PARAMETER ESTIMATION OF URBAN DRAINAGE MODELS

By

Nilmini Rukma Siriwardene

Thesis Submitted in Fulfillment of the Requirement for the Degree of Master of Engineering

School of Architectural, Civil and Mechanical Engineering
Victoria University, Australia

December 2003

ABSTRACT

Urbanisation is one of the key factors that contributes to urban flooding, which has caused major destruction to the environment and the human race. In particular, the increase in population and building density influence the change in hydrological characteristics in urban areas. Conversion of pervious areas into impervious areas increases the stormwater runoff quantity dramatically.

One way of minimising urban flooding is to convey stormwater to receiving waters through stormwater drainage systems, which has been practised in the past. This practice is currently changing and the current stormwater management deals with the holistic management of the urban water cycle, which includes stormwater drainage, improvement of stormwater quality and use of stormwater as an alternative supply source (to meet increasing urban water demand).

The most practical and economical way of designing the urban stormwater drainage systems is by the application of computer based mathematical software tools. These tools can be used to identify flood prone areas by modelling the catchment. Currently, there are several software tools available to develop urban drainage models, and to design and analyse stormwater drainage systems in urban areas. The widely used tools in Australia are SWMM, MOUSE, DRAINS and XP-UDD.

The accuracy of these models depends on the correct selection of model parameter values. Some of these parameters can be physically measured, whereas the other parameters are impossible or difficult to measure. Therefore, these parameter values, which are impossible or difficult to measure physically, have to be estimated through model calibration. Model calibration is done through an iterative process by comparing model predictions with observations, until the two sets match with each other within a reasonable accuracy.

There are several methods available to calibrate mathematical models ranging from trial and error to optimisation methods. Traditionally, model calibration is done through trial and error. With this method, the experienced modellers estimate the model parameter

values starting with educated guesses and refining these guesses by comparing observations and predictions (due to these parameter values). However, this method is subjective, time consuming and can also miss the optimum parameter set. On the other hand, computer based automatic optimisation methods have proven to be robust and efficient. In this project, one of the most popular automatic calibration optimisation method known as genetic algorithms (GAs) are used to calibrate the urban drainage models.

Recently, GAs have proven to be successful and efficient in identifying the optimal solution for water resource modelling applications. These applications include rainfall-runoff modelling, river water quality modelling, pipe system optimisation and reservoir optimisation. However, in order to produce efficient and robust solutions, proper selection of GAs operators is necessary for the application, before conducting the optimisation. These GA operators include population size, number of simulations, selection method, and crossover and mutation rates.

There are some general guidelines available to choose GAs operators for standard GAs optimisation applications. However, there are no specific guidelines available for selecting GAs operators for urban drainage model parameter optimisation. Therefore, the sensitivity of these operators were analysed in this study through numerical experiments by repetitive simulation considering one GAs operator at a time, by integrating GAs and urban drainage modelling software tools. This produced appropriate GAs operators for use in urban drainage model parameter optimisation.

XP-UDD urban stormwater drainage software and GENESIS GAs software tools were used in this study to model the urban drainage catchment(s) and model parameter optimisation. These two software tools were linked through their input and output files to conduct the model parameter optimisation. Two typical urban catchments in Victoria (Australia) were used in selecting the appropriate GAs operators. For each catchment, two design storm events (i.e. *small* and *large*) were considered. The *small* storm considered runoff only from the impervious areas, while the *large* storm produced runoff from both impervious and pervious areas. Seven parameters were identified in the urban drainage model (which required calibration), two related to impervious area and the other five related to pervious area. Typical parameter values were assumed and used in XP-UDD models of the study catchments to produce the hydrographs corresponding to these two design storms and these hydrographs were then considered in the integrated GENESIS/XP-UDD as observed hydrographs in optimising GAs operators. Numerical experiments produced consistent and robust GAs operators for parameter optimisation of urban drainage models. Although there is no mathematical basis for optimising parameter values through repetitive simulation, this is an acceptable practice for complex systems.

Model calibration was carried out only for one of the two study catchments used for GAs operator study, because of the time constraints. Furthermore, one catchment was considered sufficient, since the purpose of this part of the study was to investigate and demonstrate the use of GAs for optimising parameter values of urban drainage models. Observed rainfall/runoff data were available for this catchment only for *small* storms, which produced runoff only from impervious areas. Therefore, only the impervious area parameter values were estimated. The results obtained from GAs optimisation were compared with previous studies and found to be satisfactory.

The soil infiltration parameters, which represent a sub-set of pervious area parameters, were determined through soil infiltrometer tests, which were conducted at several sites in the study catchment, which was used for model calibration. Soil infiltration tests were conducted, because the soil infiltration parameter values could not be estimated through model calibration, due to unavailability of observed data related to *large* storms. A standard double-ring infiltrometer was used to estimate these parameter values through field measurements and these measurements were taken over a period of six hours. Rainfall was measured for five days prior to the field test using a pluviometer, to determine the antecedent rainfall depths at the study sites. Soil infiltration parameter values were estimated by fitting soil infiltrometer test data to Horton's infiltration equation, since the Horton's infiltration equation is built into XP-UDD and is widely used in urban drainage modelling applications in Australia. Soil samples were also tested and analysed to determine the soil particle size distribution of each site to determine the soil type. In order to understand different soil types and to determine the soil infiltration rates in different urban catchments, these soil infiltrometer tests were conducted at another nineteen sites of seven urban drainage catchments in four city councils in Victoria. The infiltration parameter values found in this study were in general significantly different to the values given in DRAINS and XP-UDD software user manuals.

DECLARATION

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university or institution and, to the best of the author's knowledge and belief, contains no materials previously written or published by another person except where due reference is made in the text.

Nilmini Rukma Siriwardene

18 December 2003

[redacted]

ACKNOWLEDGMENTS

This research study could not have been accomplished successfully without the help of many people and it is my pleasure to acknowledge them here.

Firstly, I would like to express my deep gratitude and sincere thanks to my supervisor Associate Professor Chris Perera, who has been a valuable source of knowledge and very supportive throughout this study. I very much appreciate and thank him for giving me this opportunity to take up this scholarship. I am also grateful to him for always making time available for discussions on the subject and sharing ideas and experience, critical comments and suggestions on my writing and even encouraging me to write and present conference papers, in which I have gained very good experiences and confidence. I very much appreciated his valuable time and effort in helping me getting through this research in a flexible research environment.

I wish to express my sincere thanks to my friend Shiroma Maheepala, who has encouraged me to take up this research. I am grateful for the financial support provided by the University of Victoria. I would also like to thank officers of the research, library, technical and administrative staff of Victoria University. I appreciate the contribution of City Council staff of Banyule, Boroondara, Melbourne and Warrnambool and residents of the study sites, who involved in this project for collecting necessary data. I would also like to thank all the follow postgraduate students, especially Anne Ng, Ben Cheung and Carolyn Goonrey for their extreme support and willingness to help.

I gratefully acknowledge my parents for my upbringing and giving me a priceless education. I am extremely grateful and like to convey my special thanks to my loving husband Jagath, who is always a constant source of encouragement and for being there for me during the period of frustrations and long hours of work. Last but not least, I like to express my special thanks and great appreciation to my loving son Ashan, who has been always concern about my work and volunteered to help me in whatever way he can. I affectionately dedicated this thesis to both of you, for love, support and encouragement you have shown.

PUBLICATIONS AND PRESENTATIONS

This thesis is the result of two years and three months of research work since September 2001 at the school of Architectural, Civil and Mechanical Engineering of Victoria University of Technology. During this period, the following research papers and reports were published and one conference paper was presented.

Publications

- N. R. Siriwardene, and B.J.C. Perera. *Selection of genetic algorithm operators for urban drainage model parameter optimisation* for international congress proceedings on modelling and simulation - Modsim '2003, (Natural Computing Methods for Modelling Water Resources and Hydrology), Townsville, Australia, 14-17 July, 2003.

- N.R. Siriwardene, B.P.M. Cheng and B.J.C. Perera. *Estimation of soil infiltration rates in urban catchments* for 28th International Hydrology and Water Resources Symposium, Wollongong NSW Australia, 10-13 November 2003.

- N. R. Siriwardene, and B.J.C. Perera. *Urban drainage model calibration using genetic algorithm*, International Conference on Advance Modelling Techniques for Sustainable Management of Water Resources, India, 28–30 January 2004 (Abstract accepted and paper is in progress).

- N.R. Siriwardene, B.P.M. Cheng and B.J.C. Perera, *Estimation of soil infiltration parameters of Banyule city council*, Report for Banyule city council, 2003.

- N.R. Siriwardene, B.P.M. Cheng and B.J.C. Perera, *Estimation of soil infiltration parameters of Boroondara city council*, Report for Boroondara city council, 2003.

- B.P.M. Cheng, N.R. Siriwardene and B.J.C. Perera, *Estimation of soil infiltration parameters of Melbourne City Councils*, Report for Melbourne city council, 2003.

- B.P.M. Cheng, N.R. Siriwardene and B.J.C. Perera, *Estimation of soil infiltration parameters of Warrnambool city council*, Report for Warrnambool city council, 2003.

Conference Presentation

Presented a paper on *Selection of genetic algorithm operators for urban drainage model parameter optimisation* for International Conference on Modelling and Simulation - MODSIM 2003 (Natural Computing Methods for Modelling Water Resources and Hydrology) on 14 July 2003 at Jupiters Hotel, Townsville, Australia.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Background

Hydrological events such as rainfall, runoff, droughts and floods have played an important role in the history of mankind and they are still important in the modern world. Therefore, accurate prediction of such events is necessary for the well being of the human society. Flooding has become a major catastrophe all around the world including Australia. As indicated in a study conducted by the Department of Primary Industries and Energy (1992), flood damage costs Australia around 300 million dollars per year with about 200,000 urban properties prone to flooding due to a 100-year flood. Flooding not only causes direct accountable property damage, but also creates major social problems due to relocation, emotional disturbances, loss of important records/articles and in some cases loss of human life. Furthermore, flooding has caused environmental problems such as the destruction of native vegetation and extinction of some wildlife species.

The balance of the natural hydrological cycle is greatly disturbed by urban development, in terms of stormwater volume and quality, as urban development reduces the percolation of rainwater to the soil due to replacement of large pervious areas of land by impervious areas (such as buildings, paved roads, walkways and car parks). As cited in http://www.catchment.crc.org.au/ordresearch/urban.html, a study conducted by the University of Melbourne during 1993-1999 indicated that urbanisation of a catchment brought in dramatic changes in hydrology. It also indicated that the runoff volume was typically doubled or tripled, and storm flow rates increased up to 20 times higher than in the pre-urban condition. These increase of flow rates obviously result in more flash floods and higher peak flow rates.

Although stormwater was considered as a nuisance prior to 1980s, with increasing awareness of stormwater quality issues, a new approach to stormwater management has emerged throughout Australia as well as overseas. These new stormwater management concepts include land-use planning and management, use of natural stormwater treatment processes and managing pollution at source through grass swales, soakage trenches, etc. In recent times, there has also been interest in the use of stormwater as an alternative supply source due to limited availability of fresh water sources and also due to increasing awareness on the concept of sustainability. Therefore, the management of stormwater runoff from urban catchments has changed over the recent past to include the management of the complete urban water cycle and dealt with stormwater quantity, quality and (re)use. The stormwater drainage is still a major and important part of this overall stormwater management process, and stormwater drainage systems are still necessary due to continuing urban development, to manage urban flooding.

Mathematical computer software tools are widely used to develop urban stormwater drainage system models, and to design and analyse complex urban stormwater drainage systems. These software tools allow modelling of hydrological (eg. rainfall, infiltration, overland flow, evaporation) and hydraulic (eg. pipe and open channel flow) processes of urban catchments. Some of the urban drainage software tools widely used in Australia are SWMM (USEPA 1992), MOUSE (Danish Hydraulic Institute 1993), XP-UDD (XP-Software 1997) and DRAINS (O'Loughlin and Stack 1998). Flood hydrographs and peak flow runoff can be computed by using these software tools, which are required to design or upgrade the drainage systems to minimize flood damage. However the reliability of these models depends on the accuracy in choosing the model parameter values of the catchments being modelled. Some of these parameter values can be physically measured, where as the other parameter values (such as depression storage and flow roughness) are impossible or difficult to measure. However, these parameter values, which are impossible or difficult to measure physically, can be estimated through model calibration by using good quality rainfall/runoff data, if they are available.

Model calibration is done through an iterative process by comparing model predictions with observations, until the two sets match with a reasonable accuracy. Traditionally, urban drainage model calibration was done through a manual trial and error process. With this method, the estimation of model parameter values are carried out by experienced modelers providing educated guesses and refining these guesses by comparing observed and modeled hydrographs. However, this method is subjective, time consuming and can also miss the optimum parameter set. In an effort to improve this process, optimisation methods have been developed to automatically calibrate these models.

Recently, an automatic optimisation technique called genetic algorithms – GAs (Goldberg 1989a) have proven to be successful and efficient in identifying the optimal solution for water resource applications. Even though GAs have been recognized as a robust optimisation method for estimating model parameter values in many fields, it has not been widely used for urban drainage models. Furthermore, many researchers have put forward different formulations and refinements to the GAs method, which has become one of the difficulties facing potential users of genetic algorithms, since it is hard to judge a priori which variation might be the best for a particular application (Cui 2003). Therefore, an investigation was carried out in this study to demonstrate the use of the GAs optimisation method in optimising the model parameter values of drainage model of an urban catchment.

GAs operators (i.e. parameter representation, population size, selection method, crossover and mutation rates) play an important role in the convergence to the optimum model parameter values in GAs optimisation process. However, there are no clear guidelines available to select appropriate GAs operators for urban drainage model parameter optimisation. Schaffer et al. (1989) reported that the theory behind the GA has given little guidance for selecting proper GA operators, even though these operators have a significance impact on GAs performance. Therefore a detailed investigation was conducted in this study to select the appropriate GAs operators (or *optimum* GAs operators) for use in urban drainage model parameter optimisation before attempting the model parameter optimisation.

The XP-UDD software tool was selected for this study to model urban stormwater drainage systems, since it is an enhanced and user-friendly version of SWMM and its input and output files are in ASCII format, which can be accessed by the GAs software tool. The access to input and output files of the urban stormwater drainage software is necessary to optimise the urban drainage parameter values through the optimisation method such as GAs. GENESIS was used as the GAs software tool, since it has been successfully used in water resource applications in the past.

Two urban drainage catchments in Victoria (Australia) were considered as case studies in optimising GAs operators and one of these catchments was used for the model calibration using GAs in this study. In both these studies, attention was given to the different runoff generation mechanisms in impervious and pervious areas of urban catchments with respect to the magnitude of storm events. That is in general, *small* storms produce runoff only from the impervious areas and *large* storms generate runoff from both impervious and pervious areas. Two design storms (*small* and *large)* were considered in optimising GAs operators, while observed storm data was used for model calibration. Unfortunately, observed rainfall and runoff data of the study catchment were available only for *small* events and therefore only the impervious area parameter values were calibrated using the available observed *small* storms. However, the three Horton's infiltration parameter values of pervious areas were determined through soil infiltrometer tests, since the soil infiltration parameter values could not be estimated through model calibration, due to unavailability of observed data related to *large* storms.

1.2 Significance of the Project

Flooding can be devastating for communities and industry, as stated in Section 1.1. Lately, this problem has been aggravated due to continued urban development. However, flooding is one of the most manageable of the natural disasters and can be managed by identifying flood prone areas and implementing suitable flood mitigation strategies. The most practical way of identifying flood prone areas is by the application of mathematical models, which consider complex hydrological and hydraulic processes of these areas. These models can also be used to develop stormwater infrastructure management plans to reduce flood damage. The alternative to use of mathematical models is to conduct experimental studies on these areas, which in general is not economically and technically feasible because of the large inundation areas.

As part of the infrastructure management plans, local government authorities spend millions of dollars on planning, design, installation, upgrade and maintenance of urban stormwater drainage systems. For example, Cullino (1995) reported that the drainage network in Waverly, Victoria (Australia) was significantly under capacity due to recent greater building densities, and an expenditure of about $200 million as at 1995 was required for the existing underground network to be replaced or augmented to cope with a five-year storm event. Therefore, it is necessary to adopt appropriate design standards dealing with major and minor storms, to achieve the best practice in design and whole-life cycle management of stormwater infrastructure.

The planning and designing phases of the urban stormwater drainage systems are extremely important, since they affect the other phases and more importantly the overall cost of such works. Comprehensive predictive computer software models, which consider the physical processes of urban drainage systems, are widely used in such studies. However, they require calibration or estimation of model parameter values. This was addressed in this project by using a recent optimisation technique called genetic algorithms (GAs) and field soil infiltrometer tests.

The results of this research project enable to use GAs optimisation technique for calibration of urban drainage models by selecting the appropriate GAs operators for urban drainage models. These will encourage the users to employ GAs technique in model parameter calibration in urban drainage modelling, which had already been proved to be successful and effective in identifying the optimal solutions for other water resource applications. Furthermore, methodologies were developed to estimate the soil infiltration parameter values (which are also model parameter values of urban drainage models) through soil infiltrometer tests. The above methods will assist in the development of well-calibrated urban drainage models. These well-calibrated models will enable the hydrologists, hydraulic engineers and urban planners to calculate floodwater volumes, levels and velocities, to plan for flood mitigation strategies to alleviate flooding in urban areas, and to assess risks associated with flood hazards. This in turn will produce significant economic and social benefits in urban areas.

1.3 Aim of the Project

The aims of this project were to investigate the feasibility of using GAs for parameter optimisation of urban drainage models and to develop an automatic calibration methodology for use of GAs for urban drainage catchment modelling. A further aim was to conduct soil infiltration tests to study the soil infiltration parameters of the study catchments. The following tasks were completed to achieve the above aims:

- Literature review of urban drainage processes, modelling and GAs.
- Linking of GAs and urban drainage modelling software tools.
- Collection and collation of drainage and storm data for the study catchments.
- Assembly of urban drainage models of the study catchments.
- Selection of appropriate GAs operators for urban drainage model parameter optimisation.
- Optimisation of impervious area parameter values of urban drainage model of the study catchment through GAs.
- Estimation of soil infiltration parameter values (i.e. sub set of pervious area parameters) of the study catchment using field infiltrometer tests.

It should be noted that two catchments were used in the study of selecting the appropriate GAs operators, while only one catchment (one of the above two) was used in parameter estimation of the urban drainage model.

1.4 Structure of the Thesis

Chapter 2 describes the urban drainage processes, urban drainage modelling software tools and GAs. Different methods that can be used for calibration of mathematical models, and the literature on GAs including its operators are reviewed in this chapter.

Chapter 3 describes the XP-UDD and GENESIS software tools and different options available in these two software tools to model various processes. Linking of GENESIS/XP-UDD software tools for the study are also reviewed in this chapter.

Two main studies conducted in estimating model parameter values of XP-UDD urban drainage model are presented in Chapter 4. First, the detailed study of selecting appropriate GAs operators for urban drainage model calibration is presented. Then, the XP-UDD model calibration of the study catchment is presented, which also includes the validation of model parameters.

Chapter 5 describes the soil infiltrometer tests, which were conducted to estimate soil infiltration parameter values of pervious areas. The literature on infiltrometer test methods and procedures were also reviewed. The details of this part of the study and the results are discussed in this Chapter.

A summary, conclusions and recommendations drawn from the study (described in this thesis) are presented in Chapter 6.

CHAPTER 2

REVIEW OF URBAN DRAINAGE PROCESSES AND MODELLING AND GENETIC ALGORITHMS

2.1 Introduction

Rain that falls to the earth undergoes through various processes such as evaporation, interception by vegetation and structures, retaining in surface storage areas, infiltration into the soils, ponding above ground surface and surface runoff. These processes describe the hydrological cycle and are shown in Figure 2.1.

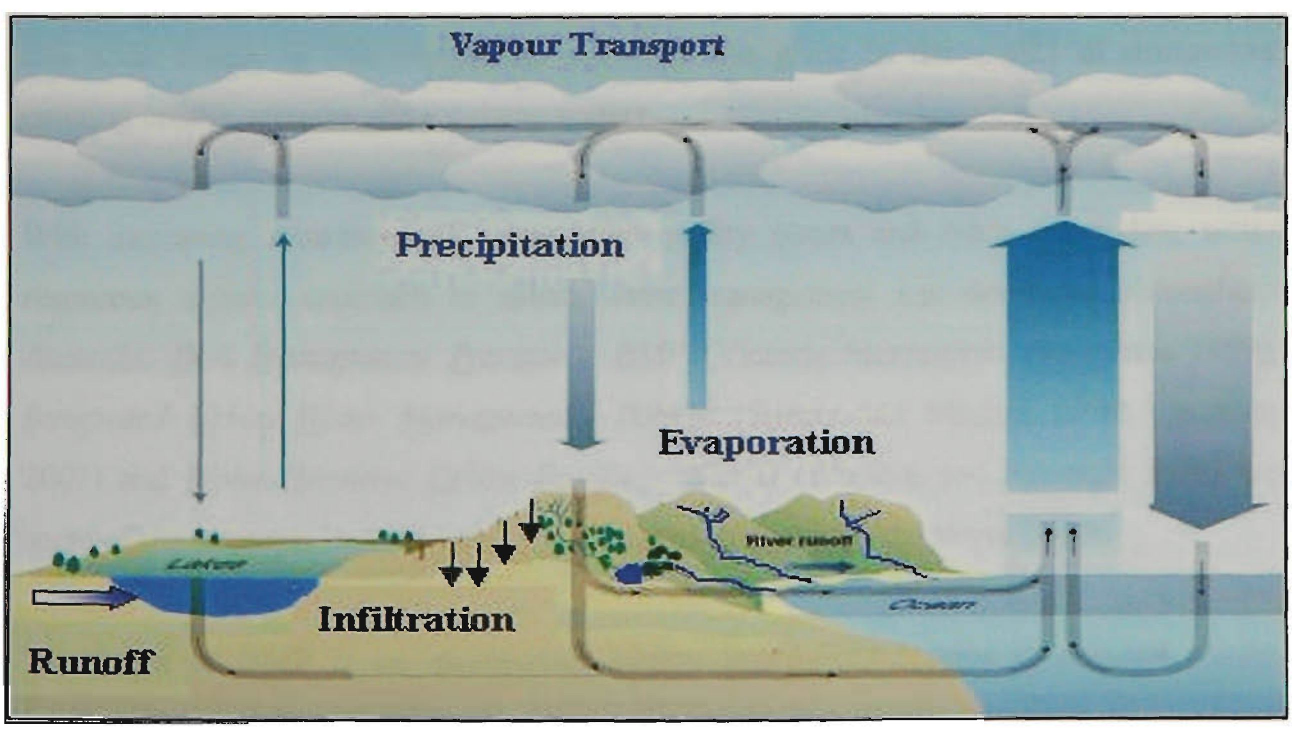


Figure 2.1 Hydrological Cycle (Ref: www.unep.org/vitalwater)

The rainfall reaching the soil surface will partly enter the soil through infiltration, where it may be retained in the upper layers or percolate to the deeper layers. The rainfall, which initially fails to infiltrate remains ponded on the land, mainly filling up depression storage. Once the storage potential on the soil surface has been occupied, the water will start to move down the slope as overland flow (Smedema and Rycroft 1983). The overland flow initially flows over the ground surface in very shallow depths before reaching streams, rivers and drains. As flow moves downstream, flows from other sources join these streams, rivers and drains. This process increases the flow rates, resulting in flooding during heavy storms.

The urban hydrological cycle is a special case of the general hydrological cycle described above and the main difference is that most pervious surfaces are replaced by impervious surfaces in urban areas. The increase of high proportion of sealed areas greatly reduces the amount of water infiltrating to the soil and consequently, most rainfall is converted to stormwater runoff in urban areas. Urban stormwater management involves the control and management of water that runs off urban surfaces. In traditional stormwater management practice, stormwater had been considered as a problem to be managed to protect people and properties from the build-up stormwater and from flooding rather than a resource to be utilised. Therefore, stormwater had been disposed as quickly and efficiently away using stormwater drainage systems, which consist of underground concrete pipes, culverts and open drains. In this process no attention was given to the quality of stormwater entering creeks, streams and receiving waters.

With increasing awareness of stormwater quality issues and more demanding water resources, a new approach to urban water management has developed throughout Australia. ***B**est **M**anagement **P**ractice* – BMP (Victoria Stormwater Committee 1999), ***I**ntegrated **U**rban **W**ater **M**anagement* –IUWM (Speers and Mitchell 2000; Coombes 2003) and ***W**ater **S**ensitive **U**rban **D**esign* – WSUD (Whelans and Maunsell 1994) are some of the concepts that are being implemented to deal with the above issues.

The focus of BMP is on stormwater quality improvement prior to disposal to the environment and has been in use around the world including Australia in more recent times. In this method several measures have been applied to reduce the impact of stormwater on receiving water bodies that include structural measures to treat the stormwater before disposal and public educational programs to raise awareness and reduce litter and oil entering to receiving water bodies (Goonrey 2003).

The IUWM emphasises the need to consider all aspects of the water cycle (i.e. water, wastewater and stormwater) together as an interdependent system. Traditional water management on the other hand, does not consider interaction among various aspects of the water cycle. For example, stormwater management in traditional practice only focuses on capacity and transport of stormwater runoff and does not consider its impact on receiving waters or the amenity value of retention/detention basins or as a total impact to the environment.

WSUD is a design approach that focuses on implementing the principles of IUWM on a site by site basis. However, the Victoria Stormwater Committee (1999) have shown the focus for implementation of WSUD in Melbourne on only the stormwater design by minimising impervious areas to increase infiltration, maximising local on-site retention, efficient stormwater treatment to protect the receiving water bodies, (re)use of stormwater and using stormwater beneficially for the environment (Goonrey 2003). The Lynbrook Estate, located in the outer eastern suburb of Melbourne is the first residential estate in Victoria to incorporate WSUD, including a series of linked gravel-filled, vegetated drains along wide strips designed to absorb and filter stormwater, swales and constructed wetlands (Wong 2001).

In recent times, there has been more interest on using of stormwater as an alternative supply source due to scarcity of water resources. This approach converts the zero value stormwater into a valuable urban water source for the future water needs of growing urban population. However, the stormwater drainage systems are still a major and important part of this overall stormwater management process to meet the communities need to minimise the threat of urban flooding.

The design methods for stormwater drainage systems include a wide range from manual methods to computer models. The most simple and widely used manual method is the Statistical Rational Method (SRM), which is commonly known as the Rational Formula.

The RatHGL software tool combines SRM with Hydraulic Grade Line (HGL) analysis in an iterative manner to design urban drainage systems and is widely used for small sub-divisions in Australia and elsewhere. In RatHGL, the SRM is used to estimate the peak flow rates, and these flow rates are then used in HGL calculations to compute pipe/channel sizes and grades.

The three major assumptions that underline the basis of the SRM method are listed below.

- Rainfall is uniform in intensity on the catchment in both time and space
- Rainfall duration is equal to the time of concentration of the catchment
- The return period of the peak flow rate is equal to that of the rainfall intensity

In practice, uniformly distributed storms are rarely experienced throughout the catchment and they would not normally be uniform in intensity. Furthermore the return period of runoff and rainfall would rarely agree. In the SRM, all losses are included in the runoff coefficient. Because of these limitations of the SRM methods, generally this method is applicable only to relatively small catchments. Although urban catchments are relatively small, spatial and temporal rainfall variability is a significant problem when modelling actual storm events (Pilgrim 1987).

On the other hand, the computer models are capable of producing continuous hydrographs by routing the hyetograph through the catchment by using various advanced routing methods. Furthermore, the computer models use separate loss models for impervious and pervious areas to handle losses explicitly, and model the unsteady flows better than the manual methods. This type of analysis would be virtually impossible to carry out manually because of the detailed computations required. Therefore, the use of computer based mathematical models in analysing and designing stormwater drainage systems in urban catchments has become more and more popular in the recent past.

This chapter first describes the urban drainage process briefly, followed by the main features of urban drainage systems. A brief review of urban drainage computer modelling software tools including calibration of these models is then presented. Then, a detailed description of genetic algorithms and their operators are presented, followed by the schema theorem, which explains the fundamental theory of GAs in producing the optimal solution. Finally, a review of the past applications of GAs (including in water resources and urban drainage) and GAs software are discussed.

2.2 Urban Drainage Process

Ferguson (1998) defined the stormwater runoff generation as an environmental process, combining atmosphere, soil, vegetation, land use and streams. Urban development is greatly disturbing the balance of this process due to replacement of large pervious areas of land by impervious areas. The impervious areas include road surfaces, roofs and other man-made hard surfaces. The pervious area includes bare surfaces, porous pavements, grass courts and lawns. Impervious surfaces produce direct runoff, as they prevent water absorption to the soil underneath them. As a result more flash floods can be experienced in urban areas. Surface runoff in urban areas is termed urban stormwater runoff. The Commonwealth Environment Protection Agency (1993) reported that, in a natural environment, only 2% of the rain becomes surface runoff in an area with good ground cover. However, in urban areas, 98-100% of the rain becomes surface runoff.

Boyd et al. (1993) reported that urban catchments respond differently to storm events of different magnitudes and the impervious surfaces were the major contributors to urban stormwater runoff. The knowledge of the contribution to urban stormwater runoff from impervious and pervious areas is useful for the design of stormwater drainage systems (Boyd et al. 1993). In general, during *small* storm events, runoff is generated only from the impervious areas, since rain falling on the pervious areas is absorbed into the soil producing no runoff. However, during *large* storm events, pervious areas contribute to runoff, in addition to the impervious areas. These differences in runoff generation mechanisms of impervious and pervious areas were considered in this study. Part of the rainfall is lost through evaporation, depression storage in both surfaces before they produce runoff. The rainfall loss from pervious areas is more difficult to predict than the rainfall loss from impervious areas because the loss from pervious areas depends on soil, vegetation types, antecedent wetness condition, storm intensity and duration.

2.2.1 Rainfall loss from impervious areas

The runoff for impervious areas is simply calculated by subtracting depression storage from rainfall. Depression storage prevents initial running off of stormwater because of surface ponding, surface wetting and interception. Water stored as depression storage on impervious areas is depleted by evaporation. Typical values for impervious area depression storage are 0 to 2 mm (Dayaratne 2000).

In XP-UDD (XP-Software 1997) and SWMM (USEPA 1992) software tools, the impervious areas are modelled in two ways as follows:

- Impervious area with depression storage
- Impervious area without depression storage – This is introduced to promote immediate runoff from the catchment.

In ILSAX (O'Loughlin 1993) and DRAINS (O'Loughlin and Stack 1998) software tools, the impervious areas are considered as:

- Directly connected impervious areas
- Supplementary areas

The directly connected impervious areas are the impervious areas that are directly connected to the drainage system. The supplementary areas are the impervious areas that are not directly connected to the drainage system, but runoff from these areas flows over the pervious areas before reaching the drainage system.

2.2.2 Rainfall loss from pervious areas

The pervious area depression storage is similar to the impervious area depression storage, but the water stored as depression storage is subject to infiltration and evaporation. However, the evaporation loss is small compared to infiltration losses. Typical values for pervious area depression storage are 2 to 10mm (O'Loughlin 1993).

Runoff occurs when the rate of rainfall exceeds the ability of the soil to absorb water (i.e. infiltration rate). The infiltration process is a complex interaction between rainfall, soil type, and surface cover and condition. Infiltration is often treated as a one-dimensional flow and there are number of theoretical and empirical methods that have been proposed to calculate the infiltration rate. The empirical models are based on observed behavior of soil infiltration and therefore, some parameters in empirical models have no physical meaning. The Horton's infiltration model (Horton 1940) is one such empirical equation and is perhaps the best-known infiltration equation (USEPA 1992). The Green-Ampt model (Green and Ampt 1911; Mein and Larson 1971) is an example of theoretical equations used in urban drainage models.

Loss of precipitation due to evaporation has negligible effect on single event simulation (i.e. flood events) compared to other losses, but it is important for continuous simulations. Evaporation is taken into account as an average monthly value (or as a default daily evaporation rate of 3 mm per day) in SWMM and XP-UDD urban drainage models.

2.2.3 Rainfall-runoff depth plots

A plot of rainfall depth versus runoff depth for storm event is known as rainfall-runoff depth plot (i.e. RR plot). The RR plot of a catchment can be used to determine the accuracy of observed rainfall/runoff data, to separate *small* and *large* storm events and to estimate the impervious area percentage (i.e. $\%A_i$) and its depression storage (DS_i). In these plots, the runoff depths are computed as the ratio of runoff volume at the catchment outlet to the total area of the catchment. Bufill and Boyd (1992) and Boyd et al. (1993) conceptualized the RR plots, as shown in Figure 2.2.

In Figure 2.2, Bufill and Boyd (1992) and Boyd et al. (1993) considered that the urban catchment is made up of three types of surfaces namely directly connected impervious areas (A_i), additional impervious areas (i.e. supplementary areas – A_s), which are not directly connected to the stormwater drainage system and pervious areas (A_p). Furthermore, they assumed that the urban stormwater runoff from directly connected impervious area responds first, followed by supplementary areas and finally by pervious areas. In Figure 2.2, the segment FG represents runoff contributing from the directly connected impervious areas and slope of FG gives the directly connected impervious area percentage. The depression storage of directly connected areas is given by OF. The segment GH represents runoff contribution from directly connected impervious areas and supplementary areas, and the segment HB represents runoff from all three areas. The gradient of GH and HB give percentage of total impervious [i.e. $(A_i+A_s)/A$] area and [i.e. $(A_i+A_s+A_p)/A$] respectively. OJ and OK give the depression storage of supplementary and pervious areas respectively.

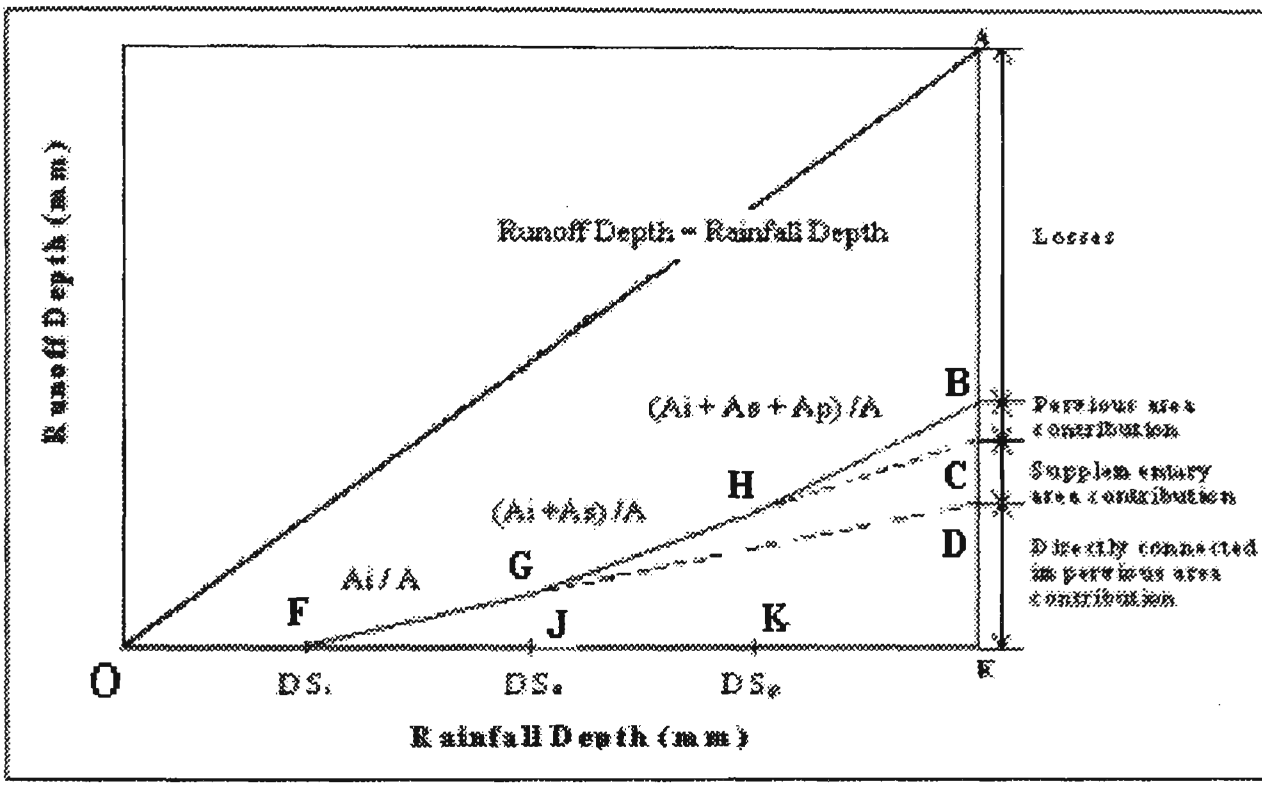


Figure 2.2 Rainfall-Runoff Plot (Ref: Boyd et al. 1993)

Although in Figure 2.2 it has been assumed that directly connected impervious areas, supplementary areas and pervious areas respond to runoff in that order, it is difficult to say which areas respond first, since the response depends on the location of these areas with respect to the catchment outlet. For this reason, Bufill and Boyd (1992), Boyd et al. (1993), Maheepala (1999) and Dayaratne (2000) used RR plots in their studies to estimate parameters related to directly connect impervious areas only.

2.3 Urban Stormwater Drainage Systems

The main purpose of an urban stormwater drainage system is to collect stormwater from its catchment and convey it to the receiving waters, with minimum nuisance, damage or danger to its operating environment. Traditionally, these systems provide man-made impervious pathways for guiding stormwater flow over the land surface and underground. Main components of a stormwater drainage system are property drainage, street drainage, trunk drainage, retention basins, detention basins and receiving waters, which are described briefly below. Both retention and detention basins have been and are being used extensively throughout Australia and overseas.

- Property drainage – The property drainage system collects stormwater from both impervious and pervious surfaces of the properties. The roof is the main impervious portion of the property. The roof drainage system consists of gutters, down pipes and receiver boxes (in some cases). Runoff collected through property drainage is discharged to the street drainage system.
- Street drainage – The street drainage system collects runoff from road surfaces and land-adjoining streets through gutters, pits and pipes. The street drainage system then discharges this runoff to the trunk drainage system.
- Trunk drainage - The trunk drainage system generally consists of large open channels to convey the runoff from street drainage to receiving waters. They are generally located in an open area reserved as a drainage easement.
- Retention basin – The retention basin is a small lake located in or off stream along the urban waterways. It is also used as a water quality control pond as it holds the runoff water for a considerable period.
- Detention basin – The detention basin is commonly known as a retarding or compensating basin in Australia. It holds runoff for a short time period (especially during high runoff period) to reduce peak flow rates.
- Receiving water – The receiving water consists of large water bodies such as rivers, lakes, bays, the sea and groundwater storage.

2.4 Urban Drainage Software Tools

Urban drainage software tool is a computer base representation of the behaviour of complex stormwater runoff processes of urban catchment in the form of mathematical equations. The roots of modern urban drainage software tools can be located in the late 1960s, when the ***S**torm **W**ater **M**anagement **M**odel* - SWMM model was developed (Metcalf and Eddy Engineers 1971).

There are several computer software tools that are currently available for urban catchment drainage modelling. Since the urban drainage systems consist of pits, pipes and channels, it is necessary to model both hydrology and hydraulics to get a better representation of the flows in these systems. The widely used models in Australia were/are SWMM (USEPA 1992), MOUSE (Danish Hydraulic Institute 1993), ILSAX (O'Loughlin 1993) , XP-UDD (XP-Software 1997) and DRAINS (O'Loughlin and Stack 1998), which model both hydrology and hydraulics of urban drainage systems. It should be noted that XP-UDD is an enhanced and user-friendly version of SWMM, while DRAINS is an upgrade of ILSAX model. Brief descriptions of these models are given below.

SWMM

The SWMM model is probably the most popular of all urban drainage models. It is a comprehensive dynamic rainfall-runoff simulation model, capable of simulating the runoff quantity and quality in storm and combined sewer systems. The modeller can simulate all aspects of the urban hydrologic and quality cycles, including surface runoff, transfer through pipe/channel networks and storage/treatment facilities and to receiving waters. It can be used to simulate a single storm event or long, continuous storms (Pitt et al. 2002). XP-SWMM (WP Software and XP Software 1993), is an enhanced and user-friendly version of SWMM Version 4 (Huber and Dickinson 1988; Roesner et al. 1988), which included a graphical interface for pre and post-processing of input and output data.

MOUSE

MOUSE stands for ***Mo**delling **O**f **U**rban **SE**wers* and can only be applied for modelling of hydrology and hydraulics of urban catchments (Dayaratne 2000). MOUSE, like SWMM, is well suited for analyzing the hydraulic performance of complex looped sewer systems including overflow, storage basins, pumping stations and water quality modelling.

XP-UDD

XP-UDD uses the same engine of XP-SWMM, except the water quality management module (http://www.xpsoftware.com.au). In XP-UDD, it is possible to import data from ASCII text files in XPX file format. This format allows the creation of new data and objects as well as updating and adding to existing XP-UDD networks. Large data sets up to 10,000 conduits can be managed easily using XP-UDD. It allows importing existing information from ILSAX, XP-RAFTS (WP Software 1991), and version 3 and 4 SWMM data files. Input and output files of XP-UDD can be accessed by other external software tools.

ILLSAX/DRAINS

ILSAX and DRAINS simulate the rainfall-runoff processes of urban catchments, generating flow hydrographs at each entry point to the pipe or channel system, then routing and combining flows through the drainage network. ILSAX contains a comprehensive hydrological module for calculating flow rates, and an approximate procedure for pipe system hydraulics. DRAINS software is an upgrade of ILSAX with improved procedures for modelling pipe hydraulics.

