism demand: application to Las Vegas arrivals data”, *Journal of Travel Research,* 31 (1), pp. 36-41.

Witt, C.A. and Witt, S.F., 1989, “Measures of forecasting accuracy: turning point error vs size of error”, *Tourism Management,* 10 (3), pp. 255-260.

Witt, S.F. and Witt, C.A., 1992, "Modelling and Forecasting Demand in Tourism", Academic Press, London.

Witt, C.A., Witt, S.F. and Wilson, N., 1994, "Forecasting international tourist flows", *Annals of Tourism Research*, Volume 21, (3), pp. *612-628*

Witt, S.F. and Witt, C.A., 1995, “Forecasting Tourism Demand: A Review of Empirical Research”, *International Journal of Forecasting,* 11, pp. 447-75.

Wong, S.Q. and Long, J.A., 1995, “A neural network approach to stock market holding period returns”, *American Business Review,* 13 (2), pp. 61-64.

Wong, F. and Tan, C., 1994, “Hybrid neural, genetic and fuzzy systems”, In: Deboeck, G. J., (Ed.), Trading on the Edge, Neural, Genetic, and Fuzzy Systems for Chaotic Financial Markets, New York: Wiley, pp. 243-262.

Wong, F.S., Wang, P.Z., Goh, T.H. and Quek, B.K., 1992, “Fuzzy neural systems for stock selection”, *Financial Analysis Journal*, Jan/Feb, pp. 47-52.

World Tourism Organisation Travel Compendium, 2005, Compendium of Tourism Statistics Data 1999-2003, World Trade Organisation, Madrid, Spain.

World Trade Organisation: Japan Trade Policy Review 1998.

World Trade Organisation: Japan Trade Policy Review 2000.

World Trade Organisation: Japan Trade Policy Review 2002.

Wu, B., 1995, “Model-free forecasting for nonlinear time series (with application to exchange rates)”, *Computational Statistics and Data Analysis*, 19, pp. 433-459.

Ye, Z. and Gu, L., 1994, “A fuzzy system for trading the Shanghai stock market”, In: Deboeck, G. J., (Ed.), Trading on the Edge, Neural, Genetic, and Fuzzy Systems for Chaotic Financial Markets, New York: Wiley, pp. 207-214.

Yoon, Y. and Swales, G., 1991, “Predicting stock price performance: A neural network approach”, *Proceedings of the 24th Hawaii International Conference on System Sciences*, 4, pp. 156-162.

Yupu, Y., Xiaoming, X. and Wengyuan, Z., 1998, "Real-time stable self learning FNN controller using genetic algorithm," *Fuzzy Sets Syst.*, 100, pp. 173-178.

Zadeh, L. A., 1965, “Fuzzy sets”, *Information and Control,* 8, pp. 338-353.

Zadeh, L. A., 1973, “ Outline of a new approach to the analysis of complex systems and decision processes”, *IEEE Transactions on Systems, Man and Cybernetics*, 3 (1), pp. 28-44.

Zhang, G., Patuwo, B.E. and Hu, M.Y., 1998, “Forecasting with artificial neural networks: The state of the art”, *International Journal of Forecasting*, 14, pp. 35-62.

Zimmermann, H., 1991, Fuzzy set theory and its applications, 2nd edition, Kluwer, Boston.

APPENDIX I

Appendix to Chapter 4

Table 4.4.1a

ARIMA 1 results for tourist arrivals from all countries
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0058431	0.01453	0.40	0.6876	0
MA1,1	0.59720	0.04704	12.70	<.0001	1
MA2,1	0.64257	0.05147	12.48	<.0001	12
AR1,1	0.98607	0.0058861	167.53	<.0001	12

Variance Estimate	0.00414
Std Error Estimate	0.064345
AIC	-733.19
SBC	-718.538
Number of Residuals	288

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.55	3	0.1358	-0.037	0.076	0.046	0.003	-0.029	0.093
12	18.36	9	0.0312	-0.114	-0.045	-0.044	-0.108	0.119	-0.005
18	22.95	15	0.0853	-0.010	0.067	-0.054	0.040	0.070	0.031
24	26.90	21	0.1741	-0.021	-0.030	-0.012	0.060	0.039	-0.077
30	35.53	27	0.1258	0.103	-0.107	-0.059	-0.012	-0.020	0.032
36	38.74	33	0.2265	-0.047	-0.004	0.043	-0.020	0.008	0.072
42	43.97	39	0.2691	-0.101	-0.040	-0.029	-0.039	0.024	-0.031
48	51.70	45	0.2287	-0.013	-0.030	-0.079	-0.011	0.018	-0.120

Model for variable visit1

Estimated Mean: 0.005843

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98607 B**(12)

Moving Average Factors

Factor 1: 1 - 0.5972 B**(1)
Factor 2: 1 - 0.64257 B**(12)

Table 4.4.1b

ARIMA 1 results for tourist arrivals from all countries
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0065499	0.01459	0.45	0.6534	0
MA1,1	0.59092	0.04636	12.75	<.0001	1
MA2,1	0.65262	0.04845	13.47	<.0001	12
AR1,1	0.98674	0.0055195	178.77	<.0001	12

Variance Estimate	0.004057
Std Error Estimate	0.063698
AIC	-768.22
SBC	-753.418
Number of Residuals	299

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.93	3	0.1151	-0.035	0.082	0.044	-0.013	-0.038	0.089
12	20.05	9	0.0176	-0.117	-0.050	-0.054	-0.103	0.124	-0.018
18	25.80	15	0.0401	-0.001	0.083	-0.067	0.038	0.070	0.020
24	29.61	21	0.1001	-0.013	-0.028	-0.020	0.063	0.041	-0.068
30	39.22	27	0.0605	0.108	-0.109	-0.059	-0.018	-0.027	0.034
36	43.11	33	0.1119	-0.048	0.003	0.041	-0.017	0.013	0.083
42	48.25	39	0.1471	-0.099	-0.040	-0.030	-0.043	0.020	-0.021
48	56.79	45	0.1118	-0.007	-0.025	-0.083	-0.010	0.014	-0.126

Model for variable visit1

Estimated Mean: 0.00655

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98674 B**(12)

Moving Average Factors

Factor 1: 1 - 0.59092 B**(1)
Factor 2: 1 - 0.65262 B**(12)

Table 4.4.1c

ARIMA 1 results for tourist arrivals from all countries
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0056212	0.01452	0.39	0.6987	0
MA1,1	0.59824	0.04701	12.73	<.0001	1
MA2,1	0.64554	0.05140	12.56	<.0001	12
AR1,1	0.98629	0.0058112	169.72	<.0001	12

Variance Estimate	0.004147
Std Error Estimate	0.064398
AIC	-729.996
SBC	-715.358
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.76	3	0.1237	-0.040	0.078	0.049	0.006	-0.027	0.094
12	19.23	9	0.0233	-0.113	-0.044	-0.045	-0.109	0.128	-0.007
18	23.94	15	0.0661	-0.012	0.067	-0.054	0.041	0.072	0.030
24	27.83	21	0.1451	-0.022	-0.029	-0.015	0.062	0.037	-0.075
30	36.32	27	0.1084	0.102	-0.107	-0.058	-0.011	-0.019	0.031
36	39.66	33	0.1973	-0.049	-0.006	0.041	-0.020	0.005	0.075
42	44.91	39	0.2380	-0.102	-0.039	-0.030	-0.038	0.021	-0.032
48	52.63	45	0.2025	-0.015	-0.029	-0.079	-0.009	0.022	-0.120

Model for variable visit1

Estimated Mean: 0.005621

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98629 B**(12)

Moving Average Factors

Factor 1: 1 - 0.59824 B**(1)
Factor 2: 1 - 0.64554 B**(12)

Table 4.4.2a

ARIMA 1 results for tourist arrivals from Australia
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0032417	0.02143	0.15	0.8798	0
MA1,1	0.65633	0.04439	14.78	<.0001	1
MA2,1	0.66461	0.04973	13.37	<.0001	12
AR1,1	0.98318	0.0064970	151.33	<.0001	12

Variance Estimate	0.017047
Std Error Estimate	0.130564
AIC	-328.466
SBC	-313.814
Number of Residuals	288

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	7.53	3	0.0567	0.017	-0.093	0.099	0.047	-0.025	0.064
12	12.14	9	0.2055	-0.012	-0.101	0.026	-0.011	0.019	-0.063
18	20.05	15	0.1701	0.082	-0.002	-0.012	0.066	-0.032	-0.116
24	30.79	21	0.0772	0.042	-0.016	-0.078	0.125	0.058	-0.084
30	36.09	27	0.1133	-0.084	-0.025	0.023	-0.029	-0.084	0.023
36	43.47	33	0.1050	0.021	-0.139	0.015	-0.020	-0.024	0.040
42	48.96	39	0.1318	-0.092	0.062	-0.011	-0.029	0.024	0.051
48	50.96	45	0.2506	-0.014	0.048	0.005	-0.034	0.004	-0.046

Model for variable visit1

Estimated Mean: 0.003242

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98318 B**(12)

Moving Average Factors

Factor 1: 1 - 0.65633 B**(1)
Factor 2: 1 - 0.66461 B**(12)

Table 4.4.2b

ARIMA 1 results for tourist arrivals from Australia
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0028528	0.02110	0.14	0.8924	0
MA1,1	0.65720	0.04347	15.12	<.0001	1
MA2,1	0.66418	0.04845	13.71	<.0001	12
AR1,1	0.98330	0.0063331	155.26	<.0001	12

Variance Estimate	0.016488
Std Error Estimate	0.128405
AIC	-351.907
SBC	-337.105
Number of Residuals	299

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	7.36	3	0.0612	0.018	-0.092	0.096	0.044	-0.022	0.063
12	11.91	9	0.2183	-0.008	-0.100	0.023	-0.009	0.016	-0.062
18	20.30	15	0.1608	0.086	-0.001	-0.013	0.066	-0.031	-0.116
24	31.78	21	0.0616	0.046	-0.014	-0.081	0.127	0.054	-0.086
30	36.84	27	0.0981	-0.075	-0.028	0.022	-0.026	-0.085	0.023
36	44.21	33	0.0920	0.018	-0.137	0.015	-0.019	-0.020	0.042
42	50.31	39	0.1061	-0.094	0.064	-0.012	-0.035	0.029	0.050
48	52.44	45	0.2079	-0.012	0.051	0.002	-0.035	0.004	-0.045

Model for variable visit1

Estimated Mean: 0.002853

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.9833 B**(12)

Moving Average Factors

Factor 1: 1 - 0.6572 B**(1)
Factor 2: 1 - 0.66418 B**(12)

Table 4.4.2c

ARIMA 1 results for tourist arrivals from Australia
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0028013	0.02139	0.13	0.8958	0
MA1,1	0.65712	0.04435	14.82	<.0001	1
MA2,1	0.66495	0.04971	13.38	<.0001	12
AR1,1	0.98320	0.0064917	151.46	<.0001	12

Variance Estimate	0.017067
Std Error Estimate	0.130641
AIC	-326.893
SBC	-312.255
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	7.45	3	0.0590	0.014	-0.091	0.101	0.049	-0.024	0.063
12	11.90	9	0.2189	-0.010	-0.099	0.025	-0.009	0.021	-0.062
18	20.09	15	0.1685	0.081	-0.001	-0.012	0.068	-0.031	-0.120
24	31.20	21	0.0704	0.040	-0.015	-0.081	0.128	0.059	-0.085
30	36.33	27	0.1083	-0.080	-0.023	0.023	-0.032	-0.083	0.024
36	43.86	33	0.0980	0.022	-0.141	0.017	-0.020	-0.023	0.041
42	49.68	39	0.1174	-0.097	0.064	-0.007	-0.028	0.024	0.051
48	51.83	45	0.2249	-0.014	0.051	0.003	-0.034	0.003	-0.048

Model for variable visit1

Estimated Mean: 0.002801

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.9832 B**(12)

Moving Average Factors

Factor 1: 1 - 0.65712 B**(1)
Factor 2: 1 - 0.66495 B**(12)

Table 4.4.3a

ARIMA 1 results for tourist arrivals from Canada
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0056643	0.0038282	1.48	0.1390	0
MA1,1	0.92424	0.02609	35.42	<.0001	1
MA2,1	0.58229	0.06110	9.53	<.0001	12
AR1,1	0.29361	0.06513	4.51	<.0001	1
AR2,1	0.96176	0.01525	63.05	<.0001	12

Variance Estimate	0.009354
Std Error Estimate	0.096717
AIC	-505.95
SBC	-487.636
Number of Residuals	288

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	6.69	2	0.0352	-0.028	0.062	0.085	0.088	-0.053	0.021
12	13.14	8	0.1073	-0.029	-0.080	-0.035	-0.078	-0.083	0.008
18	24.71	14	0.0376	-0.040	-0.029	-0.101	-0.094	0.039	0.121
24	31.37	20	0.0505	0.031	0.044	0.054	0.099	0.029	0.068
30	33.47	26	0.1489	0.045	0.016	-0.030	0.047	-0.031	-0.015
36	41.82	32	0.1147	0.056	0.035	-0.092	-0.027	-0.013	-0.108
42	42.70	38	0.2762	0.010	0.017	-0.030	-0.011	0.035	0.002
48	46.92	44	0.3535	0.072	-0.002	0.022	0.033	-0.046	-0.058

Model for variable visit1

Estimated Mean: 0.005664

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.29361 B**(1)
Factor 2: 1 - 0.96176 B**(12)

Moving Average Factors

Factor 1: 1 - 0.92424 B**(1)
Factor 2: 1 - 0.58229 B**(12)

Table 4.4.3b

ARIMA 1 results for tourist arrivals from Canada
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0056060	0.0036436	1.54	0.1239	0
MA1,1	0.92615	0.02510	36.90	<.0001	1
MA2,1	0.57916	0.05984	9.68	<.0001	12
AR1,1	0.29316	0.06353	4.61	<.0001	1
AR2,1	0.96062	0.01531	62.76	<.0001	12

Variance Estimate	0.009213
Std Error Estimate	0.095986
AIC	-530.86
SBC	-512.358
Number of Residuals	299

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.96	2	0.0508	-0.025	0.054	0.081	0.084	-0.048	0.013
12	11.32	8	0.1843	-0.027	-0.075	-0.038	-0.070	-0.067	0.003
18	21.84	14	0.0819	-0.042	-0.019	-0.101	-0.089	0.035	0.107
24	28.93	20	0.0891	0.045	0.052	0.038	0.099	0.034	0.068
30	31.43	26	0.2126	0.046	-0.001	-0.032	0.051	-0.036	-0.022
36	40.35	32	0.1476	0.065	0.046	-0.094	-0.028	-0.011	-0.101
42	41.75	38	0.3109	0.001	0.004	-0.026	-0.012	0.051	0.023
48	46.48	44	0.3705	0.054	-0.008	0.044	0.037	-0.051	-0.067

Model for variable visit1

Estimated Mean: 0.005606

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.29316 B**(1)
Factor 2: 1 - 0.96062 B**(12)

Moving Average Factors

Factor 1: 1 - 0.92615 B**(1)
Factor 2: 1 - 0.57916 B**(12)

Table 4.4.3c

ARIMA 1 results for tourist arrivals from Canada
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0058019	0.0038016	1.53	0.1270	0
MA1,1	0.92585	0.02568	36.05	<.0001	1
MA2,1	0.58219	0.06105	9.54	<.0001	12
AR1,1	0.29720	0.06501	4.57	<.0001	1
AR2,1	0.96222	0.01516	63.47	<.0001	12

Variance Estimate	0.009353
Std Error Estimate	0.096709
AIC	-504.032
SBC	-485.735
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	6.28	2	0.0433	-0.027	0.058	0.086	0.082	-0.052	0.022
12	12.93	8	0.1143	-0.028	-0.082	-0.030	-0.076	-0.089	0.012
18	24.78	14	0.0368	-0.038	-0.028	-0.099	-0.095	0.037	0.128
24	31.41	20	0.0500	0.029	0.043	0.058	0.099	0.032	0.065
30	33.32	26	0.1531	0.042	0.015	-0.031	0.044	-0.032	-0.008
36	42.35	32	0.1043	0.056	0.033	-0.093	-0.028	-0.014	-0.117
42	43.42	38	0.2515	0.013	0.015	-0.032	-0.002	0.041	-0.009
48	47.56	44	0.3299	0.076	0.000	0.024	0.032	-0.041	-0.055

Model for variable visit1

Estimated Mean: 0.005802

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.2972 B**(1)
Factor 2: 1 - 0.96222 B**(12)

Moving Average Factors

Factor 1: 1 - 0.92585 B**(1)
Factor 2: 1 - 0.58219 B**(12)

Table 4.4.4a

ARIMA 1 results for tourist arrivals from China
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.01998	0.03011	0.66	0.5070	0
MA1,1	0.43874	0.05174	8.48	<.0001	1
MA2,1	0.83835	0.04794	17.49	<.0001	12
AR1,1	0.98913	0.0065631	150.71	<.0001	12

Variance Estimate	0.03144
Std Error Estimate	0.177314
AIC	-156.741
SBC	-142.089
Number of Residuals	288

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	8.98	3	0.0296	0.012	-0.001	0.016	-0.171	0.028	-0.010
12	14.84	9	0.0954	0.074	0.099	0.058	-0.025	-0.007	0.015
18	23.25	15	0.0790	-0.060	-0.113	-0.074	0.001	0.054	0.053
24	26.97	21	0.1717	0.043	-0.043	0.004	-0.081	0.034	-0.023
30	28.31	27	0.3952	0.012	0.002	-0.051	0.015	-0.034	0.001
36	33.44	33	0.4460	-0.021	-0.117	-0.026	-0.001	0.025	-0.018
42	38.29	39	0.5019	0.039	0.025	-0.066	0.017	0.022	0.085
48	40.85	45	0.6484	-0.007	-0.027	-0.076	0.024	0.014	0.002

Model for variable visit1

Estimated Mean: 0.019983

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98913 B**(12)

Moving Average Factors

Factor 1: 1 - 0.43874 B**(1)
Factor 2: 1 - 0.83835 B**(12)

Table 4.4.4b

ARIMA 1 results for tourist arrivals from China
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.02038	0.03017	0.68	0.4993	0
MA1,1	0.44257	0.05083	8.71	<.0001	1
MA2,1	0.81991	0.04863	16.86	<.0001	12
AR1,1	0.98714	0.0071778	137.53	<.0001	12

Variance Estimate	0.031143
Std Error Estimate	0.176475
AIC	-166.946
SBC	-152.145
Number of Residuals	299

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	10.03	3	0.0183	0.016	-0.004	0.007	-0.178	0.032	-0.003
12	16.31	9	0.0606	0.085	0.097	0.050	-0.028	-0.015	0.016
18	24.80	15	0.0526	-0.055	-0.117	-0.071	-0.000	0.050	0.052
24	28.50	21	0.1264	0.048	-0.041	0.004	-0.079	0.025	-0.022
30	29.85	27	0.3210	0.013	0.003	-0.047	0.008	-0.039	0.003
36	34.58	33	0.3924	-0.016	-0.111	-0.024	-0.012	0.019	-0.018
42	40.23	39	0.4155	0.045	0.026	-0.068	0.013	0.014	0.093
48	42.49	45	0.5788	-0.004	-0.026	-0.073	0.012	0.010	0.006

Model for variable visit1

Estimated Mean: 0.020382

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98714 B**(12)

Moving Average Factors

Factor 1: 1 - 0.44257 B**(1)
Factor 2: 1 - 0.81991 B**(12)

Table 4.4.4c

ARIMA 1 results for tourist arrivals from China
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.01957	0.03014	0.65	0.5161	0
MA1,1	0.43761	0.05186	8.44	<.0001	1
MA2,1	0.84221	0.04799	17.55	<.0001	12
AR1,1	0.98954	0.0064436	153.57	<.0001	12

Variance Estimate	0.031516
Std Error Estimate	0.177527
AIC	-155.298
SBC	-140.66
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	9.00	3	0.0293	0.012	0.000	0.017	-0.171	0.028	-0.012
12	14.86	9	0.0949	0.074	0.100	0.057	-0.026	-0.006	0.016
18	23.15	15	0.0810	-0.060	-0.112	-0.073	0.001	0.054	0.052
24	26.83	21	0.1766	0.043	-0.042	0.002	-0.080	0.034	-0.023
30	28.19	27	0.4014	0.012	0.003	-0.052	0.015	-0.034	0.001
36	33.27	33	0.4541	-0.021	-0.116	-0.026	-0.001	0.026	-0.018
42	38.14	39	0.5089	0.040	0.025	-0.066	0.018	0.021	0.085
48	40.65	45	0.6567	-0.007	-0.026	-0.076	0.025	0.013	0.003

Model for variable visit1

Estimated Mean: 0.019568

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98954 B**(12)

Moving Average Factors

Factor 1: 1 - 0.43761 B**(1)
Factor 2: 1 - 0.84221 B**(12)

Table 4.4.5a

ARIMA 1 results for tourist arrivals from France
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0047934	0.01128	0.42	0.6709	0
MA1,1	0.80116	0.03513	22.81	<.0001	1
MA2,1	0.60017	0.05275	11.38	<.0001	12
AR1,1	0.98258	0.0067690	145.16	<.0001	12

Variance Estimate	0.010486
Std Error Estimate	0.102403
AIC	-465.995
SBC	-451.343
Number of Residuals	288

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.89	3	0.1171	0.009	-0.019	-0.049	0.091	0.095	-0.000
12	11.13	9	0.2668	-0.004	0.066	-0.054	-0.101	0.001	0.000
18	17.77	15	0.2750	-0.066	0.080	0.050	-0.084	-0.020	-0.030
24	22.05	21	0.3964	-0.011	-0.037	-0.102	-0.018	0.030	0.023
30	32.15	27	0.2264	-0.140	-0.053	-0.028	0.065	-0.042	-0.051
36	37.91	33	0.2553	0.091	-0.042	-0.072	-0.037	0.018	0.025
42	42.42	39	0.3259	-0.082	-0.009	-0.004	-0.074	-0.031	0.009
48	51.29	45	0.2408	0.031	-0.044	0.049	0.106	0.044	-0.085

Model for variable visit1

Estimated Mean: 0.004793

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98258 B**(12)

Moving Average Factors

Factor 1: 1 - 0.80116 B**(1)
Factor 2: 1 - 0.60017 B**(12)

Table 4.4.5b

ARIMA 1 results for tourist arrivals from France
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0042476	0.01116	0.38	0.7036	0
MA1,1	0.80095	0.03462	23.14	<.0001	1
MA2,1	0.59287	0.05184	11.44	<.0001	12
AR1,1	0.98211	0.0067988	144.45	<.0001	12

Variance Estimate	0.010229
Std Error Estimate	0.10114
AIC	-492.383
SBC	-477.582
Number of Residuals	299

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.68	3	0.1284	0.009	-0.019	-0.046	0.088	0.090	0.010
12	11.18	9	0.2635	-0.009	0.062	-0.056	-0.103	0.006	-0.002
18	17.75	15	0.2760	-0.064	0.083	0.049	-0.078	-0.008	-0.034
24	22.57	21	0.3674	-0.011	-0.046	-0.103	-0.020	0.031	0.027
30	32.32	27	0.2204	-0.135	-0.052	-0.027	0.058	-0.043	-0.050
36	38.12	33	0.2479	0.089	-0.042	-0.072	-0.041	0.015	0.021
42	42.75	39	0.3132	-0.083	-0.004	0.000	-0.074	-0.031	0.007
48	51.75	45	0.2272	0.027	-0.038	0.051	0.107	0.040	-0.086

Model for variable visit1

Estimated Mean: 0.004248

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98211 B**(12)

Moving Average Factors

Factor 1: 1 - 0.80095 B**(1)
Factor 2: 1 - 0.59287 B**(12)

Table 4.4.5c

ARIMA 1 results for tourist arrivals from France
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0046669	0.01130	0.41	0.6797	0
MA1,1	0.80122	0.03517	22.78	<.0001	1
MA2,1	0.60229	0.05282	11.40	<.0001	12
AR1,1	0.98276	0.0067257	146.12	<.0001	12

Variance Estimate	0.010514
Std Error Estimate	0.10254
AIC	-463.464
SBC	-448.826
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.84	3	0.1197	0.007	-0.017	-0.048	0.092	0.094	-0.001
12	11.08	9	0.2705	-0.003	0.067	-0.054	-0.101	-0.001	0.000
18	17.60	15	0.2842	-0.065	0.079	0.051	-0.084	-0.018	-0.031
24	21.90	21	0.4051	-0.013	-0.037	-0.103	-0.019	0.029	0.023
30	31.96	27	0.2336	-0.140	-0.053	-0.028	0.064	-0.042	-0.050
36	37.89	33	0.2562	0.092	-0.042	-0.074	-0.038	0.019	0.026
42	42.34	39	0.3287	-0.082	-0.009	-0.005	-0.074	-0.031	0.009
48	51.05	45	0.2479	0.030	-0.043	0.049	0.106	0.041	-0.085

Model for variable visit1

Estimated Mean: 0.004667

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98276 B**(12)

Moving Average Factors

Factor 1: 1 - 0.80122 B**(1)
Factor 2: 1 - 0.60229 B**(12)

Table 4.4.6a

ARIMA 1 results for tourist arrivals from Germany
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0029841	0.0097366	0.31	0.7592	0
MA1,1	0.86121	0.02906	29.63	<.0001	1
MA2,1	0.70491	0.04613	15.28	<.0001	12
AR1,1	0.99444	0.0026124	380.66	<.0001	12

Variance Estimate	0.008789
Std Error Estimate	0.09375
AIC	-507.65
SBC	-492.998
Number of Residuals	288

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	8.17	3	0.0426	0.069	-0.028	0.035	-0.107	0.098	-0.003
12	14.41	9	0.1086	-0.086	-0.070	-0.004	0.080	-0.006	-0.047
18	24.71	15	0.0540	0.144	0.060	-0.061	-0.042	-0.063	0.001
24	26.41	21	0.1912	0.009	0.036	-0.001	0.025	0.007	0.058
30	30.27	27	0.3020	-0.031	-0.043	0.036	-0.075	-0.046	-0.012
36	31.92	33	0.5209	-0.052	0.011	-0.002	0.020	0.007	-0.042
42	39.92	39	0.4288	0.013	-0.139	-0.025	-0.004	0.020	-0.058
48	52.40	45	0.2090	-0.072	-0.020	-0.102	0.022	0.050	-0.131

Model for variable visit1

Estimated Mean: 0.002984

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.99444 B**(12)

Moving Average Factors

Factor 1: 1 - 0.86121 B**(1)
Factor 2: 1 - 0.70491 B**(12)

Table 4.4.6b

ARIMA 1 results for tourist arrivals from Germany
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0031795	0.0087817	0.36	0.7173	0
MA1,1	0.87135	0.02764	31.53	<.0001	1
MA2,1	0.69074	0.04801	14.39	<.0001	12
AR1,1	0.99317	0.0031329	317.01	<.0001	12

Variance Estimate	0.009355
Std Error Estimate	0.096723
AIC	-511.541
SBC	-496.739
Number of Residuals	299

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations----------					
6	9.26	3	0.0260	0.069	-0.026	0.062	-0.123	0.077	0.009
12	15.11	9	0.0878	-0.085	-0.080	-0.004	0.063	0.005	-0.035
18	26.10	15	0.0369	0.141	0.063	-0.074	-0.048	-0.056	0.012
24	27.90	21	0.1430	0.010	0.050	-0.002	-0.001	0.034	0.042
30	31.68	27	0.2441	-0.032	-0.015	-0.008	-0.086	-0.043	-0.026
36	33.39	33	0.4484	-0.036	0.031	-0.001	0.019	-0.012	-0.047
42	41.21	39	0.3741	-0.004	-0.139	-0.004	-0.017	0.026	-0.048
48	52.94	45	0.1946	-0.082	-0.023	-0.097	-0.001	0.030	-0.123

Model for variable visit1

Estimated Mean: 0.00318

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.99317 B**(12)

Moving Average Factors

Factor 1: 1 - 0.87135 B**(1)
Factor 2: 1 - 0.69074 B**(12)

Table 4.4.6c

ARIMA 1 results for tourist arrivals from Germany
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0028922	0.0098470	0.29	0.7690	0
MA1,1	0.86001	0.02936	29.29	<.0001	1
MA2,1	0.70658	0.04610	15.33	<.0001	12
AR1,1	0.99452	0.0025857	384.62	<.0001	12

Variance Estimate	0.008807
Std Error Estimate	0.093847
AIC	-505.085
SBC	-490.447
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	8.26	3	0.0409	0.068	-0.029	0.037	-0.107	0.099	-0.005
12	14.75	9	0.0981	-0.088	-0.071	-0.005	0.083	-0.005	-0.046
18	24.82	15	0.0524	0.142	0.060	-0.062	-0.041	-0.061	-0.003
24	26.67	21	0.1819	0.008	0.036	-0.003	0.030	0.008	0.060
30	30.44	27	0.2946	-0.030	-0.043	0.035	-0.075	-0.046	-0.011
36	32.07	33	0.5130	-0.051	0.012	-0.000	0.018	0.010	-0.043
42	39.82	39	0.4336	0.014	-0.137	-0.024	-0.002	0.022	-0.056
48	52.17	45	0.2151	-0.072	-0.017	-0.100	0.022	0.046	-0.133

Model for variable visit1

Estimated Mean: 0.002892

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.99452 B**(12)

Moving Average Factors

Factor 1: 1 - 0.86001 B**(1)
Factor 2: 1 - 0.70658 B**(12)

Table 4.4.7a

ARIMA 1 results for tourist arrivals from Korea
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0091409	0.02568	0.36	0.7219	0
MA1,1	0.15182	0.05699	2.66	0.0077	1
MA2,1	0.66731	0.05917	11.28	<.0001	12
AR1,1	0.97874	0.01371	71.38	<.0001	12

Variance Estimate	0.005389
Std Error Estimate	0.07341
AIC	-663.353
SBC	-648.701
Number of Residuals	288

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	8.90	3	0.0306	0.012	-0.082	0.000	-0.065	0.048	0.130
12	10.41	9	0.3183	0.051	0.016	0.007	-0.044	0.009	0.014
18	12.30	15	0.6565	-0.040	0.015	0.016	-0.016	0.062	0.008
24	16.18	21	0.7595	-0.080	-0.058	0.045	0.003	-0.023	0.014
30	18.70	27	0.8805	-0.059	-0.023	-0.046	-0.014	0.002	-0.040
36	21.32	33	0.9417	-0.038	0.054	0.012	-0.018	0.008	0.055
42	25.21	39	0.9571	-0.069	0.007	0.050	-0.051	0.016	-0.037
48	28.61	45	0.9729	0.015	-0.056	0.018	-0.026	-0.067	0.031

Model for variable visit1

Estimated Mean: 0.009141

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.97874 B**(12)

Moving Average Factors

Factor 1: 1 - 0.15182 B**(1)
Factor 2: 1 - 0.66731 B**(12)

Table 4.4.7b

ARIMA 1 results for tourist arrivals from Korea
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0074407	0.02671	0.28	0.7806	0
MA1,1	0.16644	0.05558	2.99	0.0027	1
MA2,1	0.66655	0.05685	11.72	<.0001	12
AR1,1	0.98084	0.01292	75.91	<.0001	12

Variance Estimate	0.005375
Std Error Estimate	0.073312
AIC	-689.21
SBC	-674.408
Number of Residuals	299

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	11.81	3	0.0081	0.015	-0.093	0.016	-0.077	0.039	0.149
12	14.07	9	0.1197	0.055	0.015	0.011	-0.060	0.006	0.015
18	15.46	15	0.4189	-0.029	0.010	0.013	-0.013	0.055	0.006
24	18.38	21	0.6250	-0.066	-0.050	0.033	-0.002	-0.027	0.019
30	20.69	27	0.8006	-0.052	-0.029	-0.045	-0.014	-0.008	-0.033
36	22.63	33	0.9128	-0.025	0.050	-0.002	-0.015	0.006	0.048
42	25.33	39	0.9554	-0.056	0.005	0.028	-0.043	0.005	-0.045
48	27.99	45	0.9780	0.026	-0.047	-0.005	-0.020	-0.064	0.002

Model for variable visit1

Estimated Mean: 0.007441

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98084 B**(12)

Moving Average Factors

Factor 1: 1 - 0.16644 B**(1)
Factor 2: 1 - 0.66655 B**(12)

Table 4.4.7c

ARIMA 1 results for tourist arrivals from Korea
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0080335	0.02517	0.32	0.7496	0
MA1,1	0.15816	0.05686	2.78	0.0054	1
MA2,1	0.66616	0.05929	11.24	<.0001	12
AR1,1	0.97820	0.01388	70.46	<.0001	12

Variance Estimate	0.005368
Std Error Estimate	0.073267
AIC	-662.312
SBC	-647.674
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations----------					
6	8.61	3	0.0350	0.014	-0.088	0.007	-0.058	0.052	0.124
12	10.17	9	0.3366	0.052	0.016	0.009	-0.044	0.012	0.013
18	12.26	15	0.6594	-0.049	0.013	0.019	-0.007	0.062	0.003
24	16.19	21	0.7591	-0.082	-0.058	0.045	0.006	-0.022	0.008
30	19.02	27	0.8691	-0.066	-0.023	-0.043	-0.013	0.001	-0.044
36	21.78	33	0.9324	-0.045	0.058	0.012	-0.017	0.007	0.051
42	26.54	39	0.9356	-0.085	0.004	0.050	-0.055	0.015	-0.037
48	31.04	45	0.9437	0.013	-0.056	0.017	-0.034	-0.075	0.052

Model for variable visit1

Estimated Mean: 0.008034

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.9782 B**(12)

Moving Average Factors

Factor 1: 1 - 0.15816 B**(1)
Factor 2: 1 - 0.66616 B**(12)

Table 4.4.8a

ARIMA 1 results for tourist arrivals from Singapore
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0075114	0.02169	0.35	0.7291	0
MA1,1	0.75141	0.03857	19.48	<.0001	1
MA2,1	0.67369	0.04982	13.52	<.0001	12
AR1,1	0.98755	0.0067452	146.41	<.0001	12

Variance Estimate	0.025549
Std Error Estimate	0.159841
AIC	-208.672
SBC	-194.02
Number of Residuals	288

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations----------					
6	7.14	3	0.0677	-0.038	0.084	-0.021	0.016	-0.075	0.097
12	26.32	9	0.0018	0.082	-0.169	0.092	-0.063	0.126	-0.024
18	33.60	15	0.0039	0.123	0.032	-0.086	0.020	-0.001	0.002
24	38.17	21	0.0123	-0.014	0.010	0.028	0.045	0.097	-0.045
30	41.46	27	0.0372	0.044	0.051	0.045	-0.016	-0.056	-0.018
36	54.38	33	0.0110	-0.111	0.028	0.026	0.009	-0.017	0.159
42	59.11	39	0.0204	-0.028	0.007	-0.005	0.041	-0.095	-0.050
48	64.82	45	0.0280	-0.090	-0.051	-0.014	-0.004	0.049	-0.057

Model for variable visit1

Estimated Mean: 0.007511

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98755 B**(12)

Moving Average Factors

Factor 1: 1 - 0.75141 B**(1)
Factor 2: 1 - 0.67369 B**(12)

Table 4.4.8b

ARIMA 1 results for tourist arrivals from Singapore
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.01012	0.02110	0.48	0.6315	0
MA1,1	0.75650	0.03762	20.11	<.0001	1
MA2,1	0.67313	0.04936	13.64	<.0001	12
AR1,1	0.98728	0.0068256	144.64	<.0001	12

Variance Estimate	0.025819
Std Error Estimate	0.160684
AIC	-214.847
SBC	-200.045
Number of Residuals	299

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	6.52	3	0.0890	-0.022	0.085	-0.026	-0.008	-0.087	0.073
12	23.10	9	0.0060	0.080	-0.139	0.103	-0.057	0.112	-0.037
18	29.41	15	0.0142	0.099	0.034	-0.085	0.037	-0.016	-0.019
24	34.86	21	0.0292	-0.022	-0.003	0.010	0.056	0.111	-0.026
30	37.78	27	0.0814	0.047	0.039	0.037	-0.028	-0.049	-0.023
36	51.82	33	0.0197	-0.106	0.040	0.032	0.005	-0.014	0.165
42	55.66	39	0.0407	-0.025	0.010	-0.011	0.021	-0.081	-0.056
48	62.01	45	0.0470	-0.082	-0.041	0.008	-0.015	0.041	-0.086

Model for variable visit1

Estimated Mean: 0.010118

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98728 B**(12)

Moving Average Factors

Factor 1: 1 - 0.7565 B**(1)
Factor 2: 1 - 0.67313 B**(12)

Table 4.4.8c

ARIMA 1 results for tourist arrivals from Singapore
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0081199	0.02125	0.38	0.7024	0
MA1,1	0.75476	0.03825	19.73	<.0001	1
MA2,1	0.66839	0.05053	13.23	<.0001	12
AR1,1	0.98703	0.0069885	141.24	<.0001	12

Variance Estimate	0.025522
Std Error Estimate	0.159758
AIC	-208.376
SBC	-193.739
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	7.44	3	0.0592	-0.034	0.085	-0.028	0.013	-0.078	0.100
12	25.71	9	0.0023	0.081	-0.169	0.092	-0.065	0.115	-0.019
18	33.36	15	0.0042	0.129	0.031	-0.084	0.020	-0.005	0.003
24	38.48	21	0.0113	-0.015	0.008	0.031	0.046	0.101	-0.052
30	41.79	27	0.0345	0.045	0.053	0.043	-0.015	-0.056	-0.017
36	53.59	33	0.0132	-0.106	0.029	0.022	0.014	-0.010	0.152
42	58.08	39	0.0252	-0.025	0.003	-0.006	0.036	-0.093	-0.052
48	63.05	45	0.0390	-0.088	-0.053	-0.017	-0.010	0.032	-0.050

Model for variable visit1

Estimated Mean: 0.00812

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98703 B**(12)

Moving Average Factors

Factor 1: 1 - 0.75476 B**(1)
Factor 2: 1 - 0.66839 B**(12)

Table 4.4.9a

ARIMA 1 results for tourist arrivals from Taiwan
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0096383	0.01701	0.57	0.5709	0
MA1,1	0.67497	0.04302	15.69	<.0001	1
MA2,1	0.72685	0.05564	13.06	<.0001	12
AR1,1	0.97768	0.01229	79.53	<.0001	12

Variance Estimate	0.024372
Std Error Estimate	0.156114
AIC	-231.142
SBC	-216.49
Number of Residuals	288

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.86	3	0.4130	-0.012	0.040	0.050	-0.054	-0.050	0.012
12	10.47	9	0.3136	0.032	-0.092	-0.034	-0.015	0.120	0.007
18	16.49	15	0.3501	0.074	-0.029	-0.063	-0.012	0.012	0.095
24	21.07	21	0.4544	0.057	0.072	-0.036	0.037	0.053	-0.027
30	32.05	27	0.2302	0.097	-0.079	-0.042	-0.121	0.019	0.044
36	45.77	33	0.0688	0.054	-0.019	0.098	-0.055	-0.010	0.160
42	59.23	39	0.0199	-0.171	-0.069	-0.051	0.023	-0.025	0.050
48	68.69	45	0.0130	0.030	-0.083	-0.043	-0.060	-0.015	-0.118

Model for variable visit1

Estimated Mean: 0.009638

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.97768 B**(12)

Moving Average Factors

Factor 1: 1 - 0.67497 B**(1)
Factor 2: 1 - 0.72685 B**(12)

Table 4.4.9b

ARIMA 1 results for tourist arrivals from Taiwan
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.01047	0.01698	0.62	0.5374	0
MA1,1	0.67455	0.04223	15.97	<.0001	1
MA2,1	0.74162	0.05164	14.36	<.0001	12
AR1,1	0.98028	0.01085	90.34	<.0001	12

Variance Estimate	0.023597
Std Error Estimate	0.153614
AIC	-249.797
SBC	-234.996
Number of Residuals	299

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations----------					
6	3.00	3	0.3921	-0.011	0.039	0.050	-0.057	-0.048	0.014
12	10.90	9	0.2827	0.032	-0.091	-0.034	-0.015	0.121	0.003
18	18.06	15	0.2593	0.084	-0.031	-0.079	-0.004	0.009	0.091
24	22.94	21	0.3470	0.067	0.063	-0.043	0.042	0.052	-0.019
30	35.10	27	0.1363	0.093	-0.083	-0.038	-0.130	0.021	0.049
36	49.44	33	0.0329	0.052	-0.011	0.095	-0.057	-0.009	0.164
42	64.24	39	0.0066	-0.175	-0.074	-0.047	0.018	-0.022	0.062
48	74.00	45	0.0042	0.032	-0.077	-0.040	-0.068	-0.019	-0.118

Model for variable visit1

Estimated Mean: 0.01047

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98028 B**(12)

Moving Average Factors

Factor 1: 1 - 0.67455 B**(1)
Factor 2: 1 - 0.74162 B**(12)

Table 4.4.9c

ARIMA 1 results for tourist arrivals from Taiwan
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0094180	0.01708	0.55	0.5812	0
MA1,1	0.67507	0.04307	15.68	<.0001	1
MA2,1	0.72890	0.05568	13.09	<.0001	12
AR1,1	0.97805	0.01221	80.10	<.0001	12

Variance Estimate	0.024434
Std Error Estimate	0.156315
AIC	-229.443
SBC	-214.805
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.78	3	0.4265	-0.012	0.040	0.050	-0.052	-0.049	0.014
12	10.81	9	0.2891	0.032	-0.092	-0.035	-0.015	0.126	0.005
18	16.81	15	0.3304	0.074	-0.028	-0.063	-0.013	0.014	0.095
24	21.32	21	0.4395	0.057	0.072	-0.037	0.038	0.052	-0.024
30	32.23	27	0.2238	0.097	-0.080	-0.039	-0.120	0.021	0.044
36	46.04	33	0.0652	0.053	-0.020	0.096	-0.055	-0.011	0.162
42	59.54	39	0.0186	-0.171	-0.070	-0.052	0.024	-0.027	0.049
48	69.03	45	0.0121	0.027	-0.083	-0.043	-0.058	-0.012	-0.121

Model for variable visit1

Estimated Mean: 0.009418

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.97805 B**(12)

Moving Average Factors

Factor 1: 1 - 0.67507 B**(1)
Factor 2: 1 - 0.7289 B**(12)

Table 4.4.10a

ARIMA 1 results for tourist arrivals from the UK
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0034701	0.01119	0.31	0.7564	0
MA1,1	0.64237	0.04461	14.40	<.0001	1
MA2,1	0.91111	0.06808	13.38	<.0001	12
AR1,1	0.99047	0.01465	67.59	<.0001	12

Variance Estimate	0.028099
Std Error Estimate	0.167628
AIC	-194.016
SBC	-179.365
Number of Residuals	288

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.82	3	0.4196	-0.031	0.004	0.004	0.065	0.030	0.059
12	7.79	9	0.5552	-0.029	0.031	-0.056	0.004	0.093	-0.053
18	12.04	15	0.6763	0.082	0.039	-0.035	-0.003	0.063	0.021
24	15.31	21	0.8072	0.013	-0.079	-0.012	0.011	0.036	0.050
30	22.68	27	0.7022	0.102	0.028	0.062	0.086	-0.022	-0.009
36	43.15	33	0.1111	-0.093	0.005	-0.050	-0.104	-0.070	0.187
42	56.36	39	0.0355	-0.160	-0.109	0.037	-0.001	-0.016	-0.021
48	81.51	45	0.0007	-0.017	-0.054	-0.040	0.069	-0.023	-0.250

Model for variable visit1

Estimated Mean: 0.00347

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.99047 B**(12)

Moving Average Factors

Factor 1: 1 - 0.64237 B**(1)
Factor 2: 1 - 0.91111 B**(12)

Table 4.4.10b

ARIMA 1 results for tourist arrivals from the UK
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0037371	0.01049	0.36	0.7218	0
MA1,1	0.64534	0.04390	14.70	<.0001	1
MA2,1	0.89658	0.06530	13.73	<.0001	12
AR1,1	0.98572	0.01801	54.74	<.0001	12

Variance Estimate	0.028746
Std Error Estimate	0.169545
AIC	-197.577
SBC	-182.775
Number of Residuals	299

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.21	3	0.5295	-0.018	-0.007	-0.006	0.063	0.036	0.040
12	7.93	9	0.5415	-0.028	0.029	-0.077	-0.009	0.087	-0.057
18	14.16	15	0.5134	0.064	0.027	-0.051	-0.046	0.070	0.073
24	18.70	21	0.6041	0.035	-0.076	-0.025	0.012	0.063	0.048
30	25.85	27	0.5269	0.099	0.026	0.052	0.080	-0.042	-0.014
36	42.65	33	0.1212	-0.085	0.012	-0.040	-0.090	-0.053	0.171
42	58.43	39	0.0235	-0.164	-0.122	0.035	-0.010	-0.040	-0.033
48	82.85	45	0.0005	-0.018	-0.019	-0.018	0.081	-0.011	-0.246

Model for variable visit1

Estimated Mean: 0.003737

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98572 B**(12)

Moving Average Factors

Factor 1: 1 - 0.64534 B**(1)
Factor 2: 1 - 0.89658 B**(12)

Table 4.4.10c

ARIMA 1 results for tourist arrivals from the UK
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0032536	0.01128	0.29	0.7730	0
MA1,1	0.64164	0.04483	14.31	<.0001	1
MA2,1	0.90318	0.06896	13.10	<.0001	12
AR1,1	0.98892	0.01592	62.13	<.0001	12

Variance Estimate	0.028205
Std Error Estimate	0.167945
AIC	-192.769
SBC	-178.131
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations----------					
6	2.97	3	0.3961	-0.031	0.003	0.002	0.068	0.032	0.059
12	8.52	9	0.4827	-0.025	0.034	-0.057	0.005	0.105	-0.049
18	12.89	15	0.6105	0.082	0.039	-0.036	-0.003	0.066	0.020
24	16.05	21	0.7667	0.013	-0.077	-0.015	0.012	0.034	0.050
30	23.82	27	0.6403	0.105	0.030	0.064	0.088	-0.023	-0.012
36	44.88	33	0.0813	-0.095	0.007	-0.049	-0.102	-0.072	0.192
42	57.47	39	0.0285	-0.158	-0.103	0.039	0.000	-0.019	-0.025
48	83.63	45	0.0004	-0.017	-0.052	-0.042	0.068	-0.017	-0.257

Model for variable visit1

Estimated Mean: 0.003254

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.98892 B**(12)

Moving Average Factors

Factor 1: 1 - 0.64164 B**(1)
Factor 2: 1 - 0.90318 B**(12)

Table 4.4.11a

ARIMA 1 results for tourist arrivals from the USA
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0008926	0.01116	-0.08	0.9362	0
MA1,1	0.86549	0.04672	18.53	<.0001	1
MA2,1	0.22370	0.06456	3.47	0.0005	12
AR1,1	0.49348	0.07911	6.24	<.0001	1
AR2,1	0.96836	0.01166	83.05	<.0001	12

Variance Estimate	0.003216
Std Error Estimate	0.056712
AIC	-802.404
SBC	-784.089
Number of Residuals	288

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations----------					
6	11.07	2	0.0039	-0.050	0.092	0.087	-0.116	0.048	0.060
12	15.96	8	0.0429	-0.108	-0.018	-0.019	-0.061	0.018	-0.006
18	30.21	14	0.0071	-0.074	0.153	0.002	-0.042	0.112	0.057
24	46.36	20	0.0007	-0.022	0.122	0.031	-0.072	0.172	-0.015
30	55.97	26	0.0006	0.042	0.034	-0.158	0.005	0.040	-0.026
36	74.16	32	<.0001	0.022	0.171	-0.074	0.033	0.056	-0.127
42	85.99	38	<.0001	0.072	-0.031	-0.132	0.029	-0.104	-0.009
48	90.03	44	<.0001	-0.016	-0.047	-0.039	0.080	0.036	0.002

Model for variable visit1

Estimated Mean: -0.00089

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.49348 B**(1)
Factor 2: 1 - 0.96836 B**(12)

Moving Average Factors

Factor 1: 1 - 0.86549 B**(1)
Factor 2: 1 - 0.2237 B**(12)

Table 4.4.11b

ARIMA 1 results for tourist arrivals from the USA
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0016035	0.01082	0.15	0.8821	0
MA1,1	0.86980	0.04368	19.91	<.0001	1
MA2,1	0.33717	0.05814	5.80	<.0001	12
AR1,1	0.50278	0.07517	6.69	<.0001	1
AR2,1	0.97439	0.0096951	100.50	<.0001	12

Variance Estimate	0.003301
Std Error Estimate	0.057459
AIC	-826.832
SBC	-808.33
Number of Residuals	299

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	11.63	2	0.0030	-0.056	0.112	0.075	-0.118	0.020	0.051
12	16.16	8	0.0401	-0.068	-0.030	0.025	-0.090	0.019	0.006
18	30.76	14	0.0060	-0.081	0.142	0.015	-0.063	0.115	0.046
24	47.91	20	0.0004	-0.041	0.125	0.035	-0.073	0.169	-0.015
30	56.66	26	0.0005	0.029	0.041	-0.151	0.007	0.029	-0.018
36	75.36	32	<.0001	0.006	0.159	-0.084	0.015	0.076	-0.129
42	86.02	38	<.0001	0.072	-0.034	-0.121	0.030	-0.094	-0.012
48	89.31	44	<.0001	-0.012	-0.052	-0.027	0.060	0.034	-0.031

Model for variable visit1

Estimated Mean: 0.001604

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.50278 B**(1)
Factor 2: 1 - 0.97439 B**(12)

Moving Average Factors

Factor 1: 1 - 0.8698 B**(1)
Factor 2: 1 - 0.33717 B**(12)

Table 4.4.11c

ARIMA 1 results for tourist arrivals from the USA
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0008624	0.01114	-0.08	0.9383	0
MA1,1	0.86612	0.04790	18.08	<.0001	1
MA2,1	0.22356	0.06469	3.46	0.0005	12
AR1,1	0.49444	0.08095	6.11	<.0001	1
AR2,1	0.96827	0.01170	82.77	<.0001	12