Selection of Urban drainage software for the study

All above software tools use similar equations for modelling hydrological and hydraulic processes of urban catchments. The choice of these tools for use in analysing a particular problem depends on the design objectives and the available resources. However, to properly use these computer software tools, the user is required to have a good knowledge of their capabilities.

Of the above software tools, XP-UDD has ASCII (or text) input and output data files. In this study, the GAs optimisation algorithm needs to access these files and therefore, XP-UDD was selected for this study to model and calibrate the study catchments. In addition to this important property, XP-UDD has the following capabilities, which are also important in this study.

- XP-UDD has built-in Australian Rainfall and Runoff (Pilgrim 1987) design storm database, which can produce design hyetographs automatically.
- It has the capability to view output results through its multimedia capabilities.
- User-friendliness of the software
- Full support by XP Software
- Licence at Victoria University

2.5 Calibration of Mathematical Models

The reliability of urban drainage models (assembled through computer software tools) depends on the correct selection of the model parameter values, which are relevant to the catchment or the system that is being modelled. Some of these parameters can be physically measured, whereas the others are impossible or difficult to measure (eg. depression storage, flow roughness etc.). Therefore, these parameters, which are impossible or difficult to measure physically, have to be estimated through model calibration, before the models can be confidently used as decision-making tools. The model calibration is an iterative process where the model parameters are selected by comparing model predictions with observations, until the predictions and observations match with each other within a reasonable accuracy. Model calibration is also referred to as parameter estimation, because the calibration yields the 'best' values for the model parameter set. This section reviews the methods available for calibration of mathematical models, in which urban drainage models are a sub-set.

Model calibration techniques can be broadly divided into two categories namely manual and automatic methods, as shown in Figure 2.3. The manual method is the traditional trial and error approach. With this method, the simulated hydrographs corresponding to different parameter values are visually compared with the observed hydrograph (at the catchment outlet), and the parameter value set that best match the observed hydrograph is selected as the calibrated parameter set. Vale et al. (1986) and Maheepala (1999) used this approach for calibration of urban drainage models. This method is subjective, time consuming and error prone. It has been reported by Mohan (1997) and Sorooshian and

Gupta (1995) that the trial and error method may lead to unrealistic parameter sets in water resources applications.

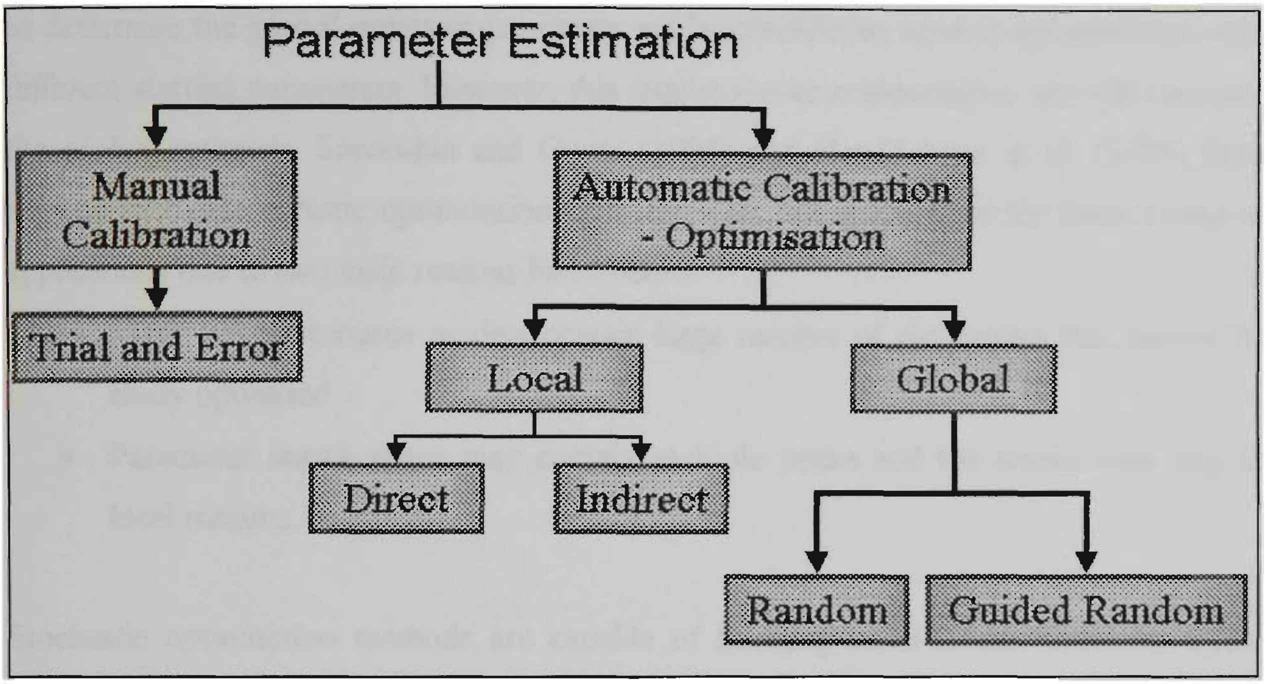


Figure 2.3 Broad Methods in Model Parameter Estimation

In the automatic calibration method, an optimisation technique is used to determine the *optimum* parameter set through a user-defined objective function within a defined parameter space. However, it has shown in previous studies (Sorooshian and Gupta 1995) that the results of the calibration may differ according to the objective function and therefore care must be taken to select the most appropriate objective function for the particular study (Ng 2001).

Automatic optimisation methods can be characterised as being either deterministic (local) or stochastic (global). Deterministic optimisation methods are designed to locate the 'optimum' parameter set when the response surface defined by the user-defined function is uni-model (i.e. function with a single peak/trough). If the response surface is multi-modal, the parameter set obtained from the deterministic method may not produce the global optimum, since the solution can be trapped at a local optimum point. The current literature identifies the most familiar two deterministic optimisation methods based on calculus as direct and indirect search methods (Ng 2001). The direct search method seeks the local optima by hopping on the function and moving in a direction related to the local gradient. The indirect search method seeks the local optima by solving the non-linear set of equations resulting from setting the gradient of the objective function value equal to zero (Goldberg 1989a). Theoretically, the deterministic optimisation methods can be used to determine the *global* optimum parameter set by considering several optimisations with different starting parameters. However, this requires more computations and still can miss the *global* optimum. Sorooshin and Gupta (1995) and Hendrickson et al. (1998) have showed that deterministic optimisation techniques are not appropriate for water resource applications due to two main reasons listed below.

- Many water resource models contain large number of parameters that cannot be easily optimised.
- Parameter search space may contain multiple peaks and the results may trap in local maxima.

Stochastic optimisation methods are capable of handling multi-modal functions. Some research works in water resource applications have shown that stochastic optimisation techniques have the ability to overcome the problems associated with deterministic optimisation techniques discussed above and are more efficient in locating the 'optimum' parameter set compared with deterministic methods (Liong et al. 1995; Franchini and Galeati 1997; Savic and Walters 1997; Vasquez et al. 2000; Ng 2001; Sen and Oztopal 2001). The stochastic methods can be divided into two main groups namely random and guided random search methods, as shown in Figure 2.3 (Ng 2001). The random search method selects the parameter sets randomly from the parameter range and optimises the parameter set. The guided random method provides guided information for the next search based on history of previously considered possible solutions, and therefore can be more efficient than the random search method.

Several guided random search methods exist, such as simulated annealing, adaptive random search, shuffled complex algorithm and evolutionary algorithm (EA) (Duan et al. 1992). EA was found to be a robust search method that outperforms the traditional optimisation methods in many ways, in particular when the response surface is multi-modal (Back and Schwefel 1993; Schwefel 1997; Mulligan and Brown 1998). EA utilises the natural process of evolution (De Jong et al. 1997).

There are five forms of Evolutionary Algorithms namely, Evolutionary Programming (Fogel 1997), Evolutionary Strategies (Schwefel 1981), Genetic Algorithm (Holland 1975), Classifier Systems and Genetic Programming. Classifier systems and genetic programming were originally derived from GAS. All these methods share common principles of EA in applying EA operators to evolve new search spaces (Ng 2001). Of these five forms, GAs have proven to provide a robust search in complex search spaces (Eshelman and Schaffer 1992; Eshelman 1997; Mayer et al. 1999b). GAs have been applied successfully in water resource applications in recent past and is discussed in Section 2.6.3.2.

2.6 Genetic Algorithms (GAs)

Genetic Algorithms are a widely used stochastic search method originally developed by Holland (1975), and later refined by Goldberg (1989a), Davis (1991) and many others. GAs are theoretically and empirically proven to provide a robust search in complex nonlinear problems (Goldberg 1989a). It uses computer based iterative procedures that employs the mechanics of natural selection and natural genetics to evolve solution for a given problem. Specially, the notion of *survival of the fittest* plays a central role in GAs. Goldberg showed that GAs contain several properties that differentiate from the traditional optimisation techniques as follows:

- GAs search the optimum solution from a set of possible solutions, rather than one solution.
- Objective function values are used as feedback to guide the search, rather than using derivatives or other information.
- GAs use probabilistic transition rules rather than deterministic rules.
- GAs work on the encoded parameter set rather than the parameter set itself (except in real-value coding, which has been used in recent applications).
- GAs can provide a number of potential solutions to a given problem and the final choice of solution is left to the user.

Genetic algorithms are rooted in both natural genetics and computer science. Therefore, the GAs terminology has a mixture of natural and artificial terms. As stated earlier, GAs search the optimum solution from one set of possible solutions at a time, rather than from one solution. This set of possible solutions is named as population. There are several populations in a GAs run and each of these populations is called a generation. Generally at each new generation, the solutions (i.e. model parameter sets) that are closer to the optimum solution are created than in the previous generation. In the GAs context, the model parameter set is defined as a *chromosome*, while each parameter present in the *chromosome* is known as a *gene*. Population size is the number of *chromosomes* present in a population. The GAs process are briefly described below and the overall GAs process are shown in Figure 2.4.

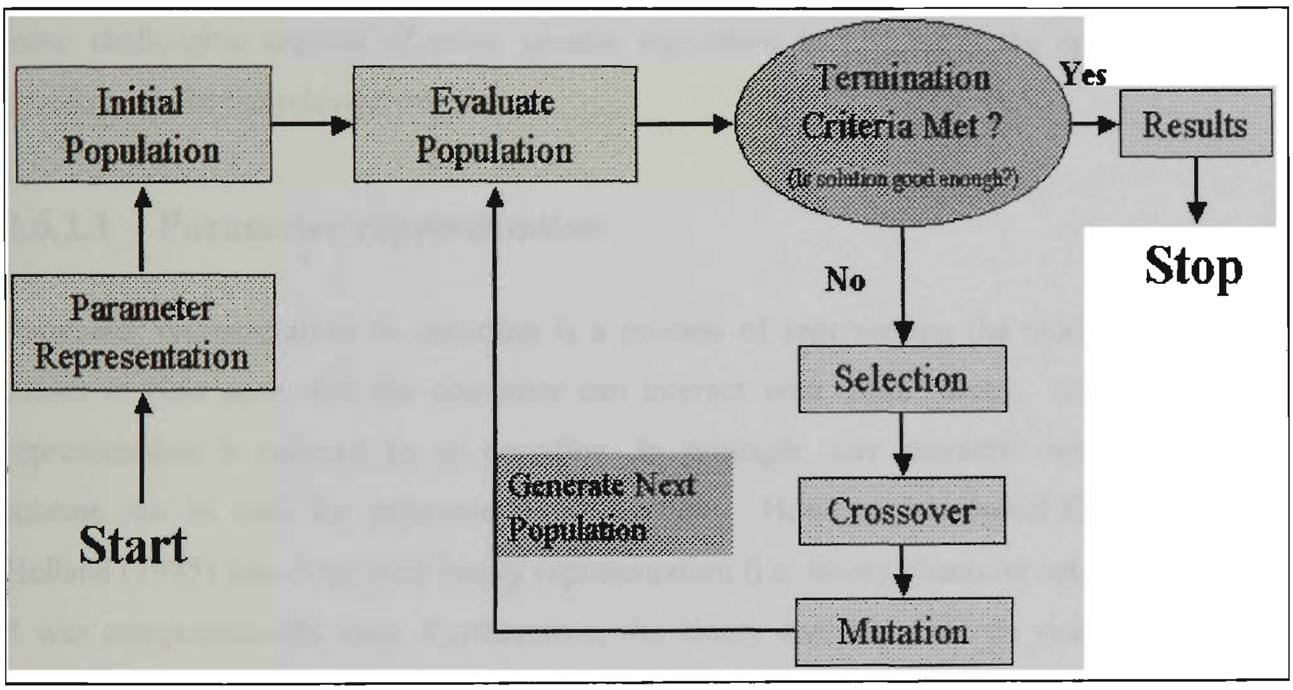


Figure 2.4 Overall GAs Process

At the start of the GAs optimisation, the user has to define the GAs operators (such as type of model parameter representation, population size, selection type, crossover rate and mutation rate), which are described in Section 2.6.1. The initial population is generated according to the selected parameter representation at random or using a priori knowledge of the search space. The initial population provides the set of all possible solutions for the first generation, according to the user defined model parameter ranges. A user-defined objective function is used to evaluate each *chromosome* in the population. These objective function values of the *chromosomes* indicate the suitability (or fitness) of the parameter set for the given problem. After computing the objective function values for each *chromosome* of the current population, GAs operators such as selection, crossover and mutation are used to generate the population in the next generation. Several generations are considered in the GAs process, until the user-defined termination criteria are reached.

2.6.1 Genetic algorithms operators

The GAs operators, namely parameter representation, population size, selection type, crossover and mutation, control the process of GAs. These operators play an important role in the efficiency of GAs optimisation in reaching the *optimum* solution. One of the more challenging aspects of using genetic algorithms is to choose the *optimum* GAs operator set for the relevant problem.

2.6.1.1 Parameter representation

Parameter representation or encoding is a process of representing the model parameter values in GAs such that the computer can interact with these values. Inverse of this representation is referred to as decoding. In principle, any character set and coding scheme can be used for parameter representation. However, the initial GAs work of Holland (1975) was done with binary representation (i.e. binary character set, 0 and 1), as it was computationally easy. Furthermore, the binary character set can yield the largest number of possible solutions for any given parameter representation (which is described in detail under binary coding), thereby giving more information to guide the genetic search (Caruana and David 1987).

In order to estimate the optimum model parameters of mathematical models using GAs, model parameters required representing in a suitable form. The GAs operators work directly (or optimization is performed) on this representation of the parameters. Currently, there are two main types of parameter representation methods available, which are bit string coding and real value coding (Wright 1991). The bit string coding is the most commonly used method by GAs researchers because of its simplicity. Furthermore, the conventional GAs operations and theory were developed on the basis of this fundamental structure, which was used in many applications (De Jong et al. 1997; Goldberg 1989b).

Bit string and real coding differ mainly in how the crossover and mutation operators are performed in the GAs process. There are two types of bit string coding methods available, namely binary and Gray coding, which use similar concepts.

(a) Binary coding

In binary representation in GAs, each parameter (i.e. *gene*) in the model parameter set (i.e. *chromosome*) is encoded as a binary sub-string. These sub-strings corresponding to each parameter are then arranged linearly to form a string to represent the entire model parameter set. The length of the binary sub-string (i.e. number of bits) of a model parameter depends on the size of the search space and the number of decimal places required for accuracy of the decoded model parameter values. The length of the binary sub-string of a model parameter can be computed from Inequality (2.1) (Michalewicz 1996). This means that the search space is divided into 2^L intervals having a width equals $(Q_{max} - Q_{min}) / 2^L$.

$$2^{L} - 1 \geq (Q_{\max} - Q_{\min})10^{d} \qquad (2.1)$$

where
- L is the length of the binary sub-string
- Q_{max} is the upper bound of the parameter range
- Q_{min} is the lower bound of the parameter range
- d is the number of decimal places required to define the accuracy of decoded values

The binary numbers are expressed in base 2 form, and use only two characters 0 and 1. A binary number N can thus express using Equation (2.2).

$$N = a_n 2^n + a_{n-i} 2^{n-1} + \ldots\ldots + a_1 2^1 + a_o 2^o = \sum_{i=0}^{n} a_i 2^i \qquad (2.2)$$

where
- a_i is either 0 or 1
- 2^i represents the power of 2 of the digit a_i.
- n number of bits in binary coded parameter, counting from zero (i.e. sub-string length – 1)

Suppose there is a model parameter with its search space ranging from -1 to 2 requires mapping into binary coding. If the accuracy required is one decimal place, the above search space can be divided into 30 intervals of 0.1 widths each as shown in Figure 2.5. To binary code this precision at least 5 bits are necessary, because $2^4 < 30 < 2^5$ (Biethahn and Nissen 1995). And also Inequality (2.1) gives the length of the binary sub-string as 5.

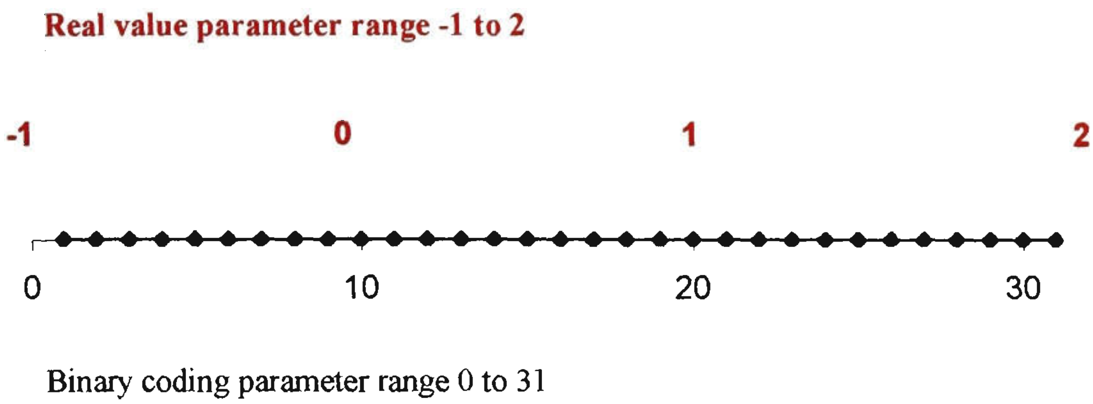


Figure 2.5 Real Value and 2^L Intervals of Binary Value Search Space

The lower bound and upper bound of the real value search space (i.e. -1 and 2) can be mapped into binary as follows using Equation (2.2) and all the other intermediate values (i.e. 1 to 30) can also be easily express in binary using the same equation.

$$0 = 0*2^4 + 0*2^3 + 0*2^2 + 0*2^1 + 0*2^0 \Longrightarrow 00000$$
$$31 = 1*2^4 + 1*2^3 + 1*2^2 + 1*2^1 + 1*2^0 \Longrightarrow 11111$$

Once the GAs optimisation is completed, the decoding of binary values to real values can be done by linearly mapping the binary values in the interval Q_{min} to Q_{max}, by using Equation (2.3).

$$Q = Q_{miin} + X\frac{Q_{\max} - Q_{\min}}{2^L - 1} \qquad (2.3)$$

where Q is the decoded real value

X is integer value of binary number

For example, the binary numbers 11111(integer value = 31) and 11110 (integer value = 30) can be decoded to the real number in its real value parameter range as follows:

Decoded value of 11111 with in the range of –1 to 2 = $(-1) + 31 \dfrac{[2.0 - (-1)]}{[2^5 - 1]} = 2$

Decoded value of 11110 with in the range of –1 to 2 = $(-1) + 30 \dfrac{[2.0 - (-1)]}{[2^5 - 1]} = 1.9$

Suppose there are three model parameters (i.e. P, Q and R) in the above example having the same search space and required the same accuracy. If the binary encoded values of these model parameters are P= 11110, Q=11111 and R=00000, then the *chromosome* representing all three parameters (i.e. model parameter set) is 111101111100000 (PQR). Although the range of values and accuracy are considered the same for each parameter in this example, different ranges and accuracies can be considered in GAs through different binary sub-string lengths for different parameters.

(b) Gray coding

Gray coding (Gray 1953) was named after Frank Gray (http://www.wikipedia.org /wiki/Gray_coding). Gray coding is an ordering of binary character sets such that all adjacent numerical numbers differ by only one bit whereas in binary coding adjacent numbers may differ in many bit positions, as explained below. The advantage of Gray coding is that random bit flips in mutation (Section 2.6.1.5) are likely to make small changes and therefore result in a smooth mapping between real search and the encoded parameters. To convert binary coding to Gray coding, truth table conversion is followed, which is shown in Table 2.1.

Table 2.1 Truth Table Conversions

A \ B	**1**	**0**
1	0	1
0	1	0

Note: A and B are adjacent bits in binary string

When converting from binary to Gray, the first bit of the binary code remains as it is and the remainder follows the truth table conversion, two bits taken sequentially at a time giving the next bit in Gray coding. As example of representation of binary and Gray coding of numeric numbers of 1-7 are shown in Table 2.2. In Table 2.2, flipping of bits was marked in red, when bits changes form one numeric number to another in both binary and Gray coding.

Table 2.2 Representations of Integer Numbers in Binary and Gray Coding

Numeric number	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Binary code	001	010	011	100	101	110	111
Gray code	001	011	010	110	111	101	100

The conversion of numeric number 3 from binary to Gray is demonstrated in Table 2.3, where the first bit remains as 0. Then (0,1) in binary gives the second bit in Gray coding as 1 and finally (1,1) gives the third bit in Gray as 0.

Table 2.3 Conversion of Binary to Gray

Binary	**Gray**
0	0
1	1
1	0

The number of bit positions differ in adjacent two bit strings of equal length is named as *Hamming distance*. For example, the *Hamming distance* between 011 and 100 is 3, since all bit positions differ, when converting numeric number 3 to 4 in binary representation. *Hamming distance* for the binary ad Gray code values in Table 2.2 is plotted in Figure 2.6.

As can be seen from Table 2.2, if the first bit of 011 and 010 (which are corresponding to numeric number 3 of binary and Gray coding respectively) changed to 1 during the mutation process in GAs, which will mapped to numeric number 7 (i.e. 111) and 4 (i.e. 110) in binary and Gray respectively. Furthermore as increase in *Hamming distance* of adjacent values in the search space necessarily leads to decrease the similarities in string templates (i.e. schemata, which described in Section 2.6.2) and this intern can reduce the effectiveness of GAs (Caruana and Schaffer 1989). Caruana and David (1987; 1989) reported that Gray coding can eliminate a hidden bias in binary coding and that the large *Hamming distances* in the binary representation could result in the search process being deceived or unable to efficiently locate the global optimum. According to them, the first suggestion of the superiority of Gray coding was by Hollstien (1971). Gray coding was recently selected as the parameter representation method, when applying GAs in several water resource applications recently (Mulligan and Brown 1998; Wardlaw and Sharif 1999; Ng 2001).

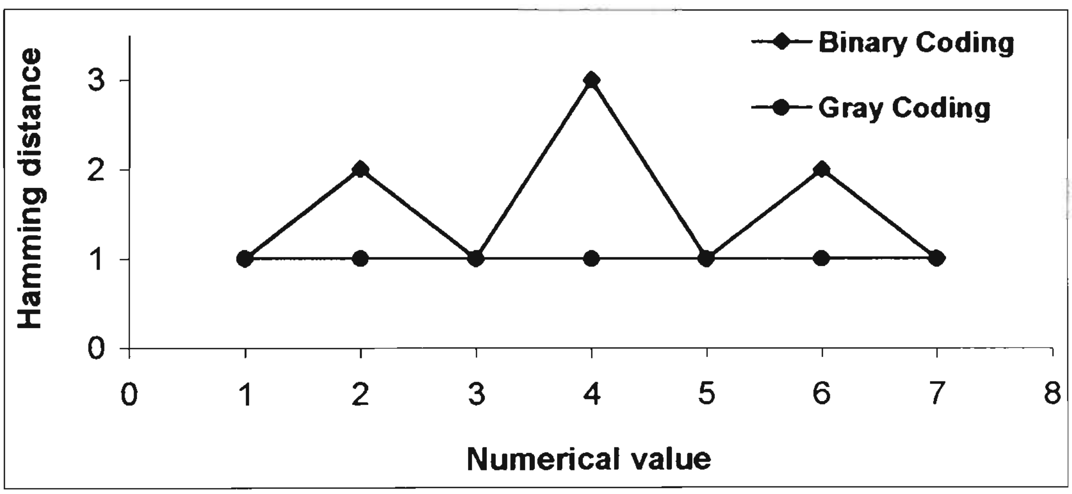


Figure 2.6 Numerical Value Vs. Hamming Distance for Binary and Gray

(c) Real value coding

Although GAs have shown to be a robust optimisation technique in many applications, it has failed to make significant acceptance in artificial intelligence applications, as they required immediately expressive parameter representation rather than bit string representation (Antonnisse 1989). The real number representation, in which each parameter is represented by its real-value, eliminates this drawback. Furthermore, for problems with a large number of parameters requiring optimisation within large parameter ranges and requiring a higher degree of precision, binary represented genetic algorithms had performed poorly (Michalewicz 1996). Anikow and Michalewicz (1991) reported that the real value representation was faster, more consistent from run to run, and provided higher precision especially with large domains where binary coding would require long string length.

Another form of real number representation is the integer coding. In integer coding, the floating-point value in the real number coding is replaced with an integer, when performing mutation. The only practical difference between real number coding and integer coding is the operation of mutation.

2.6.1.2 Population size

As stated earlier, the population size is the number of *chromosomes* in the population. Selecting a population size is a fundamental decision that has to be made in GAs optimization at the start. Larger population sizes increase the amount of variation present in the population (or population diversity), but at the expense of requiring more fitness evaluations (Goldberg, 1989a). Furthermore, when the population size is too large, there is a tendency by the user to reduce the number of generations in order to reduce the computing effort, since the computing effort depends on the multiple of population size and number of generations. Reduction in the number of generations reduces the overall solution quality. On the other hand, a small population size can cause the GAs to converge prematurely to a sub-optimal solution.

Goldberg (1989a) reported that population size ranging from 30 to 200 were the general choice of many GAs researchers. Furthermore, Goldberg pointed out that the population size was both application dependent and related to the length of the *chromosome* (i.e. string length). For longer *chromosomes* and challenging optimization problems, larger population sizes were needed to maintain diversity, as it allowed better exploration.

In GAs optimisation, the population is initially chosen at random or using a heuristic technique within a specified range for parameters. The latter method is based on prior knowledge of the parameters and hence provides a good initial estimate of parameters and hence rapid convergence. The advantage of the random method is that it prevents premature convergence to an incorrect solution due to insufficient variability in the initial population.

2.6.1.3 Selection

The selection process determines which *chromosomes* participate for reproduction in generating the next population (i.e. in the next generation) according to their fitness values in the current population. In general, this process takes advantage of the fittest solutions by giving them greater weight when selecting the next generation and hence leads to better solutions to the problem. There are two common terms related to selection process namely *generation gap* and *selection pressure*.

All *chromosomes* in the population or only a percentage of *chromosomes* in the population can undergo selection process using any selection method. This percentage is known as *generation gap*, which is a user input in GAs. However, Peck and Dhawan (1995) reported that the *generation gap* was not critical.

When selecting *chromosomes* for the next generation, *selection pressure* puts more emphasis on the fitter model parameter sets and more copies of fitter parameter sets being selected into the next generation than those with less fitness values. This loses the population diversity or the variation present in the population and could lead to a premature convergence. Whitley (1989) reported that population diversity and *selection pressure* as the two primary factors that influence the GAs search. Whitley pointed out that these two factors are inversely related and hence required to have a good balance between them. Therefore, he argued that the method used in the selection process need to have the ability to account for balance between *selection pressure* and population diversity.

There are several ways to implement selection in GAs optimisation. Proportionate selection (Grefenstette 1997), linear ranking (Baker 1987) and tournament selection (Blickle T. and Thiele L. 1997), are commonly used selection methods. They are briefly described below. However, Goldberg and Deb (1991) stated that no one selection method is superior to the other.

(a) Proportionate selection

The proportional selection method selects *chromosomes* for reproduction of next generation with probability proportional to the fitness of the *chromosomes*. In this method, the probability (P) of selecting a *chromosome* for reproduction can be expressed by Equation (2.4).

$$P = \frac{Fitness}{TotalFit} \tag{2.4}$$

where $Fitness$ is the fitness value of a *chromosome*

$TotalFit$ is the sum of the fitness values of all *chromosomes* in the population

This method provides non-integer copies of *chromosomes* for reproduction. Therefore, various methods have been suggested to select the integer number of copies of selected *chromosomes* for the next generation, including Monte Carlo, roulette wheel and stochastic universal selection. Goldberg (1989a) reported that the simplest method among them was the roulette wheel method. The roulette wheel method can be considered as having slots for each *chromosome* in the population, where each slot is equivalent to the fitness value of the *chromosome*. The higher the value of fitness the larger the area of the slot for that particular *chromosome* and vice versa. To determine the integer number of *chromosome* copies, the roulette wheel requires spinning N times, where N is the number of *chromosomes* in the population. The number of copies allocated to each *chromosome* can then be obtained by summing the number of times the spin has landed on respective slot. Therefore, there is a probability of fitter *chromosomes* (i.e. good solutions) contributing more times for reproduction.

(b) Linear ranking selection

Baker (1987) introduced the linear ranking selection to genetic algorithms practice (Goldberg and Deb 1991). In the linear ranking method, the fitness rank of each *chromosome* is used instead of its absolute value of fitness. In other words, the population in each generation is sorted in fitness order and selection is done according to the ranking, and not according to the fitness value. This reduces the influence on the selection of extremely fitter *chromosomes* for the next generation and thereby reducing *selection pressure* and increasing population diversity. This method also used the roulette wheel sample selection method to select integer number of copies of selected *chromosomes* for the next generation.

(c) Tournament selection

In the tournament selection method, *chromosomes* for reproduction are selected through competition. This is performed by randomly selecting 2 *chromosomes* in the current population regardless of their fitness and then the best is selected. With this process, one *chromosome* can win many times, and the process is continued until the required number of *chromosomes* is selected for the reproduction of the next generation. Although in general, tournaments are held between pairs, Goldberg and Deb (1991) reported that large tournaments between more than two *chromosomes* can be used as well. The tournament selection provides integer copies for reproduction in the next generation. Yang et al. (1997) provided a detailed discussion of the tournament selection.

2.6.1.4 Crossover

The crossover operator is used to create new *chromosomes* for the next generation by combining randomly two selected (Section 2.6.1.3) chromosomes from the current generation. However, some algorithms use an *elitist* selection strategy, which ensures the fittest *chromosome* from one generation is propagated into the next generation without any disturbance. The crossover rate is the probability that crossover reproduction will be performed and is an input to GAs. For example, a crossover rate of 0.9 means that 90% of the population is undergoing the crossover operation. A high crossover rate encourages good mixing of the chromosomes.

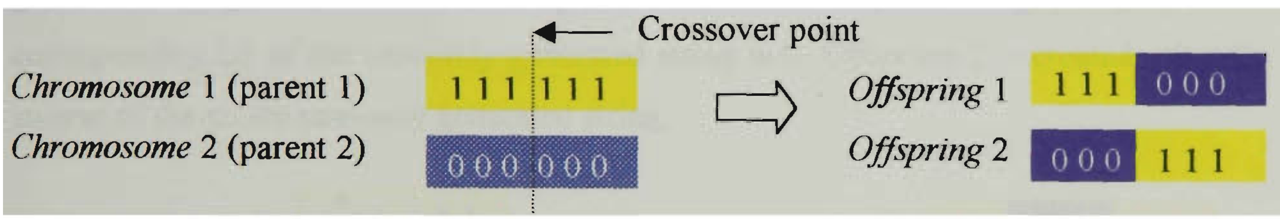
There are several crossover methods available for reproducing the next generation. In general, the crossover methods can be classified under two groups according to their parameter representation in GAs optimisation (i.e. bit string coding or real value coding). The choice of crossover method is primarily dependent on the application. Back and Schwefel (1993) reported that crossover is the dominant genetic operation, consistently having high crossover rates of 0.6 – 0.95.

(a) **Bit string value crossover types** (Davis 1991; Goldberg 1989a)

In bit string coding, crossover is performed by simply swapping bits between the crossover points. Different types of bit string crossover methods are discussed below.

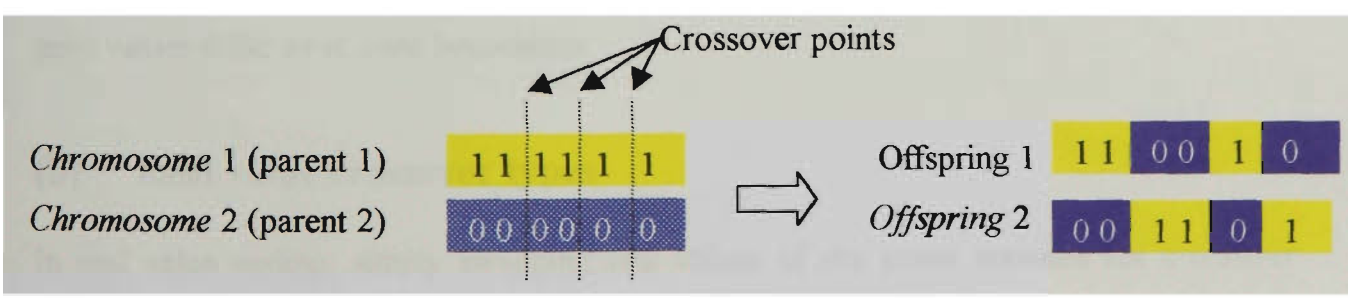
Single-point crossover

Two parent *chromosomes* are combined randomly at a randomly selected crossover point somewhere along the length of the *chromosome*, and the sections on either side are swapped. For example, consider the following two *chromosomes* each having 6 binary bits. After crossover, the new *chromosomes* (i.e. referred as *offsprings* or children) are created as follows if the randomly chosen crossover point is 3.



Multi-point crossover

In multi-point crossover, the number of crossover points are chosen at random with no duplicates and sorted in ascending order. Then, the bits between successive crossover points are exchanged between the two parents to produce two new *chromosomes*. The section between the first bit and the first crossover point is not exchanged between *chromosomes*. For example, consider the same example of two *chromosomes* used in single crossover. If the randomly chosen crossover points are 2, 4 and 5 (i.e. no duplicates and ascending order), the new *chromosomes* are created as follows.

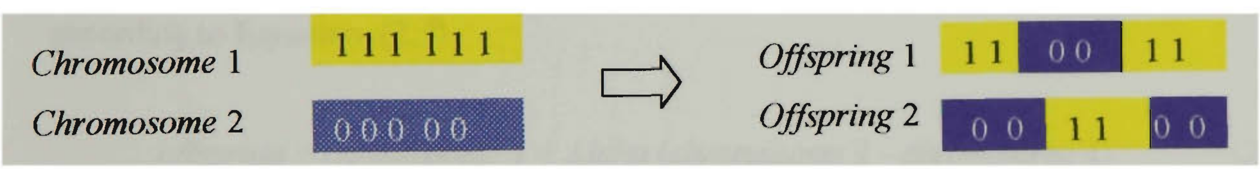


The two-point crossover is a sub-set of multi-point crossover. The disruptive nature of multi-point crossover appears to encourage the exploration of the search space, rather than favoring the convergence to highly fit chromosomes early in the search, thus making the search more robust.

Uniform crossover

Single and multi-point crossover define crossover points between first and last bit of two *chromosomes* to exchange the bits between them. Uniform crossover generalizes this scheme to make every bit position a potential crossover point. In uniform crossover, string of bits, which has the same length as the *chromosome* is created at randomly to indicate which parent will supply the bits to create offspring.

As example, consider the same above example of two *chromosomes*. If the randomly generated string for parent 1 is **110011**, then the *offsprings* are created as follows. The bit from parent 1 is taken to produce *offspring* 1, if the corresponding bit of the randomly generated string is 1. The bit from parent 2 is taken to produce *offspring* 1, if the corresponding bit of the randomly generated string is 0. *Offspring* 2 is created using the inverse of the above randomly generated string.



Syswerda (1989) reported that uniform crossover is generally the best followed by two-point and one-point crossover.

Crossover with reduced surrogate

Contrary to all above methods, the reduced surrogate crossover is implemented by restricting the location of crossover points such that crossover points only occur where gene values differ or at gene boundaries.

(b) Real value crossover types

In real value coding, simply swapping real values of the *genes* between the crossover points performs the crossover. Different types of real value crossover methods are discussed below.

Discrete crossover (Wright 1991)

The discrete crossover performs an exchange of parameter values randomly between the *chromosomes*. Consider the following example of two *chromosomes* having 3 parameters. For each parameter, the parent contributes its values to the offspring randomly with equal probability. In this example, this random selection yields *offspring* 1 generated from values of parameter 1 and 2 of parent 2 and parameter 3 of parent 1. *Offspring* 2 is generated from values of parameter 1 and 3 of parent 1 and parameter 2 from parent 2.

Chromosome 1	12	25	5	$\Rightarrow$	*Offspring* 1	123	4	5
Chromosome 2	123	4	34		*Offspring* 2	12	4	5

Intermediate/Extended crossover (Michalewicz 1996)

With these methods, the parameter values of the *offsprings* are chosen from the parents according to Equation (2.5).

$$offspring = chromosome\ 1 + Alpha\ (chromosome\ 2 - chromosome\ 1) \qquad (2.5)$$

where $Alpha$ is a scaling factor chosen uniformly at random over an interval $(-d,\ 1+d)$

For intermediate crossover d is 0, while for extended intermediate crossover d is greater than 0.

Line crossover

The line crossover is similar to the intermediate crossover, except that only one value of randomly generated *Alpha* for all parameters is used to produce one offspring. However, different values of *Alpha* may be used to produce the offspring 2.

2.6.1.5 Mutation operator

Mutation introduces innovation into the population by randomly modifying the *chromosomes*. It prevents the population from becoming saturated with *chromosomes* that all look alike and reduces the chance of premature convergence (Hessner and Männer

1991). For example, in bit string representation, mutation is done by flipping 0's to 1's and vice versa. Large mutation rates increase the probability of destroying good *chromosomes*, but prevent premature convergence. The mutation rate determines the probability that mutation will occur. For example, if the population size is 100, string length is 20 and mutation rate is 0.001, only two bit positions will alter in the whole population (i.e. 100 x 20 x 0.001 = 2). As in crossover methods, mutation methods can be classified according to GAs parameter representation (i.e. bit string coding or real value coding).

(a) Bit string mutation

For binary and Gray coding systems, mutation is done by flipping bits 0's to 1's and vice versa at randomly chosen locations. Consider the following example of a bit string mutation for a *chromosome* with 11 bits, in which bit 4 is randomly mutated.

Before mutation	1	1	1	1	1	1	1	1	1	1	0
After mutation	1	1	1	0	1	1	1	1	1	1	0

(b) Real value mutation

To achieve real value mutation, either disarrange the gene values or randomly select new values. Mutation for integer coding is performed analogous to real value coding except that after mutation the value for that gene is rounded to the nearest integer. Some research findings and proposed methods for the real value mutation are displayed in the web site http://www.geatbx.com/docu/algmutat.html.

2.6.2 Schema theorem

The Holland's schema theorem provides the theory on how GAs find the shortest path to the fittest *chromosome* (Goldberg 1989a). This theorem was developed using the binary representation, although the recent GAs work has now extended to include real and integer number representations. A *schema* is defined as a set of *genes* (i.e. *chromosome*), which can be built by introducing the asterisk (*) symbol into the binary alphabet (0,1). The asterisk is known as *don't care* symbol, which means that it can be a 0 or a 1.

Schemata (i.e. plural of *schema*) are similarity templates of a set of *chromosomes* with common binary bits at certain positions (Holland 1975). These templates are a powerful way of describing similarities among patterns in the *chromosomes*.
For example, the *schema* H_1= 011** describes a set of *genes* of a *chromosome* in binary, where the first three position are fixed as 011, and last two positions can take on a value of either 0 or 1. Therefore, the *schema* H_1 can represent four *chromosomes*, namely 011**11**, 011**10**, 011**01** and 011**00**. All these *chromosomes* are instances of the *schema* H_1. However, they are also instances of other *schema* such as H_0 = *1***, which is more general than H_1, since it contains fewer fixed bits (Biethahn and Nissen 1995). This is explained in more detail below.

The two important properties of a *schema* are the *order-o(H)* and the *defining length-L(H)*. The *order* of a *schema* is the number of fixed symbols (1 or 0) in its representation. The *order* of H_1 and H_0 are 3 and 1 respectively. The *defining length* of a *schema* is the distance between the first and the last non-asterisk bits. It represents the compactness of a *schema*. The *defining length* of H_1 and H_0 are 2 and 0 respectively. Therefore, H_0 is having a low *defining length* and a low *order* than H_1. The degree of mutation and crossover destroying the existing *schemata* are dependent upon the *order* and the *defining length* of the *schemata*. The *schema* with low *order* and *defining length* would prevent destruction by mutation and crossover.

The Holland's schema theorem states that low *defining length* (i.e. short), low *order schemata* with above average fitness values will be allocated exponentially increasing trials in subsequent generations (Biethahn and Nissen 1995). The following explanation of schema theorem follows the example used in Goldberg (1989a), which is shown in Table 2.4.

In this example, Goldberg considered the problem of maximising function $f(x) = X^2$, where X is in the binary parameter range of 0 to 31(example in Section 2.6.1.1-a). For simplicity, Goldberg selected a population size of four randomly in this example. These selected values are shown in column (1) in Table 2.4. Furthermore, Goldberg assumed that *chromosome* 1 in the initial population was in *schema* H_1 = 011** and *chromosome* 2 and 4 were in schema H_2 =1****. Corresponding integer values of the binary *chromosomes* are tabulated in column (2). The fitness value or objective function was assumed as same as the maximising function value (i.e. X^2), which was tabulated in column (3). The Proportionate selection method and the roulette wheel method were used to select the parent copies for the reproduction (i.e. mating) pool and the results are tabulated in column (4) and (5) respectively. To perform crossover, parents and crossover points were randomly selected as shown in column (6) and (7) respectively to produce the new population. There was no mutation effect on population, since the mutation rate considered was 0.001. The new population and its fitness vales are tabulated in column (8) and (9) respectively.

Table 2.4 Example of Schema Theorem (Goldberg 1989a)

Initial population (1)	**Integer value of binary no. (X)** (2)	**Fitness value = X^2** (3)	**Selected copies** (4)	**Actual copies** (5)	**Mating pool** (6)	**Cros sover point** (7)	**New population** (8)	**Fitness value** (9)
01101 (H_1)	13	169	0.58	1	0110¦1 (H_1)	4	01100 (H_1)	144
11000 (H_2)	24	576	1.97	2	1100¦0 (H_2)	4	11001 (H_2)	625
01000	8	64	0.22	0	11¦000 (H_2)	2	11011 (H_2)	729
10011 (H_2)	19	361	1.23	1	10¦011 (H_2)	2	10000 (H_2)	256
Sum		1170						1754
Ave.		293						439
Max		576						729

As can be seen from Table 2.4, the average fitness value of H_2 (i.e. (576 +361)/2 = 468.5) is greater than the average population fitness value (i.e. 293) and H_2 has low *order* and low *defining length* compared to H_1. Therefore, H_2 contributed more copies (i.e. 3 copies) to the reproduction pool as well as for the new population than in the initial population.

Holland derived an equation to express the schema theorem in mathematical form. This equation can be used to predict the number of times a particular *schema*, would have in the next generation after undergoing selection, crossover and mutation. This expression is shown in Equation (2.6).

$$m(H,t+1) \geq m(H,t) * \frac{f(H)}{f}\left[1 - p_c \frac{L(H)}{l-1} - o(H)p_m\right] \tag{2.6}$$

where H is a particular *schema*

t is the generation

$m\ (H,t)$ is the number of times the *schema* is in the current generation

$m\ (H,t+1)$ is the number of times a particular *schema* is expected in the next generation

$f(H)$ is the average fitness of all *chromosomes* that contain schema H

f is the average fitness for all *chromosomes*

l is the string length

p_c is the crossover rate

p_m is the mutation rate

$L(H)$ is the *defining length* of *schema*

$o(H)$ is the *order* of the *schema*

If Equation (2.6) is applied to *schema* H_2 in the above example:

Expected *Schemata* H_2 in next generation $= 2 \times \frac{(576 + 361)/2}{293} \times [1 - 0 - 0.001] = 3.2 = 3$

($L(H) = 0$, $o(H) = 1$ and mutation rate (p_c) was considered as 0.001).

In the above example, it was shown only the propagation of one *schema,* which was having short, low order and above average fitness of the population. In reality, there can be several *schemata* having short, low order and above average fitness of the population in a given generation. Since the GAs has the ability to process many *schemata* in a given generation, GAs are said to have the property of ***implicit parallelism***, thereby making them an efficient optimization algorithm.

2.6.3 Previous GAs applications

During the past 30 years, many researchers have applied the genetic algorithm technique to various applications. Also several studies can be found in literature, which dealt with the optimum GAs operators for various applications.

2.6.3.1 GAs non-water resources applications

De Jong (1975) used empirical studies to find the optimum GAs operators for a number of function optimisation problems. The conclusions from these studies are shown in Table 2.5. De Jong reported that good performance could be achieved from GAs using high crossover rates and low mutation rates. A similar approach was used by Grefenstette (1986) to find the optimum GAs operators for function optimisation problems and recommended different optimum GAs operators values as shown in Table 2.5.

Table 2.5 Optimum GAs Operators from the Previous Studies

GAs operators	De Jong (1975)	Grefenstette (1986)	Goldberg (1989a)	Schaffer et al. (1989)
Population size	50	30	30 -200	20-30
Crossover rate	0.6	0.95	0.6 –0.9	0.75-0.95
Mutation rate	0.001	0.01	0.01 or less	0.005-0.01

A theoretical investigation of optimal population size was conducted by Goldberg (1985) and derived an approximate equation to calculate the population size. This equation is given below.

$$Pop = 1.65 \ x \ 2^{0.21 \ x \ SL} \qquad (2.7)$$

where Pop is population size

SL is string length

This equation gives population sizes of 30, 130, 557, 2389 and 10244 for binary string lengths of 20, 30, 40, 50 and 60 respectively. However, for a wide range of problems, Goldberg (1989a) suggested the values in Table 2.5, as good estimates for an initial run.

Furthermore, Goldberg reported that the proper choice of GAs operators is problem dependent.

Schaffer et al. (1989) spent considerable effort in their empirical studies to find the optimum GAs operators for function optimisation problems. They adopted the Gray coding parameter representation claiming that it was superior to the traditional binary coding and recommended the GAs parameter values given in Table 2.5. They also reported that the GAs performance was sensitive to the population size, crossover rate, mutation rate and crossover method used. Furthermore, they argued that large populations impose a large computational time per generation and therefore Equation (2.7) derived by Goldberg (1985) was too conservative, as it leads to very large populations for large string lengths. Syswerda (1989) compared crossover types both theoretically and empirically, and reported that the uniform crossover was superior to others, followed by two-point and one-point crossover. However, Syswerda was reluctant to nominate the best crossover type in general, claiming that there was no best function-independent crossover operator.

Janikow and Michalewicz (1991) empirically studied the real value coding and binary coding of GAs for a dynamic control problem and reported that the real value representation was faster and provided higher precision compared to the binary representation, especially for problems with large parameter range, where binary coding required long string lengths.

Goldberg and Deb (1991) compared the expected behaviour of selection types theoretically and reported that the proportionate selection was significantly slower in converging to the optimum solution than the linear ranking and tournament selection method. Furthermore, they found that linear ranking and tournament selection methods have identical performance. However, Goldberg and Deb (1991) stated that no one selection method was superior to the other. De Jong and Sarma (1995) and Blickle and Thiele (1997) also found that the variety of selection types (proportionate or linear ranking methods with roulette wheel, tournament selection) did not produce a great difference in performance (Mayer et al. 1999b).

Mayer et al. (1999a) compared and reviewed the available optimisation methods and found that the evolutionary algorithms including GAs performed superior for their agricultural system model optimisation. Mayer et al. (1999b) compared binary and real-value representations in GAs with the use of GENESIS (Grefenstette 1987; Grefenstette 1995) and GENIAL (Widell 1997) GAs software tools respectively for the optimisation of agricultural system models. They selected GAs operators from the literature for their study. It was found that there were no difference between binary and real value representations in the GAs optimisation studies, although the real value representation was expected to be superior to binary coding (Back et al. 1997).

2.6.3.2 GAs water resources applications

The literature describing GAs applications in water resources is not extensive. Goldberg and Guo (1987) were the first to use GAs to a water resource application, which involved a pipe network optimisation problem (Cui 2003). Since then, there have been several applications of GAs to pipe network problems and they all found that GAs were effective in finding global optimum or near-optimum solutions for their applications (Simpson et al. 1994; Dandy et al. 1996).

Wang (1991) applied GAs to the calibration of a conceptual rainfall-runoff model successfully. Nine model parameters were optimised by minimising the sum of squares of differences between computed and observed daily discharge volumes. Wang used binary coding with sub-string length of 7 for each parameter, a population size of 100 and a mutation rate of 0.01, which were selected from previous literature. Franchini (1996) used GAs combined with of Sequential Quadratic Programming (SQP) to calibrate a conceptual rainfall-runoff model and reported that GAs-SQP was an efficient and robust calibration method. Franchini and Galeati (1997) studied the sensitivity of GAs operators and then applied GAs to calibrate 11 parameters of a conceptual rainfall-runoff model. They found that the best performance was achieved with a population size of 100-200 and a mutation rate equal to $1/n$, where n is the number of model parameters.

GAs have been successfully applied to calibration of water quality models (Mulligan 1995; Mulligan and Brown 1998; Ng 2001). Mulligan and Brown (1998) used the GENESIS GAs software with Gray coding, population sizes of 25 and 100, linear ranking selection, two-point crossover, crossover rate of 0.6 and mutation rate of 0.03. No attempt was made to optimise GAs operators, although they reported that the GA operators may affect the overall GAs performance. The results from GAs were compared with a calculus-based calibration method known as the Marquardt algorithm (Marquardt 1963) and found that both methods produced comparable results for the optimum parameter set. Ng (2001) carried out a detailed study on selecting the optimum GA operators using GENESIS GA software for river water quality models. The conclusion from this study was that GA operators have not played a significant role in predicting the water quality in that particular application and a robust GA operator set from literature can be used. Mohan and Loucks (1995) studied the sensitivity of GAs operators and found that the population size of 100-250, the crossover rate of 0.6-0.9 and the mutation rate of 0.02-0.1 were the best for their water quality prediction models.

Mohan (1997) applied GAs for the estimation of non-linear Muskingum model parameters and compared the results with those from previous studies of Yoon and Padmanabdan (1993). The results of GAs have proven to be efficient and accurate, compared to the Yoon and Padmanabdan (1993) study. Mohan studied the sensitivity of GAs operators and found that the population size of 100, the crossover rate of 0.9 and the mutation rate of 0.001 as the optimum GAs operators for his application.

Wardlaw and Sharif (1999) performed a compressive study on GAs operators in their optimal reservoir system operation study. They studied the effect of crossover rate for binary, Gray and real value coding representations for their problem. They used a population size of 100, the tournament section, the uniform crossover type and the mutation rate as inverse of the number of parameters, and reported that the real value coding clearly provided the best performance. They found that the optimum crossover rate was 0.7–0.75 for real value coding and the optimum crossover rate was 0.8 for Gray coding. Ndiritu and Daniell (2001) compared GAs and shuffled complex evolution for rainfall-runoff model calibration and function optimisation. They reported that the shuffled complex evolution method performed better than the standard GAs algorithm.

It can be seen from the above studies that there are no clear guidelines available to choose optimum GAs operators, although the significance of the GAs operators has been studied to a certain extent in above water resources applications. However, most of the studies proved that GAs were a robust optimisation method in locating optimum model parameter set in their applications. Similar findings were seen in the review of non-water resource applications described in Section 2.6.3.1.

2.6.3.3 GAs urban drainage modelling applications

Liong et al. (1995) applied GAs successfully to calibrate the SWMM model using GENESIS GAs software. They calibrated eight SWMM model parameters by minimising the sum of square of the peak flow prediction error. They used a population size of 100 and the default values of GENESIS as the other GAs operators, which were the proportionate selection, a crossover rate of 0.6 and a mutation rate of 0.001. Furthermore, they used the binary representation with the sub-string length of 5 for each parameter, resulting in a total string length of 40. However, they did not attempt to optimise the GAs operators.

Balascio et al. (1998) used micro-GAs (with a small population size of 5) to calibrate the runoff component of the SWMM model. They used multi-objective functions combining three hydrograph features, namely peak flow rate, runoff volume and time to peak. Four storm events used out of five, showed a perfect match with the observations during calibration. However, they did not comment on why they had used micro-GAs instead of the traditional GAs.

Based on the above studies, it is difficult to borrow suitable GAs operators for the urban drainage model calibration in this study. Therefore, it was decided to conduct a detailed study to determine the optimum GAs operators before attempting the model parameter optimisation in urban drainage modelling.

2.6.4 Selection of GAs software for the study

There are several GAs software tools available, which have been developed using Fortran, C/C++, Java and other (matlab etc.) programming languages. The web site http://www.aic.nrl.navy.mil/galist/src/#C provides links to some of the public domain

GAs software tools. Although these software tools use the same GAs theory, each software tool is designed and implemented in a slightly different way, using the various GAs operator options and various compilers. For example, as reported by Mardle and Pascoe (1999) only one selection method and only one crossover type are implemented in the ***S**tandard **G**enetic **A**lgorithms*-SGA (Goldberg 1989a) GAs software tool, whereas seven selection methods, four crossover types and two mutation procedures are implemented in the GENEsYs (Back 1992) GA software tool.

One of the first publicly available GAs software tool was GENESIS (Grefenstette 1987), which has since improved and used as a guide for many other GA tools such as the GENEsYs. GENESIS stands for ***GENE**tic **S**earch **I**mplementation **S**ystem* and is probably the most widely used public domain software available (Hunt 2000). GENESIS version 5.0 (Grefenstette 1995) was selected for this study, since it has been used successfully for various water resource applications in the past. Liong et al. (1995) used GENESIS for calibrating the SWMM model, Mulligan and Brown (1998) and Ng (2001) coupled GENESIS with the river water quality models to optimise the model parameters. GENESIS was written in C language, and was written to promote the study of GAs and is available in public domain.

2.7 Summary

Management of stormwater runoff from urban catchments has become an increasingly important environmental issue and stormwater drainage is a major part of this overall stormwater management. Runoff in urban areas has increased rapidly in recent times due to urbanization and hence it is required to design stormwater drainage systems, as part of the overall stormwater management.

The use of computer based mathematical models has become more and more popular in the recent past for design and analysis of urban stormwater drainage systems. There are several urban drainage software tools that have been developed to simulate the rainfall-runoff process of these systems. In order to use these software tools effectively, it is necessary to estimate the model parameters accurately for the relevant catchment. Some of these parameters can be physically measured, whereas the parameters that are impossible or difficult to measure physically need to be estimated through model calibration.

Various model calibration methods from trial and error to optimisation methods were reviewed in this chapter. Generally, the automatic stochastic optimisation methods are preferred to the traditional trial and error methods or deterministic methods, since these stochastic methods have proved to produce the global optimum parameter set.

Genetic Algorithms (GAs) is one such stochastic optimisation methods, which is gaining popularity in water resource applications. Even though GAs has been recognized as a robust optimisation method for estimating model parameters in many fields including water resources, it has not been used widely for urban drainage model parameter optimisation. This method will be used in this study and discussed in Chapter 4.

The GAs operators, such as parameter representation, population size, selection methods, crossover methods and crossover and mutation rates play an important role on the convergence of the optimum model parameter set. The review of the past studies showed that there were no clear conclusions regarding the optimum GAs operators to be used in parameter optimisation of urban drainage models. Therefore, before attempting to calibrate the urban drainage models using GAs, it is necessary to investigate the optimum GAs operators for the study, since there is no guidance available for GAs operators to be used in urban drainage model calibration.

CHAPTER 3

XP-UDD AND GENESIS SOFTWARE TOOLS

3.1 Introduction

As stated in Sections 2.4 and 2.6.4, XP-UDD and GENESIS computer software tools were selected for urban drainage modelling and facilitating GA optimisation of urban drainage model parameters respectively in this study. An overview of these software tools including capabilities is described in this Chapter. The Chapter also describes how the two software tools were linked to perform the automatic calibration of urban drainage model parameters using GA.

3.2 Overview of XP-UDD Software

As outlined in Section 2.4, XP-UDD simulates the complete rainfall-runoff cycle, including overland flow and pipe/channel flow except water quality. It uses *links* and *nodes* to represent the stormwater drainage network. A *link* represents a hydraulic element of some kind for flow transport down the system (eg. pipes, channels, weirs, etc.). A *node* represents the junction of two or more hydraulic elements, the location for input of flow into the drainage system (eg. inlet pits) or a storage device such as a pond (or lake). In general, *nodes* receive stormwater from its sub catchments and distribute them to the catchment outlets via the *links* of the drainage system. The basic modelling element in XP-UDD can be considered as the inlet pits (i.e. *nodes*) with its sub catchments and the outlet pipes (i.e. *links*), as shown in Figure 3.1. The XP-UDD hydrologic module interface allows up to five-sub catchment runoff at each *node*.

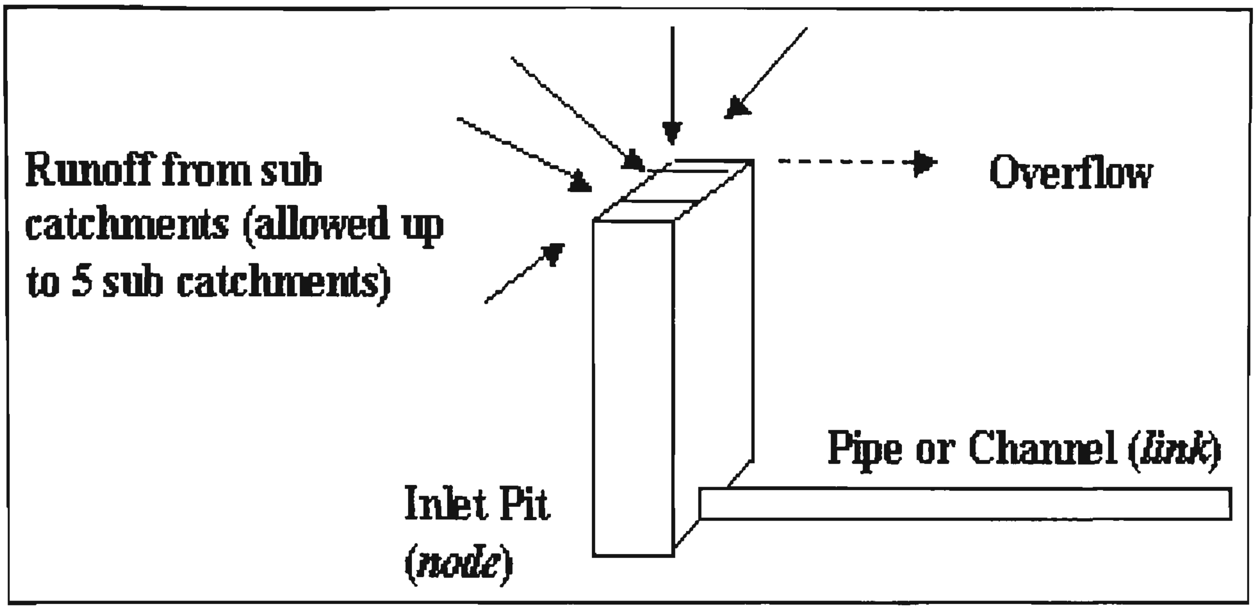


Figure 3.1 Basic XP-UDD Modelling Elements

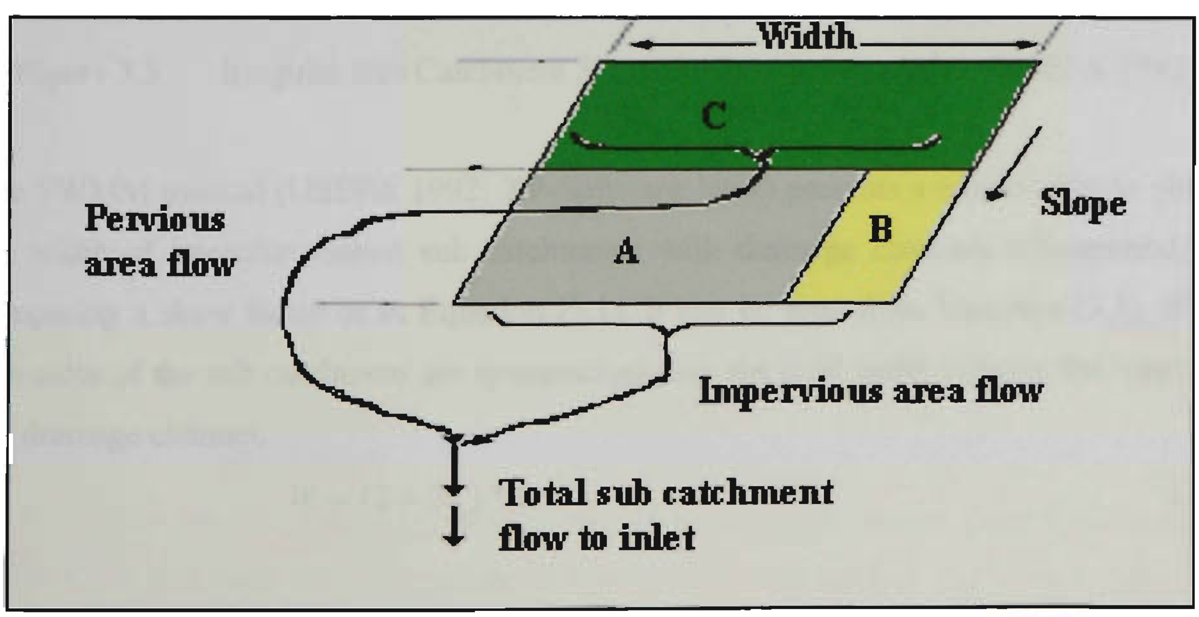
XP-UDD can be used as a planning and design tool to predict runoff in an urban catchment. It is capable of performing continuous simulations over a long period to do the overall assessment of the urban drainage system as a planning model. It is also capable of performing detailed simulation of single storm events to provide complete design hydrographs. XP-UDD provides all major hydrological methods to estimate stormwater inflows, wastewater dry weather flows and infiltration flows. The software can be used to automatically design the pipes of the entire system or of a portion of the network.

Recently, XP-UDD has been used for hydraulic modelling in Bayside council area of the Melbourne Metropolitan area (Australia) for its planning scheme (Melbourne Water 2000). It was also utilized to calculate the peak discharges of runoff events of Annual Recurrence Intervals of 20 and 50 years to improve surface water management in the upper north Moore river catchment of Australia (www.calci.org/Downloads). It was also used for flood studies on Sungai Tutong and Sungai Brunei rivers on the island of Borneo (www.yce.com.au).

XP-UDD contains two basic modules namely hydrologic and hydraulic. The hydrologic module is used to simulate overland flow, whereas the hydraulic module routes flow through the open and closed conduits of the drainage system. The user has an option to select either of these modules or both for analysis of the drainage system depending on the problem. These two modules are connected to the global database of the XP-UDD, which contains design storm events, infiltration data and other required data for simulation.

3.2.1 Hydrologic module

The hydrologic module of XP-UDD generates stormwater runoff hydrographs using catchment conditions and design or measured hyetographs. Like all other urban drainage software tools, XP-UDD is required to have the urban catchment to be divided into a number of sub catchments. As shown in Figure 3.1, the sub catchment stormwater runoffs will be the input to the *node*, which represents the inlet pit. As stated earlier, the XP-UDD hydrologic module interface allows up to five-sub catchment data inputs at each *node*. The input data related to the sub catchments include the sub catchment area, percentage of impervious areas, surface slope and width of the sub catchments. Each sub catchment is modelled in XP-UDD based on three surfaces namely the impervious area with and without depression storage, and pervious area with depression storage. These surfaces of a sub catchment are shown in Figure.3.2. The impervious area includes road surfaces, roofs and other man-made hard surfaces. The pervious area includes bare surfaces, porous pavements, grass courts and lawns.



Note: A Impervious areas with depression storage
B Impervious areas without depression storage
C Pervious areas with depression storage and infiltration

Figure 3.2 Three Surfaces of a Sub Catchment in XP-UDD (USEPA 1992)

The width of the sub catchment is an important variable in XP-UDD and SWMM modelling. If overland flow is running off down-slope as in an idealized rectangular catchment as shown in Figure 3.2, then the width is the physical width of the overland flow. However, most real sub catchments will be irregular in shape and have drainage channels, which are off-centered as shown in Figure 3.3. A good estimate of the width for these cases is the ratio of the area of the sub catchment to the average path of the overland flow (XP-Software 1997).

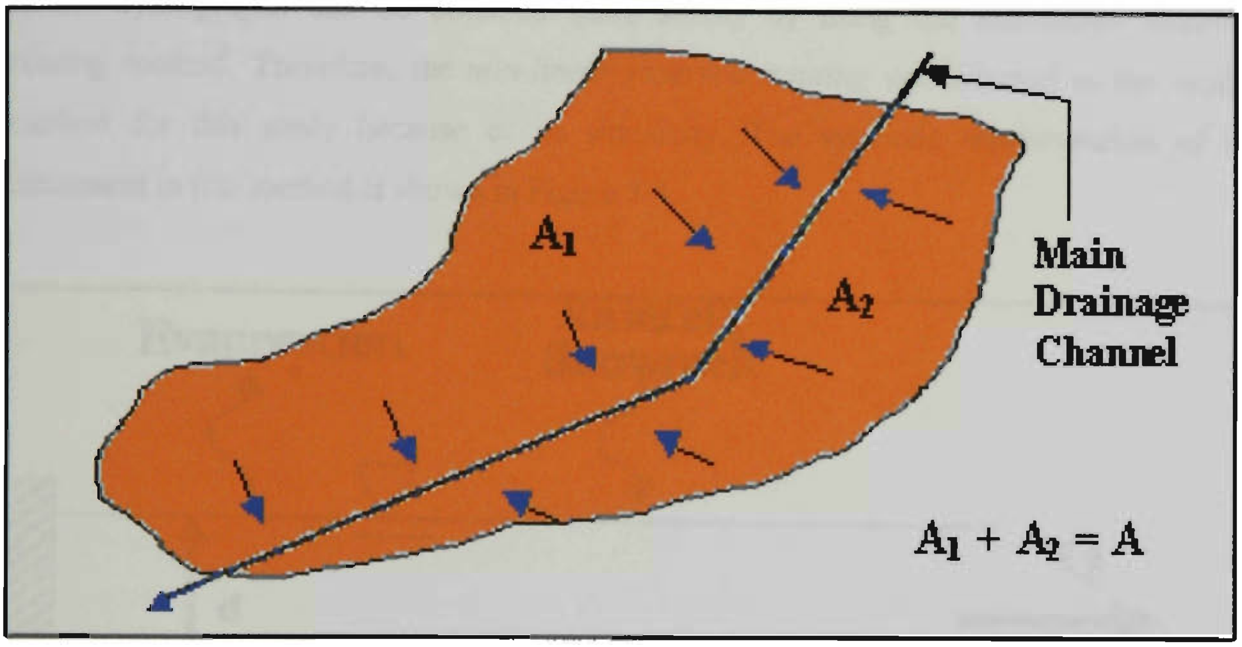


Figure 3.3 Irregular Sub Catchment Shape for Width Calculation (USEPA 1992)

The SWMM manual (USEPA 1992; XP-Software 1997) presents a relationship to obtain the width of irregular shaped sub catchments with drainage channels off-centered, by comparing a skew factor as in Equation (3.1). It can be seen from Equation (3.1), if the two sides of the sub catchment are symmetrical then the total width is twice the length of the drainage channel.

$$W = (2 - S_K) * L \tag{3.1}$$

where W is sub catchment width

S_K is skew factor, $S_K = (A_1 - A_2)/A$

A_1 is area to one side of the channel

A_2 is area to the other side of channel

A is total area of sub catchment

L is length of main drainage channel

There are several options available in XP-UDD for stormwater runoff routing over the sub catchments namely, *non-linear reservoir routing*, *Laurenson non-linear* [as in RAFTS (WP Software 1991) and RORB (Laurenson and Mein 1995) software tools], *time/area* [as in ILSAX (O'Loughlin 1993) and DRAINS (O'Loughlin and Stack 1998) software tools], *SCS unit hydrograph* and *kinematic wave* methods. The stormwater runoff hydrographs can be obtained quite simply by using the *non-linear reservoir routing* method. Therefore, the *non-linear reservoir routing* was selected as the routing method for this study because of its simplicity. The symbolic representation of the catchment in this method is shown in Figure 3.4.

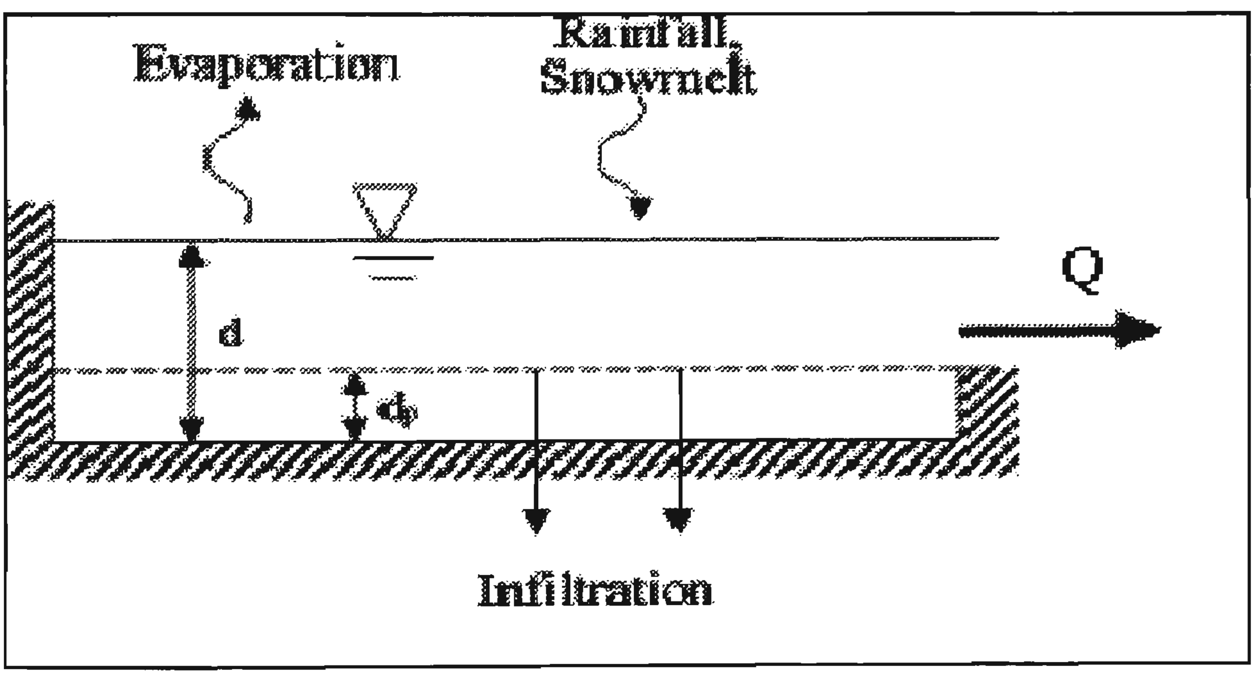


Figure 3.4 Non-Linear Reservoir Representation of Sub Catchment (Huber and Dickinson 1988)

In *non-linear reservoir routing* method, the sub catchment is modelled as an idealized rectangular area with the slope of the catchment perpendicular to the width. Each sub catchment is treated as a spatially lumped non-linear reservoir with a single inflow-rainfall. The non-linear reservoir is established by combining the Manning's equation and lumped continuity equation. Flow from one surface of sub catchment is not routed over another surface. The capacity of this *reservoir* is the maximum depression storage (i.e. d_p), which is the maximum surface storage provided by ponding, surface wetting, and interception. The water storage in the *reservoir* is reduced (or lost) by infiltration and evaporation. The surface runoff occurs only when the depth of water in the *reservoir* (i.e. d_p) exceeds the maximum depression storage.

3.2.1.1 Rainfall loss models

The rainfall loss (i.e. the component of rainfall which does not produce runoff) includes evaporation, infiltration and depression storage. In XP-UDD, depression storage and evaporation losses are modelled separately for the impervious and pervious areas through user inputs. There are two options available in XP-UDD software for computing infiltration losses from pervious areas, namely the Green-Ampt (Green and Ampt 1911) model or the Horton (Horton 1940) model. These two infiltration loss models are described below.

(a) Green-Ampt

The Green-Ampt infiltration model is a physically based model and uses measurable parameters to determine the losses due to infiltration. Mein and Larson (1971) modified the original Green-Ampt model (Green and Ampt 1911) and showed that it could be presented as a two-stage model, which computes infiltration before and after the surface is saturated. The mathematical details of the Green-Ampt infiltration model can be found in Green and Ampt (1911) and Mein and Larson (1971).

Both SWMM and XP-UDD facilitate modelling of infiltration through the Green-Ampt model. Tsihrintzis and Hamid (1998) used the Green-Ampt model to calculate the infiltration losses in calibrating the SWMM model for small urban catchments. Deletic (2001) used the Green-Ampt model to study water and sediment transport over grassed areas in an urban catchment. After comparing the Green-Ampt and *Spatially Variable Infiltration Model* (SVIM), Yu (1999) reported that the Green-Ampt model underestimated the infiltration rate (and hence overestimated the rainfall excess) in comparison to SVIM at high rainfall intensities.

(b) Horton Model

Horton (1940) suggested that the infiltration begins at some maximum or initial infiltration capacity (f_o) and exponentially decreases until it reaches a minimum or ultimate soil infiltration capacity (f_c), as the storm continues and the soil saturation increases. The value of f_o depends on the surface condition of the soil as well as on the initial soil moisture content, and therefore varies with time since the last rain.

Urban drainage computer software tools such as SWMM, XP-UDD and DRAINS allow modelling of infiltration through the Horton model. The Horton's equation describes the familiar exponential decay of infiltration capacity evident during heavy storms. However, the XP-UDD program uses the integrated form to avoid an unwanted reduction in infiltration capacity during periods of light rainfall (XP-Software 1997).

Ishaq and Khan (1999) used the Horton model to derive the infiltration curves for all types of soils in Saudi Arabia. They used standard laboratory infiltrometer to determine the infiltration rates. Skukla et al. (2003) analysed ten infiltration models including Green-Ampt and Horton models, using double-ring infiltrometer tests and reported that overall the Horton model had given the best results for most land use conditions. The Horton model was used in this study to estimate infiltration in pervious areas of the study catchments, since it had been used successfully in the past and parameters can be easily obtained through field infiltrometer tests. The Horton model is defined by Equation (3.2).

$$f_t = f_c + (f_o - f_c)\, e^{-kt} \tag{3.2}$$

where

	f_t	is the infiltration capacity (cm/h)
	f_c	is the minimum or ultimate value of f_t (cm/h)
	f_o	is the maximum or initial value of f_t (cm/h)
	k	is a decay coefficient (h^{-1})
	t	is the time from beginning of storm (h)

Since the actual values of f_o, f_c and k depend on the soil, vegetation and initial moisture content, the SWMM user manual (USEPA 1992) recommends that these parameters should be estimated through field infiltrometer tests at number of sites in the catchment.

Furthermore, the user manual gives guidelines to estimate these parameters if it is not possible to conduct field tests in the study catchments.

3.2.1.2 Selected parameters for calibration

As stated earlier, XP-UDD has several options available to compute flow routing over sub catchments and two options available for computing infiltration losses from pervious surfaces of sub catchments. Of these options, the non-linear reservoir routing method and the Horton infiltration model were selected in this study.

These methods and other processes in the hydrologic module require the estimation of model parameters for the study catchment, which are user inputs. Of all the user input parameters, only seven parameters of the hydrologic module were identified for calibration, because of their difficulty in measuring them physically. Two of them are related to the impervious areas namely the percentage of the impervious area (i.e. $\%A$) and the depression storage (i.e. DS_i). Other five are related to the pervious areas namely depression storage (i.e. DS_p) overland flow roughness of the pervious areas (i.e. n_p) and the three Horton's soil infiltration parameters (i.e. f_o, f_c *and* k).

The model parameter $\%A$ can be approximately estimated using aerial photographs or rainfall-runoff depth plots (Section 2.2.3). However, it is difficult to estimate $\%A$ accurately, as it requires the identification of individual properties that are connected to the drainage system. Therefore, $\%A$ model parameter was selected for calibration in this study, with initial values obtained from aerial photographs. Basically the calibration refines the values obtained from aerial photographs.

Sub catchment width was not considered as a calibrating parameter, since it increase the number of parameters to be calibrate immensely, as each sub catchment has a different width. Sub catchment width was estimated as the ratio of the area of the sub catchment to the average path of the overland flow in this study (XP-Software 1997).

3.2.2 Hydraulic module

The hydraulic module routes stormwater runoff entered into inlet pits through open channels and close conduits (i.e. *links* in XP-UDD) in the drainage network. In XP-UDD, the hydraulic module receives hydrograph input at specific nodal locations (i.e. inlet pits) through the interface file generated by the hydrologic module and/or by direct input by the user. The hydraulic module is capable of simulating backwater conditions and special flow devices such as weirs, orifices, pumps, storage basins and tidal gates, where these conditions occur in the lower reaches of the drainage system when pipe diameters exceed roughly 500 mm. It is capable of performing dynamic routing of stormwater throughout the drainage system to the outfall points of the receiving water system (XP-Software 1997).

Links in XP-UDD transmit flow from *node* to *node*. The primary dependant variable in the *links* is the discharge, which is computed at the center of the *link*. Inflows such as inlet hydrographs and outflows such as weir diversions, take place at the *nodes* of the network. The *node* volume changes over time due to inflow and the balance of flow entering and leaving the conduit. This change in nodal volume during a given time step within the simulation, forms the basic head and discharge calculations in the hydraulic module. The hydraulic module uses the momentum equation in the *links* and a special lumped continuity equation for the *nodes* to model these flows. These two equations are connected by solving the Kinematics wave portion of the St. Venant (Dynamic flow) equation to route stormwater runoff throughout the drainage network in hydraulic module.

There are over 30 different hydraulic conduits (i.e. *links* - circular pipes, rectangular pipes etc.) available for hydraulic routing within XP-UDD. Several user inputs are required to model each *link* in the catchment model. Upstream and downstream levels, Manning's friction coefficient, length and cross-sectional area of the conduits are the some of the user inputs associated with *links*. Conduit data such as pipe/channel shape and their dimensions can be input or can be designed according to the problem. The Manning's friction coefficient value of conduits often is a constant or at least, can be extracted from literature and less sensitive to the output responses compared to the hydrologic data

(Dayaratne 2000). Therefore, the hydraulic model parameters were not selected for calibration.

3.3 Overview of GENESIS Software

As stated in Section 2.6.4, GENESIS (*GENEtic Search Implementation System*) is the mostly used public domain software tool available (Hunt 2000). This software can be run on Unix and MS-DOS operating systems. GENESIS is a collection of function source codes written in C programming language, which are connected to construct the GAs. Therefore, the user can add or modify the code according to their application. The user needs to provide an objective function (which is also called the fitness function) of the problem as a separate source code, to use GENESIS. This function returns the fitness values of the population as a floating-point number to GAs.

3.3.1 Capabilities of GENESIS

GENESIS version 5.0 offers several enhancements over previous versions that makes the system much more user-friendly. The major improvement was that the user-level parameter representation (called *floating-point representation*) that allows the user to think about the chromosomes as real numbers, though the GAs operate in bit string representation. A number of new options have also been added in version 5.0 including a display mode, which uses an interactive user interface, the option to maximize or minimize the objective function, the choice of rank-based or proportional selection algorithm and an option to use Gray code for parameter representation. The maximum limit of simulations in GENESIS is 32,000. Several options are available in GENESIS for parameter representation, population intialisation, selection, crossover and mutation. They are described below.

Parameter representation

There are two options available for parameter representation namely binary and Gray coding, where binary representation is the default parameter representation. Within these two options, the user has the flexibility to select *floating-point representation*, as stated above. For *floating-point representation*, the user needs to input only the parameter ranges in real numbers and the number of divisions required in search space. GENESIS automatically lays out the string representation according to the binary or Gray option selected. Therefore, the user does not need to decide how to encode parameter values in bit strings.

Based on GAs theory, the real value coding is not necessarily required for optimisation problem with small number of parameters. Mayer et al. (1999b) found that there were no difference between binary and real value representations for their study. Furthermore, only bit string coding is available in GENESIS. It also can be seen from the GAs theory and some of the above studies (Caruana and Schaffer 1989) that Gray coding was superior to binary coding. Therefore, Gray coding was selected for this study.

Population initialisation

There are two options available to obtain the initial population, namely the random method and the heuristic method. The default method is the random method, which generates the initial population randomly. This method was used in this study, as it will prevent premature convergence (Section 2.6.1.2). If the heuristic option is selected, the user has to specify the parameter values of the initial population. When both the *floating-point representation* and heuristic method are selected, the use has to specify the parameter values in the population as real numbers. The user has an option to input any population size according to the optimisation problem.

Selection

There are two selection methods available namely proportionate selection and linear ranking selection in GENESIS. The default selection method is the proportionate selection method. As reviewed in Section 2.6.3, there is no clear guidance available to select one of these options for the urban drainage modelling. Therefore, investigations were conducted to select an optimum selection method through the GAs operator optimisation study, which is described in Chapter 4.

Crossover and mutation

There is only two-point crossover method available in GENESIS. However, the user can input any crossover or mutation rate relevant to the application. As reviewed in Section 2.6.3, various researchers reported different optimum values for crossover and mutation rates. Therefore, the optimum crossover and mutation rates were selected through the GAs operator optimisation study, which is described in Chapter 4.

3.4 Linking of XP-UDD and GENESIS

It is necessary to develop a computer program to link the operation of XP-UDD and GENESIS, to obtain *optimum* GAs operators and then to perform automatic calibration of model parameters of the selected study catchment, since these are two separate software tools. A program was developed in *C* programming language by the candidate to link the operations of XP-UDD and GENESIS. This computer program is shown as *MY PROGRAM* in Figure 3.5. The linked overall program is called GENESIS/XP-UDD.