Variance Estimate	0.003228
Std Error Estimate	0.056815
AIC	-798.488
SBC	-780.191
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	11.07	2	0.0039	-0.050	0.092	0.087	-0.116	0.048	0.060
12	15.92	8	0.0436	-0.108	-0.018	-0.018	-0.061	0.018	-0.006
18	30.10	14	0.0074	-0.074	0.153	0.002	-0.042	0.112	0.058
24	46.21	20	0.0008	-0.022	0.122	0.031	-0.072	0.172	-0.015
30	55.79	26	0.0006	0.042	0.034	-0.158	0.005	0.040	-0.026
36	73.93	32	<.0001	0.022	0.171	-0.074	0.033	0.056	-0.127
42	85.71	38	<.0001	0.072	-0.031	-0.132	0.029	-0.104	-0.009
48	89.71	44	<.0001	-0.016	-0.047	-0.039	0.079	0.037	0.002

Model for variable visit1

Estimated Mean: -0.00086

Period(s) of Differencing: 1

Autoregressive Factors

Factor 1: 1 - 0.49444 B**(1)
Factor 2: 1 - 0.96827 B**(12)

Moving Average Factors

Factor 1: 1 - 0.86612 B**(1)
Factor 2: 1 - 0.22356 B**(12)

Table 4.5.1a

ARIMA 1&12 results for tourist arrivals from all countries
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0002935	0.0005839	-0.50	0.6151	0
MA1,1	0.60261	0.04814	12.52	<.0001	1
MA2,1	0.65105	0.05182	12.56	<.0001	12

Variance Estimate	0.00415
Std Error Estimate	0.064424
AIC	-720.421
SBC	-709.56
Number of Residuals	276

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.72	4	0.2207	-0.053	0.071	0.030	0.004	-0.033	0.102
12	17.72	10	0.0599	-0.078	-0.014	-0.051	-0.104	0.146	0.022
18	23.52	16	0.1004	0.003	0.078	-0.097	0.010	0.057	0.032
24	27.01	22	0.2110	-0.018	-0.030	-0.056	0.044	0.050	-0.052
30	38.66	28	0.0865	0.127	-0.104	-0.095	-0.019	-0.008	0.037
36	42.93	34	0.1402	-0.043	-0.011	-0.007	-0.042	0.011	0.098
42	50.85	40	0.1168	-0.064	-0.074	-0.098	-0.061	0.040	-0.007
48	61.33	46	0.0647	0.013	-0.063	-0.125	-0.014	0.051	-0.095

Model for variable visit1

Estimated Mean: -0.00029

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.60261 B**(1)
Factor 2: 1 - 0.65105 B**(12)

Table 4.5.1b

ARIMA 1&12 results for tourist arrivals from all countries
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0002047	0.0005619	-0.36	0.7157	0
MA1,1	0.59588	0.04733	12.59	<.0001	1
MA2,1	0.66048	0.04878	13.54	<.0001	12

Variance Estimate	0.004069
Std Error Estimate	0.063786
AIC	-754.997
SBC	-744.019
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	6.20	4	0.1846	-0.050	0.078	0.028	-0.014	-0.042	0.099
12	19.24	10	0.0373	-0.083	-0.019	-0.060	-0.098	0.152	0.008
18	26.98	16	0.0417	0.013	0.096	-0.109	0.007	0.060	0.021
24	30.66	22	0.1034	-0.011	-0.026	-0.065	0.047	0.053	-0.041
30	43.37	28	0.0321	0.133	-0.104	-0.094	-0.027	-0.014	0.041
36	48.62	34	0.0498	-0.044	-0.003	-0.008	-0.038	0.016	0.111
42	56.69	40	0.0420	-0.063	-0.072	-0.098	-0.064	0.037	0.005
48	67.85	46	0.0197	0.019	-0.058	-0.128	-0.014	0.046	-0.101

Model for variable visit1

Estimated Mean: -0.0002

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.59588 B**(1)
Factor 2: 1 - 0.66048 B**(12)

Table 4.5.1c

ARIMA 1&12 results for tourist arrivals from all countries
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0003232	0.0005787	-0.56	0.5765	0
MA1,1	0.60402	0.04807	12.57	<.0001	1
MA2,1	0.65430	0.05176	12.64	<.0001	12

Variance Estimate	0.004156
Std Error Estimate	0.064467
AIC	-717.322
SBC	-706.471
Number of Residuals	275

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations----------6					
5.96	4	0.2021	-0.056	0.073	0.033	0.007	-0.031	0.103	
12	18.83	10	0.0425	-0.078	-0.013	-0.052	-0.105	0.156	0.020
18	24.69	16	0.0754	0.001	0.077	-0.097	0.010	0.060	0.031
24	28.22	22	0.1686	-0.019	-0.029	-0.061	0.046	0.047	-0.050
30	39.67	28	0.0707	0.126	-0.105	-0.094	-0.019	-0.007	0.037
36	44.18	34	0.1134	-0.046	-0.013	-0.009	-0.041	0.007	0.101
42	52.08	40	0.0956	-0.066	-0.073	-0.099	-0.059	0.037	-0.009
48	62.55	46	0.0525	0.010	-0.062	-0.124	-0.012	0.055	-0.094

Model for variable visit1

Estimated Mean: -0.00032

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.60402 B**(1)
Factor 2: 1 - 0.6543 B**(12)

Table 4.5.2a

ARIMA 1&12 results for tourist arrivals from Australia
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0004997	0.0010004	0.50	0.6175	0
MA1,1	0.65375	0.04576	14.29	<.0001	1
MA2,1	0.66445	0.05001	13.29	<.0001	12

Variance Estimate	0.017131
Std Error Estimate	0.130884
AIC	-328.666
SBC	-317.805
Number of Residuals	276

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	7.86	4	0.0968	0.001	-0.089	0.113	0.038	-0.048	0.059
12	10.60	10	0.3897	0.034	-0.074	0.012	-0.030	0.040	0.015
18	19.98	16	0.2212	0.110	-0.024	-0.037	0.051	-0.033	-0.119
24	28.10	22	0.1724	0.077	0.017	-0.099	0.070	0.077	0.011
30	33.39	28	0.2217	-0.060	-0.052	-0.013	-0.030	-0.098	0.009
36	40.91	34	0.1932	-0.004	-0.127	0.024	-0.018	-0.019	0.080
42	44.60	40	0.2846	-0.072	0.053	-0.008	-0.050	0.010	0.028
48	45.72	46	0.4839	0.026	0.011	-0.030	-0.034	0.021	0.006

Model for variable visit1

Estimated Mean: 0.0005

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.65375 B**(1)
Factor 2: 1 - 0.66445 B**(12)

Table 4.5.2b

ARIMA 1&12 results for tourist arrivals from Australia
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0004273	0.0009575	0.45	0.6554	0
MA1,1	0.65465	0.04475	14.63	<.0001	1
MA2,1	0.66498	0.04851	13.71	<.0001	12

Variance Estimate	0.016571
Std Error Estimate	0.128729
AIC	-351.699
SBC	-340.72
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	7.65	4	0.1052	0.002	-0.087	0.110	0.033	-0.045	0.058
12	10.44	10	0.4029	0.038	-0.074	0.008	-0.027	0.037	0.016
18	20.35	16	0.2048	0.114	-0.023	-0.037	0.051	-0.032	-0.118
24	29.12	22	0.1415	0.082	0.018	-0.103	0.073	0.072	0.009
30	34.41	28	0.1878	-0.051	-0.056	-0.014	-0.025	-0.099	0.010
36	42.17	34	0.1586	-0.006	-0.126	0.024	-0.018	-0.016	0.083
42	46.48	40	0.2228	-0.074	0.056	-0.009	-0.057	0.015	0.028
48	47.76	46	0.4013	0.027	0.014	-0.033	-0.034	0.021	0.007

Model for variable visit1

Estimated Mean: 0.000427

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.65465 B**(1)
Factor 2: 1 - 0.66498 B**(12)

Table 4.5.2c

ARIMA 1&12 results for tourist arrivals from Australia
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0004461	0.0010009	0.45	0.6558	0
MA1,1	0.65439	0.04573	14.31	<.0001	1
MA2,1	0.66469	0.05002	13.29	<.0001	12

Variance Estimate	0.017154
Std Error Estimate	0.130974
AIC	-327.052
SBC	-316.202
Number of Residuals	275

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations----------					
6	7.84	4	0.0977	-0.002	-0.087	0.115	0.039	-0.048	0.058
12	10.59	10	0.3904	0.037	-0.073	0.011	-0.028	0.042	0.016
18	20.21	16	0.2108	0.109	-0.023	-0.037	0.053	-0.032	-0.123
24	28.59	22	0.1571	0.075	0.019	-0.102	0.074	0.077	0.011
30	33.72	28	0.2101	-0.057	-0.050	-0.014	-0.032	-0.098	0.010
36	41.40	34	0.1791	-0.004	-0.128	0.026	-0.018	-0.019	0.080
42	45.31	40	0.2602	-0.076	0.055	-0.005	-0.049	0.010	0.028
48	46.46	46	0.4534	0.027	0.014	-0.032	-0.034	0.020	0.004

Model for variable visit1

Estimated Mean: 0.000446

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.65439 B**(1)
Factor 2: 1 - 0.66469 B**(12)

Table 4.5.3a

ARIMA 1&12 results for tourist arrivals from Canada
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0000556	0.0003004	-0.19	0.8531	0
MA1,1	0.91502	0.03111	29.41	<.0001	1
MA2,1	0.61975	0.05363	11.56	<.0001	12
AR1,1	0.29653	0.06856	4.32	<.0001	1

Variance Estimate	0.009538
Std Error Estimate	0.097663
AIC	-491.098
SBC	-476.602
Number of Residuals	277

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.51	3	0.1382	-0.029	0.065	0.057	0.084	-0.061	0.022
12	12.05	9	0.2106	-0.020	-0.067	-0.076	-0.052	-0.080	0.053
18	25.76	15	0.0406	-0.021	0.005	-0.141	-0.104	0.039	0.116
24	33.42	21	0.0418	0.025	0.036	-0.009	0.088	0.006	0.124
30	39.56	27	0.0563	0.033	0.056	-0.097	0.062	-0.046	0.017
36	50.62	33	0.0256	0.066	0.057	-0.132	-0.019	-0.022	-0.094
42	54.28	39	0.0528	0.017	0.053	-0.085	-0.005	0.024	0.016
48	58.37	45	0.0871	0.044	0.024	0.002	0.033	-0.031	-0.087

Model for variable visit1

Estimated Mean: -0.00006

Period(s) of Differencing: 1,12

Autoregressive Factors

Factor 1: 1 - 0.29653 B**(1)

Moving Average Factors

Factor 1: 1 - 0.91502 B**(1)
Factor 2: 1 - 0.61975 B**(12)

Table 4.5.3b

ARIMA 1&12 results for tourist arrivals from Canada
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0000855	0.0002890	-0.30	0.7673	0
MA1,1	0.91633	0.03024	30.30	<.0001	1
MA2,1	0.61797	0.05198	11.89	<.0001	12
AR1,1	0.29905	0.06676	4.48	<.0001	1

Variance Estimate	0.009361
Std Error Estimate	0.096754
AIC	-514.64
SBC	-500.002
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	4.56	3	0.2069	-0.025	0.049	0.059	0.080	-0.049	0.018
12	10.56	9	0.3068	-0.021	-0.065	-0.074	-0.051	-0.065	0.056
18	24.42	15	0.0583	-0.026	0.012	-0.143	-0.104	0.038	0.108
24	32.04	21	0.0580	0.030	0.047	-0.024	0.081	0.013	0.118
30	38.56	27	0.0695	0.040	0.045	-0.098	0.069	-0.047	0.011
36	49.72	33	0.0310	0.067	0.066	-0.130	-0.019	-0.016	-0.089
42	52.99	39	0.0668	0.019	0.036	-0.079	-0.004	0.030	0.030
48	58.10	45	0.0910	0.039	0.012	0.026	0.032	-0.037	-0.100

Model for variable visit1

Estimated Mean: -0.00009

Period(s) of Differencing: 1,12

Autoregressive Factors

Factor 1: 1 - 0.29905 B**(1)

Moving Average Factors

Factor 1: 1 - 0.91633 B**(1)
Factor 2: 1 - 0.61797 B**(12)

Table 4.5.3c

ARIMA 1&12 results for tourist arrivals from Canada
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0000651	0.0003038	-0.21	0.8303	0
MA1,1	0.91580	0.03119	29.36	<.0001	1
MA2,1	0.61660	0.05369	11.48	<.0001	12
AR1,1	0.30403	0.06857	4.43	<.0001	1

Variance Estimate	0.009495
Std Error Estimate	0.097444
AIC	-488.781
SBC	-474.314
Number of Residuals	275

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	4.76	3	0.1906	-0.027	0.053	0.065	0.078	-0.051	0.023
12	12.04	9	0.2111	-0.019	-0.073	-0.065	-0.057	-0.089	0.066
18	26.83	15	0.0302	-0.024	0.003	-0.140	-0.109	0.038	0.129
24	33.20	21	0.0441	0.013	0.036	-0.003	0.081	0.011	0.114
30	39.61	27	0.0557	0.035	0.061	-0.098	0.062	-0.043	0.025
36	50.68	33	0.0253	0.058	0.054	-0.131	-0.019	-0.017	-0.105
42	54.20	39	0.0535	0.034	0.046	-0.085	0.009	0.018	-0.008
48	59.32	45	0.0746	0.070	0.019	0.001	0.028	-0.020	-0.095

Model for variable visit1

Estimated Mean: -0.00007

Period(s) of Differencing: 1,12

Autoregressive Factors

Factor 1: 1 - 0.30403 B**(1)

Moving Average Factors

Factor 1: 1 - 0.9158 B**(1)
Factor 2: 1 - 0.6166 B**(12)

Table 4.5.4a

ARIMA 1&12 results for tourist arrivals from China
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0017290	0.0013028	-1.33	0.1845	0
MA1,1	0.44751	0.05364	8.34	<.0001	1
MA2,1	0.82644	0.04926	16.78	<.0001	12

Variance Estimate	0.031557
Std Error Estimate	0.177642
AIC	-153.601
SBC	-142.74
Number of Residuals	276

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	13.23	4	0.0102	0.003	0.037	0.024	-0.154	0.051	-0.136
12	42.27	10	<.0001	0.080	0.001	0.069	0.006	-0.046	0.294
18	53.67	16	<.0001	-0.083	-0.099	-0.021	-0.084	0.055	-0.108
24	61.55	22	<.0001	0.044	-0.063	0.070	-0.035	-0.001	0.118
30	67.97	28	<.0001	-0.054	-0.001	-0.070	-0.023	-0.003	-0.111
36	78.83	34	<.0001	0.018	-0.124	0.092	0.015	-0.014	0.098
42	82.89	40	<.0001	0.000	0.045	-0.091	0.001	0.030	-0.036
48	87.39	46	0.0002	0.020	-0.064	0.003	0.016	-0.021	0.091

Model for variable visit1

Estimated Mean: -0.00173

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.44751 B**(1)
Factor 2: 1 - 0.82644 B**(12)

Table 4.5.4b

ARIMA 1&12 results for tourist arrivals from China
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0016447	0.0013388	-1.23	0.2193	0
MA1,1	0.44975	0.05265	8.54	<.0001	1
MA2,1	0.80886	0.04979	16.25	<.0001	12

Variance Estimate	0.03128
Std Error Estimate	0.17686
AIC	-163.97
SBC	-152.992
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	13.66	4	0.0085	0.006	0.034	0.015	-0.161	0.055	-0.127
12	42.86	10	<.0001	0.090	0.004	0.061	0.005	-0.053	0.287
18	54.08	16	<.0001	-0.076	-0.101	-0.018	-0.082	0.052	-0.104
24	61.72	22	<.0001	0.048	-0.059	0.068	-0.034	-0.009	0.113
30	67.58	28	<.0001	-0.050	0.002	-0.065	-0.028	-0.009	-0.104
36	77.63	34	<.0001	0.022	-0.116	0.090	0.005	-0.018	0.091
42	81.51	40	0.0001	0.009	0.046	-0.091	-0.001	0.022	-0.023
48	85.83	46	0.0003	0.022	-0.060	0.002	0.004	-0.023	0.089

Model for variable visit1

Estimated Mean: -0.00164

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.44975 B**(1)
Factor 2: 1 - 0.80886 B**(12)

Table 4.5.4c

ARIMA 1&12 results for tourist arrivals from China
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0017723	0.0012910	-1.37	0.1698	0
MA1,1	0.44709	0.05371	8.32	<.0001	1
MA2,1	0.83020	0.04969	16.71	<.0001	12

Variance Estimate	0.031619
Std Error Estimate	0.177818
AIC	-152.202
SBC	-141.352
Number of Residuals	275

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	13.40	4	0.0095	0.002	0.038	0.024	-0.155	0.051	-0.138
12	42.56	10	<.0001	0.080	0.002	0.068	0.006	-0.046	0.296
18	54.05	16	<.0001	-0.083	-0.098	-0.020	-0.085	0.056	-0.109
24	61.93	22	<.0001	0.044	-0.063	0.069	-0.035	-0.002	0.119
30	68.46	28	<.0001	-0.055	-0.000	-0.070	-0.023	-0.004	-0.113
36	79.30	34	<.0001	0.018	-0.124	0.093	0.015	-0.014	0.098
42	83.40	40	<.0001	0.000	0.045	-0.091	0.002	0.030	-0.038
48	88.03	46	0.0002	0.020	-0.064	0.004	0.017	-0.023	0.093

Model for variable visit1

Estimated Mean: -0.00177

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.44709 B**(1)
Factor 2: 1 - 0.8302 B**(12)

Table 4.5.5a

ARIMA 1&12 results for tourist arrivals from France
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0001224	0.0005256	0.23	0.8158	0
MA1,1	0.79635	0.03708	21.48	<.0001	1
MA2,1	0.61443	0.05287	11.62	<.0001	12

Variance Estimate	0.010548
Std Error Estimate	0.102705
AIC	-463.28
SBC	-452.419
Number of Residuals	276

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	6.10	4	0.1919	-0.010	-0.045	-0.036	0.087	0.088	-0.054
12	13.10	10	0.2183	0.021	0.097	-0.023	-0.096	0.002	0.069
18	21.52	16	0.1593	-0.063	0.084	0.049	-0.078	-0.022	-0.093
24	27.95	22	0.1772	-0.014	-0.032	-0.119	-0.043	0.000	0.064
30	40.47	28	0.0601	-0.147	-0.070	-0.048	0.043	-0.040	-0.092
36	48.25	34	0.0536	0.109	-0.044	-0.080	-0.046	0.013	0.048
42	52.84	40	0.0840	-0.070	0.003	-0.002	-0.075	-0.059	-0.007
48	62.70	46	0.0511	0.051	-0.069	0.028	0.117	0.056	-0.069

Model for variable visit1

Estimated Mean: 0.000122

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.79635 B**(1)
Factor 2: 1 - 0.61443 B**(12)

Table 4.5.5b

ARIMA 1&12 results for tourist arrivals from France
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.00005719	0.0005169	0.11	0.9119	0
MA1,1	0.79623	0.03646	21.84	<.0001	1
MA2,1	0.60659	0.05194	11.68	<.0001	12

Variance Estimate	0.010295
Std Error Estimate	0.101463
AIC	-489.304
SBC	-478.326
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.58	4	0.2325	-0.009	-0.045	-0.034	0.084	0.084	-0.041
12	12.70	10	0.2410	0.016	0.092	-0.027	-0.099	0.007	0.067
18	21.03	16	0.1774	-0.061	0.085	0.046	-0.070	-0.010	-0.096
24	28.23	22	0.1682	-0.013	-0.043	-0.121	-0.044	0.002	0.067
30	40.36	28	0.0615	-0.142	-0.069	-0.047	0.036	-0.041	-0.089
36	48.17	34	0.0544	0.106	-0.044	-0.080	-0.050	0.011	0.042
42	52.87	40	0.0836	-0.072	0.008	0.003	-0.073	-0.059	-0.009
48	62.63	46	0.0518	0.047	-0.062	0.031	0.117	0.051	-0.070

Model for variable visit1

Estimated Mean: 0.000057

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.79623 B**(1)
Factor 2: 1 - 0.60659 B**(12)

Table 4.5.5c

ARIMA 1&12 results for tourist arrivals from France
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.0001044	0.0005247	0.20	0.8422	0
MA1,1	0.79644	0.03713	21.45	<.0001	1
MA2,1	0.61647	0.05296	11.64	<.0001	12

Variance Estimate	0.010576
Std Error Estimate	0.102839
AIC	-460.798
SBC	-449.948
Number of Residuals	275

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	6.08	4	0.1933	-0.013	-0.043	-0.034	0.088	0.087	-0.054
12	13.10	10	0.2181	0.022	0.098	-0.023	-0.095	-0.001	0.068
18	21.44	16	0.1623	-0.061	0.083	0.050	-0.078	-0.021	-0.094
24	27.89	22	0.1794	-0.016	-0.032	-0.119	-0.044	-0.000	0.064
30	40.36	28	0.0614	-0.148	-0.069	-0.048	0.042	-0.040	-0.091
36	48.36	34	0.0524	0.110	-0.044	-0.082	-0.047	0.014	0.049
42	52.90	40	0.0832	-0.070	0.003	-0.003	-0.074	-0.059	-0.007
48	62.54	46	0.0526	0.051	-0.067	0.028	0.117	0.053	-0.068

Model for variable visit1

Estimated Mean: 0.000104

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.79644 B**(1)
Factor 2: 1 - 0.61647 B**(12)

Table 4.5.6a

ARIMA 1&12 results for tourist arrivals from Germany
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0000804	0.0002713	-0.30	0.7670	0
MA1,1	0.85318	0.03174	26.88	<.0001	1
MA2,1	0.71289	0.04754	14.99	<.0001	12

Variance Estimate	0.008777
Std Error Estimate	0.093688
AIC	-510.74
SBC	-499.878
Number of Residuals	276

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	8.41	4	0.0776	0.061	-0.030	0.021	-0.119	0.103	-0.011
12	16.48	10	0.0866	-0.087	-0.091	-0.033	0.100	0.024	-0.026
18	27.80	16	0.0334	0.156	0.027	-0.077	-0.049	-0.067	0.030
24	31.12	22	0.0936	0.006	0.023	-0.021	0.014	0.031	0.094
30	33.93	28	0.2033	-0.003	-0.057	0.004	-0.067	-0.031	-0.017
36	35.60	34	0.3930	-0.048	-0.007	-0.020	0.026	0.025	-0.036
42	42.67	40	0.3572	0.033	-0.131	-0.035	-0.009	0.021	-0.045
48	55.56	46	0.1578	-0.065	-0.011	-0.108	0.049	0.076	-0.120

Model for variable visit1

Estimated Mean: -0.00008

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.85318 B**(1)
Factor 2: 1 - 0.71289 B**(12)

Table 4.5.6b

ARIMA 1&12 results for tourist arrivals from Germany
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0000585	0.0002645	-0.22	0.8249	0
MA1,1	0.86317	0.03024	28.54	<.0001	1
MA2,1	0.70043	0.04928	14.21	<.0001	12

Variance Estimate	0.009352
Std Error Estimate	0.096707
AIC	-513.731
SBC	-502.752
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	9.41	4	0.0516	0.061	-0.028	0.050	-0.137	0.081	0.004
12	17.36	10	0.0667	-0.087	-0.102	-0.031	0.080	0.034	-0.014
18	29.69	16	0.0197	0.153	0.030	-0.090	-0.056	-0.058	0.041
24	33.24	22	0.0586	0.008	0.037	-0.022	-0.012	0.058	0.076
30	36.53	28	0.1297	-0.005	-0.027	-0.040	-0.079	-0.027	-0.031
36	37.79	34	0.3002	-0.031	0.014	-0.018	0.025	0.004	-0.041
42	44.47	40	0.2892	0.014	-0.132	-0.012	-0.021	0.028	-0.032
48	55.68	46	0.1553	-0.077	-0.017	-0.103	0.024	0.054	-0.111

Model for variable visit1

Estimated Mean: -0.00006

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.86317 B**(1)
Factor 2: 1 - 0.70043 B**(12)

Table 4.5.6c

ARIMA 1&12 results for tourist arrivals from Germany
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0000930	0.0002737	-0.34	0.7340	0
MA1,1	0.85190	0.03206	26.58	<.0001	1
MA2,1	0.71478	0.04756	15.03	<.0001	12

Variance Estimate	0.008794
Std Error Estimate	0.093775
AIC	-508.273
SBC	-497.423
Number of Residuals	275

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	8.51	4	0.0747	0.060	-0.031	0.024	-0.119	0.104	-0.013
12	17.01	10	0.0742	-0.089	-0.093	-0.034	0.104	0.026	-0.025
18	27.95	16	0.0320	0.154	0.027	-0.077	-0.048	-0.064	0.026
24	31.52	22	0.0860	0.005	0.022	-0.024	0.020	0.033	0.096
30	34.27	28	0.1921	-0.002	-0.057	0.003	-0.067	-0.031	-0.016
36	35.93	34	0.3781	-0.047	-0.006	-0.017	0.024	0.028	-0.037
42	42.74	40	0.3544	0.034	-0.128	-0.035	-0.007	0.023	-0.042
48	55.43	46	0.1606	-0.065	-0.008	-0.106	0.050	0.071	-0.123

Model for variable visit1

Estimated Mean: -0.00009

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.8519 B**(1)
Factor 2: 1 - 0.71478 B**(12)

Table 4.5.7a

ARIMA 1&12 results for tourist arrivals from Korea
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0000895	0.0013388	-0.07	0.9467	0
MA1,1	0.13268	0.05946	2.23	0.0256	1
MA2,1	0.68266	0.05054	13.51	<.0001	12

Variance Estimate	0.00543
Std Error Estimate	0.073691
AIC	-645.761
SBC	-634.9
Number of Residuals	276

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations----------					
6	8.47	4	0.0758	0.010	-0.078	-0.011	-0.055	0.047	0.136
12	10.06	10	0.4351	0.052	0.023	-0.009	-0.040	0.025	-0.004
18	11.84	16	0.7550	-0.030	0.024	-0.004	-0.008	0.066	0.013
24	14.59	22	0.8791	-0.077	-0.051	0.024	0.006	-0.005	-0.001
30	17.45	28	0.9392	-0.050	-0.013	-0.078	0.002	0.002	-0.024
36	19.92	34	0.9738	-0.016	0.064	-0.019	-0.033	0.021	0.039
42	21.40	40	0.9930	-0.041	0.004	0.015	-0.047	0.011	-0.018
48	23.58	46	0.9975	0.012	-0.063	0.006	-0.020	-0.045	-0.003

Model for variable visit1

Estimated Mean: -0.00009

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.13268 B**(1)
Factor 2: 1 - 0.68266 B**(12)

Table 4.5.7b

ARIMA 1&12 results for tourist arrivals from Korea
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0002649	0.0013019	-0.20	0.8388	0
MA1,1	0.14726	0.05803	2.54	0.0112	1
MA2,1	0.67725	0.04933	13.73	<.0001	12

Variance Estimate	0.005408
Std Error Estimate	0.07354
AIC	-673.255
SBC	-662.277
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	10.90	4	0.0277	0.012	-0.088	0.005	-0.070	0.040	0.151
12	13.03	10	0.2219	0.056	0.021	-0.003	-0.055	0.021	-0.005
18	14.49	16	0.5622	-0.022	0.022	-0.005	-0.007	0.060	0.009
24	16.50	22	0.7901	-0.066	-0.043	0.014	0.002	-0.010	0.002
30	19.21	28	0.8914	-0.045	-0.019	-0.075	0.000	-0.006	-0.021
36	21.50	34	0.9527	-0.006	0.062	-0.031	-0.029	0.018	0.031
42	22.74	40	0.9872	-0.031	0.005	-0.006	-0.042	0.003	-0.030
48	24.85	46	0.9954	0.022	-0.051	-0.016	-0.014	-0.042	-0.028

Model for variable visit1

Estimated Mean: -0.00026

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.14726 B**(1)
Factor 2: 1 - 0.67725 B**(12)

Table 4.5.7c

ARIMA 1&12 results for tourist arrivals from Korea
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0002183	0.0013269	-0.16	0.8693	0
MA1,1	0.13871	0.05936	2.34	0.0194	1
MA2,1	0.68292	0.05041	13.55	<.0001	12

Variance Estimate	0.00541
Std Error Estimate	0.073552
AIC	-644.412
SBC	-633.562
Number of Residuals	275

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	8.32	4	0.0805	0.011	-0.085	-0.005	-0.049	0.052	0.131
12	9.96	10	0.4438	0.054	0.022	-0.007	-0.040	0.027	-0.004
18	11.88	16	0.7521	-0.039	0.022	-0.001	-0.001	0.067	0.010
24	14.76	22	0.8725	-0.080	-0.051	0.024	0.010	-0.004	-0.006
30	17.79	28	0.9314	-0.058	-0.014	-0.075	0.003	0.002	-0.027
36	20.34	34	0.9691	-0.022	0.068	-0.019	-0.032	0.020	0.035
42	22.45	40	0.9887	-0.056	0.000	0.014	-0.053	0.010	-0.016
48	25.08	46	0.9949	0.009	-0.063	0.005	-0.027	-0.054	0.017

Model for variable visit1

Estimated Mean: -0.00022

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.13871 B**(1)
Factor 2: 1 - 0.68292 B**(12)

Table 4.5.8a

ARIMA 1&12 results for tourist arrivals from Singapore
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0007641	0.0008376	-0.91	0.3617	0
MA1,1	0.74818	0.04046	18.49	<.0001	1
MA2,1	0.68807	0.04797	14.34	<.0001	12

Variance Estimate	0.025516
Std Error Estimate	0.159736
AIC	-217.699
SBC	-206.838
Number of Residuals	276

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	6.83	4	0.1453	-0.059	0.082	-0.018	0.019	-0.088	0.075
12	27.58	10	0.0021	0.075	-0.174	0.111	-0.047	0.144	-0.031
18	34.86	16	0.0041	0.126	0.036	-0.076	0.032	-0.004	-0.029
24	40.72	22	0.0089	-0.028	-0.001	0.041	0.057	0.092	-0.071
30	43.86	28	0.0287	0.024	0.041	0.036	-0.017	-0.066	-0.043
36	56.22	34	0.0096	-0.128	0.026	0.031	0.017	-0.004	0.144
42	61.79	40	0.0151	-0.039	-0.001	-0.011	0.039	-0.094	-0.071
48	68.98	46	0.0157	-0.106	-0.050	-0.014	0.004	0.063	-0.060

Model for variable visit1

Estimated Mean: -0.00076

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.74818 B**(1)
Factor 2: 1 - 0.68807 B**(12)

Table 4.5.8b

ARIMA 1&12 results for tourist arrivals from Singapore
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0004437	0.0008151	-0.54	0.5862	0
MA1,1	0.75190	0.03968	18.95	<.0001	1
MA2,1	0.68637	0.04752	14.44	<.0001	12

Variance Estimate	0.025848
Std Error Estimate	0.160774
AIC	-223.153
SBC	-212.175
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	6.40	4	0.1711	-0.043	0.083	-0.023	-0.006	-0.099	0.053
12	24.42	10	0.0066	0.076	-0.141	0.121	-0.043	0.127	-0.046
18	31.41	16	0.0119	0.102	0.041	-0.074	0.051	-0.020	-0.048
24	37.74	22	0.0196	-0.033	-0.011	0.022	0.069	0.105	-0.051
30	40.60	28	0.0584	0.029	0.029	0.030	-0.029	-0.058	-0.046
36	53.99	34	0.0160	-0.121	0.040	0.038	0.012	-0.002	0.152
42	58.67	40	0.0286	-0.034	0.005	-0.017	0.019	-0.080	-0.075
48	66.24	46	0.0269	-0.095	-0.039	0.009	-0.009	0.053	-0.092

Model for variable visit1

Estimated Mean: -0.00044

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.7519 B**(1)
Factor 2: 1 - 0.68637 B**(12)

Table 4.5.8c

ARIMA 1&12 results for tourist arrivals from Singapore
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0007050	0.0008382	-0.84	0.4003	0
MA1,1	0.75063	0.04023	18.66	<.0001	1
MA2,1	0.68498	0.04839	14.15	<.0001	12

Variance Estimate	0.025514
Std Error Estimate	0.159732
AIC	-216.969
SBC	-206.119
Number of Residuals	275

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations----------					
6	6.99	4	0.1365	-0.056	0.083	-0.024	0.016	-0.090	0.077
12	26.79	10	0.0028	0.074	-0.174	0.111	-0.048	0.135	-0.026
18	34.39	16	0.0048	0.132	0.036	-0.074	0.032	-0.007	-0.028
24	40.85	22	0.0086	-0.030	-0.002	0.043	0.059	0.096	-0.077
30	43.97	28	0.0280	0.025	0.042	0.035	-0.016	-0.066	-0.042
36	55.53	34	0.0113	-0.125	0.026	0.028	0.021	0.003	0.138
42	60.91	40	0.0181	-0.036	-0.004	-0.012	0.035	-0.093	-0.073
48	67.26	46	0.0221	-0.105	-0.052	-0.017	-0.001	0.049	-0.053

Model for variable visit1

Estimated Mean: -0.0007

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.75063 B**(1)
Factor 2: 1 - 0.68498 B**(12)

Table 4.5.9a

ARIMA 1&12 results for tourist arrivals from Taiwan
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0010912	0.0008063	-1.35	0.1759	0
MA1,1	0.68922	0.04303	16.02	<.0001	1
MA2,1	0.76412	0.04723	16.18	<.0001	12

Variance Estimate	0.024352
Std Error Estimate	0.156051
AIC	-227.959
SBC	-217.097
Number of Residuals	276

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.00	4	0.7356	-0.014	0.038	0.037	-0.050	-0.030	0.026
12	9.10	10	0.5224	0.061	-0.081	-0.049	-0.029	0.105	-0.005
18	16.76	16	0.4015	0.070	-0.044	-0.095	-0.026	0.013	0.097
24	22.42	22	0.4348	0.077	0.074	-0.052	0.031	0.058	-0.023
30	35.16	28	0.1653	0.118	-0.072	-0.054	-0.124	0.030	0.055
36	49.98	34	0.0379	0.075	-0.025	0.067	-0.074	-0.009	0.174
42	62.20	40	0.0138	-0.151	-0.064	-0.078	-0.002	-0.022	0.068
48	72.08	46	0.0083	0.063	-0.082	-0.067	-0.067	-0.003	-0.100

Model for variable visit1

Estimated Mean: -0.00109

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.68922 B**(1)
Factor 2: 1 - 0.76412 B**(12)

Table 4.5.9b

ARIMA 1&12 results for tourist arrivals from Taiwan
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0009152	0.0007510	-1.22	0.2230	0
MA1,1	0.68587	0.04236	16.19	<.0001	1
MA2,1	0.77604	0.04456	17.42	<.0001	12

Variance Estimate	0.023583
Std Error Estimate	0.153566
AIC	-246.289
SBC	-235.311
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations----------					
6	2.10	4	0.7168	-0.013	0.036	0.037	-0.053	-0.028	0.028
12	9.63	10	0.4737	0.061	-0.081	-0.048	-0.027	0.109	-0.007
18	18.68	16	0.2856	0.078	-0.045	-0.114	-0.020	0.011	0.090
24	24.82	22	0.3057	0.081	0.065	-0.062	0.033	0.061	-0.015
30	38.76	28	0.0848	0.113	-0.076	-0.051	-0.134	0.031	0.059
36	54.47	34	0.0144	0.070	-0.017	0.065	-0.077	-0.008	0.180
42	68.15	40	0.0036	-0.154	-0.069	-0.074	-0.006	-0.018	0.082
48	78.09	46	0.0022	0.066	-0.076	-0.062	-0.073	-0.004	-0.098

Model for variable visit1

Estimated Mean: -0.00092

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.68587 B**(1)
Factor 2: 1 - 0.77604 B**(12)

Table 4.5.9c

ARIMA 1&12 results for tourist arrivals from Taiwan
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0011263	0.0007997	-1.41	0.1590	0
MA1,1	0.69004	0.04299	16.05	<.0001	1
MA2,1	0.76680	0.04719	16.25	<.0001	12

Variance Estimate	0.024392
Std Error Estimate	0.156178
AIC	-226.512
SBC	-215.662
Number of Residuals	275

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	1.95	4	0.7455	-0.016	0.038	0.037	-0.048	-0.028	0.028
12	9.67	10	0.4700	0.061	-0.081	-0.050	-0.030	0.114	-0.009
18	17.29	16	0.3669	0.069	-0.043	-0.095	-0.026	0.015	0.097
24	22.86	22	0.4095	0.076	0.074	-0.054	0.032	0.055	-0.018
30	35.50	28	0.1558	0.117	-0.074	-0.051	-0.124	0.032	0.055
36	50.52	34	0.0339	0.073	-0.026	0.065	-0.073	-0.012	0.178
42	62.85	40	0.0120	-0.151	-0.065	-0.079	-0.001	-0.025	0.068
48	72.65	46	0.0074	0.059	-0.082	-0.066	-0.064	0.003	-0.104

Model for variable visit1

Estimated Mean: -0.00113

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.69004 B**(1)
Factor 2: 1 - 0.7668 B**(12)

Table 4.5.10a

ARIMA 1&12 results for tourist arrivals from the UK
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0009670	0.0005315	-1.82	0.0688	0
MA1,1	0.64830	0.04442	14.60	<.0001	1
MA2,1	0.93552	0.06442	14.52	<.0001	12

Variance Estimate	0.027587
Std Error Estimate	0.166093
AIC	-179.688
SBC	-168.827
Number of Residuals	276

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	1.91	4	0.7514	-0.020	0.009	0.001	0.065	0.016	0.043
12	6.24	10	0.7948	-0.040	0.012	-0.061	0.013	0.075	-0.061
18	9.82	16	0.8759	0.063	0.070	-0.039	-0.007	0.040	0.013
24	11.89	22	0.9597	0.006	-0.065	-0.027	0.031	0.020	0.021
30	20.49	28	0.8458	0.105	0.055	0.063	0.088	-0.043	-0.018
36	40.01	34	0.2207	-0.093	0.005	-0.060	-0.103	-0.096	0.171
42	50.72	40	0.1193	-0.132	-0.110	0.043	0.000	-0.035	-0.026
48	72.71	46	0.0073	-0.002	-0.062	-0.037	0.070	-0.046	-0.231

Model for variable visit1

Estimated Mean: -0.00097

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.6483 B**(1)
Factor 2: 1 - 0.93552 B**(12)

Table 4.5.10b

ARIMA 1&12 results for tourist arrivals from the UK
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0008727	0.0005308	-1.64	0.1001	0
MA1,1	0.64893	0.04361	14.88	<.0001	1
MA2,1	0.92362	0.05496	16.80	<.0001	12

Variance Estimate	0.028409
Std Error Estimate	0.168548
AIC	-181.23
SBC	-170.252
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	1.64	4	0.8019	-0.007	-0.003	-0.009	0.062	0.028	0.028
12	6.88	10	0.7368	-0.037	0.011	-0.082	-0.001	0.069	-0.067
18	12.54	16	0.7059	0.041	0.051	-0.065	-0.059	0.045	0.066
24	15.88	22	0.8218	0.024	-0.069	-0.043	0.027	0.049	0.020
30	24.29	28	0.6663	0.101	0.052	0.051	0.080	-0.062	-0.024
36	39.54	34	0.2362	-0.086	0.010	-0.047	-0.087	-0.075	0.153
42	53.39	40	0.0765	-0.139	-0.123	0.039	-0.011	-0.060	-0.042
48	74.70	46	0.0047	-0.007	-0.028	-0.013	0.083	-0.033	-0.229

Model for variable visit1

Estimated Mean: -0.00087

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.64893 B**(1)
Factor 2: 1 - 0.92362 B**(12)

Table 4.5.10c

ARIMA 1&12 results for tourist arrivals from the UK
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0010183	0.0005520	-1.84	0.0651	0
MA1,1	0.64764	0.04463	14.51	<.0001	1
MA2,1	0.92892	0.06159	15.08	<.0001	12

Variance Estimate	0.02771
Std Error Estimate	0.166465
AIC	-178.696
SBC	-167.845
Number of Residuals	275

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.06	4	0.7245	-0.020	0.008	-0.002	0.067	0.020	0.044
12	6.83	10	0.7412	-0.036	0.016	-0.062	0.015	0.090	-0.054
18	10.50	16	0.8393	0.063	0.070	-0.040	-0.006	0.044	0.011
24	12.56	22	0.9446	0.005	-0.063	-0.032	0.032	0.018	0.022
30	21.65	28	0.7971	0.108	0.057	0.065	0.090	-0.044	-0.021
36	41.89	34	0.1659	-0.097	0.006	-0.059	-0.101	-0.097	0.177
42	51.99	40	0.0969	-0.130	-0.102	0.044	0.002	-0.037	-0.031
48	74.88	46	0.0045	-0.002	-0.060	-0.039	0.068	-0.037	-0.239

Model for variable visit1

Estimated Mean: -0.00102

Period(s) of Differencing: 1,12

Moving Average Factors

Factor 1: 1 - 0.64764 B**(1)
Factor 2: 1 - 0.92892 B**(12)

Table 4.5.11a

ARIMA 1&12 results for tourist arrivals from the USA
one month ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0001034	0.0005211	-0.20	0.8426	0
MA1,1	0.86917	0.05233	16.61	<.0001	1
MA2,1	0.75667	0.13207	5.73	<.0001	12
AR1,1	0.51642	0.08533	6.05	<.0001	1
AR2,1	0.51555	0.15808	3.26	0.0011	12

Variance Estimate	0.003188
Std Error Estimate	0.05646
AIC	-795.697
SBC	-777.595
Number of Residuals	276

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	9.59	2	0.0083	-0.047	0.090	0.047	-0.116	0.034	0.083
12	13.58	8	0.0934	-0.098	0.014	-0.043	-0.038	0.028	-0.000
18	23.25	14	0.0564	-0.044	0.140	-0.037	-0.051	0.066	0.054
24	36.56	20	0.0132	-0.034	0.086	0.021	-0.059	0.166	0.063
30	46.04	26	0.0090	0.042	0.053	-0.156	0.011	0.035	-0.025
36	60.90	32	0.0015	-0.003	0.159	-0.080	0.034	0.057	-0.105
42	71.52	38	0.0008	0.065	-0.015	-0.129	0.022	-0.105	0.006
48	77.37	44	0.0014	-0.038	-0.045	-0.078	0.067	0.058	0.016

Model for variable visit1

Estimated Mean: -0.0001

Period(s) of Differencing: 1,12

Autoregressive Factors

Factor 1: 1 - 0.51642 B**(1)
Factor 2: 1 - 0.51555 B**(12)

Moving Average Factors

Factor 1: 1 - 0.86917 B**(1)
Factor 2: 1 - 0.75667 B**(12)

Table 4.5.11b

ARIMA 1&12 results for tourist arrivals from the USA
one year ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.00004960	0.0004326	0.11	0.9087	0
MA1,1	0.88081	0.04720	18.66	<.0001	1
MA2,1	0.75398	0.10192	7.40	<.0001	12
AR1,1	0.53734	0.07909	6.79	<.0001	1
AR2,1	0.43644	0.13016	3.35	0.0008	12

Variance Estimate	0.003258
Std Error Estimate	0.057075
AIC	-820.402
SBC	-802.104
Number of Residuals	287

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	10.34	2	0.0057	-0.054	0.109	0.037	-0.115	0.001	0.077
12	12.73	8	0.1213	-0.051	0.004	-0.003	-0.067	0.030	-0.005
18	21.67	14	0.0856	-0.038	0.126	-0.019	-0.072	0.068	0.043
24	35.49	20	0.0177	-0.041	0.086	0.030	-0.060	0.158	0.074
30	43.55	26	0.0169	0.038	0.054	-0.141	0.010	0.023	-0.018
36	57.57	32	0.0037	-0.010	0.145	-0.089	0.019	0.072	-0.090
42	66.14	38	0.0031	0.064	-0.015	-0.109	0.019	-0.095	0.008
48	70.28	44	0.0071	-0.033	-0.048	-0.059	0.045	0.056	-0.003

Model for variable visit1

Estimated Mean: 0.00005

Period(s) of Differencing: 1,12

Autoregressive Factors

Factor 1: 1 - 0.53734 B**(1)
Factor 2: 1 - 0.43644 B**(12)

Moving Average Factors

Factor 1: 1 - 0.88081 B**(1)
Factor 2: 1 - 0.75398 B**(12)

Table 4.5.11c

ARIMA 1&12 results for tourist arrivals from the USA
two years ahead forecast

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	-0.0000987	0.0005189	-0.19	0.8491	0
MA1,1	0.87091	0.05341	16.31	<.0001	1
MA2,1	0.75735	0.13179	5.75	<.0001	12
AR1,1	0.51911	0.08720	5.95	<.0001	1
AR2,1	0.51610	0.15794	3.27	0.0011	12

Variance Estimate	0.003199
Std Error Estimate	0.056561
AIC	-791.791
SBC	-773.707
Number of Residuals	275

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	9.69	2	0.0079	-0.046	0.090	0.047	-0.119	0.035	0.083
12	13.58	8	0.0933	-0.097	0.014	-0.042	-0.038	0.028	-0.000
18	23.20	14	0.0571	-0.043	0.141	-0.037	-0.051	0.066	0.054
24	36.51	20	0.0134	-0.033	0.086	0.021	-0.059	0.166	0.063
30	46.01	26	0.0091	0.042	0.053	-0.156	0.011	0.035	-0.025
36	60.84	32	0.0016	-0.002	0.159	-0.080	0.035	0.056	-0.105
42	71.41	38	0.0008	0.065	-0.015	-0.129	0.022	-0.106	0.007
48	77.22	44	0.0015	-0.038	-0.044	-0.078	0.066	0.059	0.016

Model for variable visit1

Estimated Mean: -0.0001

Period(s) of Differencing: 1,12

Autoregressive Factors

Factor 1: 1 - 0.51911 B**(1)
Factor 2: 1 - 0.5161 B**(12)

Moving Average Factors

Factor 1: 1 - 0.87091 B**(1)
Factor 2: 1 - 0.75735 B**(12)

Table 4.6.1a

BSM results for tourist arrivals from all countries
one month ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 23 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (1 restrictions).
Parameter estimation sample is 1978. 1 - 2002. 1. (T = 289).
Log-likelihood kernel is 2.561141.
Very strong convergence in 7 iterations.
(likelihood cvg 4.662593e-013
gradient cvg 1.489179e-008
parameter cvg 1.683058e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002. 1. (T = 289, n = 276).
Log-Likelihood is 740.17 (-2 LogL = -1480.34).
Prediction error variance is 0.00393811

Summary statistics

	Larr
Std.Error	0.062754
Normality	24.194
H(92)	0.55737
r(1)	-0.026883
r(16)	0.0032611
DW	2.0414
Q(16,13)	22.622
Rs^2	0.31582

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0015021	(1.0000)
Lvl	0.00048142	(0.3205)
Slp	7.7695e-008	(0.0001)
Sea	5.7824e-006	(0.0038)

Table 4.6.1b

BSM results for tourist arrivals from all countries
one year ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 12 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002.12. (T = 300).
Log-likelihood kernel is 2.575637.
Very strong convergence in 9 iterations.
(likelihood cvg 1.245039e-012
gradient cvg 2.426948e-008
parameter cvg 2.982662e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002.12. (T = 300, n = 287).
Log-Likelihood is 772.691 (-2 LogL = -1545.38).
Prediction error variance is 0.00385487

Summary statistics

	Larr
Std.Error	0.062088
Normality	26.605
H(95)	0.59653
r(1)	-0.024028
r(16)	0.0010471
DW	2.0318
Q(16,13)	26.816
Rs^2	0.32562

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0014886	(1.0000)
Lvl	0.00050585	(0.3398)
Slp	0.00000	(0.0000)
Sea	5.3090e-006	(0.0036)

Table 4.6.1c

BSM results for tourist arrivals from all countries
two years ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 24 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (1 restrictions).
Parameter estimation sample is 1978. 1 - 2001.12. (T = 288).
Log-likelihood kernel is 2.559537.
Very strong convergence in 7 iterations.
(likelihood cvg 6.003229e-013
gradient cvg 2.104983e-008
parameter cvg 1.833074e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2001.12. (T = 288, n = 275).
Log-Likelihood is 737.147 (-2 LogL = -1474.29).
Prediction error variance is 0.00394499

Summary statistics

	Larr
Std.Error	0.062809
Normality	23.681
H(91)	0.55533
r(1)	-0.030037
r(15)	-0.080110
DW	2.0351
Q(15,12)	23.716
Rs^2	0.31689

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0015181	(1.0000)
Lvl	0.00047929	(0.3157)
Slp	8.6752e-008	(0.0001)
Sea	5.6841e-006	(0.0037)

Table 4.6.2a

BSM results for tourist arrivals from Australia
one month ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 23 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002. 1. (T = 289).
Log-likelihood kernel is 1.883547.
Very strong convergence in 7 iterations.
(likelihood cvg 7.073184e-016
gradient cvg 3.993139e-007
parameter cvg 2.66798e-010)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002. 1. (T = 289, n = 276).
Log-Likelihood is 544.345 (-2 LogL = -1088.69).
Prediction error variance is 0.0161302

Summary statistics

	Larr
Std.Error	0.12700
Normality	31.926
H(92)	0.22760
r(1)	0.0090518
r(16)	0.046302
DW	1.9613
Q(16,13)	17.148
Rs^2	0.42994

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0071505	(1.0000)
Lvl	0.0015803	(0.2210)
Slp	0.00000	(0.0000)
Sea	2.0716e-005	(0.0029)