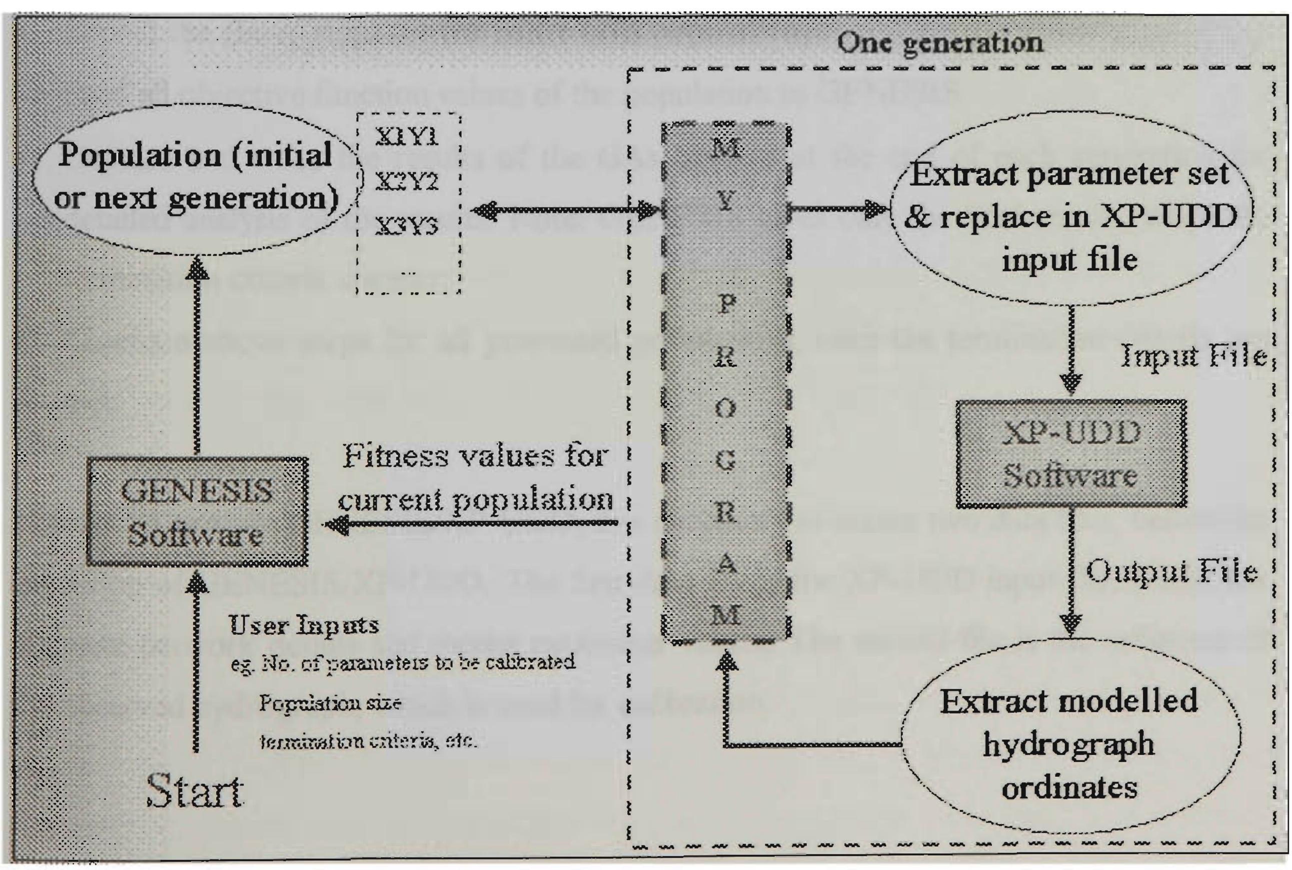


Figure 3.5 Linking of XP-UDD and GENESIS (GENESIS/XP-UDD)

GENESIS/XP-UDD is executed through a program called *setup* in GENESIS, which prompts for the user inputs such as number of parameters to be calibrated, their parameter ranges, population size, GAs operator options, termination criteria (i.e. number of simulations required) etc. It will then generate the initial population consisting of model parameter sets, according to the given user inputs. Then *MY PROGRAM* will interact automatically with the generated population, XP-UDD and GENESIS to continue the generation of new populations, as specified by the user. User intervention is required only at the start of the GENESIS/XP-UDD run. In summary, *MY PROGRAM* was written to perform the following tasks:

- Modify the XP-UDD input file by extracting one parameter set from GAs generated population.
- Run the XP-UDD model for the particular model parameter set.
- Extract the resultant hydrograph ordinates from the XP-UDD output file, relevant to the above model parameter set.
- Interact with the relevant observed hydrograph ordinates (stored in a file) to compute the objective function values for the above model parameter set.
- Repeat the above steps for the entire GAs population.
- Feed all objective function values of the population to GENESIS
- Capture and write the results of the GAs process at the end of each generation for detailed analysis of the results. Note: GENESIS gives only the final results, when the termination criteria are met.
- Continue above steps for all generated populations, until the termination criteria are met.

In order to execute GENESIS/XP-UDD, it is necessary to create two data files, before the execution of GENESIS/XP-UDD. The first data file is the XP-UDD input file, which has drainage network details and model parameter values. The second file is the ordinates of the observed hydrograph, which is used for calibration.

3.5 Summary

The XP-UDD software tool simulates the rainfall-runoff cycle, including surface runoff and flow routing in conduits except modeling of water quality. It uses *nodes* and *links* to represent the stormwater drainage network. The XP-UDD software tool can be used as a planning and design tool to predict the runoff in urban stormwater drainage systems (or urban catchment). As with other urban drainage software tools, XP-UDD requires the catchment to be subdivided into number of sub catchments. It has two modules namely hydrologic and hydraulic.

The hydrologic module is capable of generating stormwater runoff hydrographs using catchment conditions and design or measured hyetographs. In this module, several options are available for flow routing. The *non-linear reservoir routing* method was used in this study, because of its simplicity. There are two options available for pervious area infiltration loss modelling. The Horton model was selected in this study, since it had been used successfully in the past and parameters can be easily obtained through field infiltrometer tests. Seven parameters of the hydrologic module were identified for calibration, because of their difficulty in measuring them physically. Two of them are related to the impervious areas (i.e. percentage of the impervious area - $\%A$ and depression storage - DS_i) and the other five are related to the pervious areas (i.e. depression storage - DS_p, overland flow roughness of the pervious areas - n_p and the three Horton's soil infiltration parameters - f_o, f_c and k). The hydraulic module is capable of routing pipe/channel flow. Since the hydraulic model parameters are less sensitive to the output response, they were not selected for calibration in this study.

GENESIS version 5.0 is more user-friendly GAs software compared to its earlier versions. GENESIS has two options for parameter representations (i.e. binary and Gray). The Gray coding parameter representation was selected for this study, as it was found superior to binary coding according to the literature. Although some of the GAs operator options can be selected from the literature, there are no clear guidance available to select the other operators such as population size, selection method, crossover and mutation rates for urban drainage modelling.

A program (called *MY PROGRAM)* was developed to link XP-UDD and GENESIS. *MY PROGRAM* is mainly used to modify the XP-UDD input file with the GAs generated parameter sets, compute the objective function values for each parameter set and feed it into the GENESIS.

CHAPTER 4

CALIBRATION AND VALIDATION OF URBAN DRAINAGE CATCHMENT MODEL USING GAs

4.1 Introduction

As reviewed in Section 2.1, management of stormwater runoff from urban catchments has become an increasingly important environmental issue, as the urban development causes significant changes in volume and quality of stormwater runoff. Stormwater drainage is a major part of this overall stormwater management, as it helps to reduce local flooding. As stated in Sections 2.1, the most practical way of designing stormwater drainage systems is by the application of mathematical models, which consider complex hydrological and hydraulic processes of urban areas. However, the accuracy of these models depends on the correct selection of the model parameter values (Section 2.5), as it provides confidence in applying these models for planning and management of stormwater drainage systems.

The model calibration is done through an iterative process by comparing model predictions with observations, until the two sets match with each other within a reasonable accuracy. Section 2.5 reviewed the methods available to calibrate mathematical models (ranging from trial and error to optimisation methods), showing their attributes, weaknesses and applications in water resources. In this project, one of the most popular optimisation methods known as genetic algorithms (GAs) were used to calibrate the urban drainage models. Even though the GAs have been recognized as a robust optimisation method for estimating model parameters in many fields, it has not been used widely for urban drainage models (Section 2.6.3.3).

GAs operators, such as parameter representation, population size, selection methods, and crossover and mutation rates play an important role on the convergence of the optimum model parameter set. Several researchers (Davis 1991; Franchini 1996; Franchini and Galeati 1997; Ng 2001; Wardlaw and Sharif 1999) investigated the effect of GA operators on the convergence of *optimum* model parameters, as reviewed in Section 2.6.3. This review showed that there were no clear conclusions regarding the *optimum* GA operators to be used in model parameter optimisation in urban drainage applications. Therefore, a detailed study was conducted to determine the *optimum* GA operators before attempting the model parameter optimisation in urban drainage modelling.

As stated in Section 2.4, XP-UDD (XP-Software 1997) was used to model the urban drainage catchments in this study. Seven model parameters were identified for calibration of these models (Section 3.2.1), two related to the impervious areas (i.e. percentage of the impervious area - *%A* and the depression storage - DS_i) and the other five related to the pervious areas (i.e. depression storage - DS_p, overland flow roughness of the pervious areas - n_p and the three Horton's soil infiltration parameters - f_o, f_c and k).

The *optimum* GAs operator investigation was conducted as separate studies, one for impervious area parameters and the other for pervious area parameters. Two urban catchments, representing a typical *small* catchment and a typical *medium* catchment are also used. However, only one catchment (i.e. the *small* catchment) was used in urban drainage model calibration using GAs, since the purpose of this part of the study was to demonstrate the use of GAs in calibrating the urban drainage models.

This chapter first describes the study catchments used in this study for investigation of *optimum* GAs operators and calibration/validation of urban drainage models. Investigation/validation procedures adopted to find the *optimum* GAs operators were then presented followed by the results obtained for each GAs operator. The methodology used for model parameter estimation is presented, followed by the calibrations results and comparison of the model results with a previous study. Finally, the methodology and results of validation of the model parameters are presented.

4.2 Study Catchments

Victoria University, in collaboration with ten city/shire councils in Victoria (Australia) conducted a major data acquisition program for 26 urban catchments during 1996–1999, collecting data on rainfall and runoff (Maheepala and Perera 1999; Maheepala et al. 2001). Two of these urban drainage catchments namely, *Kew* and *Warringal* catchments, in the Melbourne metropolitan area were used in this study for investigating the *optimum* GAs operator set for use in GAs optimisation of urban drainage models. The *Kew* catchment was also used for calibration and validation of the XP-UDD model of the catchment. The *Kew* catchment is in the City of Boroondara, while the *Warringal* catchment is in the City of Banyule. The locations of these City Councils are shown in Figure 4.1. The drainage system details of *Kew* and *Warringal* study catchments are shown in Figures 4.2 and 4.3 respectively.

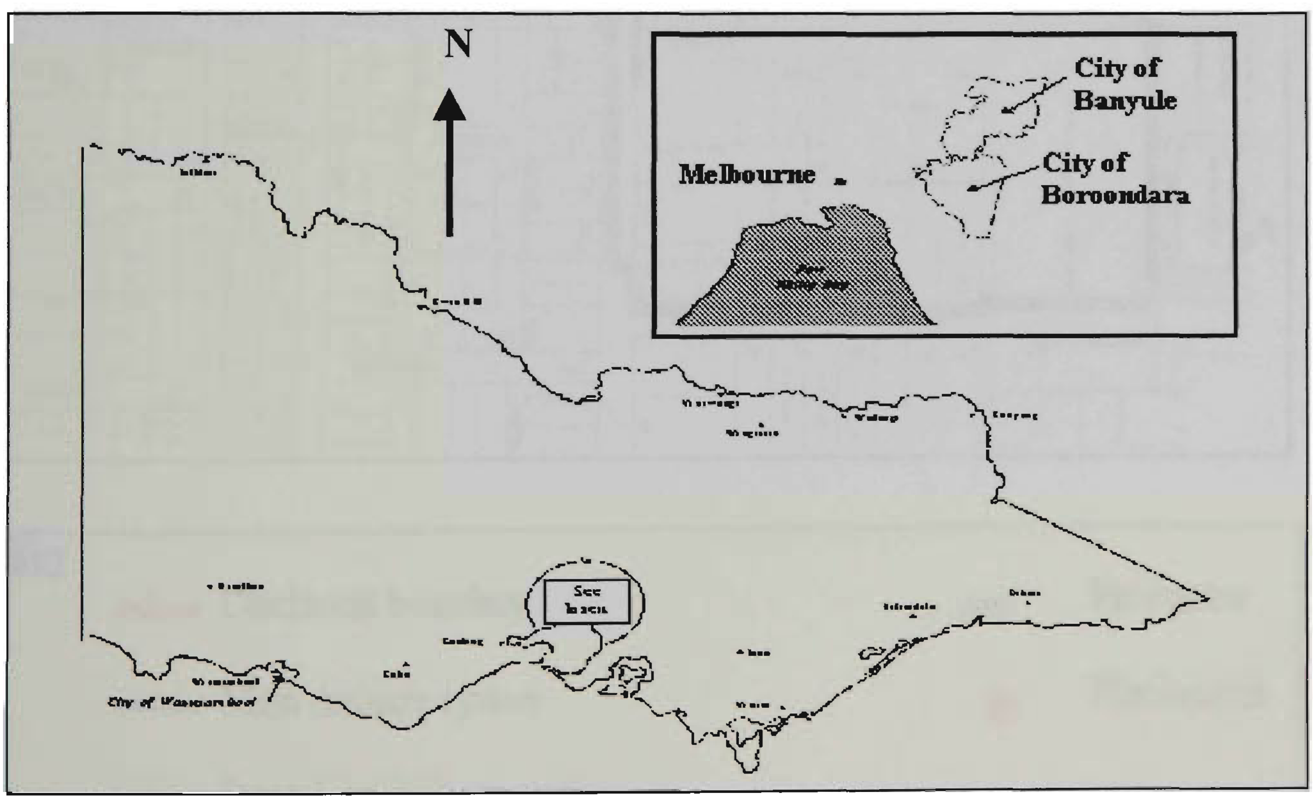


Figure 4.1 Locations of the City of Boroondara and the City of Banyule

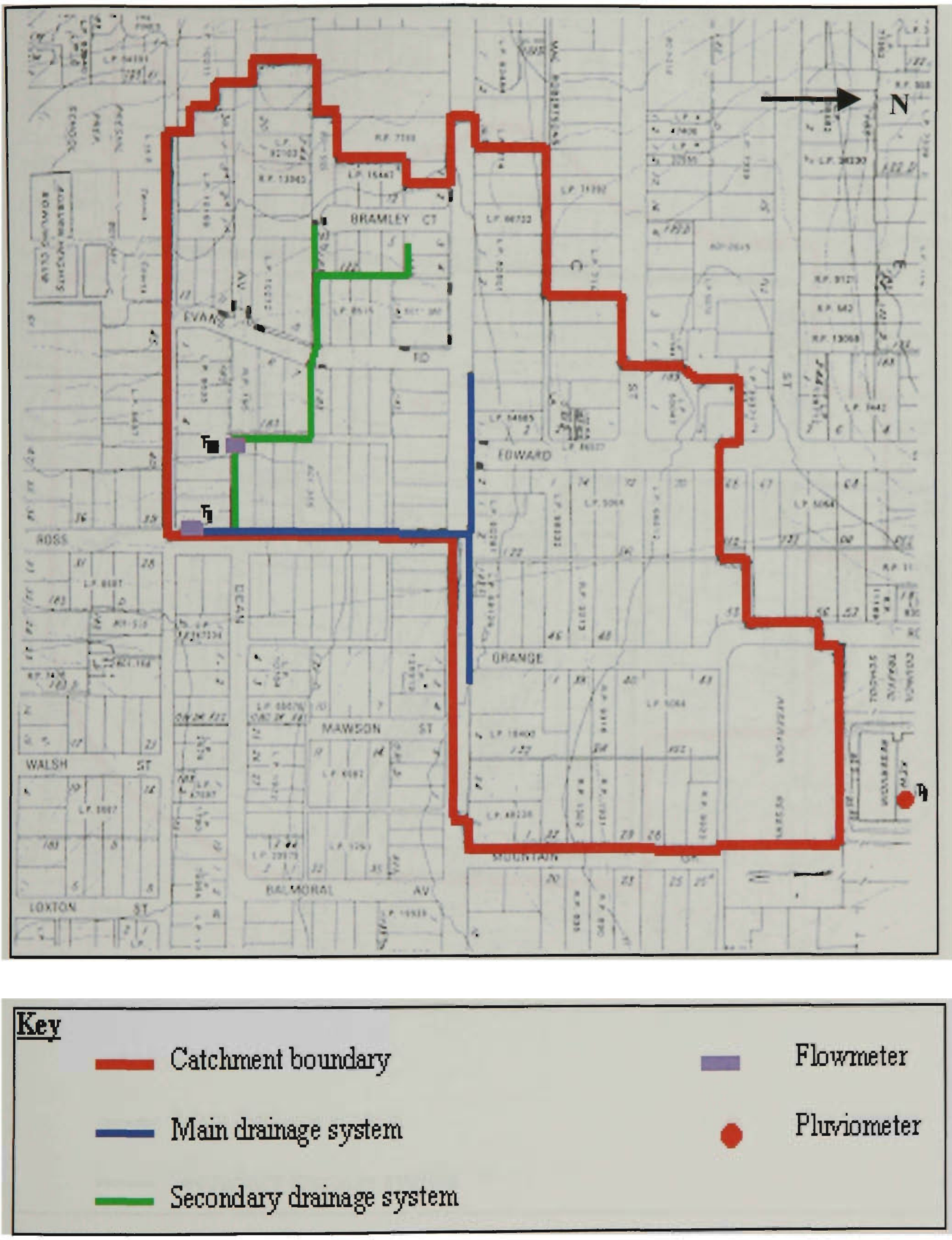


Figure 4.2 Kew Catchment in City of Boroondara

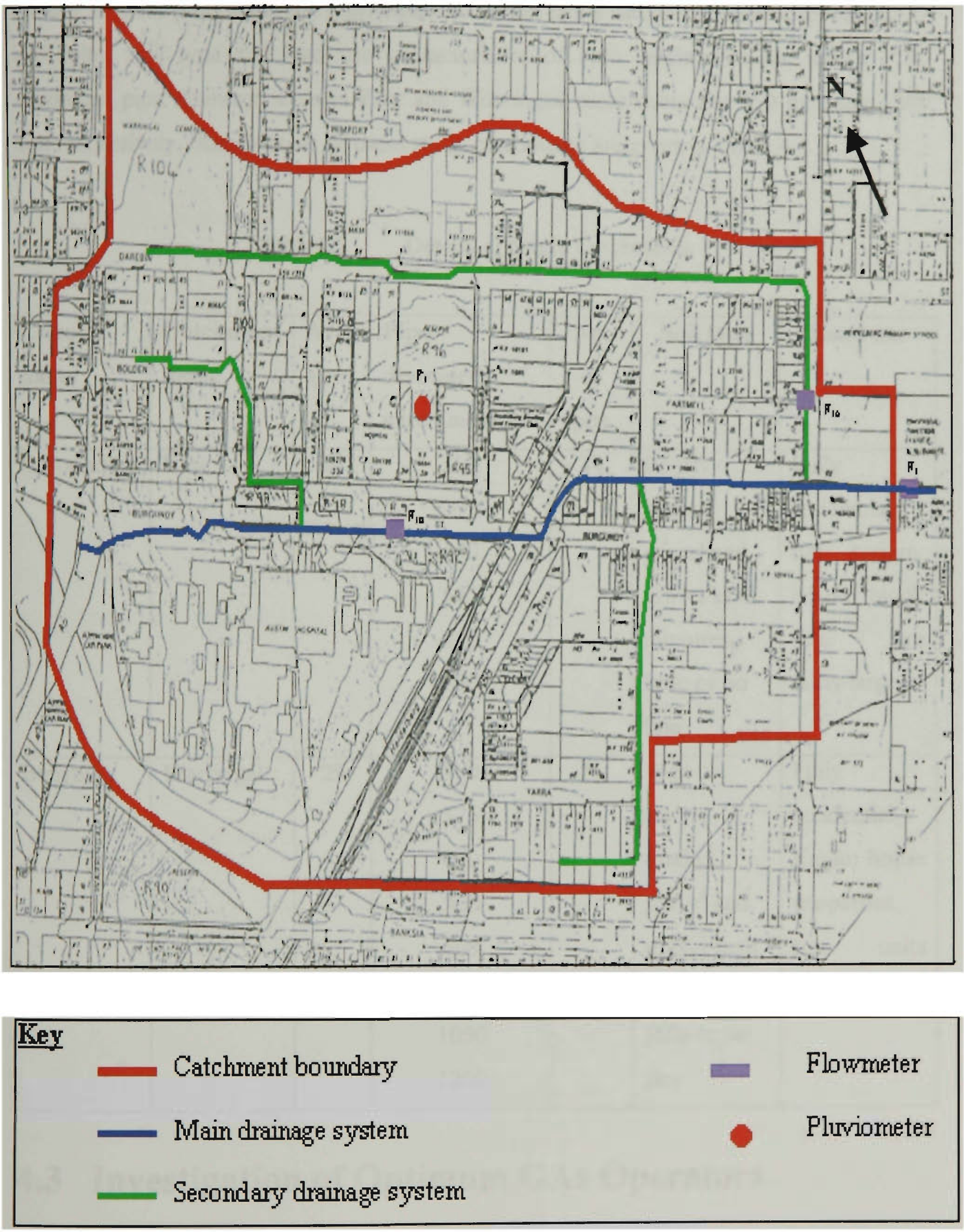


Figure 4.3 Warringal Catchment in City of Banyule

Figures 4.2 and 4.3 show the catchment boundaries, flowmeter and pluviometer locations and main and secondary drainage paths. The *Kew* catchment has a catchment area of 18 ha and 34 inlet pits, while the *Warringal* catchment has a catchment area of 29 ha and 71 inlet pits. Soil type and land use characteristics of both catchments are similar. The maximum pipe diameter sizes in *Kew* and *Warringal* catchments are 750 mm and 1200 mm respectively. Some details of these study catchments are given in Table 4.1.

Table4.1 Details of Study Catchments

Council name	Catchment name	Area (ha)	Pipe diameters used (mm)	No. of pits	Soil type	Land use
Baroondara	Kew	18	300 375 450 525 600 750	34	Poorly graded gravel and gravel sand mixtures, little or no fine	Fully residential, flat terrain, house block size are fairly large
Banyule	Warringal	29	300 375 450 525 600 900 1050 1200	71	Well or poorly graded gravel and gravel sand mixtures, little or no fine	Fully residential, single house properties, few units development

4.3 Investigation of Optimum GAs Operators

As described in Section 2.6.1, GAs operators control the process of GAs. These operators are responsible for the efficiency in achieving the optimum model parameter set of the urban drainage model. However, there is limited guidance available currently on selecting the appropriate GAs operators for use in urban drainage model calibration. Therefore, numerical experiments were conducted to find the optimum GAs operator set before attempting model parameter calibration using GAs for the urban drainage application.

4.3.1 Methodology

The study was conducted in two stages as follows:

(a) Investigation of GAs operators using the Kew catchment model

(b) Validation of the above results using the Warringal catchment model

This approach was used to reduce the computational time associated with large number of simulations of the linked GENESISS/XP-UDD model. In general, it took about 7 seconds for XP-UDD run of the Kew catchment model and about 35 seconds for the Warringal catchment model on a 312 MB RAM Pentium 4 computer. Therefore, the Kew catchment model was used to study the optimum GAs operators extensively, and the Warringal catchment model was used only to validate the results obtained from the Kew catchment.

Two studies were conducted separately for impervious and pervious area parameters, as the runoff generation mechanism is different in these two areas. In general, during *small* rainfall events, runoff is generated only from impervious areas, while during *large* rainfall events, both impervious and pervious areas contribute to runoff.

(a) Investigation of GAs operators using Kew catchment model

The XP-UDD model of the Kew stormwater drainage network was assembled using information on existing pits and pipes of the network. The catchment was divided into a number of sub catchments considering all drains and their inlets of the existing stormwater drainage network. As stated in Section 3.2.1, the XP-UDD hydrologic module interface allows up to five-sub catchment data inputs for each inlet (i.e. nodes). All existing drainage pipes that are equal or greater than 300 mm were assembled as links. Some of the sub catchment input data were estimated from the catchment contour maps and aerial photographs. These data includes total sub catchment area and slope of the sub catchments, which were entered to each node in assembling the XP-UDD network. The drainage system input data, such as conduit shape, size, length, slope, conduit invert level and ground level etc., were obtained from the drainage plans of the catchment. The catchment width was estimated by dividing the area of sub catchment by the average path of the overland flow, as specified in the XP software manual (1997), since there was insufficient information to use other methods. The XP-UDD model of the Kew stormwater drainage networks is shown in Figure 4.4.

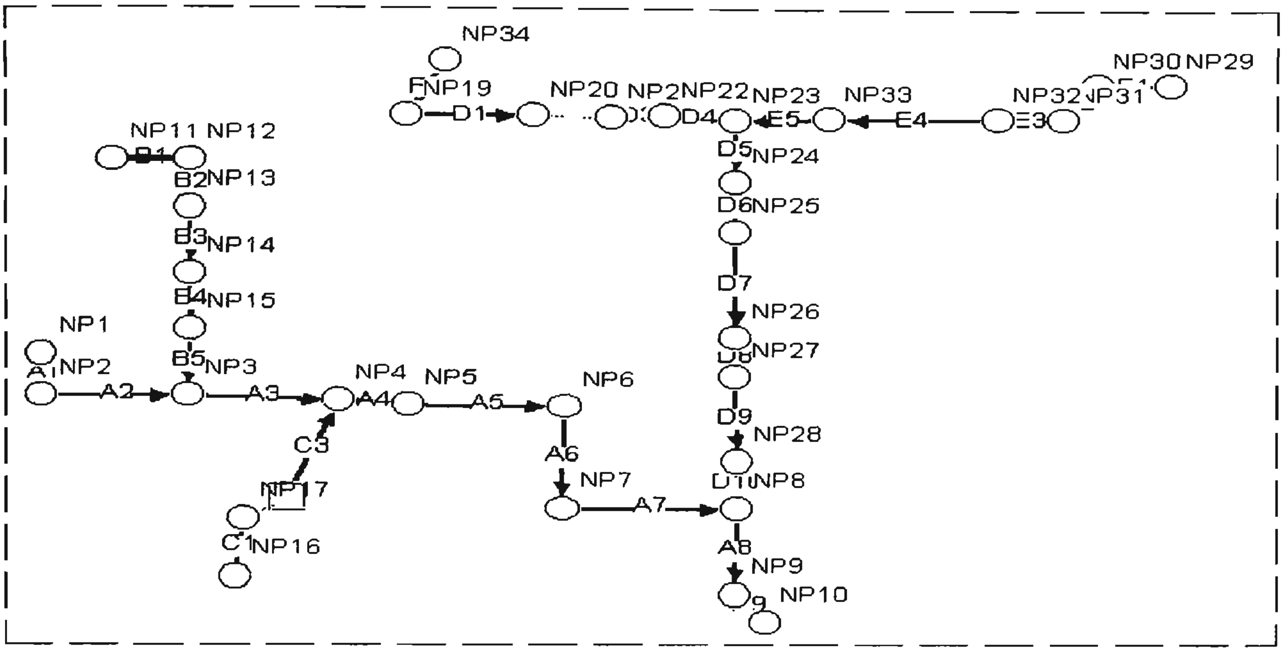


Figure 4.4 XP-UDD Model of Kew Stormwater Drainage Network

Two design storms (one *small* and the other *large*) were considered in the model. The *small* storm had an Annual Recurrence Interval (ARI) of 1 year and storm duration of 30 minutes. This storm produced runoff only from the impervious areas of the Kew catchment, as evident from the XP-UDD model output results and was used to calibrate the two impervious area parameters. The storm duration of 30 minutes was selected, since it was found from the XP-UDD output results that the time of concentration was less than 30 minutes, which indicated that the whole catchment was continuing to the runoff at the outlet. This effectively means that it is not necessary to consider any storm durations longer than 30 minutes. The *large* storm, which had an ARI of 100 years and 30 minutes duration, generated runoff from both impervious and pervious areas of the Kew catchment, as evident from the model output results and was used to calibrate the remaining five pervious area parameters after fixing the two impervious area parameters obtained from the impervious area study.

Typical values were assumed for the model parameters (i.e. two impervious area parameters and five pervious area parameters) to generate the two hydrographs due to the above *small* and *large* storm events. These parameter values were considered as the *actual* values of the model parameters for the catchment and hydrographs were considered as the observed hydrographs corresponding to *small* and *large* storm events, in optimising GAs operators. The objective function used in this study was the minimisation of the sum of square of difference of computed (due to different model parameter values generated by GAs) and observed hydrograph ordinates, as it has been widely used in many previous studies (eg. Liong et al. 1995) and implicitly allows for the other important features of the hydrographs such as peak, time to peak and volume to be matched.

Table 4.2 shows the typical model parameter values, the parameter ranges, precision required (i.e. number of decimal places) and string length [i.e. computed using Equation (2.2) considering the number of decimal places required and the parameter range of the model parameter] used for the GAs operator study. As can be seen from Table 4.2, the string lengths of the chromosomes in GAs process were 10 (i.e. adding sub-string lengths of impervious area parameters) and 38 (i.e. adding sub-string lengths of pervious area parameters) for impervious and pervious area parameter studies respectively.

Table4.2 Model Parameter Details

Group	**Parameter symbol**	**Actual parameter value**	**Parameter range**	**Precision required**	**String length**
Impervious Area (*small* storm event)	$\%A$	40	30 - 50	0	5
	DS_i	1	0 - 2	1	5
Pervious Area (*large* storm event)	n_p	0.03	0.001 – 0.1	3	10
	DS_p	3	1 – 4	1	6
	f_o	100	75 – 125	0	8
	f_c	10	5 – 15	0	4
	k	0.001	0.0001-0.01	4	10

The following options in XP-UDD software were used in the investigation of GAs operator study, as discussed in Section 3.2.1.

- Non-linear routing method

- Horton's infiltration equation for modelling infiltration in pervious areas

The following options in GENESIS software were used for this study, as discussed in Section 3.3.1.

- Gray coding
- Two-point crossover type
- Crossover and mutation rates were considered as 0.6 and 0.001 respectively and proportionate selection method was used, until these were optimised (These are the default values in GENESIS).

The linked GENESIS/XP-UDD model (Section 3.4) was used to study the effects of GAs operators. The GAs operators (i.e. population size, selection type and crossover and mutation rates) were varied one at a time, keeping all other operators constant in studying the effect of these operators. Each of these GAs operator studies and their results were discussed under their name heading below. The overall process of this study described above is shown in Figure 4.5.

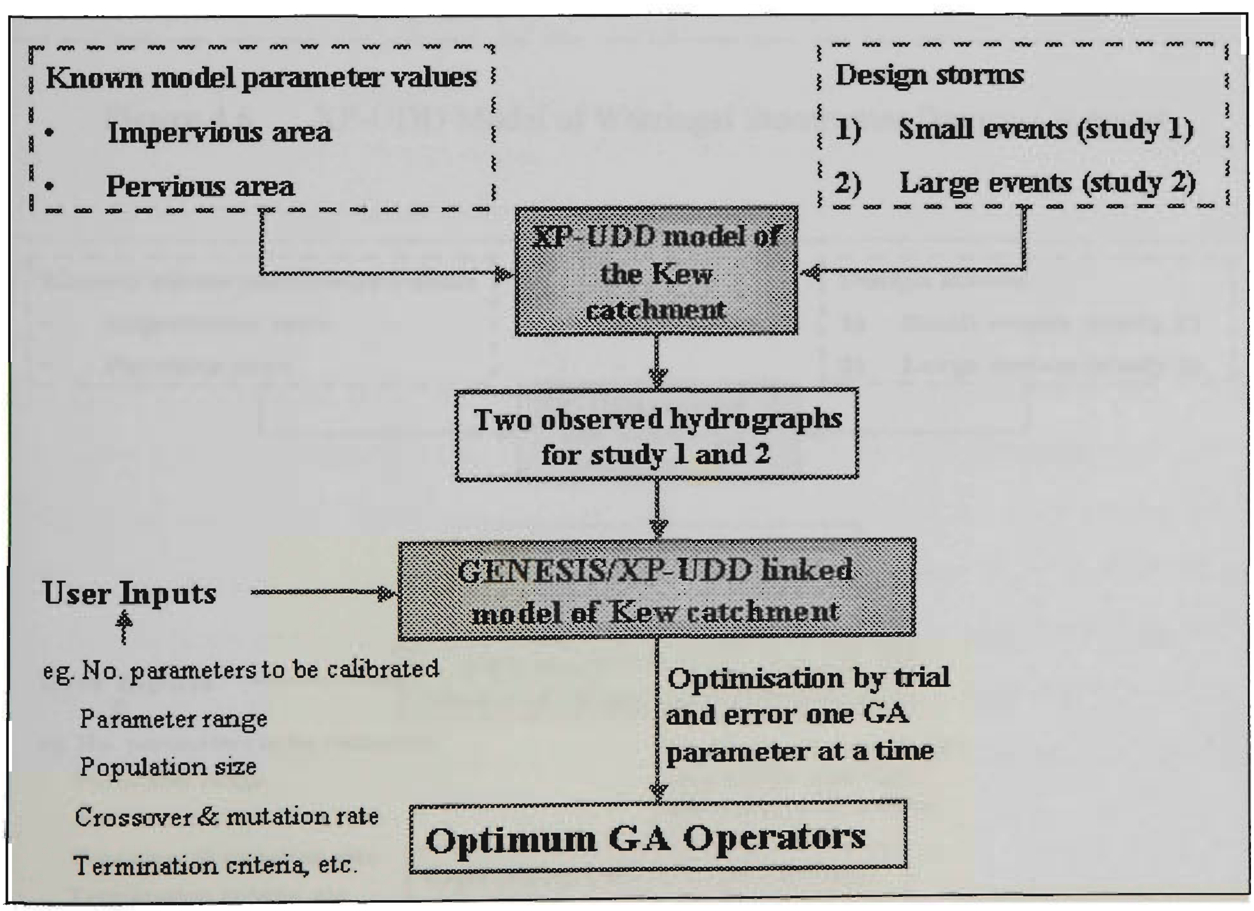


Figure 4.5 Investigation Processes of GAs Operators Using Kew Catchment Model

(b) Validation of GA operators using Warringal catchment model

Similar to the Kew catchment, the XP-UDD model was assembled first and the network is shown in Figure 4.6. The methodology of the validation study is similar to the Kew catchment and the overall process is shown in Figure 4.7

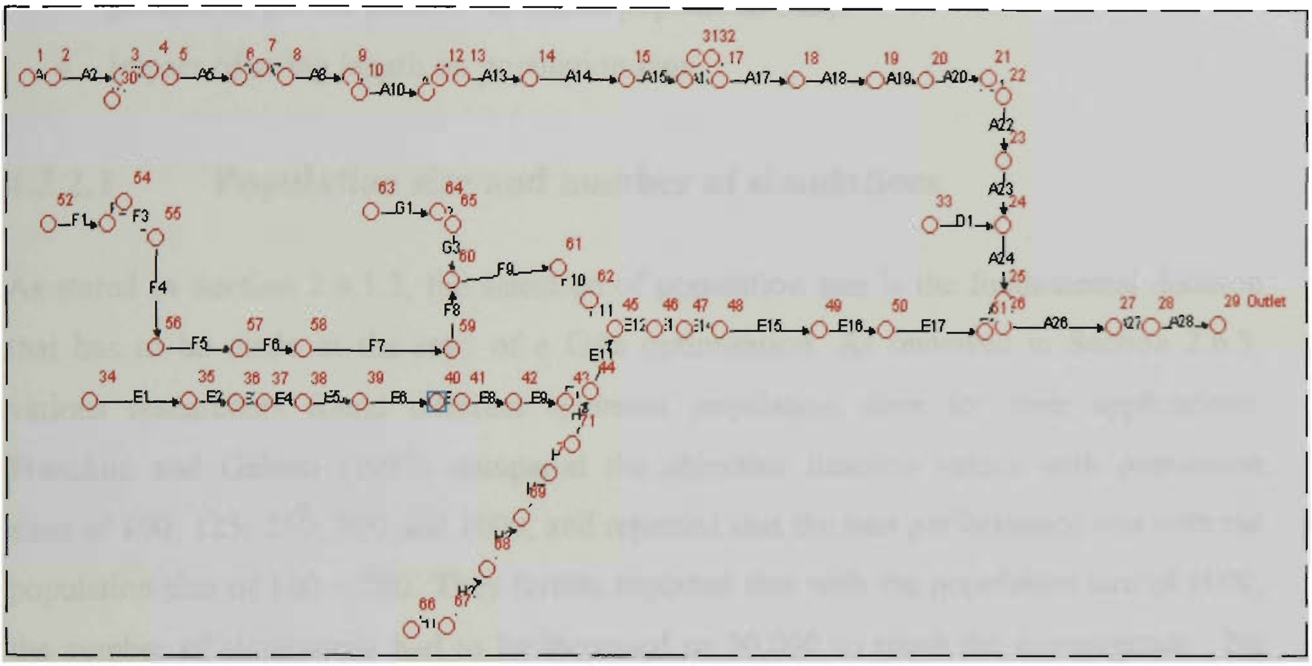


Figure 4.6 XP-UDD Model of Warringal Stormwater Drainage Network

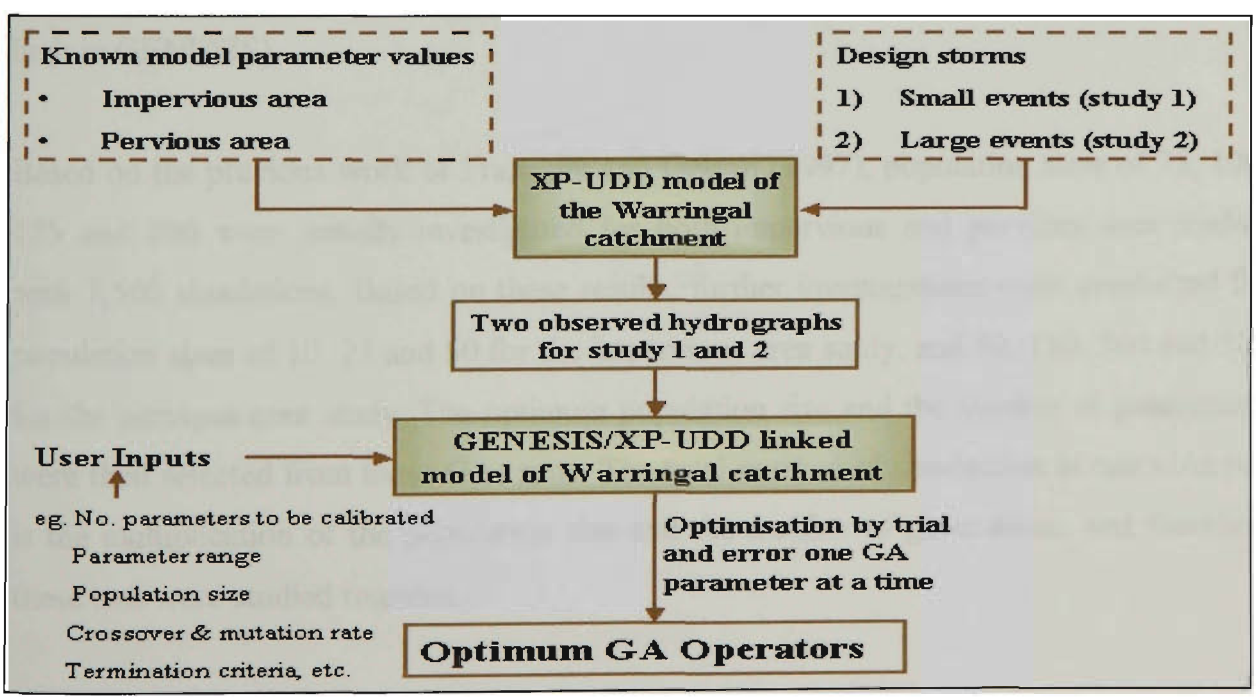


Figure 4.7 Validation Processes of GA Operators Using Warringal Catchment Model

4.3.2 Population size and associated issues

In this section, several issues related to population size were studied as follows:

- Selecting the optimum population size and number of simulations
- Number of optimum model parameter sets to be considered from the final generation (of the selected optimum population size)
- Impact of string length on population size

4.3.2.1 Population size and number of simulations

As stated in Section 2.6.1.2, the selection of population size is the fundamental decision that has to be made at the start of a GAs optimisation. As reviewed in Section 2.6.3, various researchers found different *optimum* population sizes for their applications. Franchini and Geleati (1997) compared the objective function values with population sizes of 100, 125, 250, 500 and 1000, and reported that the best performance was with the population size of 100 – 200. They further reported that with the population size of 1000, the number of simulations had to be increased to 20,000 to reach the convergence. Ng (2001) also performed similar experiment with a river water quality model and found that the population size of 125 converged with 15,000 simulations and the population size of 1000 did not converge at all even after the 32,000 simulations (which is the maximum limit in GENESIS).

Based on the previous work of Franchini and Geleati (1997), population sizes of 75, 100, 125 and 200 were initially investigated for both impervious and pervious area studies with 7,500 simulations. Based on these results, further investigations were conducted for population sizes of 10, 25 and 50 for the impervious area study, and 50, 150, 300 and 500 for the pervious area study. The optimum population size and the number of generations were then selected from these GAs runs. The total number of simulations in one GAs run is the multiplication of the population size and the number of generations, and therefore these two were studied together.