Table 4.6.2b

BSM results for tourist arrivals from Australia
one year ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 12 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002.12. (T = 300).
Log-likelihood kernel is 1.905065.
Very strong convergence in 8 iterations.
(likelihood cvg 3.496647e-015
gradient cvg 1.40632e-007
parameter cvg 3.436338e-011)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002.12. (T = 300, n = 287).
Log-Likelihood is 571.519 (-2 LogL = -1143.04).
Prediction error variance is 0.0156307

Summary statistics

	Larr
Std.Error	0.12502
Normality	35.708
H(95)	0.22797
r(1)	0.010459
r(16)	0.047020
DW	1.9620
Q(16,13)	17.532
Rs^2	0.43736

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0069409	(1.0000)
Lvl	0.0015212	(0.2192)
Slp	0.00000	(0.0000)
Sea	1.9928e-005	(0.0029)

Table 4.6.2c

BSM results for tourist arrivals from Australia
two years ahead forecast

```
Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 24 forecasts


Equation

Larr = Trend + Trigo seasonal + Irregular


Estimation report

Model with  4 parameters ( 2 restrictions).
Parameter estimation sample is 1978. 1 - 2001.12. (T =  288).
Log-likelihood kernel is 1.882663.
Very strong convergence in   8 iterations.
( likelihood cvg 9.175988e-012
  gradient cvg   2.83118e-007
  parameter cvg  5.191441e-006 )


Diagnostic summary report.

Estimation sample is 1978. 1 - 2001.12. (T =  288, n =  275).
Log-Likelihood is 542.207 (-2 LogL = -1084.41).
Prediction error variance is 0.016138


Summary statistics

                    Larr
 Std.Error       0.12704
 Normality        31.731
 H( 91)          0.22761
 r( 1)         0.0063616
 r(15)         -0.036342
 DW               1.9648
 Q(15,12)         16.382
 Rs^2            0.43136


Estimated variances of disturbances.

Component          Larr (q-ratio)
Irr           0.0071741 ( 1.0000)
Lvl           0.0015751 ( 0.2196)
Slp             0.00000 ( 0.0000)
Sea         2.0641e-005 ( 0.0029)
```

Table 4.6.3a

BSM results for tourist arrivals from Canada
one month ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 23 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

```
Model with  4 parameters ( 2 restrictions).
Parameter estimation sample is 1978. 1 - 2002. 1. (T =  289).
Log-likelihood kernel is 2.162498.
Very strong convergence in   8 iterations.
( likelihood cvg 1.437516e-015
  gradient cvg   2.300826e-007
  parameter cvg  5.223337e-012 )
```

Diagnostic summary report.

```
Estimation sample is 1978. 1 - 2002. 1. (T =  289, n =  276).
Log-Likelihood is 624.962 (-2 LogL = -1249.92).
Prediction error variance is 0.00904529
```

Summary statistics

	Larr
Std.Error	0.095107
Normality	13.498
H(92)	0.75907
r(1)	0.080651
r(16)	-0.15162
DW	1.8363
Q(16,13)	28.900
Rs^2	0.32771

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0035979	(1.0000)
Lvl	0.00078363	(0.2178)
Slp	0.00000	(0.0000)
Sea	1.7359e-005	(0.0048)

Table 4.6.3b

BSM results for tourist arrivals from Canada
one year ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 12 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002.12. (T = 300).
Log-likelihood kernel is 2.171997.
Very strong convergence in 8 iterations.
(likelihood cvg 3.291826e-013
gradient cvg 6.972201e-009
parameter cvg 3.349056e-007)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002.12. (T = 300, n = 287).
Log-Likelihood is 651.599 (-2 LogL = -1303.2).
Prediction error variance is 0.00899141

Summary statistics

	Larr
Std.Error	0.094823
Normality	12.775
H(95)	0.80854
r(1)	0.091644
r(16)	-0.14706
DW	1.8138
Q(16,13)	29.867
Rs^2	0.33723

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0036891	(1.0000)
Lvl	0.00072636	(0.1969)
Slp	0.00000	(0.0000)
Sea	1.6823e-005	(0.0046)

Table 4.6.3c

BSM results for tourist arrivals from Canada
two years ahead forecast

```
Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 24 forecasts


Equation

Larr = Trend + Trigo seasonal + Irregular


Estimation report

Model with  4 parameters ( 2 restrictions).
Parameter estimation sample is 1978. 1 - 2001.12. (T =  288).
Log-likelihood kernel is 2.160645.
Very strong convergence in   8 iterations.
( likelihood cvg 1.849819e-015
  gradient cvg   3.537171e-008
  parameter cvg  7.039957e-009 )


Diagnostic summary report.

Estimation sample is 1978. 1 - 2001.12. (T =  288, n =  275).
Log-Likelihood is 622.266 (-2 LogL = -1244.53).
Prediction error variance is 0.00906811


Summary statistics

                   Larr
 Std.Error      0.095227
 Normality        13.303
 H( 91)          0.75701
 r( 1)          0.082787
 r(15)          -0.15525
 DW               1.8289
 Q(15,12)         22.313
 Rs^2            0.32767


Estimated variances of disturbances.

Component          Larr (q-ratio)
Irr           0.0036081 ( 1.0000)
Lvl          0.00078474 ( 0.2175)
Slp             0.00000 ( 0.0000)
Sea         1.7416e-005 ( 0.0048)
```

Table 4.6.4a

BSM results for tourist arrivals from China
one month ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 23 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (1 restrictions).
Parameter estimation sample is 1978. 1 - 2002. 1. (T = 289).
Log-likelihood kernel is 1.573883.
Very strong convergence in 6 iterations.
(likelihood cvg 4.919486e-013
gradient cvg 3.251473e-008
parameter cvg 4.170549e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002. 1. (T = 289, n = 276).
Log-Likelihood is 454.852 (-2 LogL = -909.704).
Prediction error variance is 0.0305326

Summary statistics

	Larr
Std.Error	0.17474
Normality	143.57
H(92)	0.098132
r(1)	-0.00048033
r(16)	-0.092322
DW	1.9026
Q(16,13)	49.172
Rs^2	0.084193

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.010916	(1.0000)
Lvl	0.0083517	(0.7651)
Slp	1.8363e-006	(0.0002)
Sea	1.1727e-005	(0.0011)

Table 4.6.4b

BSM results for tourist arrivals from China
one year ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 12 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (1 restrictions).
Parameter estimation sample is 1978. 1 - 2002.12. (T = 300).
Log-likelihood kernel is 1.585868.
Very strong convergence in 5 iterations.
(likelihood cvg 9.157093e-012
gradient cvg 1.714776e-007
parameter cvg 7.571981e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002.12. (T = 300, n = 287).
Log-Likelihood is 475.76 (-2 LogL = -951.521).
Prediction error variance is 0.030291

Summary statistics

	Larr
Std.Error	0.17404
Normality	154.09
H(95)	0.12025
r(1)	0.0022841
r(16)	-0.088404
DW	1.8988
Q(16,13)	48.478
Rs^2	0.091767

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.010373	(1.0000)
Lvl	0.0081064	(0.7815)
Slp	1.6632e-006	(0.0002)
Sea	1.5099e-005	(0.0015)

Table 4.6.4c

BSM results for tourist arrivals from China
two years ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 24 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (1 restrictions).
Parameter estimation sample is 1978. 1 - 2001.12. (T = 288).
Log-likelihood kernel is 1.571913.
Very strong convergence in 5 iterations.
(likelihood cvg 5.455369e-013
gradient cvg 1.814104e-008
parameter cvg 3.251677e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2001.12. (T = 288, n = 275).
Log-Likelihood is 452.711 (-2 LogL = -905.422).
Prediction error variance is 0.0305936

Summary statistics

	Larr
Std.Error	0.17491
Normality	142.46
H(91)	0.098663
r(1)	-0.0012679
r(15)	-0.025896
DW	1.9045
Q(15,12)	47.030
Rs^2	0.083430

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.010997	(1.0000)
Lvl	0.0084072	(0.7645)
Slp	1.8961e-006	(0.0002)
Sea	1.1261e-005	(0.0010)

Table 4.6.5a

BSM results for tourist arrivals from France
one month ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 23 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002. 1. (T = 289).
Log-likelihood kernel is 2.125364.
Very strong convergence in 7 iterations.
(likelihood cvg 6.563038e-013
gradient cvg 2.34035e-008
parameter cvg 8.216921e-007)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002. 1. (T = 289, n = 276).
Log-Likelihood is 614.23 (-2 LogL = -1228.46).
Prediction error variance is 0.00975187

Summary statistics

	Larr
Std.Error	0.098752
Normality	23.073
H(92)	0.26009
r(1)	0.0024338
r(16)	-0.080700
DW	1.9568
Q(16,13)	19.430
Rs^2	0.49818

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0048214	(1.0000)
Lvl	0.00033659	(0.0698)
Slp	0.00000	(0.0000)
Sea	1.9276e-005	(0.0040)

Table 4.6.5b

BSM results for tourist arrivals from France
one year ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 12 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002.12. (T = 300).
Log-likelihood kernel is 2.143671.
Very strong convergence in 7 iterations.
(likelihood cvg 5.187982e-012
gradient cvg 7.891465e-008
parameter cvg 3.881713e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002.12. (T = 300, n = 287).
Log-Likelihood is 643.101 (-2 LogL = -1286.2).
Prediction error variance is 0.00952656

Summary statistics

	Larr
Std.Error	0.097604
Normality	24.817
H(95)	0.24415
r(1)	0.0034057
r(16)	-0.072705
DW	1.9569
Q(16,13)	18.777
Rs^2	0.52197

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0046397	(1.0000)
Lvl	0.00032672	(0.0704)
Slp	0.00000	(0.0000)
Sea	1.9528e-005	(0.0042)

Table 4.6.5c

BSM results for tourist arrivals from France
two years ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 24 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2001.12. (T = 288).
Log-likelihood kernel is 2.123663.
Very strong convergence in 7 iterations.
(likelihood cvg 9.520783e-012
gradient cvg 1.462608e-007
parameter cvg 5.752388e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2001.12. (T = 288, n = 275).
Log-Likelihood is 611.615 (-2 LogL = -1223.23).
Prediction error variance is 0.00977148

Summary statistics

	Larr
Std.Error	0.098851
Normality	23.086
H(91)	0.25834
r(1)	-0.0015101
r(15)	0.066484
DW	1.9517
Q(15,12)	17.355
Rs^2	0.49881

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0048549	(1.0000)
Lvl	0.00033699	(0.0694)
Slp	0.00000	(0.0000)
Sea	1.9077e-005	(0.0039)

Table 4.6.6a

BSM results for tourist arrivals from Germany
one month ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 23 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002. 1. (T = 289).
Log-likelihood kernel is 2.200785.
Very strong convergence in 7 iterations.
(likelihood cvg 4.565062e-011
gradient cvg 7.802647e-008
parameter cvg 9.924311e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002. 1. (T = 289, n = 276).
Log-Likelihood is 636.027 (-2 LogL = -1272.05).
Prediction error variance is 0.00822995

Summary statistics

	Larr
Std.Error	0.090719
Normality	3.7124
H(92)	0.69719
r(1)	0.065806
r(16)	-0.048491
DW	1.8652
Q(16,13)	27.544
Rs^2	0.35816

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0052348	(1.0000)
Lvl	0.00015776	(0.0301)
Slp	0.00000	(0.0000)
Sea	8.8400e-006	(0.0017)

Table 4.6.6b

BSM results for tourist arrivals from Germany
one year ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 12 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002.12. (T = 300).
Log-likelihood kernel is 2.177506.
Very strong convergence in 6 iterations.
(likelihood cvg 2.661469e-013
gradient cvg 1.99174e-008
parameter cvg 1.682629e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002.12. (T = 300, n = 287).
Log-Likelihood is 653.252 (-2 LogL = -1306.5).
Prediction error variance is 0.00877998

Summary statistics

	Larr
Std.Error	0.093702
Normality	15.285
H(95)	0.88260
r(1)	0.064571
r(16)	-0.054729
DW	1.8690
Q(16,13)	29.454
Rs^2	0.37900

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0055403	(1.0000)
Lvl	0.00014799	(0.0267)
Slp	0.00000	(0.0000)
Sea	1.0302e-005	(0.0019)

Table 4.6.6c

BSM results for tourist arrivals from Germany
two years ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 24 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2001.12. (T = 288).
Log-likelihood kernel is 2.199009.
Very strong convergence in 7 iterations.
(likelihood cvg 2.383006e-014
gradient cvg 1.747047e-007
parameter cvg 1.181047e-009)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2001.12. (T = 288, n = 275).
Log-Likelihood is 633.315 (-2 LogL = -1266.63).
Prediction error variance is 0.00824717

Summary statistics

	Larr
Std.Error	0.090814
Normality	3.7578
H(91)	0.69613
r(1)	0.065110
r(15)	-0.072487
DW	1.8676
Q(15,12)	27.170
Rs^2	0.35865

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.0052548	(1.0000)
Lvl	0.00016075	(0.0306)
Slp	0.00000	(0.0000)
Sea	8.7203e-006	(0.0017)

Table 4.6.7a

BSM results for tourist arrivals from Korea
one month ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 23 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002. 1. (T = 289).
Log-likelihood kernel is 2.434848.
Very strong convergence in 10 iterations.
(likelihood cvg 1.120524e-011
gradient cvg 3.264056e-009
parameter cvg 6.539006e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002. 1. (T = 289, n = 276).
Log-Likelihood is 703.671 (-2 LogL = -1407.34).
Prediction error variance is 0.00506513

Summary statistics

	Larr
Std.Error	0.071170
Normality	77.832
H(92)	1.0215
r(1)	0.027235
r(16)	-0.012295
DW	1.9366
Q(16,13)	14.281
Rs^2	0.13374

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.00021717	(0.0659)
Lvl	0.0032940	(1.0000)
Slp	0.00000	(0.0000)
Sea	3.8976e-006	(0.0012)

Table 4.6.7b

BSM results for tourist arrivals from Korea
one year ahead forecast

```
Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 12 forecasts


Equation

Larr = Trend + Trigo seasonal + Irregular


Estimation report

Model with  4 parameters ( 2 restrictions).
Parameter estimation sample is 1978. 1 - 2002.12. (T =  300).
Log-likelihood kernel is 2.442366.
Very strong convergence in  14 iterations.
( likelihood cvg 7.109454e-014
  gradient cvg   3.996803e-010
  parameter cvg  7.845198e-007 )


Diagnostic summary report.

Estimation sample is 1978. 1 - 2002.12. (T =  300, n =  287).
Log-Likelihood is 732.71 (-2 LogL = -1465.42).
Prediction error variance is 0.00507022


Summary statistics

                    Larr
 Std.Error      0.071205
 Normality        81.063
 H( 95)           1.0753
 r( 1)          0.031947
 r(16)         -0.012606
 DW               1.9331
 Q(16,13)         17.888
 Rs^2            0.16845


Estimated variances of disturbances.

Component          Larr (q-ratio)
Irr          0.00027324 ( 0.0869)
Lvl           0.0031435 ( 1.0000)
Slp             0.00000 ( 0.0000)
Sea         4.1597e-006 ( 0.0013)
```

Table 4.6.7c

BSM results for tourist arrivals from Korea
two years ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 24 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2001.12. (T = 288).
Log-likelihood kernel is 2.436333.
Very strong convergence in 16 iterations.
(likelihood cvg 1.697006e-013
gradient cvg 5.107026e-010
parameter cvg 1.603622e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2001.12. (T = 288, n = 275).
Log-Likelihood is 701.664 (-2 LogL = -1403.33).
Prediction error variance is 0.00504162

Summary statistics

	Larr
Std.Error	0.071004
Normality	80.406
H(91)	1.0075
r(1)	0.026686
r(15)	-0.010995
DW	1.9427
Q(15,12)	14.071
Rs^2	0.13760

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.00023606	(0.0727)
Lvl	0.0032466	(1.0000)
Slp	0.00000	(0.0000)
Sea	3.8711e-006	(0.0012)

Table 4.6.8a

BSM results for tourist arrivals from Singapore
one month ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 23 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (1 restrictions).
Parameter estimation sample is 1978. 1 - 2002. 1. (T = 289).
Log-likelihood kernel is 1.689465.
Very strong convergence in 6 iterations.
(likelihood cvg 1.843949e-013
gradient cvg 1.102822e-009
parameter cvg 6.582105e-007)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002. 1. (T = 289, n = 276).
Log-Likelihood is 488.255 (-2 LogL = -976.511).
Prediction error variance is 0.0244165

Summary statistics

	Larr
Std.Error	0.15626
Normality	11.666
H(92)	1.0515
r(1)	-0.013790
r(16)	0.0072498
DW	2.0223
Q(16,13)	32.520
Rs^2	0.32327

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.013526	(1.0000)
Lvl	0.00043356	(0.0321)
Slp	5.7478e-006	(0.0004)
Sea	2.9288e-005	(0.0022)

Table 4.6.8b

BSM results for tourist arrivals from Singapore
one year ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 12 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (1 restrictions).
Parameter estimation sample is 1978. 1 - 2002.12. (T = 300).
Log-likelihood kernel is 1.687628.
Very strong convergence in 7 iterations.
(likelihood cvg 7.016733e-013
gradient cvg 6.757557e-009
parameter cvg 6.203056e-007)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002.12. (T = 300, n = 287).
Log-Likelihood is 506.289 (-2 LogL = -1012.58).
Prediction error variance is 0.0248105

Summary statistics

	Larr
Std.Error	0.15751
Normality	9.5371
H(95)	1.0890
r(1)	-0.0051355
r(16)	0.034637
DW	2.0062
Q(16,13)	29.621
Rs^2	0.32823

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.013512	(1.0000)
Lvl	0.00068651	(0.0508)
Slp	3.1152e-006	(0.0002)
Sea	3.0004e-005	(0.0022)

Table 4.6.8c

BSM results for tourist arrivals from Singapore
two years ahead forecast

```
Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 24 forecasts


Equation

Larr = Trend + Trigo seasonal + Irregular


Estimation report

Model with  4 parameters ( 1 restrictions).
Parameter estimation sample is 1978. 1 - 2001.12. (T =  288).
Log-likelihood kernel is 1.689142.
Very strong convergence in   7 iterations.
( likelihood cvg 2.366173e-015
  gradient cvg   2.594221e-008
  parameter cvg  5.274326e-010 )


Diagnostic summary report.

Estimation sample is 1978. 1 - 2001.12. (T =  288, n =  275).
Log-Likelihood is 486.473 (-2 LogL = -972.946).
Prediction error variance is 0.0244092


Summary statistics

                    Larr
 Std.Error       0.15623
 Normality        11.723
 H( 91)           1.0349
 r( 1)         -0.010884
 r(15)         -0.088786
 DW               2.0193
 Q(15,12)         32.061
 Rs^2            0.31798


Estimated variances of disturbances.

Component          Larr (q-ratio)
Irr            0.013477 ( 1.0000)
Lvl          0.00044407 ( 0.0329)
Slp         5.3089e-006 ( 0.0004)
Sea         2.9971e-005 ( 0.0022)
```

Table 4.6.9a

BSM results for tourist arrivals from Taiwan
one month ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 23 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002. 1. (T = 289).
Log-likelihood kernel is 1.684258.
Very strong convergence in 9 iterations.
(likelihood cvg 9.604199e-013
gradient cvg 4.074519e-009
parameter cvg 3.958752e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002. 1. (T = 289, n = 276).
Log-Likelihood is 486.751 (-2 LogL = -973.501).
Prediction error variance is 0.0224342

Summary statistics

	Larr
Std.Error	0.14978
Normality	12.930
H(92)	0.86767
r(1)	0.023855
r(16)	-0.035201
DW	1.9422
Q(16,13)	24.668
Rs^2	0.31243

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.016636	(1.0000)
Lvl	0.0014753	(0.0887)
Slp	2.7912e-006	(0.0002)
Sea	0.00000	(0.0000)

Table 4.6.9b

BSM results for tourist arrivals from Taiwan
one year ahead forecast

```
Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 12 forecasts


Equation

Larr = Trend + Trigo seasonal + Irregular


Estimation report

Model with  4 parameters ( 2 restrictions).
Parameter estimation sample is 1978. 1 - 2002.12. (T =  300).
Log-likelihood kernel is 1.704772.
Very strong convergence in  10 iterations.
( likelihood cvg 1.953732e-015
  gradient cvg   1.154632e-008
  parameter cvg  2.169434e-009 )


Diagnostic summary report.

Estimation sample is 1978. 1 - 2002.12. (T =  300, n =  287).
Log-Likelihood is 511.432 (-2 LogL = -1022.86).
Prediction error variance is 0.0218124


Summary statistics

                    Larr
 Std.Error       0.14769
 Normality        14.505
 H( 95)          0.85477
 r( 1)          0.024548
 r(16)         -0.039268
 DW               1.9447
 Q(16,13)         27.562
 Rs^2            0.31056


Estimated variances of disturbances.

Component          Larr (q-ratio)
Irr            0.016044 ( 1.0000)
Lvl           0.0015297 ( 0.0953)
Slp         2.2887e-006 ( 0.0001)
Sea             0.00000 ( 0.0000)
```

Table 4.6.9c

BSM results for tourist arrivals from Taiwan
two years ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 24 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2001.12. (T = 288).
Log-likelihood kernel is 1.683422.
Very strong convergence in 7 iterations.
(likelihood cvg 1.631612e-012
gradient cvg 1.280087e-008
parameter cvg 3.260192e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2001.12. (T = 288, n = 275).
Log-Likelihood is 484.825 (-2 LogL = -969.651).
Prediction error variance is 0.0224458

Summary statistics

	Larr
Std.Error	0.14982
Normality	13.075
H(91)	0.86223
r(1)	0.023706
r(15)	-0.13040
DW	1.9435
Q(15,12)	23.915
Rs^2	0.31427

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.016715	(1.0000)
Lvl	0.0014107	(0.0844)
Slp	3.1278e-006	(0.0002)
Sea	0.00000	(0.0000)

Table 4.6.10a

BSM results for tourist arrivals from the UK
one month ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 23 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002. 1. (T = 289).
Log-likelihood kernel is 1.624104.
Very strong convergence in 10 iterations.
(likelihood cvg 6.499586e-013
gradient cvg 8.881784e-010
parameter cvg 3.327675e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002. 1. (T = 289, n = 276).
Log-Likelihood is 469.366 (-2 LogL = -938.732).
Prediction error variance is 0.025462

Summary statistics

	Larr
Std.Error	0.15957
Normality	37.537
H(92)	1.1287
r(1)	-0.0090781
r(16)	-0.014219
DW	1.9742
Q(16,13)	8.0366
Rs^2	0.30440

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.017381	(1.0000)
Lvl	0.0025113	(0.1445)
Slp	5.0142e-006	(0.0003)
Sea	0.00000	(0.0000)

Table 4.6.10b

BSM results for tourist arrivals from the UK
one year ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 12 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (3 restrictions).
Parameter estimation sample is 1978. 1 - 2002.12. (T = 300).
Log-likelihood kernel is 1.616424.
Very strong convergence in 11 iterations.
(likelihood cvg 2.828541e-012
gradient cvg 6.883383e-010
parameter cvg 5.566104e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002.12. (T = 300, n = 287).
Log-Likelihood is 484.927 (-2 LogL = -969.854).
Prediction error variance is 0.0260202

Summary statistics

	Larr
Std.Error	0.16131
Normality	37.675
H(95)	1.2615
r(1)	-0.017403
r(16)	-0.061289
DW	1.9846
Q(16,13)	9.0585
Rs^2	0.30025

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.017115	(1.0000)
Lvl	0.0036079	(0.2108)
Slp	0.00000	(0.0000)
Sea	0.00000	(0.0000)

Table 4.6.10c

BSM results for tourist arrivals from the UK
two years ahead forecast

```
Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 24 forecasts


Equation

Larr = Trend + Trigo seasonal + Irregular


Estimation report

Model with  4 parameters ( 1 restrictions).
Parameter estimation sample is 1978. 1 - 2001.12. (T =  288).
Log-likelihood kernel is 1.624557.
Very strong convergence in  16 iterations.
( likelihood cvg 3.265479e-011
  gradient cvg   7.921293e-007
  parameter cvg  8.526342e-006 )


Diagnostic summary report.

Estimation sample is 1978. 1 - 2001.12. (T =  288, n =  275).
Log-Likelihood is 467.872 (-2 LogL = -935.745).
Prediction error variance is 0.0264995


Summary statistics

                    Larr
 Std.Error       0.16279
 Normality        37.464
 H( 91)           1.1010
 r( 1)       -0.00044528
 r(15)         -0.048138
 DW               1.9607
 Q(15,12)         9.4618
 Rs^2            0.27698


Estimated variances of disturbances.

Component          Larr (q-ratio)
Irr            0.017247 ( 1.0000)
Lvl           0.0021346 ( 0.1238)
Slp         7.8325e-006 ( 0.0005)
Sea         1.4314e-006 ( 0.0001)
```

Table 4.6.11a

BSM results for tourist arrivals from the USA
one month ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 23 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (3 restrictions).
Parameter estimation sample is 1978. 1 - 2002. 1. (T = 289).
Log-likelihood kernel is 2.664939.
Very strong convergence in 21 iterations.
(likelihood cvg 2.085955e-008
gradient cvg 3.748113e-008
parameter cvg 1.625864e-007)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002. 1. (T = 289, n = 276).
Log-Likelihood is 770.167 (-2 LogL = -1540.33).
Prediction error variance is 0.00320611

Summary statistics

	Larr
Std.Error	0.056623
Normality	26.269
H(92)	0.88300
r(1)	0.11336
r(16)	-0.096691
DW	1.7662
Q(16,13)	40.064
Rs^2	0.44257

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.00000	(0.0000)
Lvl	0.00065621	(1.0000)
Slp	0.00000	(0.0000)
Sea	1.9579e-005	(0.0298)

Table 4.6.11b

BSM results for tourist arrivals from the USA
one year ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 12 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 1978. 1 - 2002.12. (T = 300).
Log-likelihood kernel is 2.659517.
Very strong convergence in 10 iterations.
(likelihood cvg 1.41266e-013
gradient cvg 7.580603e-008
parameter cvg 2.687685e-006)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2002.12. (T = 300, n = 287).
Log-Likelihood is 797.855 (-2 LogL = -1595.71).
Prediction error variance is 0.00328983

Summary statistics

	Larr
Std.Error	0.057357
Normality	26.188
H(95)	1.0180
r(1)	0.096593
r(16)	-0.11905
DW	1.8046
Q(16,13)	42.753
Rs^2	0.44246

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.00011524	(0.1578)
Lvl	0.00073036	(1.0000)
Slp	0.00000	(0.0000)
Sea	1.6681e-005	(0.0228)

Table 4.6.11c

BSM results for tourist arrivals from the USA
two years ahead forecast

Method of estimation is Maximum likelihood
The present sample is: 1978 (1) to 2003 (12) less 24 forecasts

Equation

Larr = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (3 restrictions).
Parameter estimation sample is 1978. 1 - 2001.12. (T = 288).
Log-likelihood kernel is 2.665304.
Very strong convergence in 21 iterations.
(likelihood cvg 1.811709e-008
gradient cvg 1.290967e-007
parameter cvg 5.823335e-007)

Diagnostic summary report.

Estimation sample is 1978. 1 - 2001.12. (T = 288, n = 275).
Log-Likelihood is 767.607 (-2 LogL = -1535.21).
Prediction error variance is 0.00319915

Summary statistics

	Larr
Std.Error	0.056561
Normality	26.907
H(91)	0.87062
r(1)	0.10542
r(15)	-0.022380
DW	1.7580
Q(15,12)	34.113
Rs^2	0.44532

Estimated variances of disturbances.

Component	Larr	(q-ratio)
Irr	0.00000	(0.0000)
Lvl	0.00063938	(1.0000)
Slp	0.00000	(0.0000)
Sea	1.9827e-005	(0.0310)

APPENDIX II

Appendix to Chapter 5

Table 5.4.1a **Microfit output for ECM**
Arrivals from All Countries, one month ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
288 observations from 1978M2  to 2002M1 . Order of VAR = 1, chosen r =1.
List of variables included in the cointegrating vector:
ARR             IMPJAP
*******************************************************************************
                 Vector  1
ARR                 -.15796
                 (  -1.0000)

IMPJAP               .24872
                 (   1.5746)

*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
Dependent variable is DARR
288 observations used for estimation from 1978M2  to 2002M1
*******************************************************************************
Regressor              Coefficient       Standard Error         T-Ratio[Prob]
CONST                     .037614             .015937             2.3602[.019]
S2                      -.059397             .022152            -2.6814[.008]
S3                        .10881             .022148             4.9127[.000]
S4                        .10332             .022234             4.6469[.000]
S5                      -.071246             .022495            -3.1672[.002]
S6                       -.10586             .022368            -4.7326[.000]
S7                        .11529             .022278             5.1749[.000]
S8                      -.075927             .022595            -3.3603[.001]
S9                       -.10337             .022451            -4.6043[.000]
S10                       .11746             .022335             5.2587[.000]
S11                      -.21747             .022639            -9.6060[.000]
S12                      -.20169             .022256            -9.0623[.000]
UT(-1)                  -.033191             .012901            -2.5727[.011]
*******************************************************************************
R-Squared                    .71389   R-Bar-Squared                      .70140
S.E. of Regression          .076723   F-stat.    F( 12, 275)   57.1801[.000]
Mean of Dependent Variable  .0063225   S.D. of Dependent Variable         .14040
Residual Sum of Squares      1.6188   Equation Log-likelihood          337.4534
Akaike Info. Criterion     324.4534   Schwarz Bayesian Criterion       300.6442
DW-statistic                 2.6006
*******************************************************************************
```

Table 5.4.1b **Microfit output for ECM**
Arrivals from All Countries, 12 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
******************************************************************************
 299 observations from 1978M2  to 2002M12. Order of VAR = 1, chosen r =1.
 List of variables included in the cointegrating vector:
 ARR              IMPJAP
******************************************************************************
                  Vector  1
 ARR                 -.15720
                  (  -1.0000)

 IMPJAP               .24753
                  (   1.5746)

******************************************************************************

Ordinary Least Squares Estimation
******************************************************************************
 Dependent variable is DARR
 299 observations used for estimation from 1978M2  to 2002M12
******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                     .037317           .015853             2.3539[.019]
 S2                      -.057647           .021821            -2.6418[.009]
 S3                        .10628           .021815             4.8719[.000]
 S4                        .10059           .021916             4.5899[.000]
 S5                      -.071210           .022168            -3.2123[.001]
 S6                       -.10248           .022038            -4.6499[.000]
 S7                        .11605           .021961             5.2841[.000]
 S8                      -.076004           .022280            -3.4114[.001]
 S9                       -.10754           .022135            -4.8584[.000]
 S10                       .11802           .022002             5.3642[.000]
 S11                      -.21573           .022306            -9.6715[.000]
 S12                      -.19605           .021923            -8.9428[.000]
 UT(-1)                  -.034489           .012759            -2.7030[.007]
******************************************************************************
 R-Squared                    .71195  R-Bar-Squared                    .69986
 S.E. of Regression          .076335  F-stat.    F( 12, 286)   58.9070[.000]
 Mean of Dependent Variable  .0060992  S.D. of Dependent Variable       .13934
 Residual Sum of Squares      1.6665  Equation Log-likelihood        351.5957
 Akaike Info. Criterion     338.5957  Schwarz Bayesian Criterion     314.5429
 DW-statistic                 2.5597
******************************************************************************
```

Table 5.4.1c Microfit output for ECM
Arrivals from All Countries, 24 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
******************************************************************************
 287 observations from 1978M2  to 2001M12. Order of VAR = 1, chosen r =1.
 List of variables included in the cointegrating vector:
 ARR             IMPJAP
******************************************************************************
                  Vector  1
 ARR                 -.15799
                  (  -1.0000)

 IMPJAP               .24876
                  (   1.5745)

******************************************************************************

Ordinary Least Squares Estimation
******************************************************************************
 Dependent variable is DARR
 287 observations used for estimation from 1978M2  to 2001M12
******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                     .036429            .016324             2.2316[.026]
 S2                       -.058232            .022431            -2.5961[.010]
 S3                         .10996            .022424             4.9039[.000]
 S4                         .10451            .022524             4.6401[.000]
 S5                       -.070017            .022797            -3.0713[.002]
 S6                        -.10465            .022666            -4.6169[.000]
 S7                         .11649            .022571             5.1610[.000]
 S8                       -.074688            .022901            -3.2613[.001]
 S9                        -.10215            .022752            -4.4896[.000]
 S10                        .11867            .022631             5.2434[.000]
 S11                       -.21623            .022947            -9.4232[.000]
 S12                       -.20049            .022547            -8.8920[.000]
 UT(-1)                   -.033426            .012939            -2.5834[.010]
******************************************************************************
 R-Squared                     .71386  R-Bar-Squared                    .70133
 S.E. of Regression           .076845  F-stat.    F( 12, 274)   56.9650[.000]
 Mean of Dependent Variable  .0061291  S.D. of Dependent Variable       .14061
 Residual Sum of Squares       1.6180  Equation Log-likelihood        335.8480
 Akaike Info. Criterion      322.8480  Schwarz Bayesian Criterion     299.0614
 DW-statistic                  2.5820
******************************************************************************
```

Table 5.4.2a Microfit output for ECM
Arrivals from Australia, one month ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

288 observations from 1978M2 to 2002M1 . Order of VAR = 1, chosen r =3.
List of variables included in the cointegrating vector:
ARR OPR TRO JTRO GNI
AIR

	Vector 1	Vector 2	Vector 3
ARR	-.19243	-.058941	-.021248
	(-1.0000)	(-1.0000)	(-1.0000)
OPR	.079322	-.36429	-.058584
	(.41222)	(-6.1806)	(-2.7571)
TRO	.33690	-.53578	.13664
	(1.7508)	(-9.0900)	(6.4304)
JTRO	.16045	-.26093	.057647
	(.83381)	(-4.4270)	(2.7130)
GNI	-.086615	.88748	.066179
	(-.45012)	(15.0570)	(3.1145)
AIR	-.045491	-.14103	-.15197
	(-.23640)	(-2.3926)	(-7.1520)

Ordinary Least Squares Estimation

Dependent variable is DARR
277 observations used for estimation from 1979M1 to 2002M1

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	.5752E-3	.033837	.016999[.986]
DOPR	-.57376	.18739	-3.0618[.002]
DGNI(-4)	1.4792	.56295	2.6276[.009]
DGNI(-9)	1.3772	.56319	2.4454[.015]
DGNI(-11)	-1.4097	.56275	-2.5050[.013]
DAIR(-3)	-1.0954	.45928	-2.3850[.018]
S2	-.36972	.044718	-8.2678[.000]
S3	.40772	.044860	9.0889[.000]
S4	.19569	.044998	4.3488[.000]
S5	-.050412	.048666	-1.0359[.301]
S6	-.023083	.044951	-.51352[.608]
S7	-.017458	.044714	-.39044[.697]
S8	-.053385	.045064	-1.1846[.237]
S9	.31032	.045298	6.8506[.000]
S10	-.12644	.048738	-2.5943[.010]
S11	-.24846	.044922	-5.5310[.000]
S12	.16375	.049345	3.3185[.001]
UT(-1)	-.0066844	.0062212	-1.0745[.284]

R-Squared	.67273	R-Bar-Squared	.65124
S.E. of Regression	.15320	F-stat. F(17, 259)	31.3168[.000]
Mean of Dependent Variable	.0071719	S.D. of Dependent Variable	.25942
Residual Sum of Squares	6.0791	Equation Log-likelihood	135.9086
Akaike Info. Criterion	117.9086	Schwarz Bayesian Criterion	85.2925
DW-statistic	2.7157		

Table 5.4.2b Microfit output for ECM
Arrivals from Australia, 12 months ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

299 observations from 1978M2 to 2002M12. Order of VAR = 1, chosen r =3.
List of variables included in the cointegrating vector:
ARR OPR TRO JTRO GNI
AIR

	Vector 1	Vector 2	Vector 3
ARR	-.18614	.065769	.016019
	(-1.0000)	(-1.0000)	(-1.0000)
OPR	.090517	.37026	.029076
	(.48628)	(-5.6297)	(-1.8151)
TRO	.36688	.49677	-.14951
	(1.9710)	(-7.5533)	(9.3332)
JTRO	.17962	.23068	-.048172
	(.96494)	(-3.5074)	(3.0072)
GNI	-.13381	-.86624	-.028988
	(-.71884)	(13.1709)	(1.8096)
AIR	-.042043	.15313	.13817
	(-.22587)	(-2.3284)	(-8.6251)

Ordinary Least Squares Estimation

Dependent variable is DARR
288 observations used for estimation from 1979M1 to 2002M12

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	-.1024E-4	.033968	-.3015E-3[1.00]
DOPR	-.56634	.18252	-3.1028[.002]
DGNI(-4)	1.3741	.54711	2.5115[.013]
DGNI(-9)	1.3842	.54761	2.5278[.012]
DGNI(-11)	-1.5165	.54708	-2.7719[.006]
DAIR(-3)	-1.1039	.45445	-2.4291[.016]
S2	-.36783	.043737	-8.4100[.000]
S3	.40234	.043874	9.1704[.000]
S4	.19027	.044046	4.3198[.000]
S5	-.041651	.047195	-.88254[.378]
S6	-.020926	.043979	-.47582[.635]
S7	-.012777	.043737	-.29213[.770]
S8	-.056912	.044090	-1.2908[.198]
S9	.30818	.044237	6.9666[.000]
S10	-.12914	.047234	-2.7341[.007]
S11	-.24679	.043945	-5.6160[.000]
S12	.17316	.047810	3.6219[.000]
UT(-1)	-.0044226	.0048099	-.91948[.359]

R-Squared	.67467	R-Bar-Squared	.65419
S.E. of Regression	.15144	F-stat. F(17, 270)	32.9367[.000]
Mean of Dependent Variable	.0071482	S.D. of Dependent Variable	.25753
Residual Sum of Squares	6.1922	Equation Log-likelihood	144.2577
Akaike Info. Criterion	126.2577	Schwarz Bayesian Criterion	93.2910
DW-statistic	2.7044		

Table 5.4.2c **Microfit output for ECM**
Arrivals from Australia, 24 months ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

287 observations from 1978M2 to 2001M12. Order of VAR = 1, chosen r =3.
List of variables included in the cointegrating vector:
ARR OPR TRO JTRO GNI
AIR

	Vector 1	Vector 2	Vector 3
ARR	-.19372	-.057234	.021415
	(-1.0000)	(-1.0000)	(-1.0000)
OPR	.079376	-.36445	.061534
	(.40974)	(-6.3677)	(-2.8735)
TRO	.33556	-.54089	-.13274
	(1.7322)	(-9.4506)	(6.1984)
JTRO	.15813	-.26265	-.057475
	(.81625)	(-4.5891)	(2.6839)
GNI	-.079619	.88681	-.068336
	(-.41099)	(15.4945)	(3.1911)
AIR	-.048814	-.13774	.14979
	(-.25198)	(-2.4067)	(-6.9947)

Ordinary Least Squares Estimation

Dependent variable is DARR
276 observations used for estimation from 1979M1 to 2001M12

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	.0054227	.034863	.15554[.877]
DOPR	-.57480	.18762	-3.0636[.002]
DGNI(-4)	1.4878	.56393	2.6382[.009]
DGNI(-9)	1.3862	.56418	2.4571[.015]
DGNI(-11)	-1.4004	.56378	-2.4839[.014]
DAIR(-3)	-1.0915	.45978	-2.3740[.018]
S2	-.37352	.045260	-8.2527[.000]
S3	.40364	.045462	8.8786[.000]
S4	.19184	.045548	4.2119[.000]
S5	-.054425	.049216	-1.1059[.270]
S6	-.026881	.045497	-.59082[.555]
S7	-.021269	.045260	-.46994[.639]
S8	-.057260	.045622	-1.2551[.211]
S9	.30640	.045865	6.6806[.000]
S10	-.13045	.049290	-2.6466[.009]
S11	-.25222	.045459	-5.5483[.000]
S12	.15949	.049945	3.1933[.002]
UT(-1)	-.0072919	.0063451	-1.1492[.252]

R-Squared	.67308	R-Bar-Squared	.65154
S.E. of Regression	.15340	F-stat. F(17, 258)	31.2463[.000]
Mean of Dependent Variable	.0074300	S.D. of Dependent Variable	.25986
Residual Sum of Squares	6.0708	Equation Log-likelihood	135.1066
Akaike Info. Criterion	117.1066	Schwarz Bayesian Criterion	84.5230
DW-statistic	2.7053		

Table 5.4.3a Microfit output for ECM
Arrivals from Canada, one month ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

288 observations from 1978M2 to 2002M1 . Order of VAR = 1, chosen r =3.
List of variables included in the cointegrating vector:
ARR OPR TRO JTRO GNI
AIR

	Vector 1	Vector 2	Vector 3
ARR	.33774	.055851	-.0027564
	(-1.0000)	(-1.0000)	(-1.0000)
OPR	.049296	-.047543	-.073901
	(-.14596)	(.85124)	(-26.8104)
TRO	-.35007	.75365	.026944
	(1.0365)	(-13.4939)	(9.7751)
JTRO	-.11974	-.23657	-.011813
	(.35453)	(4.2357)	(-4.2855)
GNI	-.23389	.061156	-.031229
	(.69251)	(-1.0950)	(-11.3295)
AIR	.11735	-.53283	.038323
	(-.34747)	(9.5402)	(13.9032)

Ordinary Least Squares Estimation

Dependent variable is DARR
276 observations used for estimation from 1979M2 to 2002M1

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	.12038	.025490	4.7229[.000]
DOPR(-12)	-.33537	.15713	-2.1344[.034]
DTRO	.44242	.16112	2.7459[.006]
DJTRO(-5)	.32761	.15057	2.1757[.030]
DJTRO(-11)	-.38353	.16122	-2.3789[.018]
DGNI	-1.3840	.46722	-2.9623[.003]
DGNI(-7)	-1.7645	.45001	-3.9210[.000]
DGNI(-8)	1.1295	.46170	2.4464[.015]
S2	-.36802	.031849	-11.5553[.000]
S3	.065435	.032737	1.9988[.047]
S4	-.083251	.033060	-2.5182[.012]
S5	-.14078	.032506	-4.3308[.000]
S6	-.32155	.032112	-10.0134[.000]
S7	.041483	.031831	1.3032[.194]
S8	-.12226	.036763	-3.3256[.001]
S9	-.21411	.036473	-5.8705[.000]
S10	.11072	.031571	3.5069[.001]
S11	-.20449	.034721	-5.8896[.000]
S12	-.20096	.032184	-6.2441[.000]
UT(-1)	-.51083	.051866	-9.8491[.000]

R-Squared	.83494	R-Bar-Squared	.82269
S.E. of Regression	.091524	F-stat. F(19, 256)	68.1537[.000]
Mean of Dependent Variable	.0052030	S.D. of Dependent Variable	.21735
Residual Sum of Squares	2.1444	Equation Log-likelihood	278.7118
Akaike Info. Criterion	258.7118	Schwarz Bayesian Criterion	222.5078
DW-statistic	2.1430		

Table 5.4.3b Microfit output for ECM
Arrivals from Canada, 12 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 299 observations from 1978M2  to 2002M12. Order of VAR = 1, chosen r =3.
 List of variables included in the cointegrating vector:
 ARR             OPR             TRO             JTRO            GNI
 AIR
*******************************************************************************
                  Vector  1      Vector  2      Vector  3
 ARR                  .33094        .054050      -.0014914
                  (  -1.0000)    (  -1.0000)    (  -1.0000)
 OPR                 .069717       -.046504       -.058987
                  (  -.21066)    (   .86039)    ( -39.5521)
 TRO                 -.33401         .75509        .030773
                  (   1.0093)    ( -13.9702)    (  20.6341)
 JTRO                -.10852        -.23418      -.0037240
                  (   .32790)    (   4.3326)    (  -2.4970)
 GNI                 -.23902        .060353       -.042285
                  (   .72224)    (  -1.1166)    ( -28.3530)
 AIR                  .10846        -.53220        .037471
                  (  -.32772)    (   9.8465)    (  25.1247)
*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 291 observations used for estimation from 1978M10 to 2002M12
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                       .12805            .025816           4.9599[.000]
 DTRO                        .45801             .16331           2.8046[.005]
 DGNI                       -1.4818             .46240          -3.2045[.002]
 DGNI(-7)                   -1.8192             .45857          -3.9671[.000]
 DGNI(-8)                    1.3066             .46889           2.7865[.006]
 S2                         -.36559            .032248         -11.3371[.000]
 S3                         .068892            .032615           2.1123[.036]
 S4                         -.10701            .032970          -3.2458[.001]
 S5                         -.14744            .032867          -4.4859[.000]
 S6                         -.32245            .032223         -10.0068[.000]
 S7                         .044036            .032083           1.3726[.171]
 S8                         -.12890            .037071          -3.4772[.001]
 S9                         -.24120            .036490          -6.6100[.000]
 S10                         .10479            .031552           3.3212[.001]
 S11                        -.20924            .034810          -6.0109[.000]
 S12                        -.19938            .032058          -6.2193[.000]
 UT(-1)                     -.48070            .049112          -9.7878[.000]
*******************************************************************************
 R-Squared                      .82046   R-Bar-Squared                   .80997
 S.E. of Regression            .093729   F-stat.    F( 16, 274)   78.2567[.000]
 Mean of Dependent Variable  .0046053   S.D. of Dependent Variable      .21501
 Residual Sum of Squares        2.4071   Equation Log-likelihood       284.7468
 Akaike Info. Criterion       267.7468   Schwarz Bayesian Criterion    236.5235
 DW-statistic                   2.1465
*******************************************************************************
```

Table 5.4.3c **Microfit output for ECM**
Arrivals from Canada, 24 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 287 observations from 1978M2  to 2001M12. Order of VAR = 1, chosen r =3.
 List of variables included in the cointegrating vector:
 ARR             OPR             TRO             JTRO            GNI
 AIR
*******************************************************************************
                  Vector  1      Vector  2      Vector  3
 ARR                 .33801        .057337      -.0036617
                  (  -1.0000)    (  -1.0000)    (  -1.0000)
 OPR                .042780       -.035093       -.096290
                  (  -.12656)    (   .61206)    ( -26.2963)
 TRO                -.35560         .75518        .033435
                  (   1.0520)    ( -13.1709)    (   9.1309)
 JTRO               -.12265        -.22996       -.028841
                  (   .36286)    (   4.0107)    (  -7.8762)
 GNI                -.23046        .052543       -.012427
                  (   .68181)    (  -.91639)    (  -3.3938)
 AIR                 .12057        -.53341        .029855
                  (  -.35672)    (   9.3030)    (   8.1534)
*******************************************************************************
Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 275 observations used for estimation from 1979M2  to 2001M12
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                      .11806            .026298            4.4895[.000]
 DOPR(-12)                 -.34228             .15780           -2.1690[.031]
 DTRO                       .44167             .16187            2.7286[.007]
 DJTRO(-5)                  .32718             .15134            2.1618[.032]
 DJTRO(-11)                -.38825             .16196           -2.3972[.017]
 DGNI                      -1.3728             .47075           -2.9163[.004]
 DGNI(-7)                  -1.7727             .45210           -3.9209[.000]
 DGNI(-8)                   1.1260             .46415            2.4260[.016]
 S2                        -.36552            .032562          -11.2254[.000]
 S3                        .068991            .033129            2.0825[.038]
 S4                       -.080532            .033869           -2.3778[.018]
 S5                        -.13845            .033284           -4.1598[.000]
 S6                        -.31901            .032828           -9.7174[.000]
 S7                        .045014            .032281            1.3944[.164]
 S8                        -.11932            .037530           -3.1792[.002]
 S9                        -.21095            .037191           -5.6721[.000]
 S10                        .11369            .032168            3.5341[.000]
 S11                       -.20281            .035627           -5.6925[.000]
 S12                       -.19841            .032899           -6.0309[.000]
 UT(-1)                    -.50682            .052259           -9.6983[.000]
*******************************************************************************
 R-Squared                     .83407   R-Bar-Squared                    .82171
 S.E. of Regression           .091937   F-stat.    F( 19, 255)   67.4639[.000]
 Mean of Dependent Variable  .0050468   S.D. of Dependent Variable       .21773
 Residual Sum of Squares       2.1554   Equation Log-likelihood        276.5043
 Akaike Info. Criterion      256.5043   Schwarz Bayesian Criterion     220.3366
 DW-statistic                  2.1313
*******************************************************************************
```

Table 5.4.4a Microfit output for ECM
Arrivals from China, one month ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

288 observations from 1978M2 to 2002M1 . Order of VAR = 1, chosen r =3.
List of variables included in the cointegrating vector:
ARR OPR TRO GNI AIR

	Vector 1	Vector 2	Vector 3
ARR	-.17350	-.0031254	-.010104
	(-1.0000)	(-1.0000)	(-1.0000)
OPR	-.17761	-.17800	-.023547
	(-1.0237)	(-56.9540)	(-2.3304)
TRO	.0046900	-.038512	.013159
	(.027031)	(-12.3223)	(1.3023)
GNI	.031801	-.17349	.083534
	(.18329)	(-55.5096)	(8.2671)
AIR	.27461	.18784	-.029325
	(1.5827)	(60.1014)	(-2.9022)

Ordinary Least Squares Estimation

Dependent variable is DARR
277 observations used for estimation from 1979M1 to 2002M1

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	.29412	.036466	8.0656[.000]
DGNI(-11)	1.2287	.51594	2.3815[.018]
S2	-.50501	.040924	-12.3402[.000]
S3	.015701	.041032	.38265[.702]
S4	-.20012	.040902	-4.8925[.000]
S5	-.25318	.040815	-6.2031[.000]
S6	-.42132	.040814	-10.3229[.000]
S7	-.20771	.040833	-5.0868[.000]
S8	-.10452	.040804	-2.5615[.011]
S9	-.21410	.040794	-5.2483[.000]
S10	-.23068	.040799	-5.6540[.000]
S11	-.35617	.040820	-8.7253[.000]
S12	-.68190	.053457	-12.7560[.000]
UT(-1)	-.0041337	.0039654	-1.0424[.298]

R-Squared	.64035	R-Bar-Squared	.62257
S.E. of Regression	.13980	F-stat. F(13, 263)	36.0204[.000]
Mean of Dependent Variable	.016134	S.D. of Dependent Variable	.22756
Residual Sum of Squares	5.1401	Equation Log-likelihood	159.1455
Akaike Info. Criterion	145.1455	Schwarz Bayesian Criterion	119.7774
DW-statistic	2.5767		

Table 5.4.4b Microfit output for ECM
Arrivals from China, 12 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 299 observations from 1978M2  to 2002M12. Order of VAR = 1, chosen r =3.
 List of variables included in the cointegrating vector:
 ARR             OPR             TRO             GNI             AIR
*******************************************************************************
                  Vector  1      Vector  2      Vector  3
 ARR                 -.17148      -.0037989      -.0056839
                  (  -1.0000)    (  -1.0000)    (  -1.0000)

 OPR                 -.17190        -.17707       -.012938
                  (  -1.0025)    ( -46.6092)    (  -2.2763)

 TRO                .0062483       -.037938        .012498
                  (  .036438)    (  -9.9865)    (   2.1987)

 GNI                 .014102        -.17711        .096463
                  (  .082237)    ( -46.6215)    (  16.9711)

 AIR                  .27651         .18932       -.045164
                  (   1.6125)    (  49.8354)    (  -7.9458)

*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 288 observations used for estimation from 1979M1  to 2002M12
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                       .28815             .037272            7.7310[.000]
 DGNI(-11)                   1.2014              .52103            2.3058[.022]
 S2                         -.49875             .041047          -12.1506[.000]
 S3                         .013022             .041127             .31662[.752]
 S4                         -.19789             .041006           -4.8258[.000]
 S5                         -.26322             .040888           -6.4375[.000]
 S6                         -.43177             .040889          -10.5595[.000]
 S7                         -.19228             .040895           -4.7018[.000]
 S8                         -.10669             .040853           -2.6115[.010]
 S9                         -.21639             .040841           -5.2985[.000]
 S10                        -.23369             .040824           -5.7244[.000]
 S11                        -.36544             .040829           -8.9505[.000]
 S12                        -.67518             .053710          -12.5709[.000]
 UT(-1)                   -.0017095            .0022777           -.75053[.454]
*******************************************************************************
 R-Squared                     .63196   R-Bar-Squared                     .61450
 S.E. of Regression            .14142   F-stat.    F( 13, 274)   36.1913[.000]
 Mean of Dependent Variable   .014519   S.D. of Dependent Variable        .22777
 Residual Sum of Squares       5.4796   Equation Log-likelihood         161.8621
 Akaike Info. Criterion      147.8621   Schwarz Bayesian Criterion      122.2214
 DW-statistic                  2.5655
*******************************************************************************
```