Impervious area study results (study 1)

(a) Kew catchment model

It was observed that the two model parameters (i.e. *%A* and DS_i) converge to the actual values easily achieving zero objective function values. Figure 4.8 shows the plot of number of simulations Vs. the number of zero objective functions expressed as a percentage of the population size for population sizes of 25, 50, 75, 100, 125 and 200 with 7500 simulations. As can be seen from Figure 4.8, the convergence rate decreases with the increase of the population size, which is due to increase of redundant solutions with increase in population size. The population size of 10 is not shown in Figure 4.8, since it did not converge to the actual model parameters at all. This is due to not having enough variation in parameters in the population.

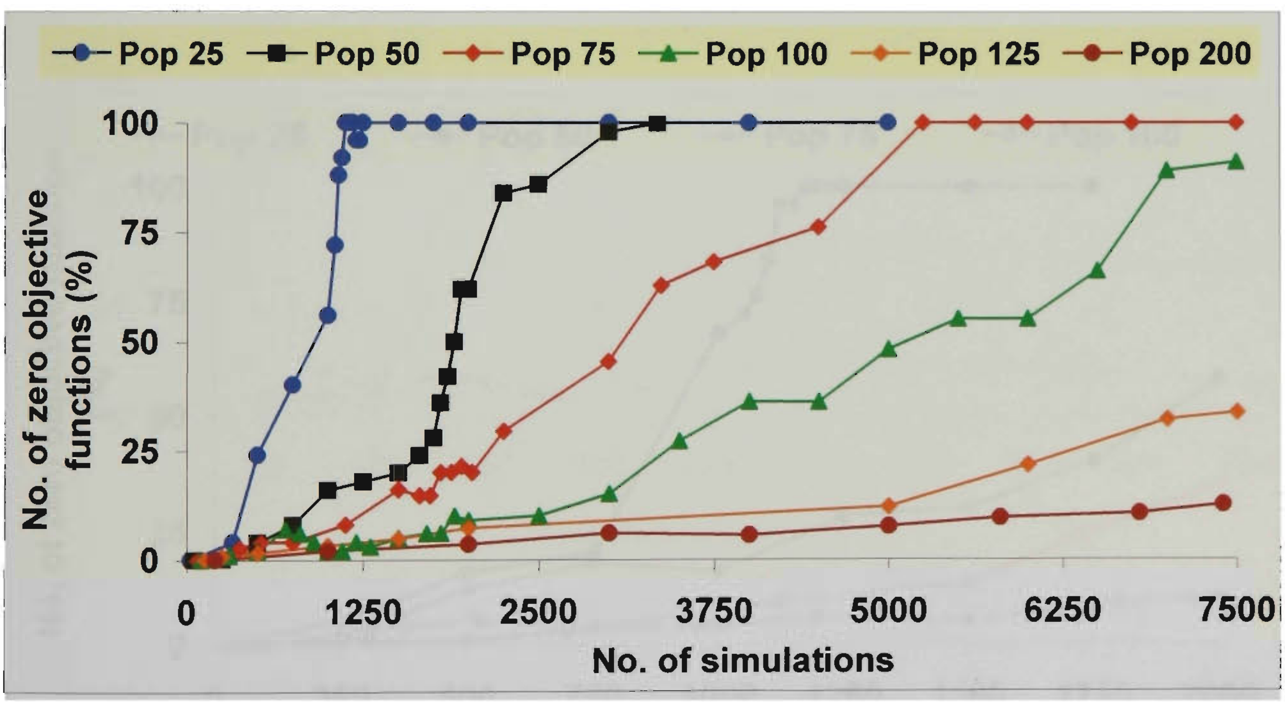


Figure 4.8 No. of Simulations Vs. No. of Zero Objective Functions % for Kew Catchment

As can be seen from Figure 4.8, all parameter sets converged very quickly with a population size of 25 within 1125 simulations (45 generations). However, the other population sizes were not able to give similar results with the same number of generations.

(b) Warringal catchment model

As stated in Section 4.3.1, the XP-UDD model of the Warringal catchment required large computer time to run 7500 simulations, compared to the Kew catchment. Therefore, the number of simulations was reduced with the Warringal catchment model, by judging the Kew catchment model investigation results. Hence, this study was conducted only with 2000 simulations to confirm the Kew catchment results.

Figure 4.9 shows the plot of number of simulation Vs. the number of zero objective functions expressed as a percentage of the population size for population sizes of 25, 50, 75 and 100 with 2000 simulations. As can be seen from Figure 4.9, all parameter sets converged very quickly with a population size of 25 and the other population sizes were not able to give similar results with the same number of generations. This result is similar to the Kew catchment model result.

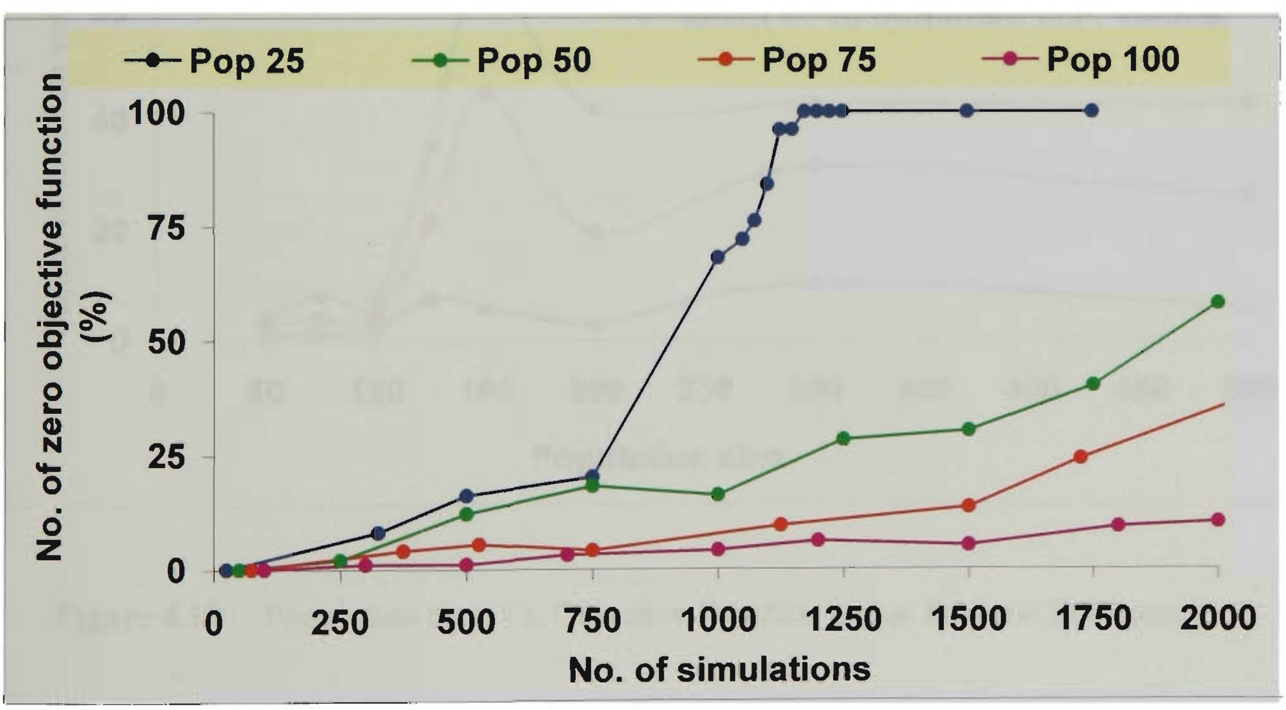


Figure 4.9 No. of Simulations Vs. No. of Zero Objective Functions % for Warringal Catchment

Based on these results, the population size of 25 with 1,200 simulations was identified as the *optimum* population size and the number of simulations respectively for optimising impervious area parameters in this study. This was used in the rest of the GA operator study, except in string length study, where the investigations were conducted to find the effect of string lengths on population size.

Pervious area study results (study 2)

(a) Kew catchment Model

Five pervious area parameters did not easily converge to the zero objective function values, as in the impervious area study. Therefore, Figure 4.10 was produced to illustrate the results in terms of minimum objective function, mean of minimum five objective functions and mean of minimum ten objective functions in the final generation (i.e. after 7500 simulations).

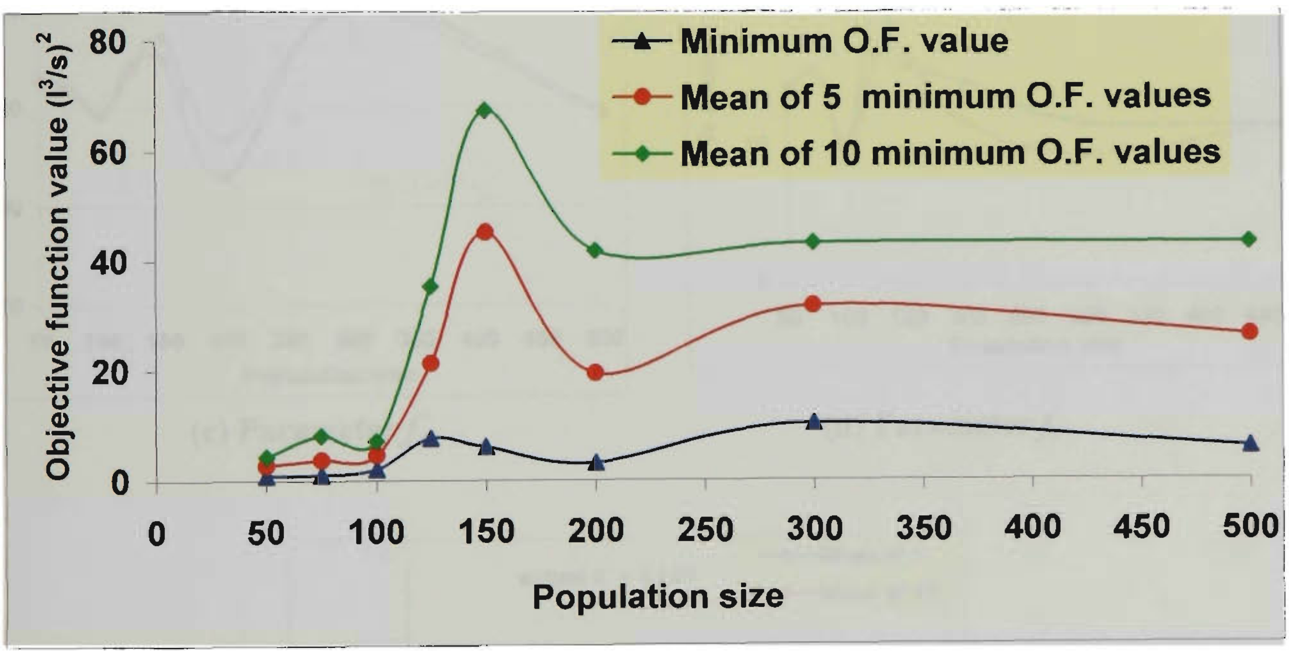
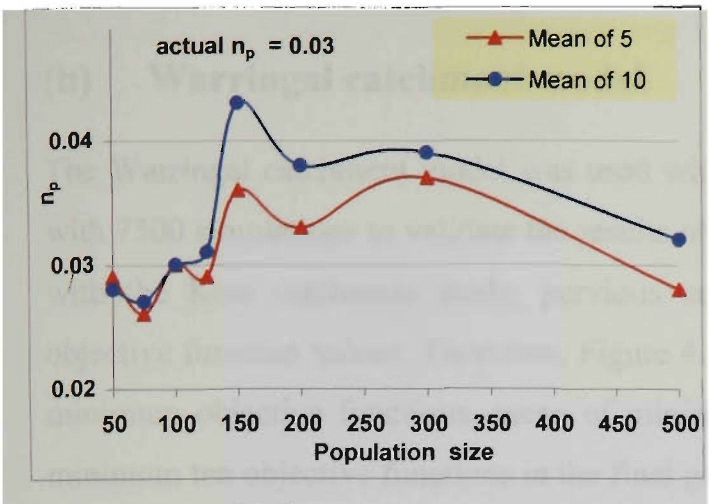
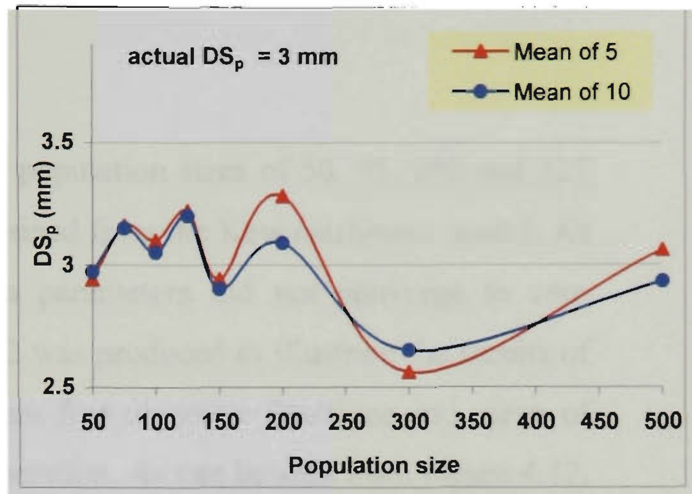


Figure 4.10 Population Size Vs. Objective Function Value for Kew Catchment

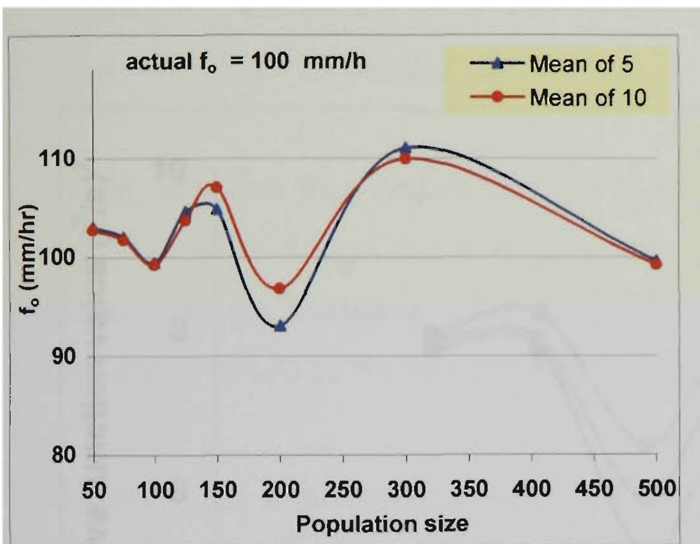
Although it can be seen from Figure 4.10 that the population sizes of 50, 75 and 100 were equally good in terms of the objective function, only the population size of 100 converged all five-model parameters accurately. This can be seen from Figure 4.11, which shows the variations of model parameter values with the population sizes. Minimum objective function values are not shown in Figure 4.11, since it gave similar results to the mean of minimum five objective function values.



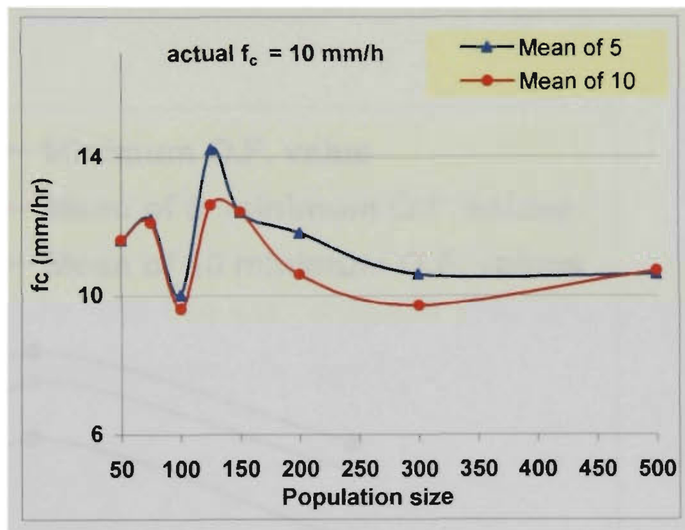
(a) Parameter n_p



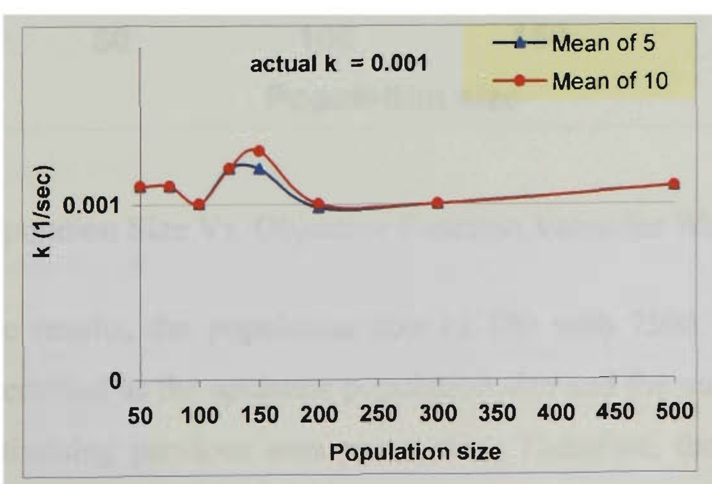
(b) Parameter DS_p



(c) Parameter f_o



(d) Parameter f_c



(e) Parameter k

Figure 4.11 Variation of Model Parameter Values Vs. Population Sizes

(b) Warringal catchment model

The Warringal catchment model was used with population sizes of 50, 75, 100 and 125 with 7500 simulations to validate the results obtained from the Kew catchment model. As with the Kew catchment study, pervious area parameters did not converge to zero objective function values. Therefore, Figure 4.12 was produced to illustrate the results of minimum objective functions, mean of minimum five objective functions and mean of minimum ten objective functions in the final generation. As can be seen from Figure 4.12, population size of 100 gave the best results. It was also observed that the population size of 100 converged all five-model parameters accurately.

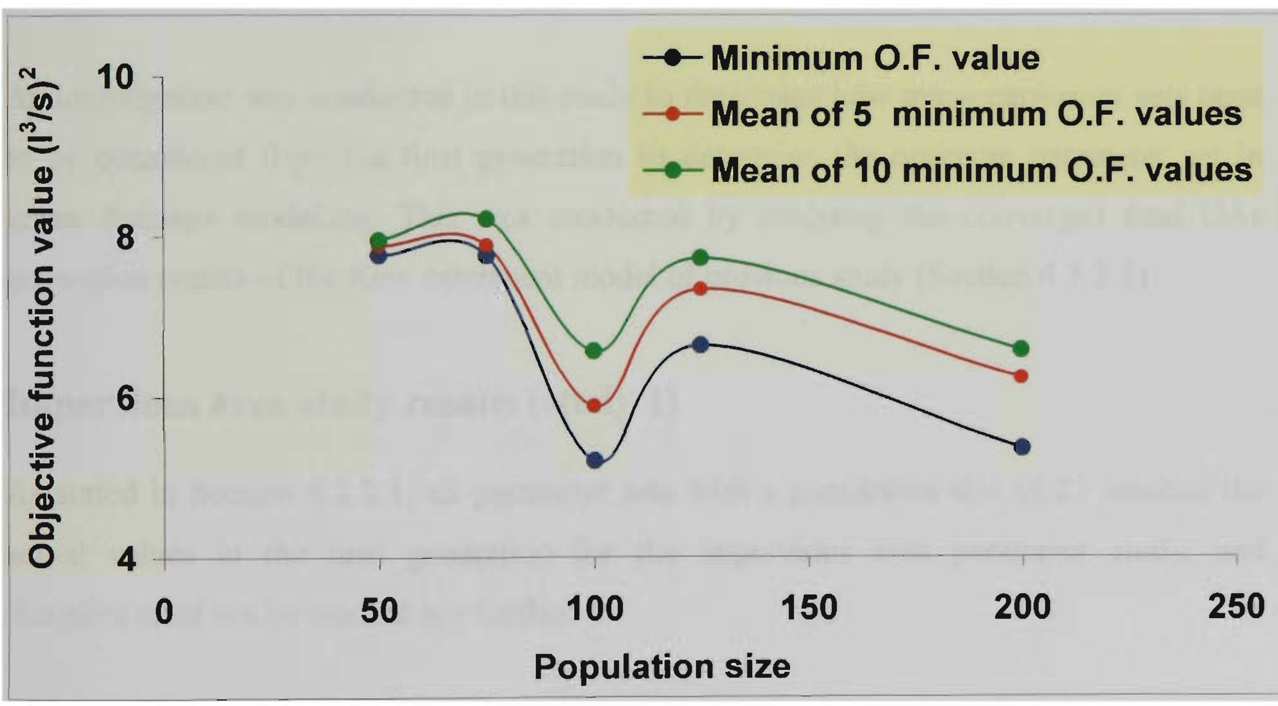


Figure 4.12 Population Size Vs. Objective Function Value for Warringal catchment

Based on the above results, the population size of 100 with 7500 simulations (i.e. 75 generations) was identified as the *optimum* population size and the number of simulations respectively for optimising pervious area parameters. Therefore, the population size of 100 with 7500 simulations was used in the rest of the study, except in the string length study.

4.3.2.2 Number of optimum model parameter sets to be considered from the final generation

There could be several equally good parameter sets giving the best objective function in the final generation. The objective functions of these sets may differ only by a small margin, though there could be significant differences in their parameters. Therefore, it is not appropriate to select a single parameter set from the final generation. However, Wang (1991) and Liong et al. (1995) selected a single parameter set based on objective functions, Franchini and Galeati (1997) determined the mean value of the best 20-parameter sets based on objective functions in their rainfall runoff model. Ng (2001) selected the mean value of the best 10 parameter sets based on objective function in her river water quality modelling application.

An investigation was conducted in this study to determine how many parameter sets need to be considered from the final generation to determine the optimum parameter set in urban drainage modelling. This was conducted by analysing the converged final GAs generation results of the Kew catchment model of previous study (Section 4.3.2.1).

Impervious area study results (study 1)

As stated in Section 4.3.2.1, all parameter sets with a population size of 25 reached the actual values in the final generation for the impervious area parameter study, and therefore need not be studied any further.

Pervious area study results (study 2)

(a) Kew catchment model

The values of the pervious area parameters and their objective function values of the final generation for a population size of 100 were studied in detail, and plots (i.e. Figures 4.13-4.17) were made of these parameters to show their mean, minimum and maximum with respect to a number of parameter sets taken from the final generation. The actual parameter value is also shown as a horizontal dashed line in these plots. As can be seen from these figures, in general the number of parameter sets beyond six deviated from the actual parameter values. Therefore, the mean of the best five parameter sets based on sets based on objective function from the final generation was considered as the value of the optimum parameter set.

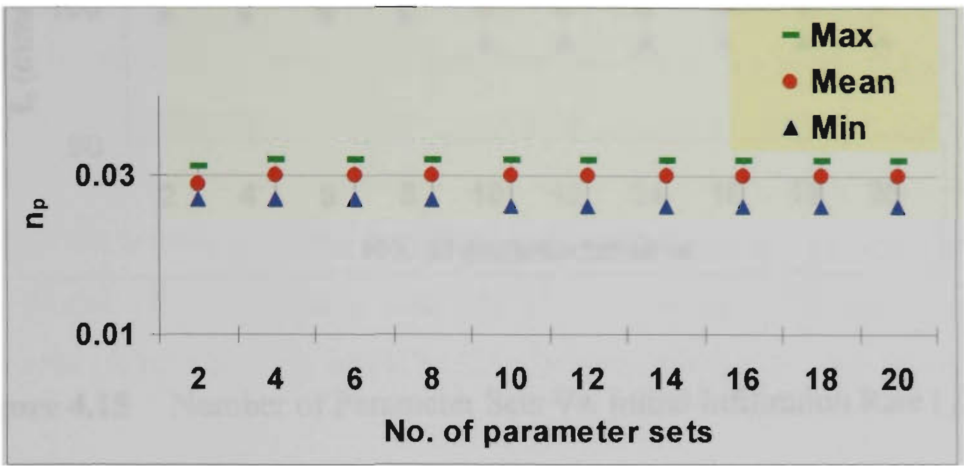


Figure 4.13 Number of Parameter Sets Vs. Overland Flow Roughness (n_p)

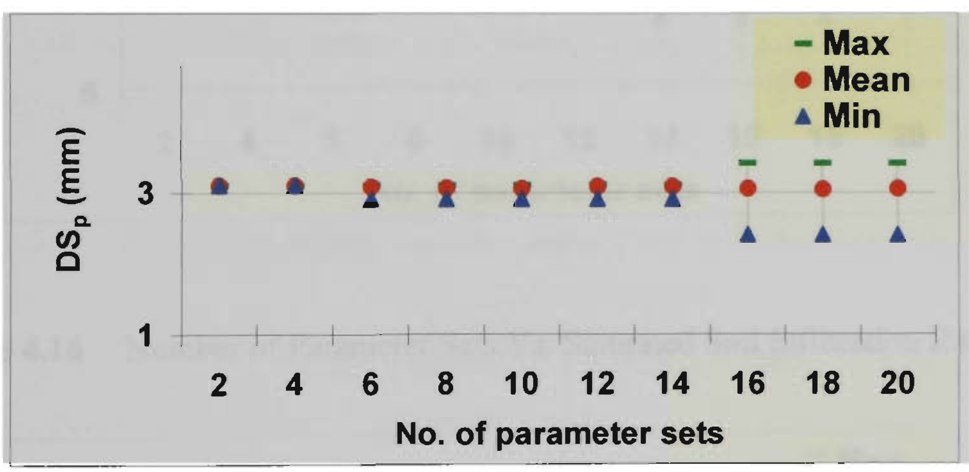


Figure 4.14 Number of Parameter Sets Vs. Pervious Area Depression Storage (DS_P)

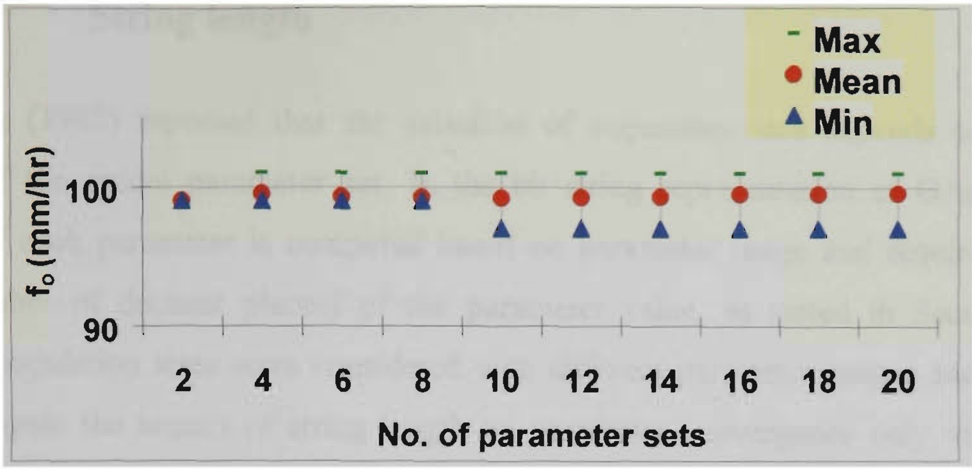


Figure 4.15 Number of Parameter Sets Vs. Initial Infiltration Rate (f_o)

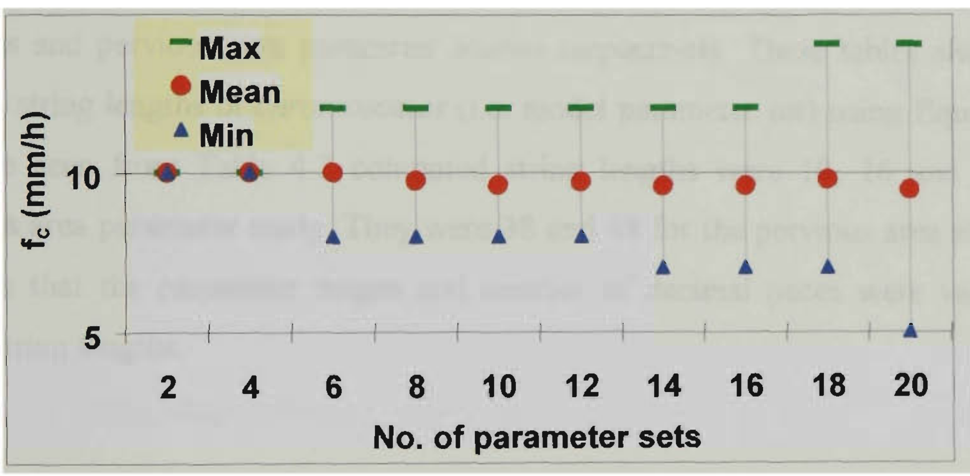


Figure 4.16 Number of Parameter Sets Vs. Saturated Soil Infiltration Rate (f_c)

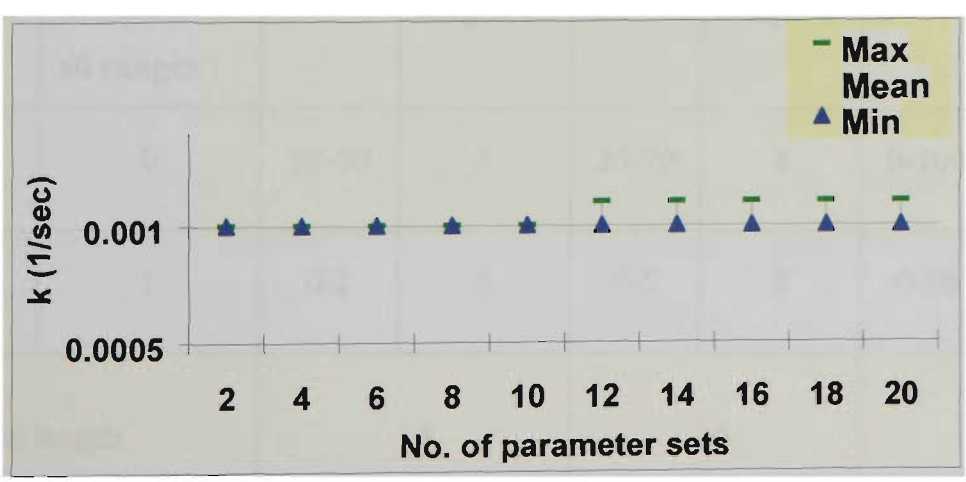


Figure 4.17 Number of Parameter Sets Vs. Infiltration Coefficient (k)

4.3.2.3 String length

Goldberg (1985) reported that the selection of population size depends on the string length of the model parameter set. In the bit string representation of GAs, the string length of each parameter is computed based on parameter range and required precision (i.e. number of decimal places) of the parameter value, as stated in Section 2.6.1.1. Several population sizes were considered with different parameter ranges and precisions, to investigate the impact of string length on parameter convergence only with the Kew catchment model. The population sizes of 25, 50, 75 and 100 were used for the impervious area parameter study and 100, 125, 150 and 200 for the pervious area study.

The parameter ranges and precision used are tabulated in Tables 4.3 and 4.4 for impervious and pervious area parameter studies respectively. These tables also show the computed string lengths of *chromosomes* (i.e. model parameter set) using Equation (2.2). As can be seen from Table 4.3 computed string lengths were 10, 16 and 20 for the impervious area parameter study. They were 38 and 48 for the pervious area study (Table 4.4). Note that the parameter ranges and number of decimal paces were varied to get different string lengths.

Table 4.3 Parameter Ranges and Precision Used in Impervious Area Study

Model parameter	**Number of decimals for all ranges**	**Range 1**	**String length 1**	**Range 2**	**String length 2**	**Range 3**	**String length 3**
$\%A$	0	30-50	5	20-70	8	0-100	10
DS_i	1	0-2	5	0-5	8	0-10	10
Total string length		10		16		20	

Table 4.4 Parameter Ranges and Precision Used in Pervious Area Study

Model parameter	**Range 1**	**Number of decimals - range 1**	**String length 1**	**Range 2**	**Number of decimals - range 2**	**String length 2**
n_p	0.001-0.1	3	10	0.001-0.1	3	10
DS_p	1-4	1	6	0-10	2	10
f_o	75-125	0	8	50-155	0	10
f_c	5-15	0	4	0-20	1	8
k	0.0001-0.01	4	10	0.0001-0.01	4	10
Total string length	38			48		

Impervious area study results (study 1)

(a) Kew catchment model

Figures 4.18-4.21 show the plots of number of simulations versus number of zero objective function values expressed as a percentage of population size for the population size of 25, 50, 75 and 100. It can be seen from these figures that the number of simulations required for convergence was increased with increase of string length. Therefore, GAs efficiency can be achieved with reduced string lengths by limiting parameter range and the accuracy of the model parameters (i.e. number of decimal places required) to the required level only.

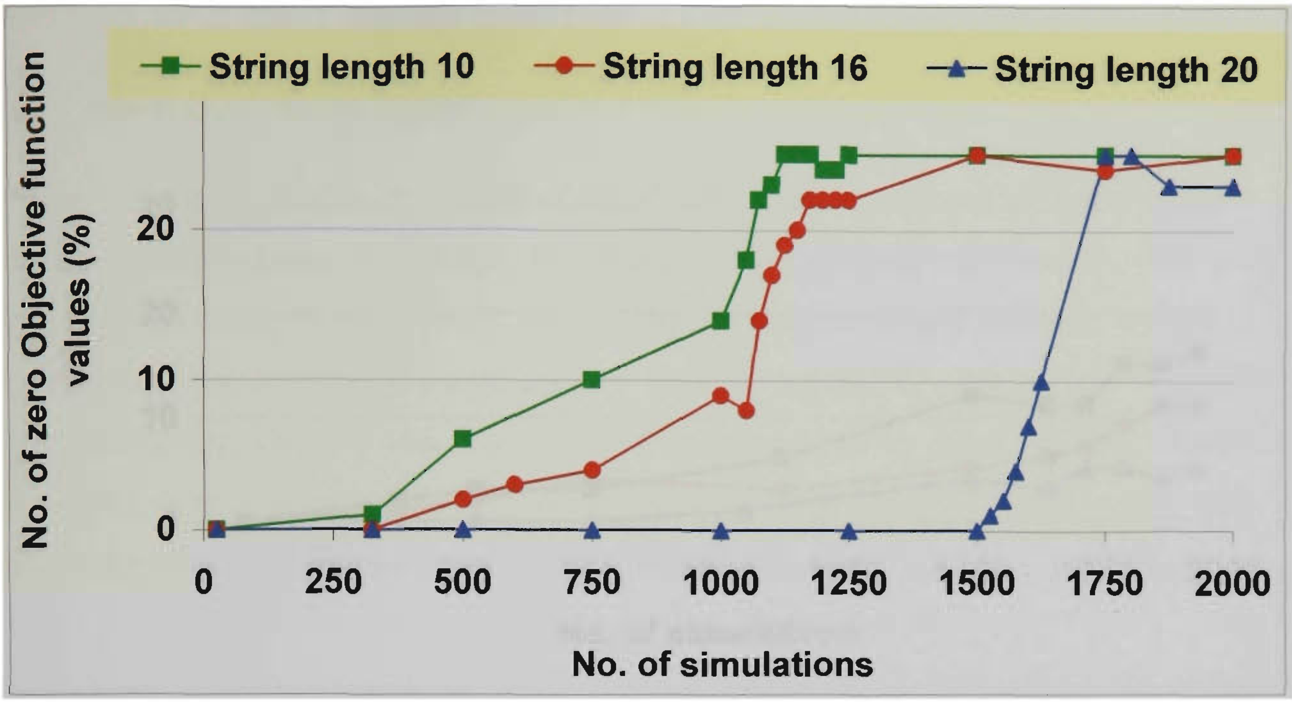


Figure 4.18 Effect of String Length on Parameter Convergence with Population of 25 for Impervious Area Study

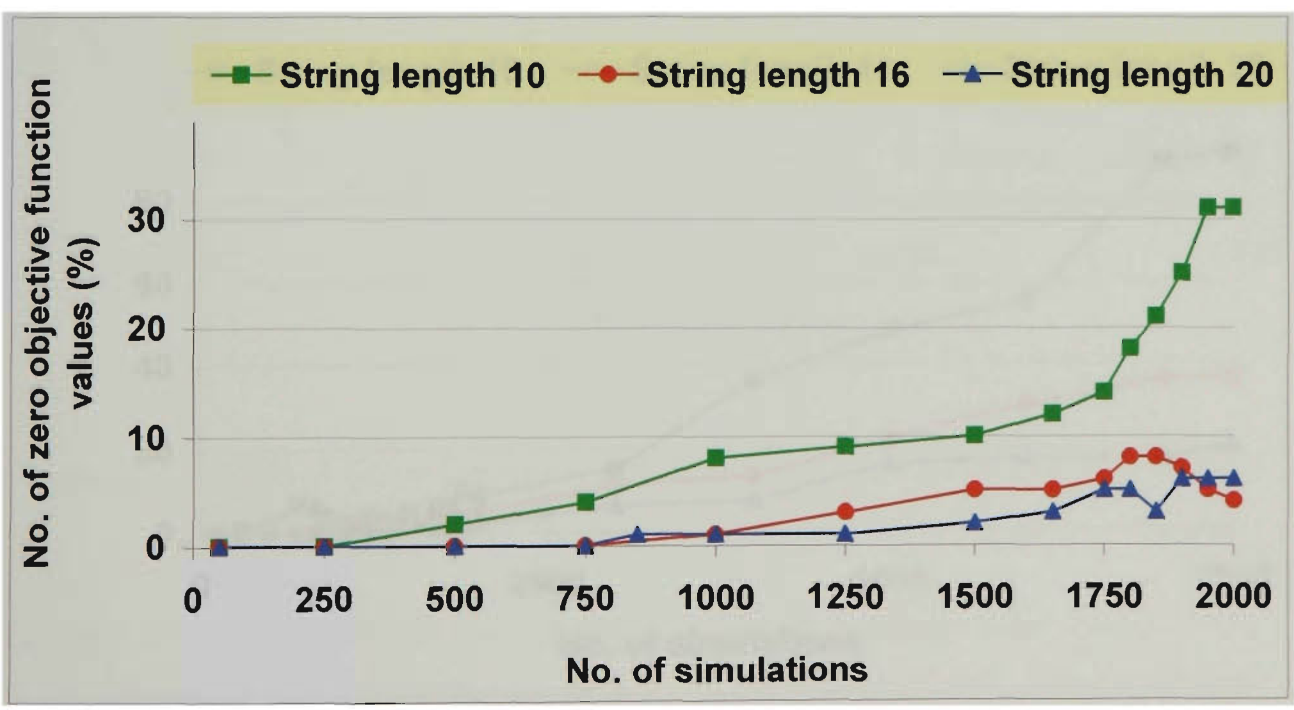


Figure 4.19 Effect of String Length on Parameter Convergence with Population of 50 for Impervious Area Study

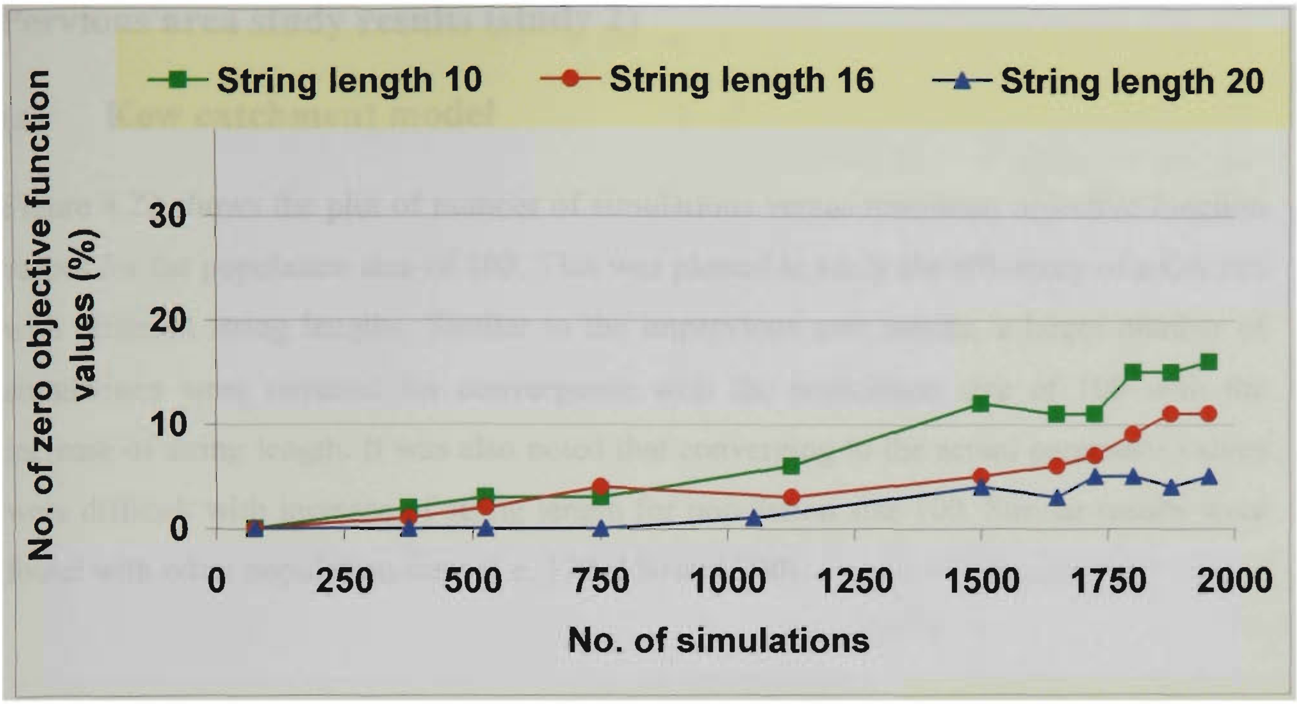


Figure 4.20 Effect of String Length on Parameter Convergence with Population of 75 for Impervious Area Study

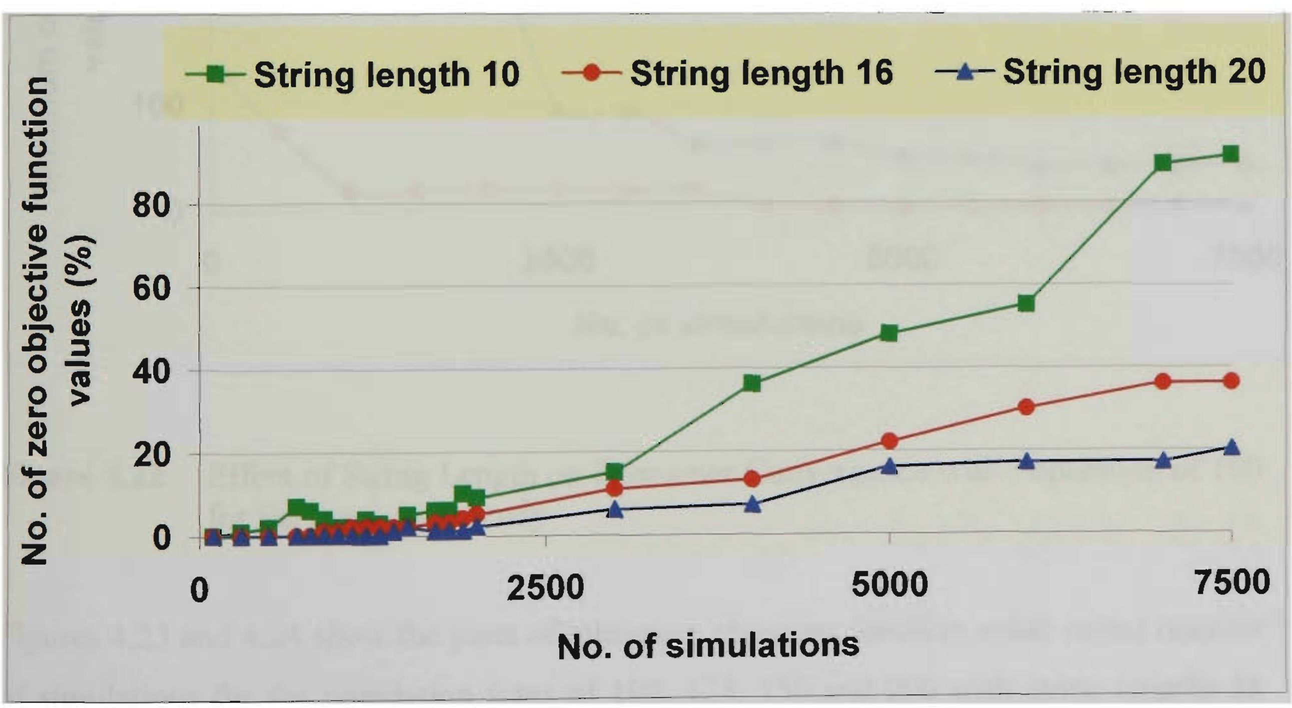


Figure 4.21 Effect of String Length on Parameter Convergence with Population of 100 for Impervious Area Study

Pervious area study results (study 2)

(a) Kew catchment model

Figure 4.22 shows the plot of number of simulations versus minimum objective function values for the population size of 100. This was plotted to study the efficiency of a GA run with different string lengths. Similar to the impervious area results, a larger number of simulations were required for convergence with the population size of 100 with the increase of string length. It was also noted that converging to the actual parameter values were difficult with increase of string length for population size 100. Similar results were found with other population sizes (i.e. 125, 150 and 200).