Table 5.4.4c Microfit output for ECM
Arrivals from China, 24 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
******************************************************************************
 287 observations from 1978M2  to 2001M12. Order of VAR = 1, chosen r =2.
 List of variables included in the cointegrating vector:
 ARR            OPR             TRO             GNI
******************************************************************************
                  Vector  1      Vector  2
 ARR                 -.10203       -.026990
                  (  -1.0000)    (  -1.0000)

 OPR                 .025762       -.066071
                  (   .25250)    (  -2.4480)

 TRO                 .032179        .010980
                  (   .31539)    (   .40684)

 GNI                  .20282         .11063
                  (   1.9879)    (   4.0988)

******************************************************************************

Ordinary Least Squares Estimation
******************************************************************************
 Dependent variable is DARR
 276 observations used for estimation from 1979M1  to 2001M12
******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                       .29761             .034228            8.6949[.000]
 DGNI(-11)                   1.2768              .51365            2.4858[.014]
 S2                         -.49773             .041056          -12.1233[.000]
 S3                         .019688             .041207            .47777[.633]
 S4                         -.19282             .041051           -4.6971[.000]
 S5                         -.24400             .041042           -5.9451[.000]
 S6                         -.41204             .041043          -10.0392[.000]
 S7                         -.20090             .041041           -4.8951[.000]
 S8                        -.096838             .041034           -2.3599[.019]
 S9                         -.20412             .041074           -4.9695[.000]
 S10                        -.22011             .041122           -5.3525[.000]
 S11                        -.34473             .041192           -8.3688[.000]
 S12                        -.67491             .053478          -12.6203[.000]
 UT(-1)                    -.017502            .0094867           -1.8449[.066]
******************************************************************************
 R-Squared                     .64099   R-Bar-Squared                   .62318
 S.E. of Regression            .13915   F-stat.    F( 13, 262)   35.9836[.000]
 Mean of Dependent Variable   .014684   S.D. of Dependent Variable      .22669
 Residual Sum of Squares       5.0732   Equation Log-likelihood       159.8790
 Akaike Info. Criterion      145.8790   Schwarz Bayesian Criterion    120.5362
 DW-statistic                  2.5770
******************************************************************************
```

Table 5.4.5a Microfit output for ECM
Arrivals from France, one month ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 287 observations from 1978M3  to 2002M1 . Order of VAR = 2, chosen r =2.
 List of variables included in the cointegrating vector:
 ARR            OPR             TRO             GNI
*******************************************************************************
                  Vector  1      Vector  2
 ARR                 -.29372       -.010795
                  (  -1.0000)    (  -1.0000)

 OPR                -.045211         .10592
                  (  -.15393)    (   9.8119)

 TRO                  .20605         .25887
                  (   .70151)    (  23.9800)

 GNI                  .18242        -.22672
                  (   .62107)    ( -21.0017)

*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 283 observations used for estimation from 1978M7  to 2002M1
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                    -.051453           .028703            -1.7926[.074]
 DGNI(-5)                  -.49074            .23367            -2.1001[.037]
 S2                        -.12022           .033519            -3.5867[.000]
 S3                         .21746           .033354             6.5199[.000]
 S4                         .18609           .037304             4.9884[.000]
 S5                         .11404           .040940             2.7855[.006]
 S6                        -.12701           .041279            -3.0769[.002]
 S7                         .18408           .034498             5.3360[.000]
 S8                        .017845           .038778             .46018[.646]
 S9                         .14810           .036918             4.0116[.000]
 S10                        .34284           .039543             8.6700[.000]
 S11                       .024944           .047495             .52518[.600]
 S12                       -.34198           .040840            -8.3735[.000]
 UT(-1)                    -.48854           .051664            -9.4561[.000]
*******************************************************************************
 R-Squared                     .80610   R-Bar-Squared                    .79673
 S.E. of Regression            .11428   F-stat.    F( 13, 269)   86.0252[.000]
 Mean of Dependent Variable  .0048420   S.D. of Dependent Variable       .25348
 Residual Sum of Squares       3.5132   Equation Log-likelihood        219.4739
 Akaike Info. Criterion      205.4739   Schwarz Bayesian Criterion     179.9557
 DW-statistic                  2.1987
*******************************************************************************
```

Table 5.4.5b Microfit output for ECM
Arrivals from France, 12 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 298 observations from 1978M3  to 2002M12. Order of VAR = 2, chosen r =2.
 List of variables included in the cointegrating vector:
 ARR            OPR             TRO             GNI
*******************************************************************************
                  Vector  1      Vector  2
 ARR                 -.28814       -.012931
                  (  -1.0000)    (  -1.0000)

 OPR                -.038675         .10632
                  (  -.13423)    (   8.2220)

 TRO                  .21579         .25751
                  (   .74893)    (  19.9150)

 GNI                  .16694        -.22339
                  (   .57938)    ( -17.2756)

*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 294 observations used for estimation from 1978M7  to 2002M12
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                    -.050639             .028930           -1.7504[.081]
 DGNI(-5)                  -.59197              .23517           -2.5172[.012]
 S2                        -.11320             .033804           -3.3488[.001]
 S3                         .21803             .033581            6.4926[.000]
 S4                         .18826             .037448            5.0272[.000]
 S5                         .10251             .040960            2.5027[.013]
 S6                        -.11364             .040968           -2.7738[.006]
 S7                         .18337             .034894            5.2551[.000]
 S8                        .012859             .038873            .33080[.741]
 S9                         .14353             .037005            3.8787[.000]
 S10                        .33613             .039399            8.5315[.000]
 S11                       .017440             .046835            .37236[.710]
 S12                       -.33709             .040612           -8.3002[.000]
 UT(-1)                    -.47310             .049804           -9.4993[.000]
*******************************************************************************
 R-Squared                     .79438   R-Bar-Squared                    .78483
 S.E. of Regression            .11621   F-stat.    F( 13, 280)   83.2111[.000]
 Mean of Dependent Variable  .0042494   S.D. of Dependent Variable       .25052
 Residual Sum of Squares       3.7812   Equation Log-likelihood        222.8038
 Akaike Info. Criterion      208.8038   Schwarz Bayesian Criterion     183.0187
 DW-statistic                  2.2095
*******************************************************************************
```

Table 5.4.5c Microfit output for ECM
Arrivals from France, 24 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 286 observations from 1978M3  to 2001M12. Order of VAR = 2, chosen r =2.
 List of variables included in the cointegrating vector:
 ARR             OPR             TRO             GNI
*******************************************************************************
                  Vector  1      Vector  2
 ARR                 -.29388       -.010987
                  (  -1.0000)    (  -1.0000)

 OPR                -.045789         .10625
                  (  -.15581)    (   9.6700)

 TRO                  .20424         .26106
                  (   .69499)    (  23.7603)

 GNI                  .18413        -.22828
                  (   .62656)    ( -20.7769)

*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 282 observations used for estimation from 1978M7  to 2001M12
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                    -.061400            .029681            -2.0687[.040]
 DGNI(-5)                  -.48721             .23336            -2.0878[.038]
 S2                        -.11281            .033925            -3.3254[.001]
 S3                         .22428            .033689             6.6576[.000]
 S4                         .19654            .038066             5.1632[.000]
 S5                         .12609            .041871             3.0114[.003]
 S6                        -.11522            .042152            -2.7335[.007]
 S7                         .19304            .035092             5.5010[.000]
 S8                        .029134            .039638             .73500[.463]
 S9                         .15856            .037685             4.2075[.000]
 S10                        .35451            .040440             8.7662[.000]
 S11                       .039440            .048658             .81056[.418]
 S12                       -.32976            .041792            -7.8905[.000]
 UT(-1)                    -.50023            .052346            -9.5562[.000]
*******************************************************************************
 R-Squared                     .80731   R-Bar-Squared                   .79796
 S.E. of Regression            .11412   F-stat.    F( 13, 268)   86.3692[.000]
 Mean of Dependent Variable  .0045983   S.D. of Dependent Variable      .25389
 Residual Sum of Squares       3.4905   Equation Log-likelihood       219.1137
 Akaike Info. Criterion      205.1137   Schwarz Bayesian Criterion    179.6204
 DW-statistic                  2.1736
*******************************************************************************
```

Table 5.4.6a **Microfit output for ECM**
Arrivals from Germany, one month ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

288 observations from 1978M2 to 2002M1 . Order of VAR = 1, chosen r =3.
List of variables included in the cointegrating vector:
ARR OPR TRO GNI AIR

	Vector 1	Vector 2	Vector 3
ARR	-.20815	-.041008	.020014
	(-1.0000)	(-1.0000)	(-1.0000)
OPR	-.030475	.040025	.17743
	(-.14641)	(.97603)	(-8.8653)
TRO	.15491	.18634	.14366
	(.74424)	(4.5440)	(-7.1778)
GNI	.11732	-.18211	-.17594
	(.56364)	(-4.4409)	(8.7910)
AIR	-.0069730	.046896	-.022766
	(-.033500)	(1.1436)	(1.1375)

Ordinary Least Squares Estimation

Dependent variable is DARR
286 observations used for estimation from 1978M4 to 2002M1

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	.0075045	.030995	.24212[.809]
DOPR(-2)	.19938	.10277	1.9401[.053]
S2	-.12862	.031041	-4.1435[.000]
S3	.31141	.031125	10.0052[.000]
S4	.10933	.041412	2.6400[.009]
S5	-.022697	.043685	-.51956[.604]
S6	-.32375	.040410	-8.0118[.000]
S7	.089396	.031637	2.8257[.005]
S8	-.086688	.035764	-2.4239[.016]
S9	.12049	.034424	3.5000[.001]
S10	.34267	.039283	8.7230[.000]
S11	-.095090	.050898	-1.8682[.063]
S12	-.58568	.042274	-13.8542[.000]
UT(-1)	-.39112	.047293	-8.2703[.000]

R-Squared	.89514	R-Bar-Squared	.89013
S.E. of Regression	.10317	F-stat. F(13, 272)	178.6154[.000]
Mean of Dependent Variable	.0019746	S.D. of Dependent Variable	.31125
Residual Sum of Squares	2.8950	Equation Log-likelihood	250.9815
Akaike Info. Criterion	236.9815	Schwarz Bayesian Criterion	211.3895
DW-statistic	2.2273		

Table 5.4.6b Microfit output for ECM
Arrivals from Germany, 12 months ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

299 observations from 1978M2 to 2002M12. Order of VAR = 1, chosen r =4.
List of variables included in the cointegrating vector:
ARR OPR TRO GNI AIR

	Vector 1	Vector 2	Vector 3	Vector 4
ARR	-.20585	.036968	.018525	.0080093
	(-1.0000)	(-1.0000)	(-1.0000)	(-1.0000)
OPR	-.030447	-.039043	.17769	-.0089466
	(-.14791)	(1.0561)	(-9.5918)	(1.1170)
TRO	.16087	-.17619	.14259	-.27952
	(.78149)	(4.7661)	(-7.6970)	(34.8990)
GNI	.10504	.17427	-.17237	.25894
	(.51026)	(-4.7140)	(9.3045)	(-32.3302)
AIR	-.0024530	-.043308	-.023968	-.013787
	(-.011917)	(1.1715)	(1.2938)	(1.7214)

Ordinary Least Squares Estimation

Dependent variable is DARR
290 observations used for estimation from 1978M11 to 2002M12

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	-.010816	.032210	-.33580[.737]
DAIR(-9)	-.30677	.13700	-2.2392[.026]
S2	-.11675	.031888	-3.6613[.000]
S3	.31959	.031912	10.0146[.000]
S4	.13446	.043053	3.1231[.002]
S5	-.0010701	.044956	-.023802[.981]
S6	-.27202	.041600	-6.5390[.000]
S7	.090949	.033107	2.7471[.006]
S8	-.077903	.037199	-2.0942[.037]
S9	.13120	.035502	3.6957[.000]
S10	.36527	.040395	9.0424[.000]
S11	-.053299	.052489	-1.0154[.311]
S12	-.54411	.043626	-12.4722[.000]
UT(-1)	-.42908	.048984	-8.7596[.000]

R-Squared	.88682	R-Bar-Squared	.88149
S.E. of Regression	.10668	F-stat. F(13, 276)	166.3606[.000]
Mean of Dependent Variable	.0010631	S.D. of Dependent Variable	.30990
Residual Sum of Squares	3.1412	Equation Log-likelihood	244.6746
Akaike Info. Criterion	230.6746	Schwarz Bayesian Criterion	204.9854
DW-statistic	2.2109		

Table 5.4.6c **Microfit output for ECM**
Arrivals from Germany, 24 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
******************************************************************************
 287 observations from 1978M2  to 2001M12. Order of VAR = 1, chosen r =3.
 List of variables included in the cointegrating vector:
 ARR              OPR              TRO              GNI              AIR
******************************************************************************
                  Vector  1      Vector  2      Vector  3
 ARR                 -.20795       -.043026        .021016
                  (  -1.0000)    (  -1.0000)    (  -1.0000)

 OPR                -.030945        .042183         .17700
                  (  -.14881)    (   .98041)    (  -8.4222)

 TRO                  .15358         .18646         .13986
                  (   .73855)    (   4.3337)    (  -6.6552)

 GNI                  .11888        -.17852        -.17316
                  (   .57166)    (  -4.1491)    (   8.2394)

 AIR               -.0073754        .044791       -.023091
                  ( -.035467)    (   1.0410)    (   1.0988)

******************************************************************************

Ordinary Least Squares Estimation
******************************************************************************
 Dependent variable is DARR
 285 observations used for estimation from 1978M4  to 2001M12
******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                   -.0031311             .031784          -.098513[.922]
 DOPR(-2)                   .20459              .10265            1.9931[.047]
 S2                        -.12139             .031407           -3.8651[.000]
 S3                         .31894             .031522           10.1180[.000]
 S4                         .11957             .041997            2.8472[.005]
 S5                       -.011941             .044295           -.26958[.788]
 S6                        -.31373             .040982           -7.6554[.000]
 S7                        .097283             .032074            3.0331[.003]
 S8                       -.077566             .036294           -2.1371[.033]
 S9                         .12924             .034927            3.7002[.000]
 S10                        .35257             .039854            8.8467[.000]
 S11                      -.083126             .051538           -1.6129[.108]
 S12                       -.57516             .042872          -13.4155[.000]
 UT(-1)                    -.39755             .047422           -8.3834[.000]
******************************************************************************
 R-Squared                     .89566   R-Bar-Squared                   .89066
 S.E. of Regression            .10299   F-stat.    F( 13, 271)  178.9511[.000]
 Mean of Dependent Variable  .0011336   S.D. of Dependent Variable      .31147
 Residual Sum of Squares       2.8746   Equation Log-likelihood       250.6123
 Akaike Info. Criterion      236.6123   Schwarz Bayesian Criterion    211.0448
 DW-statistic                  2.2265
******************************************************************************
```

Table 5.4.7a Microfit output for ECM
Arrivals from Korea, one month ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
******************************************************************************
 288 observations from 1978M2  to 2002M1 . Order of VAR = 1, chosen r =2.
 List of variables included in the cointegrating vector:
 ARR             OPR             TRO             JTRO            GNI
 AIR
******************************************************************************
                  Vector  1      Vector  2
 ARR                  .20156        -.15965
                  (  -1.0000)    (  -1.0000)
 OPR                  .12086        .060669
                  (  -.59960)    (   .38002)
 TRO                -.088474         .11520
                  (   .43895)    (   .72158)
 JTRO                -.19733        .021971
                  (   .97900)    (   .13762)
 GNI                 -.26560         .15402
                  (   1.3177)    (   .96472)
 AIR                 .073886       -.016778
                  (  -.36657)    (  -.10509)
******************************************************************************

Ordinary Least Squares Estimation
******************************************************************************
 Dependent variable is DARR
 277 observations used for estimation from 1979M1  to 2002M1
******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                      .091663            .019720             4.6481[.000]
 DTRO                       -.18626            .088078            -2.1147[.035]
 DGNI                        .60376             .16137             3.7414[.000]
 DGNI(-8)                    .28097             .14230             1.9745[.049]
 DAIR(-11)                 -.076414            .035267            -2.1668[.031]
 S2                         -.23773            .025301            -9.3958[.000]
 S3                         .012159            .024828             .48971[.625]
 S4                        -.058762            .024988            -2.3516[.019]
 S5                        -.067387            .025189            -2.6752[.008]
 S6                         -.15605            .025178            -6.1979[.000]
 S7                         .085710            .024970             3.4326[.001]
 S8                         .023960            .025823             .92786[.354]
 S9                         -.33392            .029172           -11.4463[.000]
 S10                        .037099            .025109             1.4775[.141]
 S11                        -.10449            .025927            -4.0302[.000]
 S12                        -.18960            .025729            -7.3690[.000]
 UT(-1)                    -.051455            .022134            -2.3246[.021]
******************************************************************************
 R-Squared                     .75906   R-Bar-Squared                    .74423
 S.E. of Regression           .073691   F-stat.    F( 16, 260)   51.1930[.000]
 Mean of Dependent Variable  .0099610   S.D. of Dependent Variable       .14571
 Residual Sum of Squares       1.4119   Equation Log-likelihood        338.1058
 Akaike Info. Criterion      321.1058   Schwarz Bayesian Criterion     290.3016
 DW-statistic                  2.2125
******************************************************************************
```

Table 5.4.7b Microfit output for ECM
Arrivals from Korea, 12 months ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
****
299 observations from 1978M2 to 2002M12. Order of VAR = 1, chosen r =2.
List of variables included in the cointegrating vector:
ARR OPR TRO JTRO GNI
AIR
****

	Vector 1	Vector 2
ARR	.21522	.13552
	(-1.0000)	(-1.0000)
OPR	.11233	-.079422
	(-.52195)	(.58607)
TRO	-.097554	-.094967
	(.45328)	(.70079)
JTRO	-.19720	-.0016385
	(.91628)	(.012091)
GNI	-.27613	-.12580
	(1.2830)	(.92831)
AIR	.071633	.0061791
	(-.33284)	(-.045597)

****

Ordinary Least Squares Estimation
****
Dependent variable is DARR
291 observations used for estimation from 1978M10 to 2002M12
****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	.091150	.020187	4.5152[.000]
DGNI	.48958	.15125	3.2369[.001]
DGNI(-8)	.32924	.14443	2.2795[.023]
S2	-.24349	.025510	-9.5445[.000]
S3	.0058579	.025201	.23244[.816]
S4	-.056585	.025333	-2.2336[.026]
S5	-.071340	.025479	-2.8000[.005]
S6	-.15738	.025489	-6.1743[.000]
S7	.094645	.025328	3.7368[.000]
S8	.024413	.026087	.93585[.350]
S9	-.35308	.029305	-12.0483[.000]
S10	.038845	.025337	1.5331[.126]
S11	-.10639	.026101	-4.0761[.000]
S12	-.18840	.025866	-7.2836[.000]
UT(-1)	-.061823	.021304	-2.9019[.004]

****

R-Squared	.75381	R-Bar-Squared	.74133
S.E. of Regression	.075404	F-stat. F(14, 276)	60.3642[.000]
Mean of Dependent Variable	.0083589	S.D. of Dependent Variable	.14826
Residual Sum of Squares	1.5693	Equation Log-likelihood	346.9918
Akaike Info. Criterion	331.9918	Schwarz Bayesian Criterion	304.4418
DW-statistic	2.1855		

****

Table 5.4.7c Microfit output for ECM
Arrivals from Korea, 24 months ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

287 observations from 1978M2 to 2001M12. Order of VAR = 1, chosen r =2.
List of variables included in the cointegrating vector:
ARR OPR TRO JTRO GNI
AIR

	Vector 1	Vector 2
ARR	.20865	.15406
	(-1.0000)	(-1.0000)
OPR	.11760	-.071297
	(-.56361)	(.46278)
TRO	-.092397	-.10230
	(.44283)	(.66404)
JTRO	-.19839	-.017707
	(.95081)	(.11493)
GNI	-.27302	-.15095
	(1.3085)	(.97982)
AIR	.074344	.012760
	(-.35631)	(-.082822)

Ordinary Least Squares Estimation

Dependent variable is DARR
276 observations used for estimation from 1979M1 to 2001M12

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	.084651	.020161	4.1988[.000]
DTRO	-.20966	.087689	-2.3910[.018]
DGNI	.63502	.16147	3.9327[.000]
DAIR(-9)	.068791	.034985	1.9663[.050]
DAIR(-11)	-.075092	.035146	-2.1366[.034]
S2	-.23144	.025612	-9.0366[.000]
S3	.017811	.025110	.70933[.479]
S4	-.052919	.025281	-2.0932[.037]
S5	-.060997	.025495	-2.3925[.017]
S6	-.15016	.025484	-5.8924[.000]
S7	.085388	.025465	3.3531[.001]
S8	.030849	.026152	1.1796[.239]
S9	-.30179	.026889	-11.2235[.000]
S10	.043433	.025414	1.7091[.089]
S11	-.097575	.026254	-3.7165[.000]
S12	-.18435	.026060	-7.0739[.000]
UT(-1)	-.053679	.022348	-2.4020[.017]

R-Squared	.75968	R-Bar-Squared	.74483
S.E. of Regression	.073490	F-stat. F(16, 259)	51.1692[.000]
Mean of Dependent Variable	.0092421	S.D. of Dependent Variable	.14548
Residual Sum of Squares	1.3988	Equation Log-likelihood	337.6750
Akaike Info. Criterion	320.6750	Schwarz Bayesian Criterion	289.9016
DW-statistic	2.2175		

Table 5.4.8a Microfit output for ECM
Arrivals from Singapore, one month ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 288 observations from 1978M2  to 2002M1 . Order of VAR = 1, chosen r =2.
 List of variables included in the cointegrating vector:
 ARR             JTRO             GNI              AIR
*******************************************************************************
                  Vector  1      Vector  2
 ARR                 -.15484       -.017927
                  (  -1.0000)    (  -1.0000)

 JTRO                .099051         .21040
                  (   .63972)    (  11.7366)

 GNI                 .074505        .089131
                  (   .48118)    (   4.9719)

 AIR                 .051157        -.17630
                  (   .33039)    (  -9.8344)