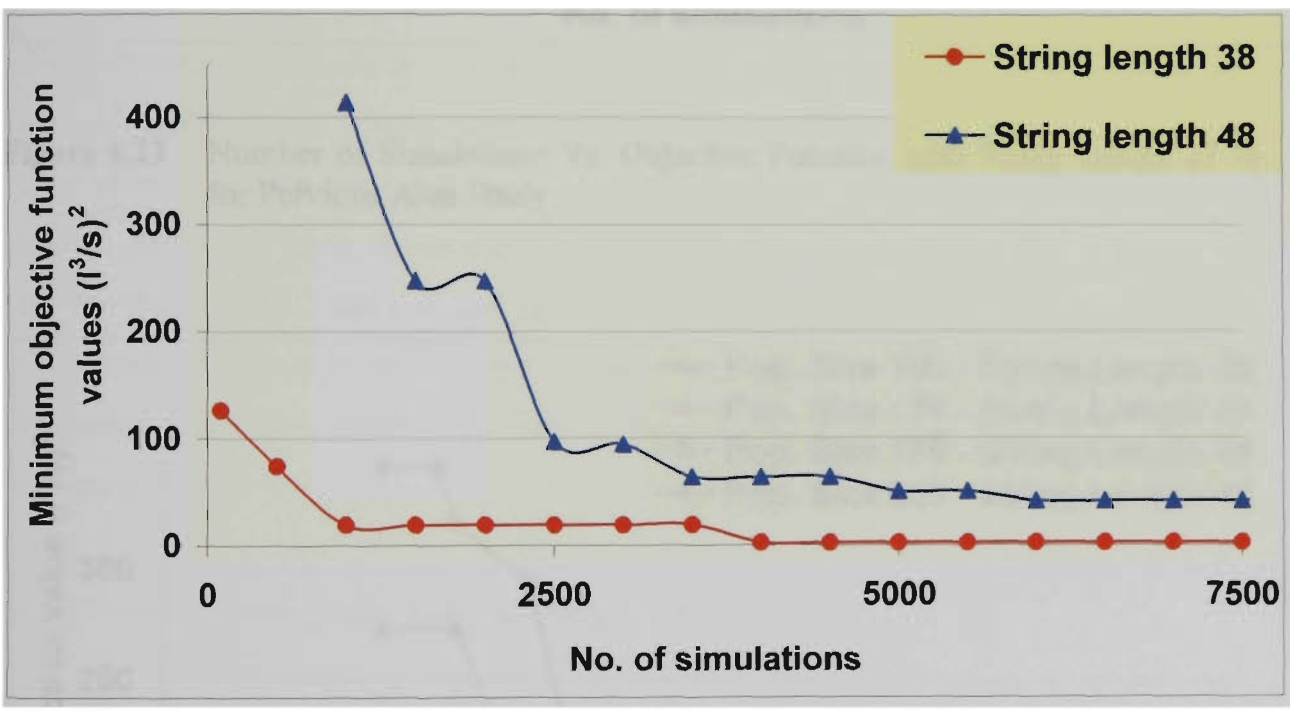


Figure 4.22 Effect of String Length on Parameter Convergence with Population of 100 for Pervious Area Study

Figures 4.23 and 4.24 show the plots of minimum objective function value versus number of simulations for the population sizes of 100, 125, 150 and 200 with string lengths 38 and 48 respectively. Population size of 100 with string length 38 gave the best results in Figure 4.23. As can be seen from Figure 4.24 population size 125, 150 and 200 with string length of 48 converged to objective function values faster than population size 100.

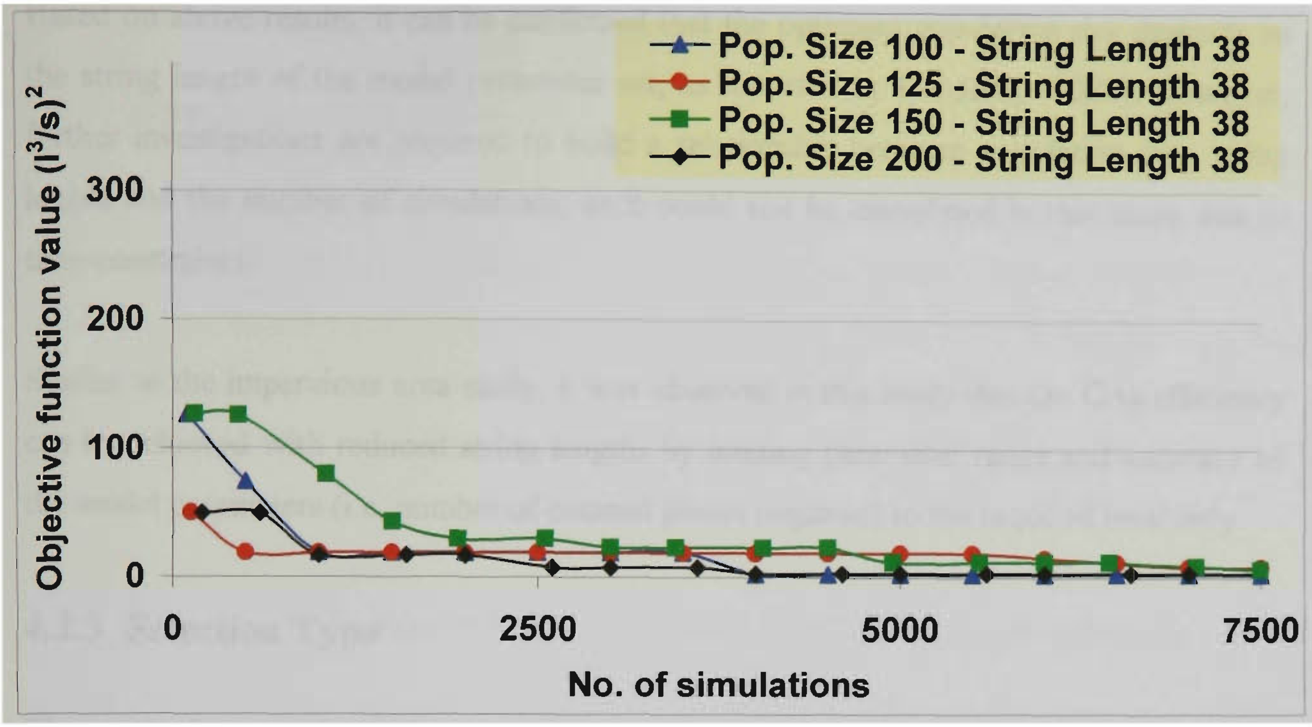


Figure 4.23 Number of Simulations Vs. Objective Function with String Length of 38 for Pervious Area Study

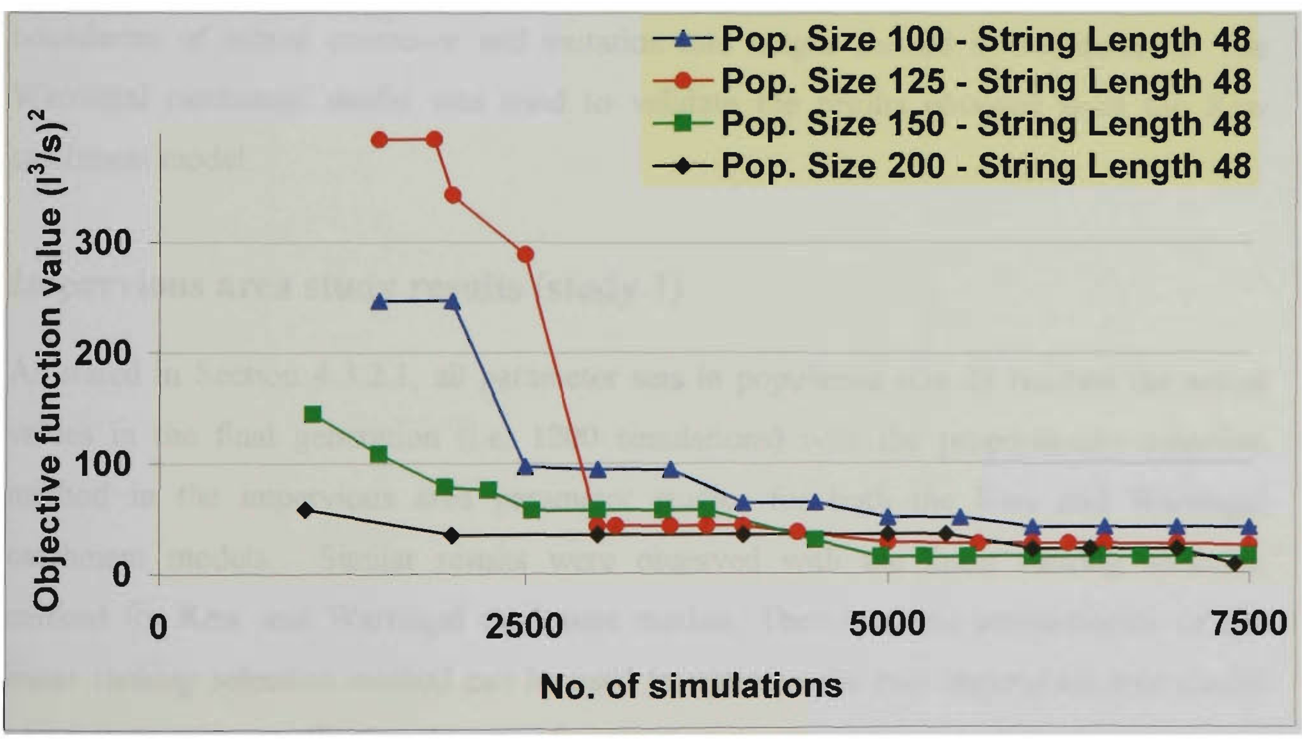


Figure 4.24 Number of Simulations Vs. Objective Function with String Length of 48 for Pervious Area Study

Based on above results, it can be confirmed that the optimum population size depends on the string length of the model parameter set, as reported by Goldberg (1985). However, further investigations are required to build a relationship between population size, string length and the number of simulations, as it could not be completed in this study due to time constraints.

Similar to the impervious area study, it was observed in this study that the GAs efficiency can be achieved with reduced string lengths by limiting parameter range and accuracy of the model parameters (i.e. number of decimal places required) to the required level only.

4.3.3 Selection Type

The proportionate selection and the linear ranking selection method are the only options available in GENESIS. Therefore, the effect of these two methods on the convergence to the optimum model parameter set was investigated for impervious and pervious area studies with the Kew catchment model. Each selection method was studied with crossover rates of 0.6 and 0.9, and mutation rates of 0.001 and 0.01. These values are the boundaries of robust crossover and mutation rate ranges defined in the literature. The Warringal catchment model was used to validate the results obtained from the Kew catchment model.

Impervious area study results (study 1)

As stated in Section 4.3.2.1, all parameter sets in population size 25 reached the actual values in the final generation (i.e. 1200 simulations) with the proportionate selection method in the impervious area parameter studies for both the Kew and Warringal catchment models. Similar results were observed with the linear ranking selection method for Kew and Warringal catchment models. Therefore, the proportionate or the linear ranking selection method can be used to optimise the two impervious area model parameters, without affecting the rate of convergence.

Pervious area study results (study 2)

(a) Kew catchment model

It was observed that convergence for the pervious area studies was slightly faster with the linear ranking method compared to the proportionate selection method. However, the pervious area model parameters converged to the actual values more accurately with the proportionate selection method than the linear ranking method as shown in Table 4.5. The population size of 100 was used in this study, as suggested in Section 4.3.2.1. Actual parameter values are shown in bold type under each parameter.

Table 4.5 Results of Selection Methods with Kew Catchment Model

Crossover and mutation rates	**Selection method**	**Mean of 5 objective functions**	n_p **0.03**	DS_p **3 mm**	f_o **100 mm/h**	f_c **10 mm/h**	k **0.001 1/sec**
Crossover - 0.6 Mutation - 0.001	Proportionate	4.52	0.029	3.1	99.4	10	0.001
	Linear ranking	3.14	0.028	2.93	97	12	0.0011
Crossover - 0.6 Mutation - 0.01	Proportionate	13.79	0.032	2.72	107	11.6	0.001
	Linear ranking	10.5	0.036	2.5	107	12	0.0011
Crossover - 0.9 Mutation - 0.001	Proportionate	4.03	0.028	3.02	103	13.4	0.0011
	Linear ranking	3.24	0.025	3.5	105	14	0.0012
Crossover - 0.9 Mutation - 0.01	Proportionate	9.75	0.03	2.96	102	10.4	0.0011
	Linear ranking	5.99	0.028	2.92	105	12	0.0012

(b) Warringal Catchment model

Only crossover rates of 0.6 and mutation rates of 0.001 were used to validate the above results with Warringal catchment, since all above results showed a similar pattern (i.e. more accurate parameter values with the proportionate selection method compared to the linear ranking method, but with relatively higher objective function values). Results obtained from this study were similar to the Kew catchment as shown in Table 4.6. Therefore, the proportionate selection method was used for the rest of the study.

Table 4.6 Results of Selection Methods with Warringal Catchment Model

Item	Crossover rate = 0.6 & Mutation rate = 0.001	
	Proportionate selection	Linear ranking
Mean objective Function value of 5	10.88	8.55
n_p (actual value - 0.03)	0.033	0.02
DS_p (actual value - 3)	2.8	3.9
f_o (actual value - 100)	98.5	94
f_c (actual value -10)	10	10
k (actual value- 0.001)	0.001	0.002

4.3.4 Crossover and Mutation Rate

In this part of the study, the effects of crossover rate (XOR) were first investigated for the impervious and pervious area parameter studies with the Kew and Warringal catchment models. For both studies, crossover rates ranging from 0.1 to 1, with steps of 0.1 (i.e. 10 crossover rates), were initially investigated, keeping the mutation rate at 0.001, which is the default value in GENESIS. Then, these results were analysed to produce a narrow range of crossover rates. This narrow range was then used with different mutation rates (MR), to produce suitable crossover and mutation rates for urban drainage model calibration. This procedure was adopted, since the mutation rate has less (or no depending on the population size) effect on convergence compared to crossover rate. In this study, crossover and mutation rates were studied together, as they (together) determine the convergence.

Impervious area study results (study 1)

(a) Kew catchment model

Table 4.7 shows the results obtained with crossover rate ranging from 0.1 to 1 for the population size of 25 with 1200 simulations and mutation rate of 0.001. All ten runs with the 1200 simulations converged to the actual parameter set.

Table 4.7 No. of Zero Objective Function Values Achieved for Different Crossover Rates in Impervious Area Study - Kew Catchment Model

Crossover rates / No. of simulations	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
25	0	0	0	0	0	0	0	0	0	0
325	0	1	2	0	2	1	2	0	4	0
500	1	2	5	0	4	6	10	2	5	2
750	17	9	24	4	3	10	22	9	14	7
900	19	25	25	6	4	13	25	9	24	23
950	19	25	25	10	7	12	25	16	24	24
1000	25	25	25	18	10	14	25	20	24	24
1050	25	25	25	23	13	18	25	23	25	25
1100	25	25	25	24	19	23	25	24	25	25
1200	25	25	25	25	24	25	25	25	25	25

As can be seen from Table 4.7, any crossover rate can be used for small number of model parameter estimation. Therefore only the crossover rate of 0.6 (which is the default value of GENESIS) was studied with different mutation rates. Table 4.8 shows the results obtained for the mutation variation with crossover rate of 0.6 for population size of 25. As can be seen from Table 4.8, mutation rates of 0.05, 0.01, 0.005 and 0.001 were equally good in achieving the zero objective function values, and therefore no further mutation rate investigations were conducted.

Table 4.8 Impervious Area Study Results for Different Mutation Rates with Crossover Rate of 0.6 – Kew Catchment Model

Mutation Rate	Minimum objective function	Mean of 5 objective function	Mean of 5 *%A*	Mean of 5 *DSi*
0.05	0	0	40	1
0.01	0	0	40	1
0.005	0	0	40	1
0.001	0	0	40	1

(b) Warringal catchment model

Table 4.9 shows the results obtained for the crossover rates of 0.2, 0.4, 0.6, 0.8, 0.9 and 1 for the population size of 25 with 1200 simulations and mutation rate of 0.001. At least 5 parameter sets were converged to the actual parameter set in all six runs with 1200 simulations. Similar to the Kew catchment model, the crossover rate of 0.6 was then studied with different mutation rates and the results were tabulated in Table 4.10.

Table 4.9 Impervious Area Study Results for Different Crossover Rates – Warringal Catchment Model

Crossover rate	Minimum objective function	Mean of 5 objective functions	Average of objective functions in total population	No of zero objective function values	No of zero objective function as a percentage of population
0.2	0	0	230.45	20	80
0.4	0	0	59.48	10	40
0.6	0	0	0	25	100
0.8	0	0	12.58	24	96
0.9	0	0	29.43	24	96
1	0	0	196.01	6	24

Table 4.10 Impervious Area Study Results for Different Mutation Rates with Crossover Rate of 0.6 – Warringal Catchment Model

Mutation rate	Minimum objective function	Mean of 5 objective function	Mean of 5 $\%A_i$	Mean of 5 DS_i
0.05	0	0	40	1
0.01	0	0	40	1
0.005	0	0	40	1
0.001	0	0	40	1

Based on these results, it can be concluded that the crossover and mutation rates do not significantly affect the convergence to the actual values of the two parameters in this study.

Pervious area study results (study 2)

(a) Kew catchment model

Figure 4.25 shows the plot of crossover rates versus objective function values with mutation rate of 0.001 for population size of 100 after 7500 simulations. As can be seen from Figure 4.25, the crossover rate of 0.2, 0.3 and 0.5 to 1 only gave the best results in the pervious area study. The five model parameter values (based on 5 minimum objective functions) obtained from each run were tabulated in Table 4.11. Actual parameter values are shown in bold type under each parameter. When the model parameters obtained from these GAs runs and the actual values were compared, it was found that they were closely matched with each other only with the crossover rates between 0.6 - 0.9. Therefore, the conclusion was made that the crossover rates between 0.6 – 0.9 need to be considered for further study with mutation rates varying from 0.001 to 0.1. The results of this study are discussed in the next paragraph.

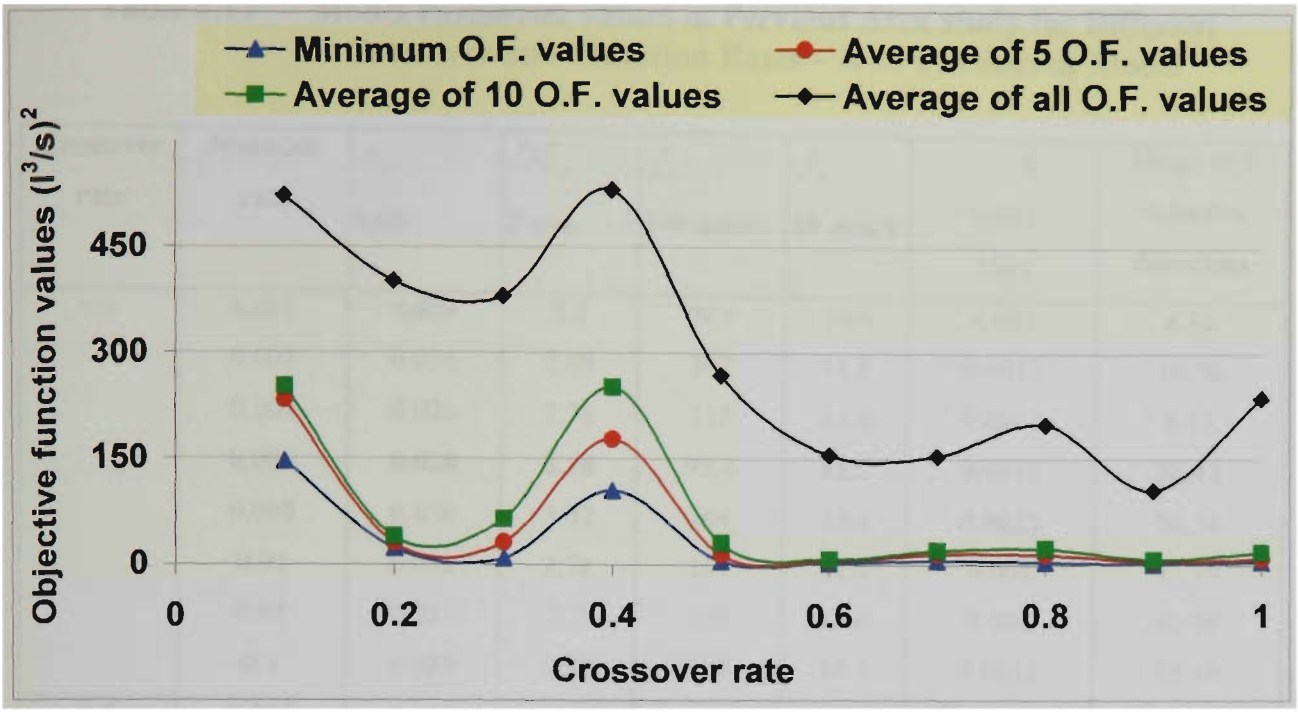


Figure 4.25 Different Crossover Rate Vs. Objective Function Values

Table 4.11 Model Parameters in pervious Area Study for Different Crossover Rates

Crossover rate	n_p **0.03**	DS_p **3 mm**	f_o **100 mm/h**	f_c **10 mm/h**	k **0.001 1/sec**	**Mean of 5 objective functions**
0.2	0.036	2.7	110	12.8	0.0012	29.3
0.3	0.035	2.9	107	14.2	0.0013	30.4
0.5	0.038	2.82	106	14.4	0.0011	15.8
0.6	0.029	3.1	99.4	10	0.001	4.52
0.7	0.029	2.2	120	13	0.0014	13.9
0.8	0.031	3.12	97.8	10.6	0.001	13.7
0.9	0.028	3.02	103	11.4	0.0011	4.03
1	0.03	2.8	105	13.6	0.0012	7.88

The five model parameter values based on mean of 5 minimum objective functions obtained for these crossover and mutation rates are tabulated in Table 4.12. Actual parameter values are shown in bold type under each parameter. It can be seen from Table 4.12 that the crossover rate of 0.6 with 0.001 mutation rate gave the best result based on convergence to the actual parameter values for this application. The other acceptable crossover and mutation rates are shown in bold type in Table 4.12.

Table 4.12 Model Parameter values in Pervious Area study for Different Crossover and Mutation Rates – Kew Catchment Model

Crossover rate	Mutation rate	n_p 0.03	DS_p 3 mm	f_o 100 mm/h	f_c 10 mm/h	k 0.001 1/sec	Mean of 5 objective functions
0.6	**0.001**	**0.029**	**3.1**	**99.4**	**10.0**	**0.001**	**4.52**
	0.002	0.034	2.68	107	11.8	0.0012	16.56
	0.004	0.026	2.76	112	13.6	0.0013	8.33
	0.006	**0.028**	**3.18**	**99.4**	**13.2**	**0.0011**	**18.42**
	0.008	**0.030**	**3.02**	**104**	**13.4**	**0.0012**	**24.34**
	0.01	0.032	2.72	107	11.6	0.001	13.79
	0.05	0.023	2.7	109	12.6	0.001	40.39
	0.1	0.039	2.52	106	10.2	0.0011	42.49
0.7	0.001	0.029	2.2	120	14.0	0.0014	13.9
	0.002	0.024	3.1	111	12.8	0.0013	18.01
	0.004	0.060	2.42	107	11.8	0.0012	75.31
	0.007	0.034	2.32	115	14.0	0.0013	23.44
	0.008	0.029	2.84	110	13.2	0.0013	24.59
	0.01	**0.029**	**3.02**	**102**	**13.2**	**0.0012**	**15.92**
	0.05	0.039	2.52	113	9.6	0.0012	53.41
	0.1	**0.034**	**2.98**	**95.8**	**11.2**	**0.001**	**22.83**
0.8	**0.001**	**0.031**	**3.12**	**97.8**	**10.6**	**0.001**	**13.7**
	0.002	**0.028**	**3**	**102**	**12.4**	**0.0011**	**14.22**
	0.004	0.034	1.98	121	14.8	0.0014	10.69
	0.006	0.027	2.86	107	12.6	0.0012	28.10
	0.008	**0.033**	**2.96**	**100**	**12.3**	**0.0011**	**20.42**
	0.01	0.035	2.78	101	13.0	0.0011	39.03
	0.05	0.027	2.34	120	13.6	0.001	39.23
	0.1	0.050	2.46	107	12.8	0.0013	94.77
0.9	**0.001**	**0.028**	**3.02**	**103**	**13.4**	**0.0011**	**4.03**
	0.002	**0.031**	**2.84**	**104**	**12.8**	**0.001**	**6.06**
	0.005	0.038	3.1	98.2	11.8	0.0011	29.36
	0.008	**0.030**	**3.26**	**99.4**	**12.4**	**0.0011**	**18.98**
	0.01	**0.030**	**2.96**	**102**	**10.4**	**0.0011**	**9.75**
	0.05	0.033	3.6	92.6	10.2	0.0009	28.51
	0.1	0.031	2.92	105	9.8	0.001	64.48

Note: Acceptable crossover and mutation rates (i.e. based on convergence to the actual parameter values) are shown in bold type.

(b) Warringal Catchment model

Crossover rate of 0.6 with mutation rates of 0.01 and 0.001 and crossover rate of 0.9 with mutation rates of 0.01 and 0.001 were studied using the Warringal catchment model, after reviewing the Kew catchment model results and since these are the robust boundaries recommended in Literature (Section 4.3.3). The results are tabulated in Table 4.13 for population size of 100 after 7500 simulations.

It can be seen from Table 4.13 that the crossover rate of 0.6 with 0.001 mutation rate gave the best result based on convergence to the actual parameter values for the Warringal catchment, similar to the Kew catchment. It should be noted that these are also the default values of GENESIS and therefore are recommended for use in XP-UDD model parameter calibration.

Table 4.13 Model Parameter Values in Pervious Area study for Different Crossover and Mutation Rates – Warringal Catchment Model

Crossover rate	Mutation rate	n_p 0.03	DS_p 3 mm	f_o 100 mm/h	f_c 10 mm/h	k 0.001 1/sec	Mean of five objective functions
0.6	**0.001**	**0.033**	**2.8**	**98.5**	**10**	**0.001**	**10.88**
	0.01	0.02	3.8	112	13	0.002	16.36
0.9	0.001	0.03	3.82	119.6	14.8	0.002	10.23
	0.01	0.03	2.7	106	11.6	0.001	15.77

Note: Acceptable crossover and mutation rates (i.e. based on convergence to the actual parameter values) are shown in bold type.

4.3.5 Conclusions of GAs operator study

Following conclusions were made based on the results of Sections 4.3.1-4.3.4

- GAs operators are sensitive to the number of model parameters that needs to be optimised in the application.

- If the number of parameters to be optimised is small (i.e. 2 or less), GAs operators did not play an important role in converging to the *optimum* model parameter set and therefore GAs operators recommended in the literature can be used.
- Small population sizes (i.e. between 25 – 50) are very efficient to use for optimisation of urban drainage models with a small number of parameters (i.e. 2 or less).
- For models with large number of parameters (5 or more), GAs operators play an important role in converging to the *optimum* parameter set.
- In this study, population size of 100, proportionate selection method, crossover rate of 0.6 and mutation rate of 0.001 gave the best results for pervious area parameters, and therefore they are recommended for optimisation of urban drainage models with large number of parameters (i.e. 5 or more).
- Furthermore, the efficiency of the parameter convergence can be improved by limiting the parameter range and accuracies of model parameters to the required level.
- Further studies are required to study the behaviour of population size and number of simulations with string length.

4.4 Estimation of Impervious Area Model Parameters Using GAs

4.4.1 Overview

As stated in Section 4.2, genetic algorithms (GAs) optimisation technique was used for calibration of the XP-UDD model of the Kew catchment, using available rainfall/runoff data. Then the model was validated using different data sets of rainfall/runoff events of the catchment, which were not used in calibration. Seven model parameters were identified for calibration of the XP-UDD model, two related to the impervious areas and the other five related to the pervious areas. These seven parameters were the percentage of the impervious area (*%A*), depression storage of the impervious area (DS_i), overland flow roughness of the pervious area (n_p), depression storage of the pervious area (DS_p), and the three Horton's soil infiltration parameters (f_o, f_c and k). These parameters were also considered in the GAs operator study of Section 4.3.

As stated in Section 2.2, different areas (i.e. impervious and pervious areas) of urban catchments respond differently to storm events of different magnitudes, and therefore it is necessary to consider the magnitude of storm events in calibration of urban drainage models. Hence, the observed *small* storm events of the catchment can be used to estimate the impervious area parameters, as they (generally) produce runoff only from impervious areas. However, the *large* storm events produce runoff from both impervious and pervious areas. Therefore, the observed *large* storm events can be used to estimate the pervious area parameters, keeping the impervious area parameters obtained from calibration using the *small* storm events constant.

The Kew catchment was continuously monitored for rainfall and runoff as part of the data acquisition program conducted by Victoria University during 1996-1999 (Section 4.2). However, it was found that no significant *large* storms were recorded during the monitoring period for this catchment, which were large enough to produce pervious area runoff (Dayaratne 2000). Therefore, only the impervious area parameters were estimated using the available observed *small* storm events. The magnitude and the temporal pattern of storms were measured using automatic electronic tipping bucket type pluviometers with 0.2 mm accuracy. Ultrasonic Doppler type flow meters were used to monitor the stormwater runoff at the catchment outlet and one other location of the catchment (Figure 4.2), continuously at two-minute intervals. The details of the data acquisition program can be found in Maheepala (1999), Maheepala and Perera (1999) and Maheepala et al. (2001)

Dayaratne (2000) used several Melbourne metropolitan area catchments (including the Kew catchment used in this study), which were monitored under the above data acquisition program to calibrate the ILSAX (O'Loughlin 1993) models of these catchments. He used several methods to check the consistency and accuracy of the observed data, before using them for model calibration. These methods are described in detailed in Maheepala et al. (1999), Dayaratne (2000) and Maheepala et al. (2001) and they are listed briefly below.

- Graphical time series plots of measured runoff depth and velocity with rainfall for storm events - These plots should match the flow and velocity patterns and should be consistent with rainfall (i.e. plot should show runoff peak sometime after the rainfall peak). Similarly, as the runoff velocity increases, these plots should show an increase in the runoff depth and vice versa.

- Use of plots showing flow at the catchment outlet and upstream monitoring points when there were several monitoring stations within the catchment – These plots in general can be used to detect timing errors, as the runoff peak occurs sometime after the rainfall peak. Furthermore, the time of concentration of internal sub catchments represented by upstream flow monitoring sites should be smaller than that of the whole catchment.
- Use of Rainfall-runoff depth plots (Section 2.2.3) - The consistency of the observed data can be checked for each storm event, by computing and comparing the rainfall and runoff depths. The total runoff depth should be always less than the total rainfall depth for each storm event.

Based on above data consistency and accuracy checks, Dayaratne (2000) identified five storm events for calibration of the Kew catchment, as listed in Table 4.14. However, as stated earlier they were all *small* storm events and have low runoff coefficients because of the high initial losses. Of these five *small* storm events, three storm events were considered for calibration and the other two were considered for validation in this study (Table 4.14). It should be noted that only total catchment was considered in this study, as the aim of this study was to demonstrate the capability of using GAs for urban drainage model calibration.

4.4.2 Model calibration

First, it was necessary to prepare the XP-UDD model of the Kew catchment for model calibration. This model has already been assembled for the GAs operator study (Section 4.3), except that the design storms were replaced with calibration storm events showing details of both rainfall hyetograph and runoff hydrograph. Detail descriptions of the preparation of XP-UDD and GENESIS input data files were given in Section 4.4.2.1. Once these data files were prepared for each calibration storm event, the integrated GENESIS/XP-UDD (Section 3.4) was run and the results analysed to yield the calibration model parameters.

Table 4.14 Details of the Selected Storm Events for Kew Catchment (Dayaratne 2000)

Event properties	Calibration events			Validation events	
Event number	1	2	3	4	5
Date of occurrence	29/05/97	25/01/98	20/04/98	31/10/97	12/04/98
Total rainfall duration (min)	130	192	298	148	136
Total rainfall depth (mm)	5.7	4.8	6.0	4.8	2.4
Maximum 2 min. intensity (mm/h)	30	12	8	12	3
ARI of storm event (year)	<1	< 1	< 1	< 1	< 1
Average intensity of most severe burst (mm/h)	24	6.5	6.5	18	2.3
Stormwater runoff volume (m^3)	131	154	228	137	82
Maximum discharge (m^3/s)	0.101	0.032	0.050	0.097	0.020

4.4.2.1 Input data files

(a) XP-UDD

As described in Section 4.3.1(a), the XP-UDD model of the Kew stormwater drainage network was assembled using the information on existing pits and pipes on the network, as shown in Figure 4.4. In addition, the two impervious area parameters that require calibration and the five pervious area parameters were also entered into the data file. Two impervious area parameters were refined in the GAs calibration process. The pervious area parameters were not considered in calibration, since it was considered that there was no pervious area runoff contribution from these small events. This was checked for calibration and validation storm events and found that there was no pervious area runoff contribution. Therefore, reasonable values from literature were used for pervious area parameters. The value of *%A* was estimated from drainage plans and contour maps. Even though *%A* was initially estimated from the drainage plans and contour maps for each sub catchment area separately and entered them in the input data files, when calibrating it was assumed *%A* as a single value for the whole catchment to avoid the increase of number of parameters to be calibrated. During calibration, GENESIS generated a single value of

%A, according to the user specified parameter range. A reasonable value from literature was used for DS_i since there was no other guidance available to obtain this parameter, and again DS_i was optimised during calibration. The above XP-UDD data file was prepared for each calibration storm event by entering relevant rainfall/runoff data.

(b) GENESIS

The results of the *optimum* GAs operator set investigations carried out in Section 4.3 were used in preparing the GENESIS input data file. These results were:

- Any GAs operator set could be used for estimating urban stormwater drainage model parameters with two or less model parameters. Therefore, the default values of GENESIS, which include proportionate selection, two-point crossover, crossover rate of 0.6 and mutation rate of 0.001 can be used.
- A population size of 25 with 1200 simulations was found to be adequate.
- Gray coding was found to be superior to binary coding from literature.

4.4.2.2 Results of calibration

The impervious area parameters of *%A* and DS_i were calibrated for the Kew catchment with the selected three observed rainfall/runoff storm events (Table 4.13). All parameter sets converged to one single set in the final generation, which was considered as the *optimum* parameter set for each of these storm events. The XP-UDD model was then run with this parameter set to obtain the modelled hydrograph. The modelled hydrograph was compared with the corresponding observed hydrograph, as shown in Figures 4.26 to 4.28. All events produced reasonable calibration results and a reasonable match was seen between modelled and observed hydrographs, which was considered to be satisfactory. All three events had multi peaks, and calibration showed that the shape, peak discharge, time to peak and multi peaks were modelled for events 1 and 3 with good accuracy (Figures 4.26 and 4.28). However, there were some differences in the shapes of the modelled and observed hydrographs for event 2 (Figure 4.27). The differences in all these events could be due to following reasons (Maheepala 1999).

- Inaccuracy of measured rainfall and runoff that was used in the modelling

- Non-uniform rainfall distribution over the study catchment - Since the catchment is relatively small, the distribution of rainfall was assumed uniform in the models. However, if the actual rainfall that occurred were not uniformly distributed over the entire catchment, the peaks and the shapes of the modelled and observed hydrographs would be different.
- Leakage of groundwater into the drainage system through pipes joints or pipes cracks. This was not modelled in this study.

The *optimum* parameter set obtained for each calibration event was tabulated in Table 4.15. As can be seen from this table, there is a fair amount of scatter in the model parameters obtained from different storm events. This scatter could be due to the deficiency in the model structure (i.e. model does not simulate all processes of the drainage system adequately), and inaccuracies in rainfall/runoff and other data used. In addition, when two (or more) parameters have to be calibrated simultaneously, there may be different combinations of parameters that yield the same output response (Dayaratne 2000).

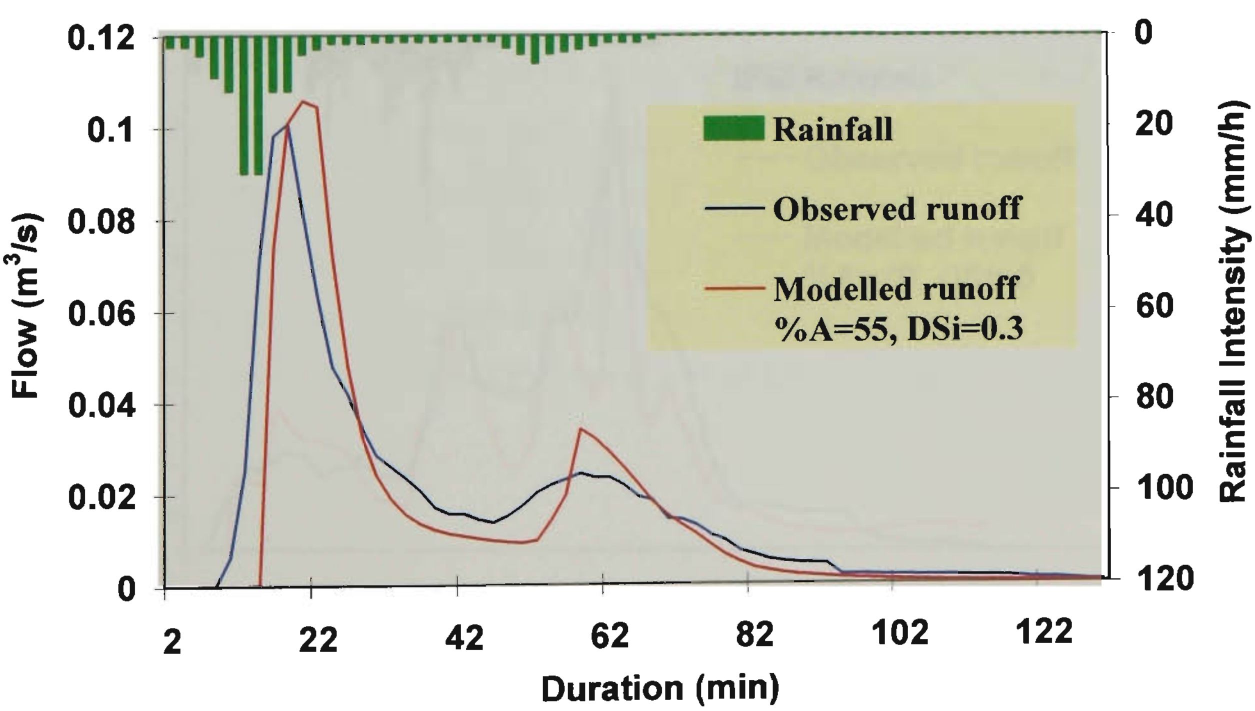


Figure 4.26 Calibration Results of Event 1

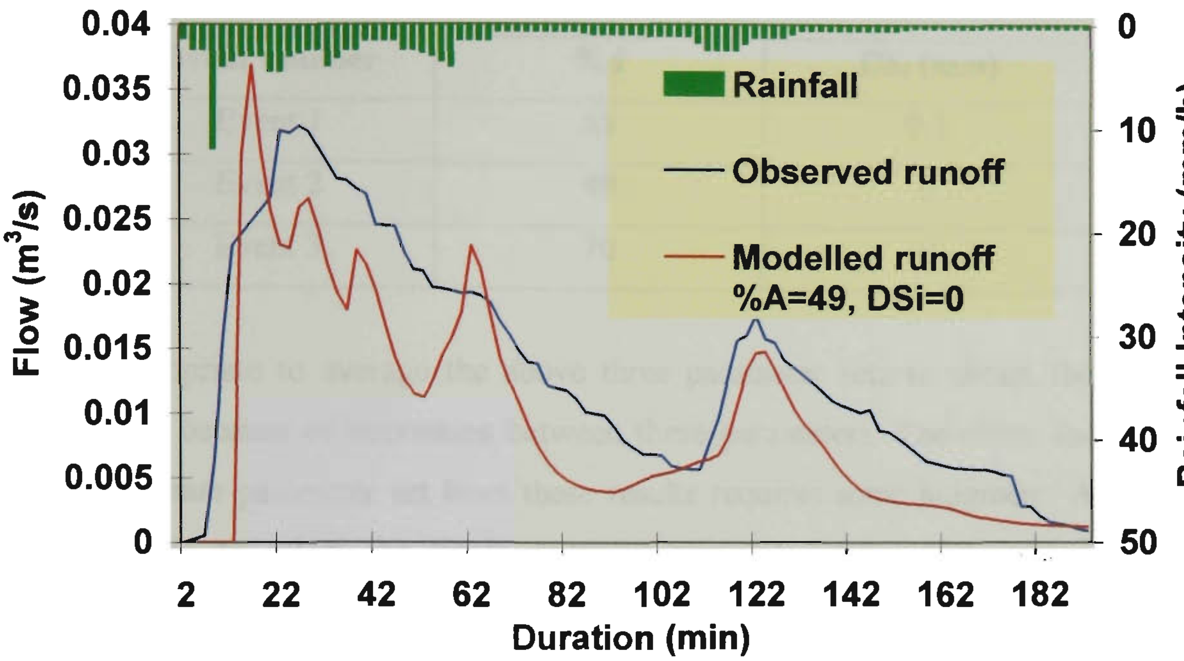


Figure 4.27 Calibration Results of Event 2

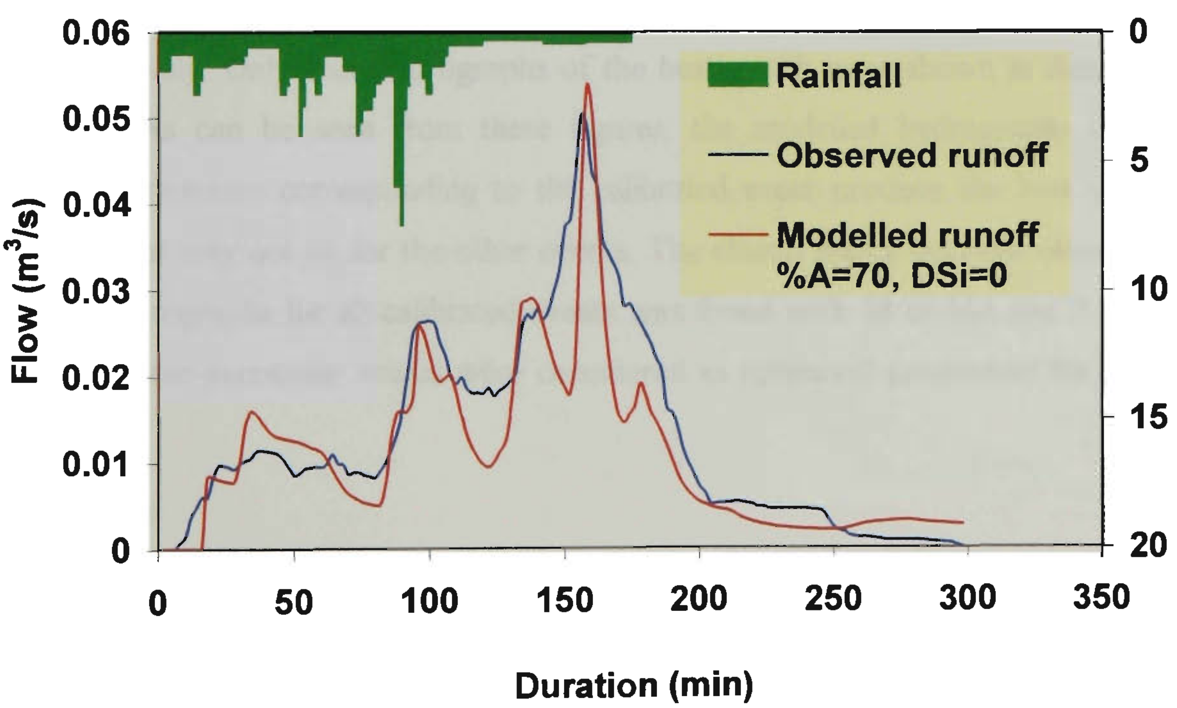


Figure 4.28 Calibration Results of Event 3

Table 4.15 Calibration Results

Event number	%A	DS_i (mm)
Event 1	55	0.3
Event 2	49	0
Event 3	70	0

It is not appropriate to average the above three parameter sets to obtain the *optimum* parameter set, because of interaction between these parameters. Therefore, the selection of single *optimum* parameter set from these results requires some judgment. An attempt was then made to select the single *optimum* parameter set, which best models all calibration events simultaneously.

The three *optimum* parameter sets in Table 4.16 and the mean parameter set of the optimised sets (i.e. $\%A$ = 58, DS_i = 0.1) were used in XP-UDD to simulate the three events used for calibration. All data of the XP-UDD data file except $\%A$ and DS_i were same as for calibration in these simulations. The predicted hydrographs obtained for events 1, 2 and 3 with these different $\%A$ and DS_i were shown in Figures 4.29, 4.30 and 4.31 respectively. Only four hydrographs of the best match were shown in these figures for clarity. As can be seen from these figures, the modelled hydrographs using the calibrated parameters corresponding to the calibrated event produce the best match for that event, but may not be for the other events. The closest match between observed and modelled hydrographs for all calibrated events was found with 58 of $\%A$ and 0.1 of DS_i. Therefore, these parameter values were considered as optimised parameters for the Kew catchment.

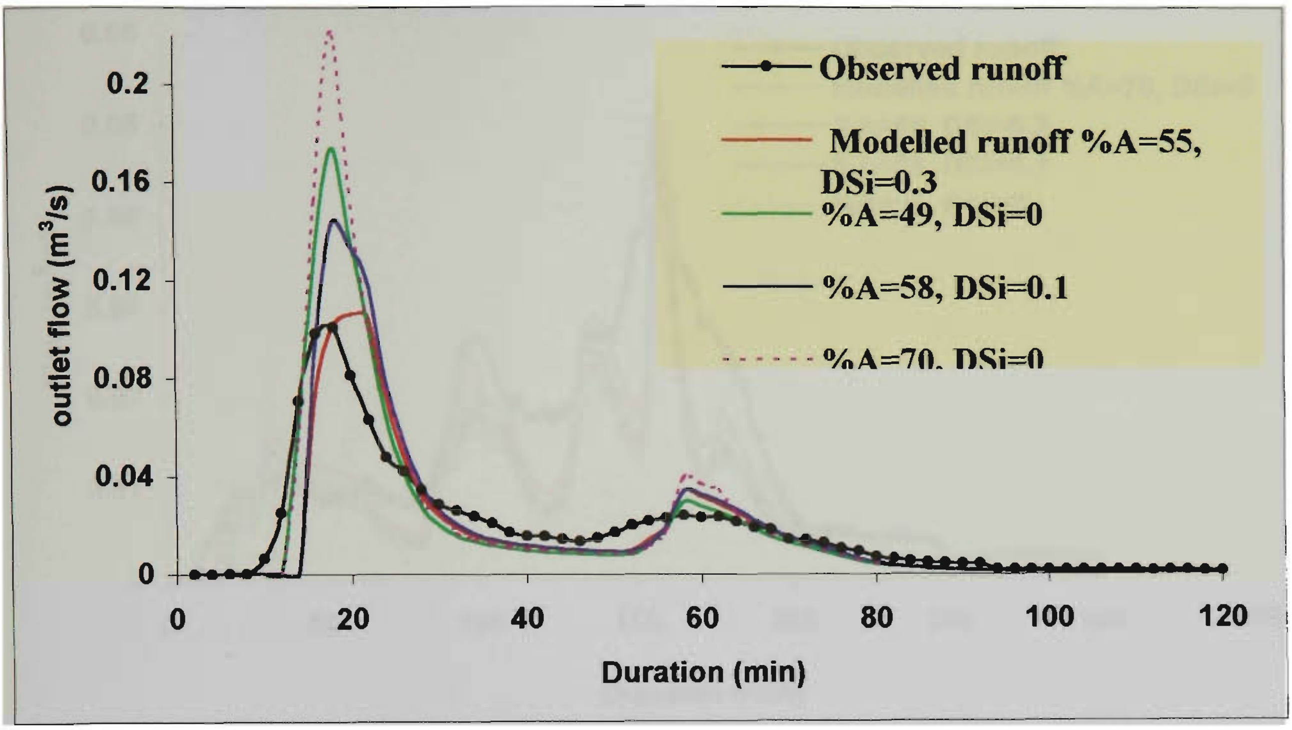


Figure 4.29 Selection of Single Parameter Set - Event 1

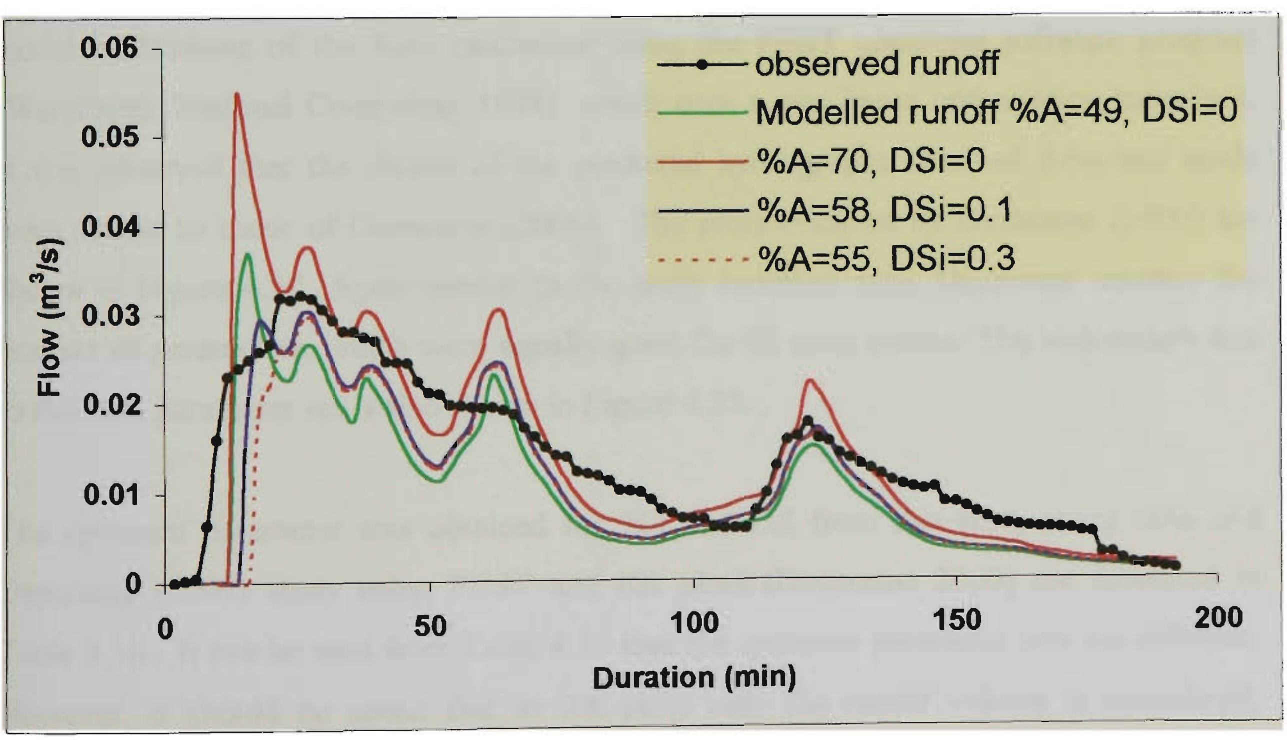


Figure 4.30 Selection of Single Parameter Set - Event 2

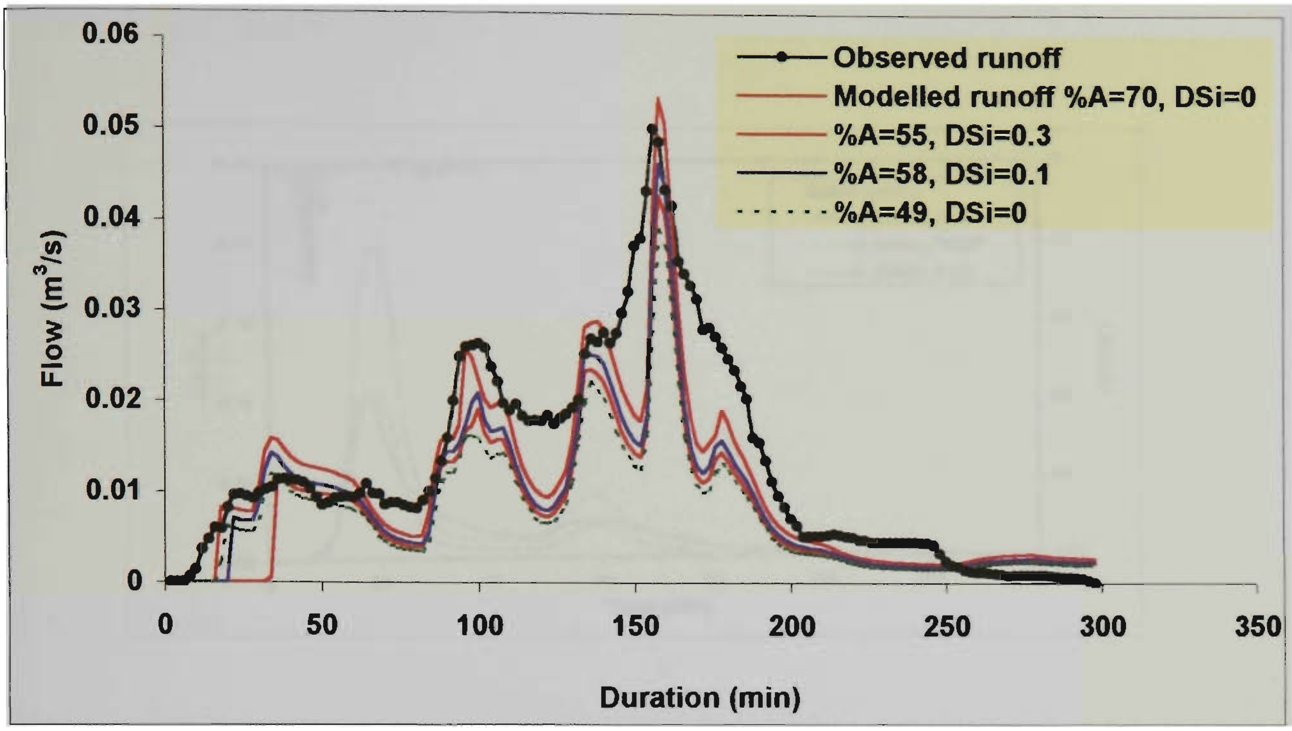


Figure 4.31 Selection of Single Parameter Set - Event 3

As stated in Section 4.4.1, Dayaratne (2000) used the above calibration events for ILSAX model calibrations of the Kew catchment using the PEST computer software program (Watermark National Computing 1998), which uses a non-linear optimisation technique. It was observed that the shapes of the predicted hydrographs obtained from this study were similar to those of Dayaratne (2000). The plots obtained by Dayaratne (2000) are shown in Figure 4.32. Again similar to the study reported here, Dayaratne selected the *best* set of parameters, which were equally good for all three events. The hydrograph due to this best parameter set is also shown in Figure 4.32.

The *optimum* parameter sets obtained for *%A* and DS_i from this study using GAs and Dayaratne (2000) study using PEST and RR plots (Dayaratne 2000) are tabulated in Table 4.16. It can be seen from Table 4.16 that the *optimum* parameter sets are different. However, it should be noted that in RR plots only the runoff volume is considered, whereas in model calibration using both GAs and PEST all hydrograph attributes such as runoff volume, peak discharge, time to peak discharge and hydrograph shape are considered and therefore model calibration values can be considered as more realistic than the values from the RR plots.

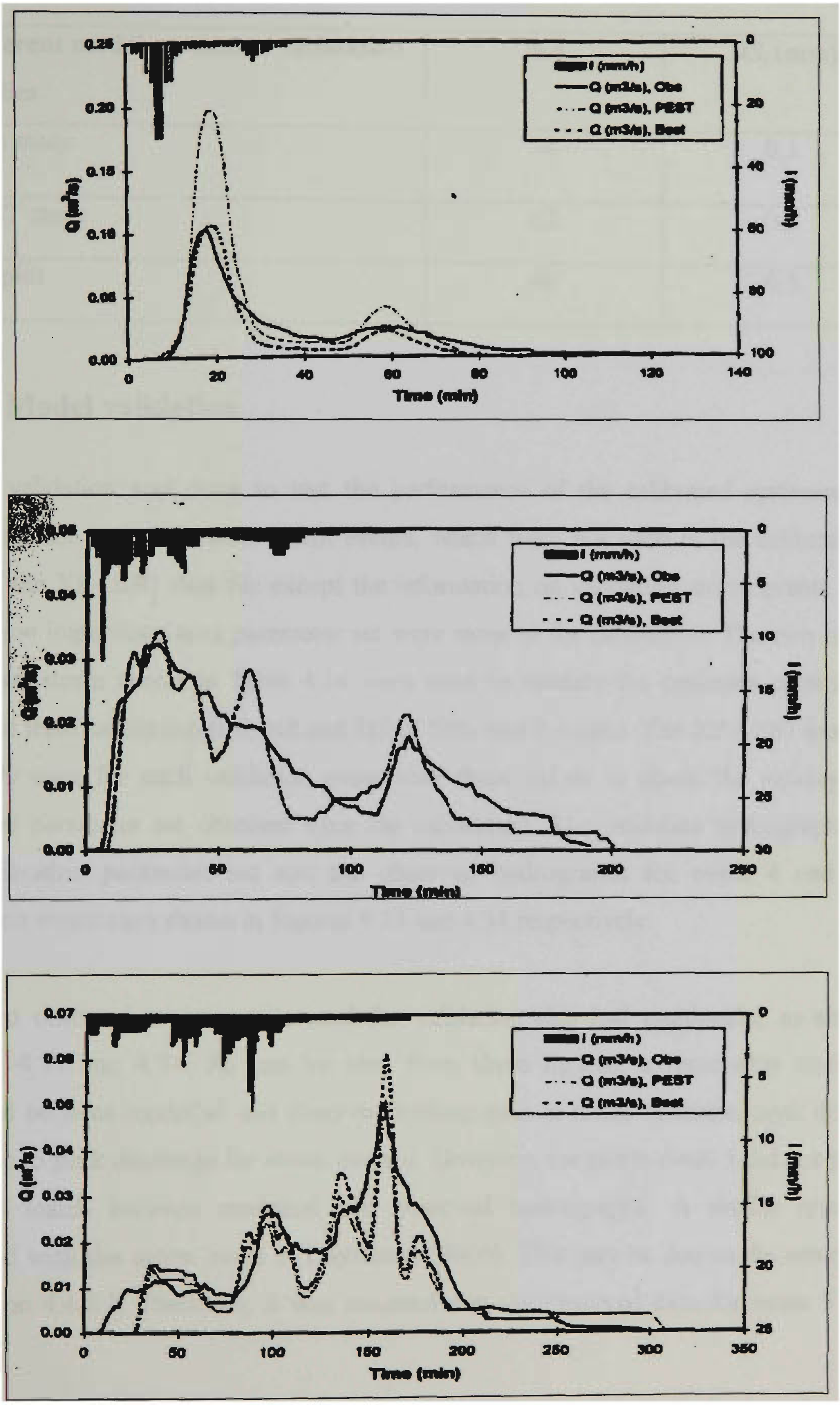


Figure 4.32 Calibration Results of Event1, 2 and 3 of Dayaratne (2000) Study

Table 4.16 Impervious Area Parameter Sets Obtained from GAs, PEST and RR Plots

Different model parameter estimation studies	***%A***	**DS_i (mm)**
GAs study	58	0.1
PEST study	62	0.5
RR plot	40	0.5

4.4.3 Model validation

Model validation was done to test the performance of the calibrated *optimum* model parameter set on independent storm events, which were not used in the calibration. All data of the XP-UDD data file except the information on validation storm events and the calibration impervious area parameter set were same as for calibration. The two observed validation storm events in Table 4.14 were used to validate the optimum parameter set obtained from calibration (i.e. *%A* and DS_i of 58% and 0.1 mm). The XP-UDD model was run only once for each validation event with these values to check the validity of the *optimum* parameter set obtained from the calibration. The modelled hydrographs using the calibration parameter set and the observed hydrographs for event 4 and 5 (i.e. validation events) are shown in Figures 4.33 and 4.34 respectively.

The two observed storm events used for validation also had multipeaks, as shown in Figures 4.33 and 4.34. As can be seen from these figures, a reasonable match was obtained between modelled and observed hydrographs in terms of shape, peak discharge and time to peak discharge for storm event 4. However, the storm event 5 did not produce a good match between modelled and observed hydrographs. A similar result was observed with this storm event in Dayaratne (2000). This may be due to the errors listed in Section 4.4.2.2. Therefore, it was assumed that the observed data for event 5 was in error.

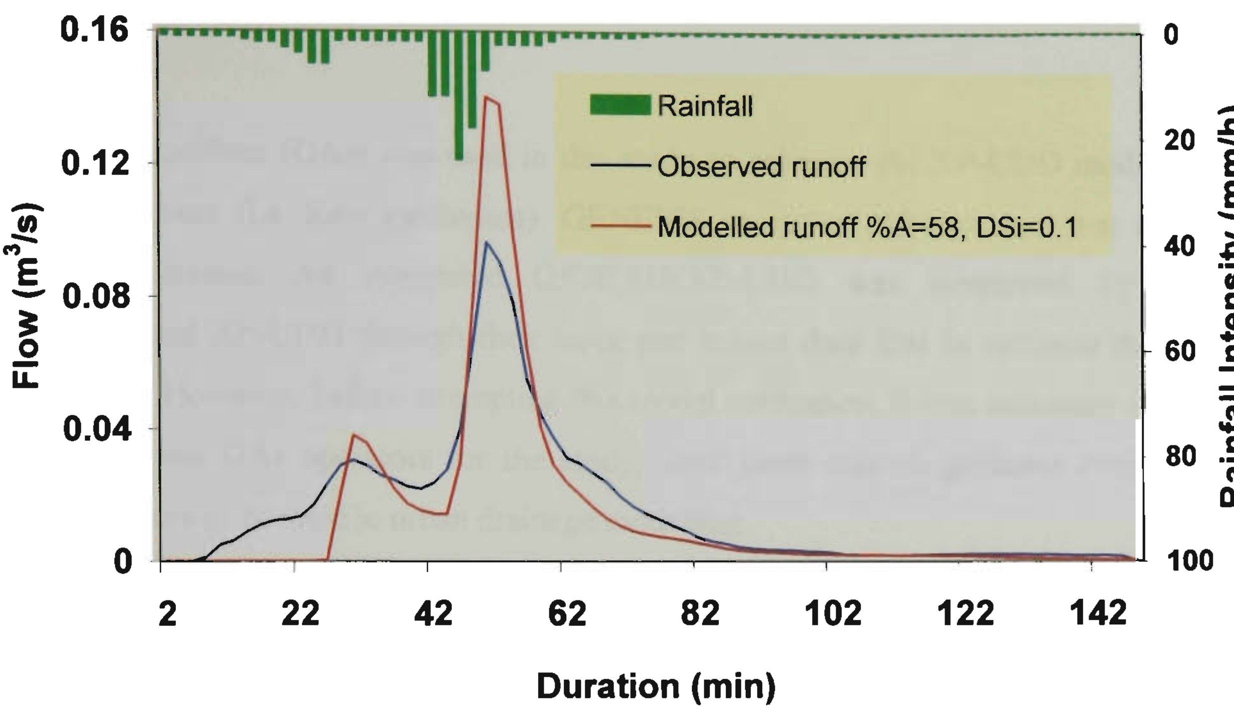


Figure 4.33 Validation Results of Event 4

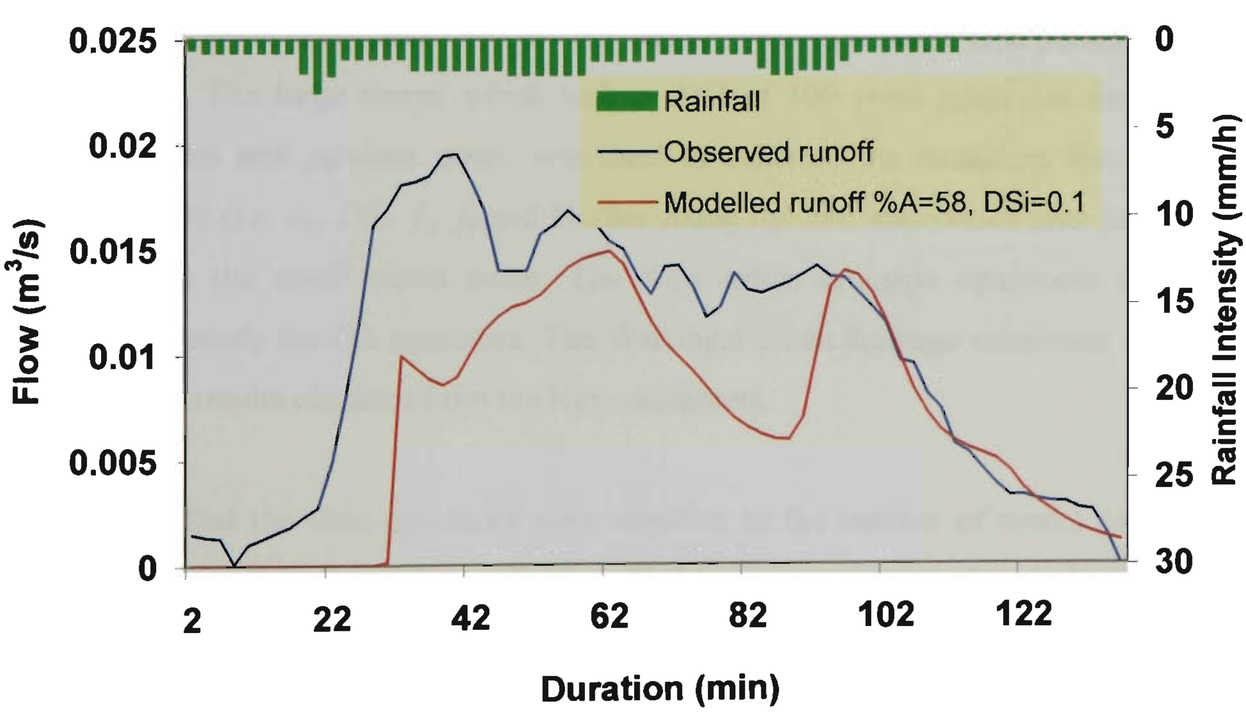


Figure 4.34 Validation Results of Event5

4.5 Summary

Genetic Algorithms (GAs) was used in this study to calibrate the XP-UDD model of the study catchment (i.e. Kew catchment). GENESIS computer software tool was used for GAs optimisation. An integrated GENESIS/XP-UDD was developed by linking GENESIS and XP-UDD through their input and output data files to optimise the model parameters. However, before attempting this model calibration, it was necessary to obtain the appropriate GAs operators for the study, since there was no guidance available for GAs operators to be used in urban drainage modelling.

A systematic trial and error procedure was used to investigate the *optimum* GAs operators for this study. The study was conducted as two investigations to estimate impervious and pervious area parameters, as the runoff generation mechanism is different in these two areas, which vary according to the magnitude of the rainfall intensity. Two design storm events of duration 30 minutes were considered as input rainfall in the study. The *small* storm, which had an Annual Recurrence Interval (ARI) of 1 year produced runoff only from the impervious areas, was used to calibrate the two impervious area parameters (i.e. $\%A$ and DS_i). The *large* storm, which had an ARI of 100 years generated runoff from both impervious and pervious areas, was used to calibrate the remaining five pervious area parameters (i.e. n_p, DS_P, f_c, f_0 and k) after fixing the two impervious area parameters obtained from the *small* storm event. The Kew urban drainage catchment was used extensively to study the GA operators. The Warringal urban drainage catchment was used to validate the results obtained from the Kew catchment.

It was found that the GAs operators were sensitive to the number of model parameters that needs to be optimised in the application. If the number of parameters to be optimised was small as in the case of estimating impervious area parameters (i.e. only 2 parameters considered), GAs operators did not play an important role in converging to the optimum model parameter set, and therefore general GAs operators recommended in literature can be used. Furthermore, the small population sizes (i.e. between 25-50) were very efficient for use in model parameter optimisation of urban drainage models with two or less parameters.

For models with large number of parameters (5 or more), GAs operators played an important role in converging to the optimum parameter set. It was observed that the string length of the chromosome had an impact on the selection of the size of the population. However, further investigations need to be carried out to define a relationship between string length and population size for urban stormwater drainage model parameter optimisation. Furthermore, the efficiency of the parameter convergence can be improved by minimising the parameter range and precision of the coding (i.e. reducing the string length). In this study with five parameters, population size of 100, proportionate selection, crossover rate of 0.6 and mutation rate of 0.001 gave the best results, and therefore they are recommended for optimisation in urban drainage models with large number of parameters (i.e. more than 5).

After selecting the *optimum* GAs operator set, the XP-UDD model calibration of the Kew catchment was conducted using GAs. Rainfall/runoff data available for this catchment at Victoria University during the period of 1996-1999 had been analysed to select storm events for use in calibration in a previous study. It was found that the catchments had reliable data only for *small* storms during this period, where the runoff was generated only from the impervious areas. These events were not large enough to produce pervious area runoff. Therefore, only the two impervious area parameters (i.e. $\%A$ and DS_i) were estimated using *small* storm events in this study. Five observed storm events were selected from the previous study to use in this study. Of these five events, three were used for calibration of model parameters, while the other two were used for validation of the results obtained from the calibration.

The results of the calibration showed that the shape, peak discharge, time to peak and multi peaks were modelled with a reasonable accuracy. However, it was observed that there was a fair amount of scatter in the model parameters obtained from different calibration storm events. Therefore, to obtain a single *optimum* parameters set, the three *optimum* parameter sets and the mean parameter set of the optimised parameter sets were used in XP-UDD to simulate the three events used for calibration. The single *optimum* parameter set was then selected as the parameter set, which best modelled all three calibration events. This parameter set was then validated using the two validation storm events and found a reasonable comparison between modelled and observed hydrographs.

The percentage of impervious area and the impervious area depression storage (i.e. $\%A$ and DS_i) for the Kew catchment had also computed using rainfall-runoff depth plots (i.e. RR plots) and using a non-linear parameter optimisation method (but with a different urban stormwater drainage model) in a previous study. It was found that the results obtained from GA were different to those of the RR plot, but reasonably close with the other study. It should be noted that only the runoff volume is considered in RR plots, whereas model calibration using GA and the non-linear parameter optimisation method used all hydrograph attributes such as runoff volume, peak discharge, time to peak discharge and hydrograph shape. Therefore, the parameters produced from calibration using hydrograph modelling (i.e. using GA and non-linear parameter optimisation) can be considered more realistic compared to those from the RR plot. It was found in this study that GA could be used to estimate the model parameter values successfully in urban stormwater drainage models.

CHAPTER 5

ESTIMATION OF SOIL INFILTRATION PARAMETERS

5.1 Introduction

As reviewed in previous chapters, management of stormwater runoff from urban catchments is a complex task. The stormwater drainage software tools are being commonly used to design and analyse stormwater drainage systems in managing stormwater. However, the reliability of these models depends on the correct selection of the model parameter values. In order to reduce the uncertainty and errors in the model prediction, the model parameter values that can be effectively measured by field measurements should be determined through such measurements. If the measurable parameters are estimated through field tests or other means, then the other parameters can be effectively obtained through model calibration, which reduces uncertainty in overall calibration and model prediction.

Infiltration plays an important role in runoff generation in pervious areas of urban catchments. It is a complex process that can be defined, as vertical movement of water through the soil surface and into the soil profile in pervious areas. Water infiltrated through the soil may be retained in the upper soil layers or percolated through to the deeper layers eventually reaching groundwater. The maximum rate at which water can enter the soil at a particular point under a given set of conditions is known as the infiltration capacity (f_t). The actual infiltration rate equals the infiltration capacity only when the rainfall intensity equals or exceeds infiltration capacity. Otherwise, it is equal to the rainfall intensity. The infiltration rate of a soil profile approaches to a minimum constant rate as the storm continues and the soil profile becomes saturated. This infiltration rate is known as the saturated infiltration capacity (f_c).

Estimation of infiltration parameters, which represent the whole catchment, is a difficult task because of the presence of significant variability with respect to soil type and land use in the catchment. There are different types of infiltration measuring instruments available such as single-ring, double-ring, basin, furrow and sprinkler infiltrometers. Mbagwu (1997) carried out the double-ring infiltrometer tests to study the influence of soil physical properties on Philip (1957) and Kostiakov (1932) infiltration models in a farm area in Nigeria. Al-Qinna and Abu-Awwad (1998) compared the infiltrometer rates measured using different infiltrometers (sprinkler, furrow and basin) with the rates measured by single and double-ring infiltrometers. They reported that sprinkler and furrow infiltrometers gave similar infiltration rates to the double-ring infiltrometer, while the basin infiltrometer gave rates similar to the single-ring infiltrometer. Furthermore, they reported that increase in the initial moisture content decreased the initial infiltration rate by about 4-11% regardless of the infiltrometer type used.

As described in Chapter 3, the XP-UDD urban drainage software was selected to model the Kew catchments. XP-UDD has the option of using Green-Ampt (1973) or Horton (1940) models to model infiltration. The Horton's model was proposed to use in this study to model infiltration in pervious areas of the Kew catchment, since it had been used successfully in the past and the parameters can be easily obtained through field infiltrometer tests (Section 3.2.1).

The soil parameters that are responsible for infiltration in pervious areas of the Kew catchment were determined by conducting field infiltrometer tests. Three tests were conducted on three sites to allow for heterogeneity of the soil in the catchment. These test measurements were used to estimate Horton's infiltration parameters. These measured soil infiltration parameters can provide a reasonable parameter range for GA optimisation and can be then fine-tuned during the calibration process (through GA optimisation) to allow for heterogeneity of the soil characteristics, if sufficiently *large* observed rainfall/runoff data are available for the catchment. However, this was not done for the Kew catchment, since *large* storm events, which produce pervious area runoff were not available for the catchment. In order to understand different soil types and to determine the soil infiltration rates in different urban catchments, further nineteen soil infiltrometer field tests were conducted at several selected urban catchments in Victoria in this study.

This chapter begins with a description of the factors affecting infiltration, followed by the description of the double-ring infiltrometer apparatus. The aim and methodology including the details of installation and test procedures, and data analysis are then described. The detailed description of calculations and results of the Kew catchment tests are presented then, followed by the other Victoria-wide infiltration test results. Finally, the conclusions drawn from the study are presented.

5.2 Factors Affecting Infiltration

The process of water infiltrating through the soil is a complex interaction between rainfall intensity, soil type, surface cover conditions and many other factors. The main factors affecting the soil infiltration process are described below.

(a) Soil properties

The soil infiltration depends to a great extent on the soil type. In general, coarse-textured gravels and sands have higher infiltration capacities than fine-textured clays. Although the particle size and distribution have a major influence on infiltration rates, organic matter content, aggregation, tillage and compaction often modify the soil characteristics. Akram and Kemper (1979) reported that compaction from trucks being driven over a sandy loam soil just after a rain, reduced infiltration rates from 15 to 0.3 cm/h.

(b) Antecedent moisture conditions

The soil moisture content plays an important role since it determines how much storage is available for infiltration. If the soil is dry, the initial rate of infiltration is higher compared to the soil with high moisture content. If the water table is close to the soil surface, the soil will become quickly saturated and consequently less infiltration.

(c) Layered soils

In general, any profile discontinuity such as change in texture, pore size distribution will result in change in the rate of water movement through the soil. A course-textured material (eg. sand) overlies a fine textured material (eg. loam), the course layer controls the infiltration rate until the wetting front reaches the fine layer. Then the rate of infiltration depends upon the fine layer and water will accumulate in the surface layer (sand). If a finer textured material overlies a coarse material, the fine surface layer will govern the initial rate of infiltration. Water will not enter through the surface until it has accumulated in the fine layer to a point, where it can overcome the adhesive and cohesive forces of the pores in the fine layer. Then only, flow can take place into the larger pores of the underlying coarse layer (Gardner 1979).

(d) Rainfall intensity and surface sealing

Extremely high rainfall rates may cause destruction of the soil surface leading to surface sealing or the formation of soil crusts as the aggregates break down. This greatly reduces infiltration capacity and increases the potential for runoff and erosion. If rainfall occurs over a long period of time, the rate of infiltration decreases due to the high moisture condition of soil.

(e) Vegetation cover and entrapment of air

Vegetation cover can increase the infiltration rates through modification of the soil porosity and pore size distribution, and through interception of the raindrops by the plant canopy.

If air is trapped in the soil, the hydraulic conductivity is reduced, which reduces the rate of infiltration.

(f) Soil slope and land use

The soil surfaces with steeper gradients allow water to runoff quickly and therefore would have less infiltration, and vice versa.

The infiltration process varies according to the land use. As an example, the forest area has soil surface covered with mulch, which helps to retain more water for a long time, and therefore more infiltration in a forest area compared to an urban area (which has more impermeable surfaces).

5.3 Double-Ring Infiltration Test Apparatus

The standard double-ring infiltrometer (ASTM, 1994) was used in this study to measure the pervious area soil infiltration parameters of the study catchment (i.e. the Kew catchment). The apparatus consists of the following components, as shown in Figure 5.1.

Figure 5.1 Double-Ring Infiltrometer

- Two concentric rings (i.e. open cylinders) made of 3 mm hard alloy aluminum sheet approximately 500 mm high and having diameters of about 300 and 600 mm - These two rings are used to retain water above the ground surface. The outer ring acts as a barrier to encourage only vertical flow from the inner ring.

- Two calibrated Mariotte tubes (or graduated cylinders) having minimum volume capacity of 3000 ml - These tubes have closed-airtight tops designed to maintain a constant water head in the rings by delivering water, as water is lost through infiltration.

- Driving cap made of hard alloy aluminum (13 mm thick), diameter larger than that of the outer infiltrometer ring - This is to cover the rings to minimize evaporation of water during the test.

- Splash guards of 150 mm square rubber sheets - They are placed inside the rings to prevent erosion when water is poured at the start of the experiment.

- Driving equipment having a 5.5 kg mall and 50 mm x 100 mm x 900 mm wood or jack - This is used to drive the two rings into the ground.

5.4 Aim and Methodology

5.4.1 Aim

As stated earlier, the main aim of this part of the study was to measure the soil infiltration parameters of the Kew catchment. Soil infiltrometer field tests were conducted at three sites of the Kew catchment, which were selected after consultation with City of Boroondara officers to adequately represent the different soil conditions of the catchment. The study sites of the Kew catchment are shown in Figure 5.2.