*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 276 observations used for estimation from 1979M2  to 2002M1
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                      -.84433            .056761         -14.8753[.000]
 DGNI(-11)                  -1.4756             .49217          -2.9983[.003]
 DGNI(-12)                   1.4114             .49215           2.8679[.004]
 S2                          .97969            .068862          14.2269[.000]
 S3                          1.0602            .068857          15.3968[.000]
 S4                          1.1771            .068731          17.1258[.000]
 S5                          .83759            .068748          12.1833[.000]
 S6                          1.1911            .068735          17.3293[.000]
 S7                         .084492            .068771           1.2286[.220]
 S8                          .80355            .068733          11.6908[.000]
 S9                          1.1054            .068744          16.0806[.000]
 S10                         .95902            .068761          13.9472[.000]
 S11                         .96240            .068748          13.9989[.000]
 S12                         1.1050            .079195          13.9525[.000]
 UT(-1)                   -.0024109           .0045834          -.52601[.599]
*******************************************************************************
 R-Squared                      .78953   R-Bar-Squared                    .77824
 S.E. of Regression             .19119   F-stat.    F( 14, 261)   69.9354[.000]
 Mean of Dependent Variable  .0062739   S.D. of Dependent Variable        .40601
 Residual Sum of Squares        9.5410   Equation Log-likelihood         72.7161
 Akaike Info. Criterion        57.7161   Schwarz Bayesian Criterion      30.5631
 DW-statistic                   2.8975
*******************************************************************************
```

Table 5.4.8b **Microfit output for ECM**
Arrivals from Singapore, 12 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 299 observations from 1978M2  to 2002M12. Order of VAR = 1, chosen r =2.
 List of variables included in the cointegrating vector:
 ARR            JTRO           GNI            AIR
*******************************************************************************
                  Vector  1      Vector  2
 ARR                 -.15220       -.018203
                  (  -1.0000)    (  -1.0000)

 JTRO                 .10106         .21220
                  (   .66400)    (  11.6570)

 GNI                 .076551        .089539
                  (   .50295)    (   4.9188)

 AIR                 .045627        -.17724
                  (   .29977)    (  -9.7365)

*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 287 observations used for estimation from 1979M2  to 2002M12
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                     -.84424            .057405          -14.7067[.000]
 DGNI(-11)                 -1.4576             .48312           -3.0171[.003]
 DGNI(-12)                  1.4112             .49797            2.8339[.005]
 S2                         .99448            .069201           14.3710[.000]
 S3                         1.0604            .069192           15.3252[.000]
 S4                         1.1653            .069056           16.8746[.000]
 S5                         .83532            .069066           12.0944[.000]
 S6                         1.1748            .069056           17.0122[.000]
 S7                         .10114            .069087            1.4639[.144]
 S8                         .79844            .069061           11.5614[.000]
 S9                         1.1049            .069074           15.9955[.000]
 S10                        .96370            .069094           13.9476[.000]
 S11                        .97650            .069078           14.1361[.000]
 S12                        1.1023            .078174           14.1007[.000]
 UT(-1)                  -.0025124           .0046630           -.53880[.590]
*******************************************************************************
 R-Squared                     .77945   R-Bar-Squared                   .76810
 S.E. of Regression            .19346   F-stat.    F( 14, 272)   68.6642[.000]
 Mean of Dependent Variable   .010609   S.D. of Dependent Variable      .40173
 Residual Sum of Squares      10.1799   Equation Log-likelihood        71.9213
 Akaike Info. Criterion       56.9213   Schwarz Bayesian Criterion     29.4752
 DW-statistic                  2.8754
*******************************************************************************
```

Table 5.4.8c Microfit output for ECM
Arrivals from Singapore, 24 months ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

287 observations from 1978M2 to 2001M12. Order of VAR = 1, chosen r =2.
List of variables included in the cointegrating vector:
ARR JTRO GNI AIR

	Vector 1	Vector 2
ARR	-.15563	-.020025
	(-1.0000)	(-1.0000)
JTRO	.098351	.20681
	(.63195)	(10.3275)
GNI	.075523	.089103
	(.48527)	(4.4495)
AIR	.051548	-.17227
	(.33122)	(-8.6025)

Ordinary Least Squares Estimation

Dependent variable is DARR
275 observations used for estimation from 1979M2 to 2001M12

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	-.82589	.063083	-13.0920[.000]
DGNI(-11)	-1.4753	.49263	-2.9946[.003]
DGNI(-12)	1.2693	.54062	2.3478[.020]
S2	.96178	.074113	12.9772[.000]
S3	1.0423	.074103	14.0660[.000]
S4	1.1596	.073953	15.6808[.000]
S5	.82044	.073960	11.0930[.000]
S6	1.1739	.073951	15.8742[.000]
S7	.067543	.073985	.91293[.362]
S8	.78604	.073959	10.6281[.000]
S9	1.0878	.073974	14.7058[.000]
S10	.94148	.073990	12.7244[.000]
S11	.94494	.073973	12.7740[.000]
S12	1.0876	.083787	12.9801[.000]
UT(-1)	-.0031996	.0052127	-.61381[.540]
R-Squared	.78446	R-Bar-Squared	.77285
S.E. of Regression	.19138	F-stat. F(14, 260)	67.5895[.000]
Mean of Dependent Variable	.010170	S.D. of Dependent Variable	.40155
Residual Sum of Squares	9.5227	Equation Log-likelihood	72.2171
Akaike Info. Criterion	57.2171	Schwarz Bayesian Criterion	30.0913
DW-statistic	2.9009		

Table 5.4.9a **Microfit output for ECM**
Arrivals from Taiwan, one month ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 287 observations from 1978M3  to 2002M1 . Order of VAR = 2, chosen r =3.
 List of variables included in the cointegrating vector:
 ARR            CPITAI         JTRO           AIR
*******************************************************************************
                  Vector  1      Vector  2      Vector  3
 ARR                 -.27304       -.053080        .052080
                  (  -1.0000)    (  -1.0000)    (  -1.0000)

 CPITAI               .62189         .25261        .096016
                  (   2.2777)    (   4.7590)    (  -1.8436)

 JTRO               -.017924         .10589        -.12929
                  ( -.065646)    (   1.9949)    (   2.4826)

 AIR                 .021594        -.10169       -.059169
                  (  .079089)    (  -1.9159)    (   1.1361)

*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 277 observations used for estimation from 1979M1  to 2002M1
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                   -.0077217           .036625            -.21083[.833]
 DCPITAI                    3.3665            1.1334             2.9704[.003]
 DJTRO(-1)                  .55430            .27046             2.0494[.041]
 DAIR(-4)                   .17536           .041246             4.2516[.000]
 DAIR(-10)                  .14714           .039708             3.7056[.000]
 DAIR(-11)                 -.11974           .033533            -3.5708[.000]
 S2                         .33400           .050661             6.5929[.000]
 S3                        -.12110           .050706            -2.3882[.018]
 S4                         .21430           .050441             4.2485[.000]
 S5                        -.14676           .050658            -2.8971[.004]
 S6                       -.097342           .050477            -1.9284[.055]
 S7                         .44477           .051960             8.5599[.000]
 S8                        -.18390           .051510            -3.5701[.000]
 S9                        -.29026           .051257            -5.6629[.000]
 S10                        .13283           .050548             2.6277[.009]
 S11                       -.24058           .051644            -4.6584[.000]
 S12                       -.12449           .051218            -2.4306[.016]
 UT(-1)                   -.021019           .010137            -2.0735[.039]
*******************************************************************************
 R-Squared                     .66678   R-Bar-Squared                    .64491
 S.E. of Regression            .17026   F-stat.    F( 17, 259)   30.4858[.000]
 Mean of Dependent Variable  .0069363   S.D. of Dependent Variable       .28572
 Residual Sum of Squares       7.5081   Equation Log-likelihood        106.6662
 Akaike Info. Criterion       88.6662   Schwarz Bayesian Criterion      56.0501
 DW-statistic                  2.7848
*******************************************************************************
```

Table 5.4.9b Microfit output for ECM
Arrivals from Taiwan, 12 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 298 observations from 1978M3  to 2002M12. Order of VAR = 2, chosen r =3.
 List of variables included in the cointegrating vector:
 ARR            CPITAI          JTRO            AIR
*******************************************************************************
                  Vector  1      Vector  2      Vector  3
 ARR                 -.27140       -.050521        .051052
                  (  -1.0000)    (  -1.0000)    (  -1.0000)

 CPITAI               .62088         .24206        .098350
                  (   2.2877)    (   4.7912)    (  -1.9265)

 JTRO               -.018477         .11009        -.12889
                  ( -.068082)    (   2.1791)    (   2.5246)

 AIR                 .020505        -.10138       -.059270
                  (  .075553)    (  -2.0067)    (   1.1610)

*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 288 observations used for estimation from 1979M1  to 2002M12
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                    .0013485           .035529            .037955[.970]
 DCPITAI                    3.4372            1.0830             3.1739[.002]
 DJTRO(-1)                  .64249            .25832             2.4872[.013]
 DAIR(-4)                   .16464           .040090             4.1067[.000]
 DAIR(-5)                  -.11781           .040512            -2.9079[.004]
 DAIR(-10)                  .14236           .038506             3.6969[.000]
 DAIR(-11)                 -.18033           .038715            -4.6580[.000]
 S2                         .32362           .048553             6.6652[.000]
 S3                        -.12578           .048736            -2.5808[.010]
 S4                         .21011           .048387             4.3424[.000]
 S5                        -.15121           .048587            -3.1122[.002]
 S6                        -.10307           .048450            -2.1273[.034]
 S7                         .43998           .049815             8.8323[.000]
 S8                        -.18166           .049281            -3.6862[.000]
 S9                        -.29799           .049070            -6.0727[.000]
 S10                        .13519           .048445             2.7906[.006]
 S11                       -.24153           .049473            -4.8820[.000]
 S12                       -.12721           .049130            -2.5893[.010]
 UT(-1)                  -.0098239          .0098676            -.99557[.320]
*******************************************************************************
 R-Squared                     .68334   R-Bar-Squared                   .66215
 S.E. of Regression            .16505   F-stat.    F( 18, 269)   32.2493[.000]
 Mean of Dependent Variable  .0066863   S.D. of Dependent Variable      .28396
 Residual Sum of Squares       7.3280   Equation Log-likelihood       120.0061
 Akaike Info. Criterion      101.0061   Schwarz Bayesian Criterion     66.2079
 DW-statistic                  2.8014
*******************************************************************************
```

Table 5.4.9c Microfit output for ECM
Arrivals from Taiwan, 24 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 286 observations from 1978M3  to 2001M12. Order of VAR = 2, chosen r =3.
 List of variables included in the cointegrating vector:
 ARR             CPITAI          JTRO            AIR
*******************************************************************************
                  Vector  1      Vector  2      Vector  3
 ARR                 -.27366       -.052382        .052474
                  (  -1.0000)    (  -1.0000)    (  -1.0000)

 CPITAI               .62449         .25220        .095659
                  (   2.2820)    (   4.8147)    (  -1.8230)

 JTRO               -.017950         .10555        -.13119
                  ( -.065593)    (   2.0150)    (   2.5002)

 AIR                 .021095        -.10217       -.058666
                  (  .077084)    (  -1.9504)    (   1.1180)

*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 276 observations used for estimation from 1979M1  to 2001M12
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                    -.011070            .037456            -.29553[.768]
 DCPITAI                    3.3768             1.1353             2.9745[.003]
 DJTRO(-1)                  .56202             .27137             2.0710[.039]
 DAIR(-4)                   .17503            .041324             4.2356[.000]
 DAIR(-10)                  .14760            .039792             3.7093[.000]
 DAIR(-11)                 -.11977            .033589            -3.5657[.000]
 S2                         .33767            .051333             6.5780[.000]
 S3                        -.11771            .051337            -2.2928[.023]
 S4                         .21766            .051075             4.2616[.000]
 S5                        -.14344            .051307            -2.7956[.006]
 S6                       -.094090            .051085            -1.8418[.067]
 S7                         .44842            .052648             8.5172[.000]
 S8                        -.18074            .052132            -3.4669[.001]
 S9                        -.28715            .051848            -5.5384[.000]
 S10                        .13635            .051204             2.6629[.008]
 S11                       -.23708            .052298            -4.5333[.000]
 S12                       -.12089            .051872            -2.3305[.021]
 UT(-1)                   -.020449           .0099883            -2.0473[.042]
*******************************************************************************
 R-Squared                     .66687   R-Bar-Squared                   .64492
 S.E. of Regression            .17055   F-stat.    F( 17, 258)   30.3807[.000]
 Mean of Dependent Variable  .0066591   S.D. of Dependent Variable      .28620
 Residual Sum of Squares       7.5041   Equation Log-likelihood       105.8563
 Akaike Info. Criterion       87.8563   Schwarz Bayesian Criterion     55.2727
 DW-statistic                  2.7883
*******************************************************************************
```

Table 5.4.10a Microfit output for ECM
Arrivals from the UK, one month ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

****

288 observations from 1978M2 to 2002M1 . Order of VAR = 1, chosen r =3.
List of variables included in the cointegrating vector:
ARR OPR TRO JTRO GNI
AIR

****

	Vector 1	Vector 2	Vector 3
ARR	-.23289	.034797	.031281
	(-1.0000)	(-1.0000)	(-1.0000)
OPR	-.0045970	-.029684	.19150
	(-.019739)	(.85306)	(-6.1217)
TRO	.18262	-.29361	.37529
	(.78414)	(8.4377)	(-11.9973)
JTRO	.12146	-.18832	-.043197
	(.52155)	(5.4120)	(1.3809)
GNI	.12850	.37484	-.40541
	(.55178)	(-10.7721)	(12.9601)
AIR	-.019686	-.088104	.022108
	(-.084528)	(2.5319)	(-.70674)

****

Ordinary Least Squares Estimation

****

Dependent variable is DARR
282 observations used for estimation from 1978M8 to 2002M1

****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	-.038817	.035537	-1.0923[.276]
DTRO(-1)	.80650	.32471	2.4837[.014]
DJTRO	.73924	.27304	2.7075[.007]
DGNI(-6)	-.90818	.41568	-2.1848[.030]
S2	.14311	.050699	2.8227[.005]
S3	.017073	.050822	.33594[.737]
S4	.059463	.050723	1.1723[.242]
S5	-.14169	.051008	-2.7778[.006]
S6	-.022903	.050534	-.45323[.651]
S7	.31617	.057944	5.4565[.000]
S8	.10703	.050840	2.1052[.036]
S9	-.14211	.050935	-2.7899[.006]
S10	.11802	.049958	2.3624[.019]
S11	-.071547	.050220	-1.4247[.155]
S12	.013664	.049929	.27367[.785]
UT(-1)	-.31823	.045052	-7.0636[.000]

****

R-Squared	.47000	R-Bar-Squared	.44011
S.E. of Regression	.17275	F-stat. F(15, 266)	15.7258[.000]
Mean of Dependent Variable	.0040341	S.D. of Dependent Variable	.23087
Residual Sum of Squares	7.9378	Equation Log-likelihood	103.2672
Akaike Info. Criterion	87.2672	Schwarz Bayesian Criterion	58.1319
DW-statistic	2.5536		

****

Table 5.4.10b Microfit output for ECM
Arrivals from the UK, 12 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 299 observations from 1978M2  to 2002M12. Order of VAR = 1, chosen r =2.
 List of variables included in the cointegrating vector:
 ARR             TRO             JTRO            GNI             AIR
*******************************************************************************
                  Vector  1      Vector  2
 ARR                 -.22047        .021742
                  (  -1.0000)    (  -1.0000)

 TRO                  .23288       -.22648
                  (   1.0563)    (  10.4165)

 JTRO                .099518       -.19083
                  (   .45139)    (   8.7768)

 GNI                 .085424        .32914
                  (   .38747)    ( -15.1386)

 AIR                -.025924      -.087425
                  (  -.11758)    (   4.0210)

*******************************************************************************

Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 298 observations used for estimation from 1978M3  to 2002M12
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                    -.030832            .036320            -.84891[.397]
 DTRO(-1)                   .85963             .31987             2.6874[.008]
 DJTRO                      .71194             .27367             2.6014[.010]
 S2                         .13476            .051380             2.6228[.009]
 S3                        .024556            .050954             .48191[.630]
 S4                        .041768            .050925             .82019[.413]
 S5                        -.12741            .051212            -2.4879[.013]
 S6                       -.021621            .050739            -.42613[.670]
 S7                         .23573            .050758             4.6442[.000]
 S8                        .092165            .051353             1.7947[.074]
 S9                        -.14941            .051436            -2.9048[.004]
 S10                        .11875            .050706             2.3420[.020]
 S11                      -.082813            .050910            -1.6267[.105]
 S12                      .0061314            .050671             .12100[.904]
 UT(-1)                    -.28745            .042591            -6.7489[.000]
*******************************************************************************
 R-Squared                      .42946   R-Bar-Squared                    .40124
 S.E. of Regression             .17710   F-stat.    F( 14, 283)   15.2159[.000]
 Mean of Dependent Variable  .0028364   S.D. of Dependent Variable       .22887
 Residual Sum of Squares        8.8760   Equation Log-likelihood       100.7037
 Akaike Info. Criterion        85.7037   Schwarz Bayesian Criterion     57.9755
 DW-statistic                   2.5504
*******************************************************************************
```

Table 5.4.10c **Microfit output for ECM**
Arrivals from the UK, 24 months ahead model

```
Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR
*******************************************************************************
 287 observations from 1978M2  to 2001M12. Order of VAR = 1, chosen r =3.
 List of variables included in the cointegrating vector:
 ARR             OPR             TRO             JTRO            GNI
 AIR
*******************************************************************************
                  Vector  1      Vector  2      Vector  3
 ARR                 -.23713        .025947        .032129
                  (  -1.0000)    (  -1.0000)    (  -1.0000)
 OPR               -.0077521       -.024069         .19807
                  ( -.032691)    (   .92762)    (  -6.1649)
 TRO                  .19167        -.27655         .37876
                  (   .80831)    (  10.6583)    ( -11.7888)
 JTRO                 .12922        -.18529       -.034424
                  (   .54496)    (   7.1410)    (   1.0714)
 GNI                  .12198         .37057        -.42016
                  (   .51442)    ( -14.2818)    (  13.0774)
 AIR                -.017259       -.089088        .026393
                  ( -.072782)    (   3.4335)    (  -.82146)
*******************************************************************************


Ordinary Least Squares Estimation
*******************************************************************************
 Dependent variable is DARR
 281 observations used for estimation from 1978M8  to 2001M12
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 CONST                    -.035203            .036278           -.97038[.333]
 DTRO(-1)                   .79292             .32664            2.4275[.016]
 DJTRO                      .75484             .27474            2.7474[.006]
 DGNI(-6)                  -.88855             .41603           -2.1358[.034]
 S2                         .14109            .051455            2.7420[.007]
 S3                        .015737            .051346            .30648[.759]
 S4                        .057842            .051219            1.1293[.260]
 S5                        -.14359            .051603           -2.7826[.006]
 S6                       -.025508            .051223           -.49798[.619]
 S7                         .31217            .058471            5.3389[.000]
 S8                         .10539            .051380            2.0511[.041]
 S9                        -.14348            .051386           -2.7922[.006]
 S10                        .11571            .050578            2.2878[.023]
 S11                      -.073481            .050759           -1.4476[.149]
 S12                       .011083            .050590            .21908[.827]
 UT(-1)                    -.32266            .045833           -7.0400[.000]
*******************************************************************************
 R-Squared                     .47010   R-Bar-Squared                   .44010
 S.E. of Regression            .17296   F-stat.    F( 15, 265)   15.6729[.000]
 Mean of Dependent Variable  .0035679   S.D. of Dependent Variable      .23114
 Residual Sum of Squares       7.9272   Equation Log-likelihood       102.5897
 Akaike Info. Criterion       86.5897   Schwarz Bayesian Criterion     57.4828
 DW-statistic                  2.5402
*******************************************************************************
```

Table 5.4.11a Microfit output for ECM
Arrivals from the USA, one month ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

288 observations from 1978M2 to 2002M1 . Order of VAR = 1, chosen r =1.
List of variables included in the cointegrating vector:
ARR OPR TRO GNI AIR

	Vector 1
ARR	-.26631
	(-1.0000)
OPR	-.051441
	(-.19316)
TRO	.38927
	(1.4617)
GNI	.22785
	(.85556)
AIR	-.051685
	(-.19407)

Ordinary Least Squares Estimation

Dependent variable is DARR
277 observations used for estimation from 1979M1 to 2002M1

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	-.017359	.016919	-1.0260[.306]
DGNI(-8)	1.6801	.37560	4.4733[.000]
DGNI(-11)	-1.3925	.37627	-3.7009[.000]
S2	-.19490	.020224	-9.6370[.000]
S3	.29803	.020934	14.2367[.000]
S4	.089481	.021383	4.1847[.000]
S5	.069248	.022617	3.0618[.002]
S6	.017437	.023219	.75099[.453]
S7	.019466	.022979	.84710[.398]
S8	-.088846	.023027	-3.8583[.000]
S9	-.046530	.028861	-1.6122[.108]
S10	.25647	.021710	11.8137[.000]
S11	-.19218	.026111	-7.3600[.000]
S12	-.15701	.028973	-5.4192[.000]
UT(-1)	-.20602	.034306	-6.0054[.000]

R-Squared	.87525	R-Bar-Squared	.86858
S.E. of Regression	.069285	F-stat. F(14, 262)	131.2978[.000]
Mean of Dependent Variable	.0037159	S.D. of Dependent Variable	.19112
Residual Sum of Squares	1.2577	Equation Log-likelihood	354.1234
Akaike Info. Criterion	339.1234	Schwarz Bayesian Criterion	311.9433
DW-statistic	1.9553		

Table 5.4.11b Microfit output for ECM
Arrivals from the USA, 12 months ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

299 observations from 1978M2 to 2002M12. Order of VAR = 1, chosen r =2.
List of variables included in the cointegrating vector:
ARR OPR TRO GNI AIR

	Vector 1	Vector 2
ARR	-.26472	-.080699
	(-1.0000)	(-1.0000)
OPR	-.051329	-.11472
	(-.19390)	(-1.4216)
TRO	.38686	.0090065
	(1.4614)	(.11161)
GNI	.22635	.12214
	(.85507)	(1.5135)
AIR	-.051152	.013830
	(-.19323)	(.17138)

Ordinary Least Squares Estimation

Dependent variable is DARR
288 observations used for estimation from 1979M1 to 2002M12

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	-.024392	.017029	-1.4324[.153]
DTRO(-6)	-.70540	.31948	-2.2080[.028]
DGNI(-8)	1.7045	.37017	4.6047[.000]
DGNI(-11)	-1.4621	.37153	-3.9352[.000]
S2	-.18251	.020312	-8.9850[.000]
S3	.30955	.021039	14.7131[.000]
S4	.091118	.021311	4.2757[.000]
S5	.071224	.022377	3.1829[.002]
S6	.028960	.023011	1.2585[.209]
S7	.028833	.023018	1.2526[.211]
S8	-.088105	.022798	-3.8646[.000]
S9	-.036586	.028875	-1.2670[.206]
S10	.26147	.021520	12.1503[.000]
S11	-.17794	.026209	-6.7893[.000]
S12	-.13989	.028262	-4.9498[.000]
UT(-1)	-.21355	.033758	-6.3259[.000]

R-Squared	.87502	R-Bar-Squared	.86813
S.E. of Regression	.069150	F-stat. F(15, 272)	126.9602[.000]
Mean of Dependent Variable	.0037654	S.D. of Dependent Variable	.19042
Residual Sum of Squares	1.3006	Equation Log-likelihood	368.9601
Akaike Info. Criterion	352.9601	Schwarz Bayesian Criterion	323.6564
DW-statistic	1.9390		

Table 5.4.11c **Microfit output for ECM**
Arrivals from the USA, 24 months ahead model

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)
Cointegration with no intercepts or trends in the VAR

287 observations from 1978M2 to 2001M12. Order of VAR = 1, chosen r =1.
List of variables included in the cointegrating vector:
ARR OPR TRO GNI AIR

	Vector 1
ARR	-.26656
	(-1.0000)
OPR	-.049790
	(-.18679)
TRO	.39234
	(1.4719)
GNI	.22558
	(.84627)
AIR	-.051121
	(-.19178)

Ordinary Least Squares Estimation

Dependent variable is DARR
276 observations used for estimation from 1979M1 to 2001M12

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	-.016654	.017318	-.96167[.337]
DGNI(-8)	1.6778	.37648	4.4567[.000]
DGNI(-11)	-1.3955	.37714	-3.7004[.000]
S2	-.19503	.020482	-9.5224[.000]
S3	.29812	.021134	14.1060[.000]
S4	.089009	.021706	4.1007[.000]
S5	.068622	.022955	2.9894[.003]
S6	.016742	.023561	.71057[.478]
S7	.018800	.023321	.80615[.421]
S8	-.089492	.023371	-3.8292[.000]
S9	-.046888	.029129	-1.6096[.109]
S10	.25592	.022036	11.6138[.000]
S11	-.19311	.026465	-7.2969[.000]
S12	-.15741	.029245	-5.3825[.000]
UT(-1)	-.20454	.034371	-5.9511[.000]

R-Squared	.87514	R-Bar-Squared	.86844
S.E. of Regression	.069449	F-stat. F(14, 261)	130.6614[.000]
Mean of Dependent Variable	.0037114	S.D. of Dependent Variable	.19147
Residual Sum of Squares	1.2588	Equation Log-likelihood	352.2209
Akaike Info. Criterion	337.2209	Schwarz Bayesian Criterion	310.0679
DW-statistic	1.9237		