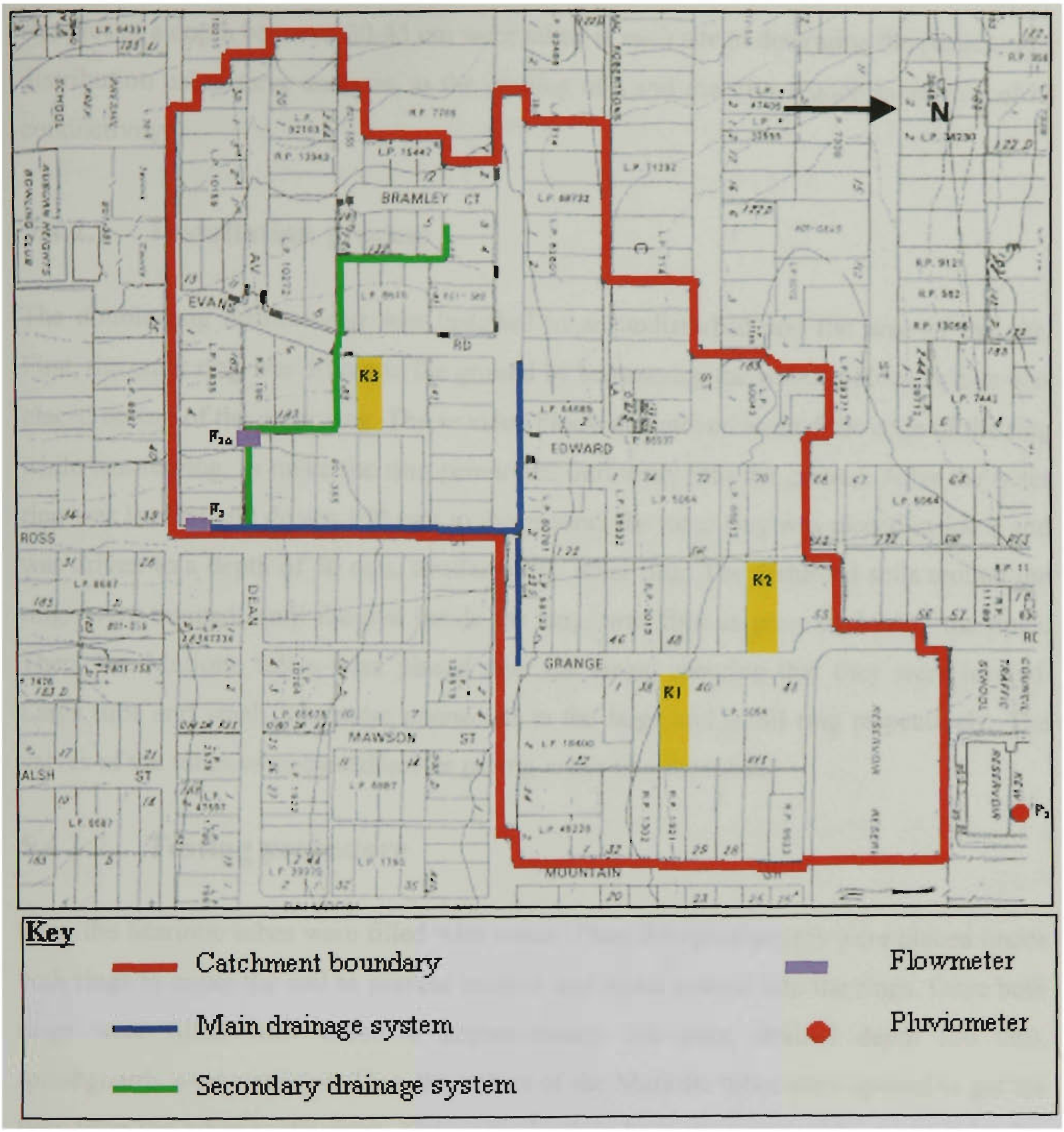


Figure 5.2 Study Sites in Kew Catchment

5.4.2 Methodology

Rainfall was measured during 5 days prior to the field test using a pluviometer, to determine the antecedent rainfall depths at the study sites. The double-ring infiltrometer was then installed at the site and the measurements were taken over approximately 6 hours, since the soils at the sites were of coarse grains. All three sites were in residential areas. Installation and testing were carried out according to ASTM (1994) standards. The tests in the Kew catchment were conducted during May in 2002. Furthermore, soil samples at a depth between 30-45 cm were taken at each site to determine the particle size distribution using sieve analysis, as the grading of a soil can give a good indication of its conductivity.

5.4.2.1 Installation process

The double-ring infiltrometer was installed in an undisturbed and flat area of the site. First, the outer ring was driven to the ground by hammering the wooden block, which was placed on top of the outer ring. The wooden block was moved around the edge of the ring while hammering, to make the ring penetrated uniformly into the ground. After the outer ring was leveled and driven 150 mm to the ground, the inner ring was placed inside it and was driven to a depth of 50 mm, similar to the outer ring. The disturbed soils around the rings were tamped, until the soil inside the rings was firm as prior to driving the rings. Then, the Mariotte tubes were placed near the rings, ensuring that they were leveled. Large tube and small tube were connected to the large and small ring respectively. The valves of the tubes were closed before poring water into the tubes.

5.4.2.2 Testing procedure

First, the Mariotte tubes were filled with water. Then the splashguards were placed inside both rings to cover the soil to prevent erosion and water poured into the rings. Once both rings were filled with water to approximately the same desired depth (30 cm), splashguards were removed. Then the valves of the Mariotte tubes were opened to get the flow from the tubes to the rings. The water depth in both rings were then measured using the attached measuring tapes on the sides of the rings, as soon as the water level of the tubes became constant and the two rings having an equal water depth. If the depth between the rings varied more than 5 mm, then the water level was adjusted by adding water. This water level was maintained for both rings at the start of each observation. The depth of water decreased in tubes and rings were recorded at intervals of 15 min for the first hour, 30 min. for the second hour and 60 min. during the remainder of the period at least for 6 hours or until after a relatively constant rate was obtained. The driving cap was placed over the rings during the intervals between measurements to minimize evaporation.

5.4.2.3 Data analysis

Soil Infiltration parameters (i.e. f_o, f_c and k) were estimated using the re-arranged form of the Horton's Equation [i.e. Equation (3.2)], as given in Equation (5.1).

$$\ln(f_t - f_c) = -kt + \ln(f_o - f_c) \qquad (5.1)$$

Data obtained from the experiment were used to compute the infiltration rate (f_t) at different times (t). A trial and error process was used first to estimate f_c and k. Several values of f_c were considered and $\ln(f_t - f_c)$ were plotted against t for each f_c. The straight line that best fitted the data, produced f_c for the site and the gradient of this line gave the parameter k. These f_c and k values were then substituted in Equation (5.1) to produce f_o corresponding each data point. The average value of these f_o values was taken as the f_o at the site. However, it should be noted that f_o depends on the soil moisture conditions at the time of the field experiment and will be different at other times.

In order to find the soil type of the site, sieve analysis was conducted in the laboratory for the soil samples collected from each site. Stack of sieves from 75 μm to 19 mm were used for this test by placing them vertically, with the mesh size decreasing downwards and the pan at the bottom. Each sieve was weighed before poured oven dried soil sample into the top sieve. Then the sieve stack was shaken using the mechanical sieve shaker and the each sieve was weighed together with the soil samples. The percentage by weight of the whole sample passing each sieve was calculated and particle size distribution was plotted on standard semi-log paper. The coefficients of uniformity (C_U) and curvature (C_C) (which are defined in Equations 5.2 and 5.2 – Craig, 1975) were determined based on percentage passing of soil particles to determine the soil type using the unified soil classification chart (Wagner 1957). A part of this chart is shown in Table 5.1.

$$C_U = \frac{D_{60}}{D_{10}} \qquad (5.2)$$

$$C_C = \frac{(D_{30})^2}{D_{60}D_{10}} \qquad (5.3)$$

where D_{10} is the particle size corresponding to 10% passing percentage

D_{30} is the particle size corresponding to 30% passing percentage

D_{60} is the particle size corresponding to 60% passing percentage

Table 5.1 Part of Unified Soil Classification Chart (Wagner 1957)

Group symbols	**Soil type**	**% Less than 0.06 mm**	C_U	C_C
GW	Well graded gravels and gravel sand mixtures, little or no fines	0-5	> 4	Between 1-3
GP	Poorly graded gravels and gravel sand mixtures, little or no fines	0-5	Fail to comply with the above	
SW	Well graded sand and gravelly sands, little or no fines	0-5	>6	Between 1-3
SP	Poorly graded sands and gravelly sands, little or no fines	0-5	Fail to comply with the above	

5.5 Calculations and Results

Although three sites (i.e. K_1, K_2 and K_3) were selected for soil infiltration tests in the Kew catchment, the test at site K_3 could not be completed, where clay soil was found and water barely penetrated through the soil. This observation is consistent with ASTM (1994), which states that the double-ring infiltrometer test is not suitable for clay soil. The soil infiltration parameters of the Horton's infiltration equation were then estimated for sites K_1 and K_2. Furthermore, the particle size distribution, the coefficients of C_U and C_C and the soil type were also determined at these sites. As an example, detail calculations are demonstrated below for site K1 and only a summary of results is given for site K_2.

5.5.1 Site K_1

The measurements obtained for the double-ring infiltrometer test at site K1 are tabulated in columns 2, 4, 5, 8 and 9 in Table 5.2. Infiltration rates (f_t) given in column (7) in Table 5.2 were computed for the inner ring by computing the volume of water lost in inner tube and ring, and then dividing it by the surface area of the inner ring and the time interval. Similar calculations were carried out for the outer ring [columns (10) and (11)].

Figure 5.3 illustrates the infiltration capacity (f_t) Vs. time for site K1. This figure shows an exponential curve, shape being similar to the curve defined by the Horton's infiltration model. The infiltration capacities computed based on water flow in both rings (i.e. inner and outer) is presented in Figure 5.3. However, only the inner ring measurements were used in subsequent calculations, as there was no lateral movement of water in the inner ring (and therefore only vertical flow) due to the presence of the outer ring. The infiltration is better represented by f_t values corresponding to the inner ring, since infiltration is defined as vertical movement of water through the soil surface and into the soil profile. As expected, the outer ring infiltration rates were higher than the inner ring rates due to the lateral movement of water from the outer ring, in addition to vertical downward flow.

As outlined in Section 5.4.2.3, f_c was obtained from trial and error, by plotting the relationship of $\ln(f_t - f_c)$ Vs. time and finding the best fit straight line for the field data set. Figure 5.4 shows the above relationship that fitted the best straight line, which produced f_c=12.51 cm/h. The gradient of this line was computed and converted to represent the units of hour. This value was the parameter k and was 0.86 h^{-1} for site K_1.

Once f_c and k were found, f_o was calculated from Equation (5.1) for each observation. Theoretically, calculated f_o values should be the same. However, due to experimental errors and the infiltration process was modeled by a theoretical curve, it varies from 19.21 to 27.10 cm/h.

Table 5.2 Observations and Calculation sheet for Site K_1

5 Days Rainfall	Day	-1	-2	-3	-4	-5
	Rainfall (mm)	3.2	0.2	0	1	0

Mariotte tube details: Large Tube: Diameter 16.2 cm, Area 206.12 cm^2; Small Tube: Diameter 9 cm, Area 63.62 cm^2

Ring details: Outer Ring Area 2073.5 cm^2; Inner Ring Area 730.91 cm^2

Time record (min)			**Inner ring reading**				**Outer ring reading**			
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
	Time interval (min)	**Total time (min)**	**Tube (cm)**	**Ring (cm)**	**Volume cm^3**	**f_t cm/h**	**Tube (cm)**	**Ring (cm)**	**Volume cm^3**	**f_t cm/h**
Start	5	5	10.5	12.0	1589.06	26.09	14.0	12.0	4208.8	24.36
End			8.5	14.0			13.7	14.0		
Start	5	10	10.0	12.0	1312.53	21.55	13.8	12.0	4208.8	24.36
End			8.9	13.7			13.5	14.0		
Start	5	15	10.0	12.0	1166.35	19.15	13.6	12.0	3752.9	21.72
End			8.9	13.5			13.5	13.8		
Start	15	30	8.9	12.1	3082.69	16.87	13.5	12.1	9475.0	18.28
End			6.4	16.1			12.8	16.6		
Start	15	45	9.0	12.0	2936.50	16.07	12.9	12.0	8811.8	17.00
End			6.5	15.8			12.4	16.2		
Start	30	75	6.5	12.0	5631.40	15.41	12.4	12.0	16419.4	15.84
End			3.0	19.4			10.2	19.7		
Start	60	135	10.6	12.0	10226.9	13.99	10.5	12.0	30361.4	14.64
End			1.5	25.2			-2.0	25.4		
Start	60	195	4.2	12.0	9648.16	13.20	13.2	12.0	30606.3	14.76
End			1.9	25.0			-2.5	25.2		
Start	60	255	1.9	12.0	9330.21	12.77	-2.5	12.0	29029.0	14.0
End			2.3	24.8			-2.5	26.0		
Start	60	315	2.3	12.0	9209.48	12.60	-2.5	12.0	28821.7	13.9
End			2.3	24.6			-2.5	25.9		

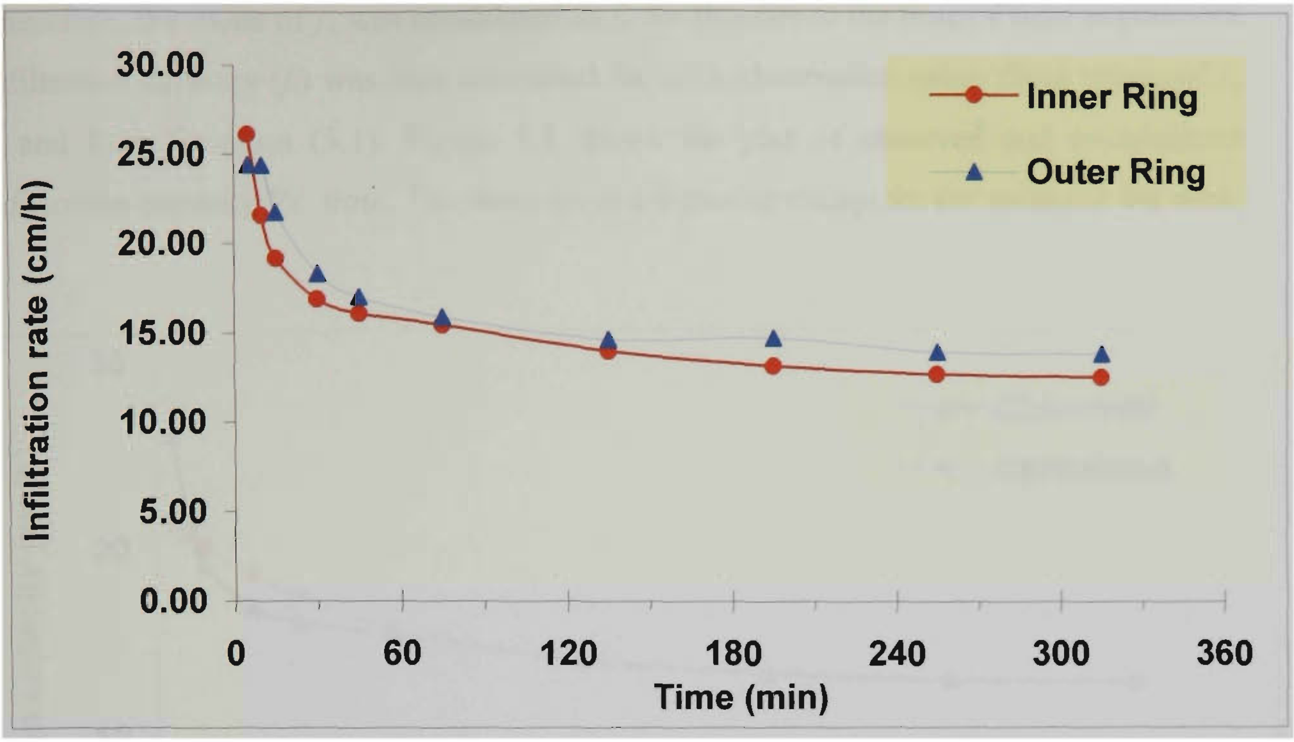


Figure 5.3 Infiltration Capacity (f_t) Vs. Time for Site K$_1$

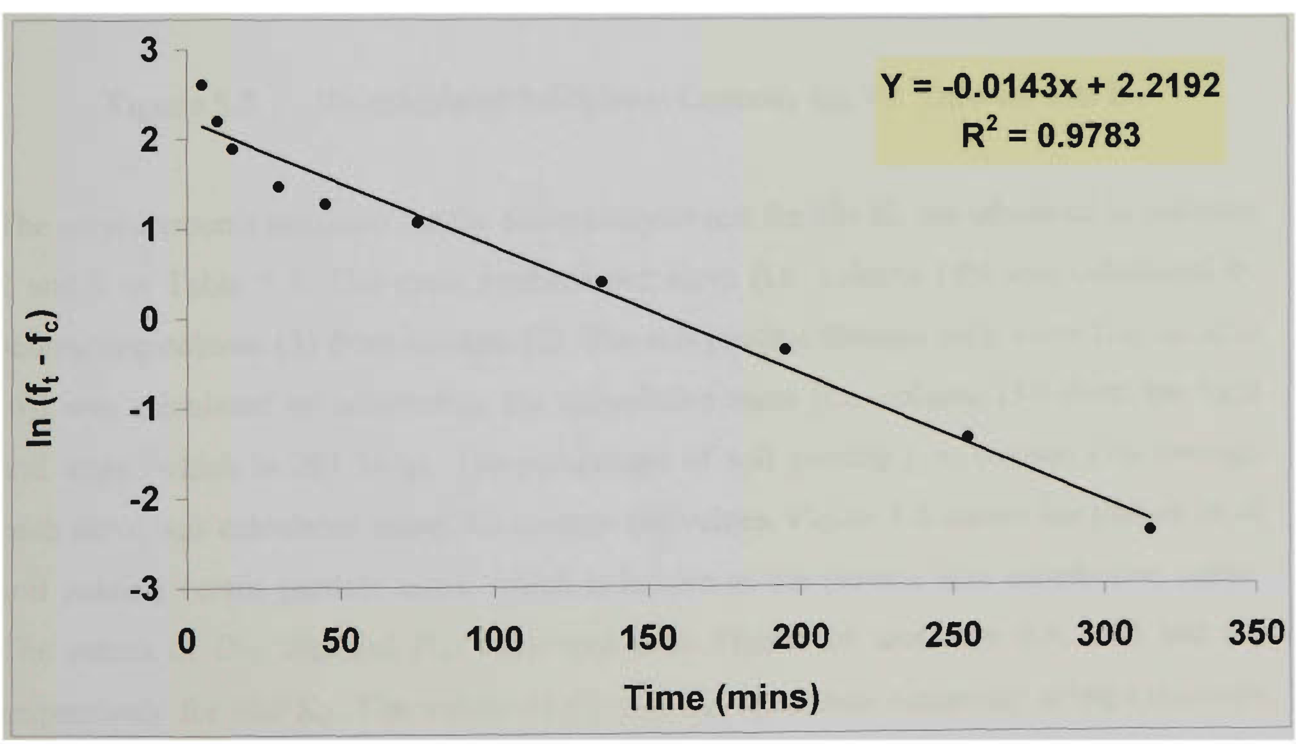


Figure 5.4 $\ln(f_t - f_c)$ Vs. Time for Site K$_1$

Therefore, the mean of f_o was considered as f_o for this site at the time of field experiment. Infiltration capacity (f_t) was then computed for each observation using these values of f_o, f_c and k in Equation (5.1). Figure 5.5 shows the plot of observed and re-calculated infiltration capacity Vs. time. The two curves are similar except for the values at the start.

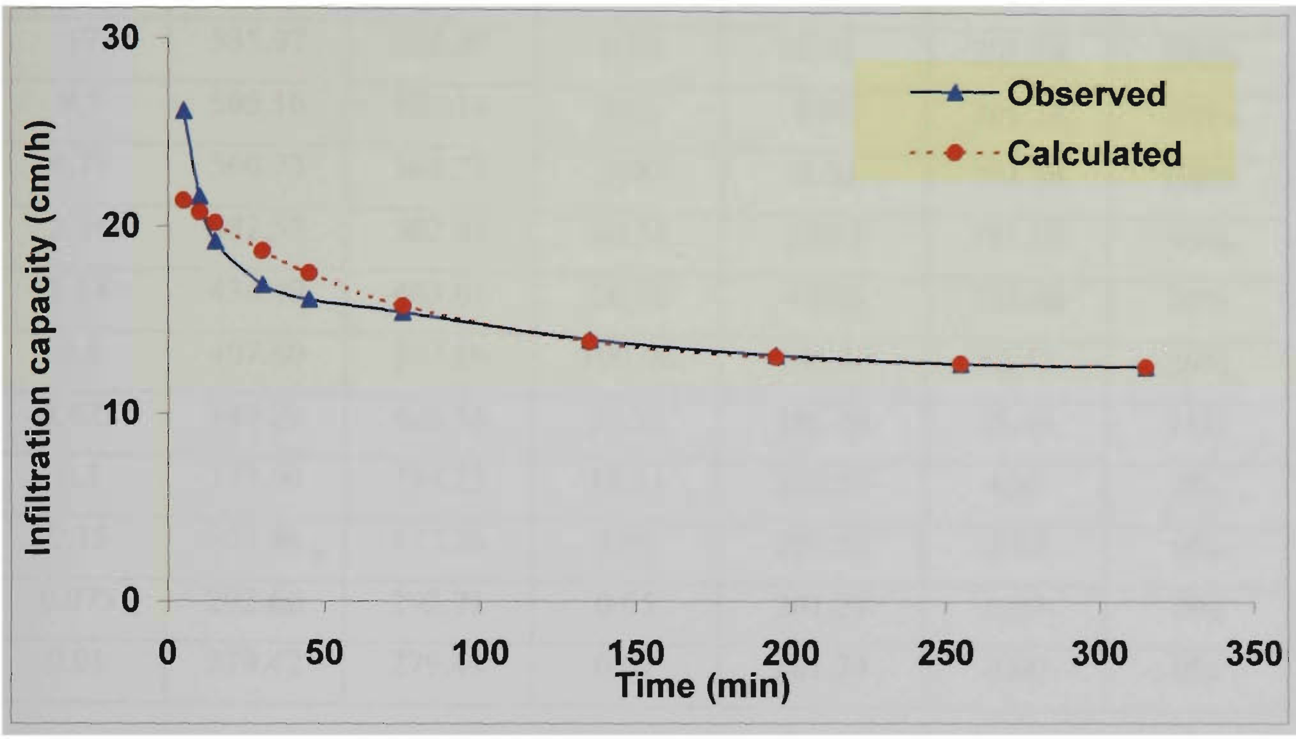


Figure 5.5 Re-calculated Infiltration Capacity (f_t) Vs. Time for Site K_1

The measurements obtained for the sieve analysis test for site K_1 are tabulated in columns 2 and 3 in Table 5.3. The mass retained per sieve [i.e. column (4)] was calculated by subtracting column (3) from column (2). The soil passing through each sieve [i.e. column (6)] was calculated by subtracting the cumulative mass [i.e. column (5)] from the total soil mass (which is 201.34 g). The percentage of soil passing [i.e. column (7)] through each sieve was calculated using the column (6) values. Figure 5.6 shows the plot of % of soil passing versus particle sizes, which is known as the particle size distribution curve. The values of D_{10}, D_{30} and D_{60} were read from Figure 5.6 and were 0.4, 0.65 and 0.9 respectively for site K_1. The values of C_U and C_C were then computed using Equations (5.2) and (5.3) respectively and these values are tabulated in Table 5.4 for site K_1. The soil type of site K_1 was identified as GP from Table 5.1 and included in Table 5.4. In addition, f_c, f_o and k values for site K_1 are tabulated in Table 5.4.

Table 5.3 Observations and Calculation of Particle Size Distribution for Site K_1

Sieve size (mm)	Sieve mass (g)	Mass of sieve and retained soil (g)	Mass retained per sieve	Cumulative mass (g)	Mass passing (g)	% Passing
(1)	(2)	(3)	(4)	(5)	(6)	(7)
19	535.97	535.97	0.00	0.00	201.34	100%
9.5	505.16	505.16	0.00	0.00	201.34	100%
4.75	560.73	560.73	0.00	0.00	201.34	100%
2.36	482.57	502.91	20.34	20.34	181.00	90%
1.18	434.49	463.01	28.52	48.86	152.48	76%
0.6	407.60	507.66	100.06	148.92	52.42	26%
0.425	389.29	420.55	31.26	180.18	21.16	11%
0.3	377.09	394.23	17.14	197.32	4.02	2%
0.15	353.86	357.76	3.90	201.22	0.12	0%
0.075	292.66	292.71	0.05	201.27	0.07	0%
0.01	279.42	279.49	0.07	201.34	0.00	0%

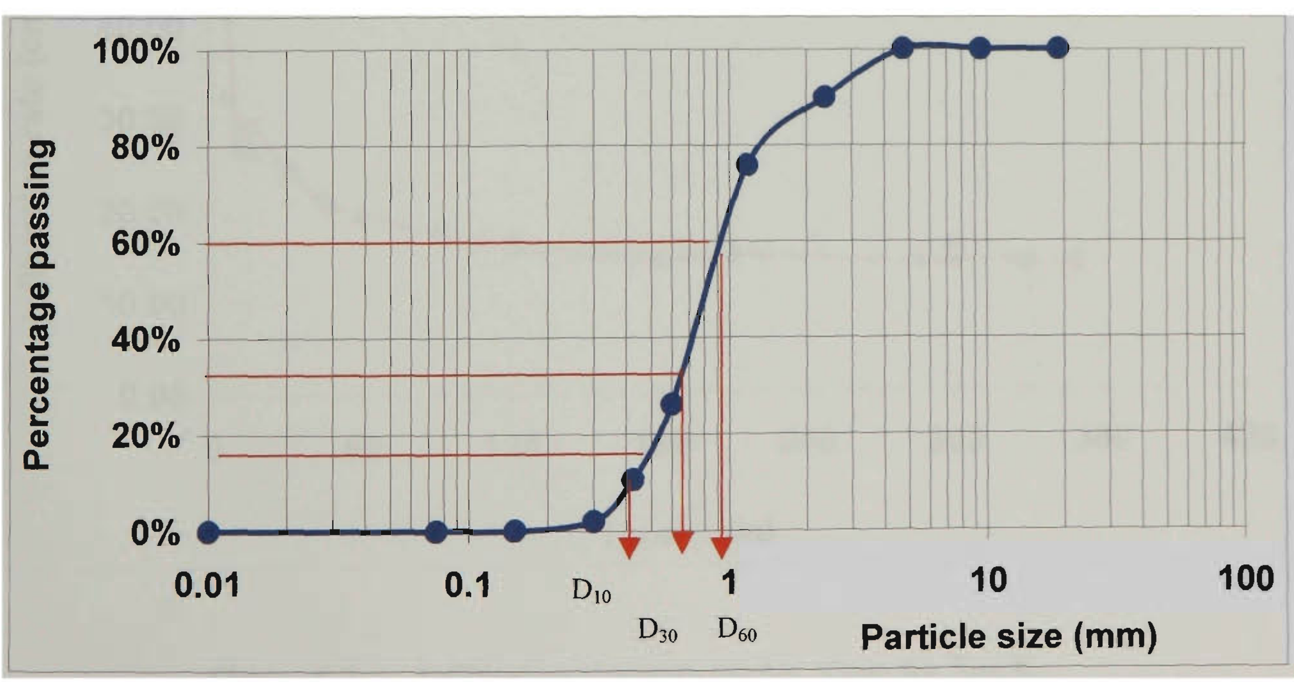


Figure 5.6 Particle Size Distribution Curve for Site K_1

Table 5.4 Infiltration Parameters for Site K_1

Site code	5-day rainfall (mm)	C_U	C_C	Soil type	f_c (cm/h)	f_o (cm/h)	k (h^{-1})
K_1	4.4	2.25	1.17	GP	12.5	22.0	0.86

Note: Fine particles were less than 5%
GP is poorly graded gravels and gravel sand mixtures, little or no fine

5.5.2 Site K_2

The measurements obtained from the double-ring infiltrometer test and calculations for site K_2 are given Table 5.5. Similarly, the plots in relation to the estimation of infiltration parameters (similar to Section 5.5.1) are shown in Figures 5.7, 5.8 and 5.9. The study results for site K_2 are tabulated in Table 5.6.

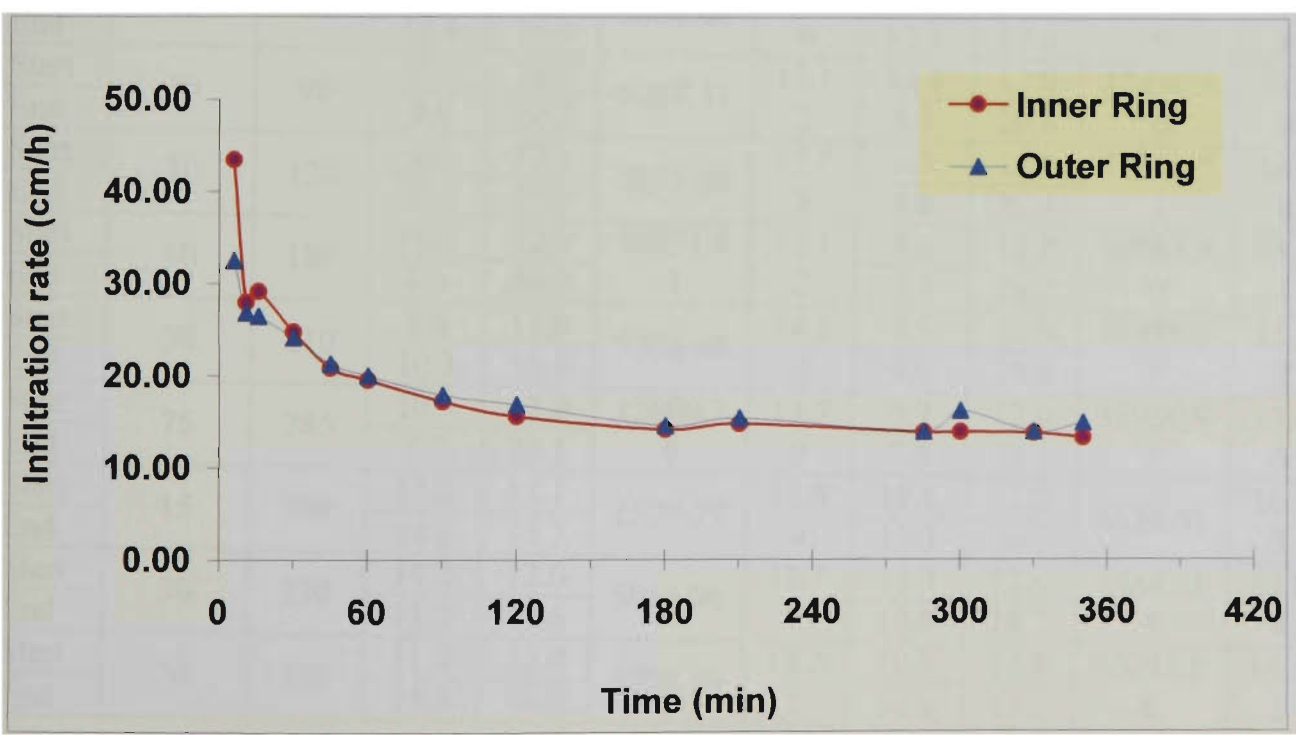


Figure 5.7 Infiltration Capacity (f_t) Vs. Time for Site K_2

Table 5.5 Observations and Calculation Sheet for Site K_2

5 Days Rainfall	Day	-1	-2	-3	- 4	-5
	Rainfall (mm)	0.04	0.04	0.04	0.04	0.04

Mariotte tube details:	Ring details:
Large Tube: Diameter 16.2 cm, Area 206.12 cm^2	Outer Ring Area 2073.5 cm^2
Small Tube: Diameter 9 cm, Area 63.62 cm^2	Inner Ring Area 730.91 cm^2

Time record (min)			**Inner ring reading**				**Outer ring reading**			
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
	Time interval (min)	**Total time (min)**	**Tube (cm)**	**Ring (cm)**	**Volume cm^3**	**f_t cm/h**	**Tube (cm)**	**Ring (cm)**	**Volume cm^3**	**f_t cm/h**
Start	6	6	17.4	12.0	3171.75	43.39	28.0	12.0	6723.50	32.43
End			13.5	16.0			15.5	14.0		
Start	5	11	13.5	12.0	1700.04	27.91	15.5	12.1	4623.54	26.76
End			15.5	14.5			15.2	14.3		
Start	5	16	15.5	12.0	1773.27	29.11	15.2	12.0	4561.70	26.40
End			15.2	14.4			15.2	14.2		
Start	14	30	15.2	12.1	4217.22	24.73	15.2	12.0	11628.52	24.03
End			12.1	17.6			12.1	17.3		
Start	15	45	12.1	12.0	3794.37	20.77	12.1	12.0	10968.94	21.16
End			12.2	17.2			12.2	17.3		
Start	15	60	12.2	12.0	3556.02	19.46	12.2	12.0	10305.66	19.88
End			12.6	16.9			12.5	17.0		
Start	30	90	12.6	12.0	6257.41	17.12	12.5	12.0	18450.46	17.80
End			9.6	20.3			9.5	20.6		
Start	30	120	9.6	12.1	5675.66	15.53	9.5	12.0	17396.79	16.78
End			10.0	19.9			9.6	20.4		
Start	60	180	10.0	12.0	10321.81	14.12	9.6	12.0	30083.90	14.51
End			8.6	26.0			7.5	26.3		
Start	30	210	8.6	12.0	5373.68	14.70	7.5	12.0	15885.96	15.32
End			10.3	19.5			9.9	19.9		
Start	75	285	10.3	12.0	12600.36	13.79	9.9	12.0	35930.93	13.86
End			8.7	29.1			7.6	29.1		
Start	15	300	17.2	12.1	2529.77	13.84	10.6	12.2	8359.53	16.13
End			14.2	15.3			13.3	16.5		
Start	30	330	14.2	12.0	5014.86	13.72	13.3	12.0	14387.14	13.88
End			11.2	18.6			10.9	18.7		
Start	20	350	11.2	12.0	3228.59	13.25	10.9	12.0	10245.06	14.82
End			13.3	16.6			12.5	17.1		

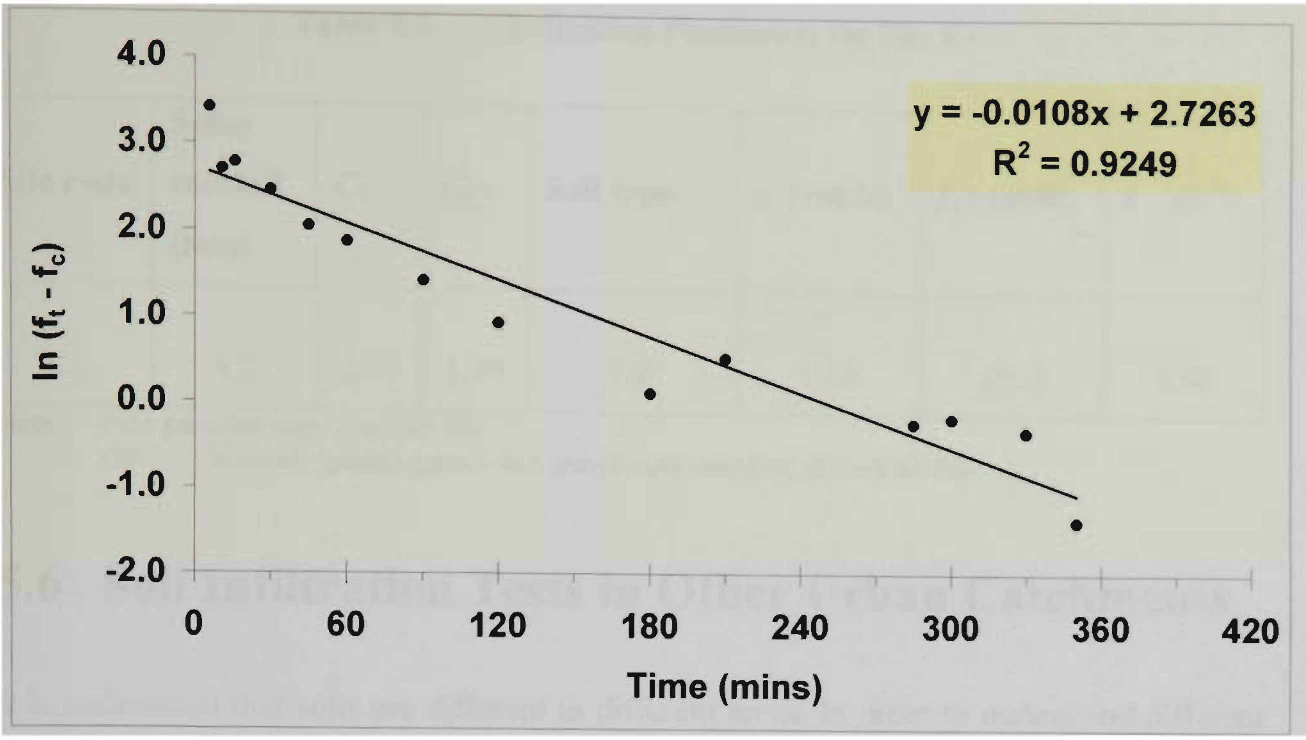


Figure 5.8 $\ln(f_t - f_c)$ Vs. Time for Site K_2

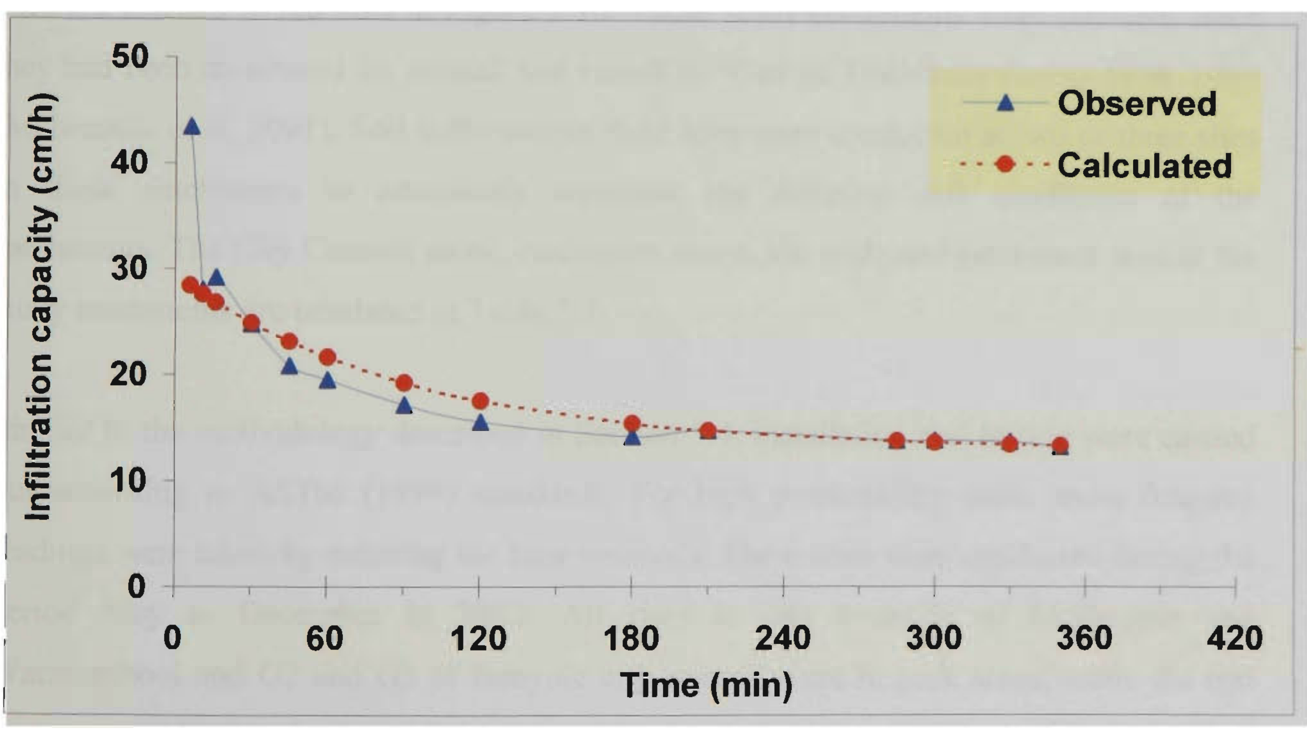


Figure 5.9 Re-calculated Infiltration Capacity (f_t) Vs.Time for Site K_2

Table 5.6 Infiltration Parameters for Site K_2

Site code	5-day rainfall (mm)	C_U	C_C	Soil type	f_c (cm/h)	f_o (cm/h)	k (h^{-1})
K_2	4.2	2.50	1.04	GP	13.0	29.4	0.65

Note: Fine particles were less than 5%
GP is poorly graded gravels and gravel sand mixtures, little or no fine

5.6 Soil Infiltration Tests in Other Urban Catchments

It is understood that soils are different in different areas. In order to understand different soil types and to determine the soil infiltration rates in different urban catchments, soil infiltrometer field tests were conducted at several selected urban catchments within City Councils of Banyule, Boroondara, Melbourne and Warrnambool in Victoria (Australia). Figure 5.10 shows the City Council areas and the locations of these study sites. The study sites are marked in red dots in Figure 5.10. These study catchments were selected, since they had been monitored for rainfall and runoff by Victoria University during 1996–1999 (Maheepala et al. 2001). Soil infiltrometer field tests were conducted at two or three sites in these catchments to adequately represent the different soil conditions of the catchments. The City Council name, catchment name, site code and catchment area of the study catchments are tabulated in Table 5.7.

Similar to the methodology described in Section 5.4, installation and testing were carried out according to ASTM (1994) standards. For high permeability soils, more frequent readings were taken by reducing the time intervals. These tests were conducted during the period May to December in 2002. All sites in city councils of Melbourne and Warrnambool and G2 and G3 of Banyule city council were in park areas, while the rest were in residentional areas. Calculations were carried out similar to the procedures described in Section 5.5. The results of (i.e. C_U, C_C, f_c, f_o and k) of all sites of the study catchments are tabulated in Table 5.8. Also shown in the table is the soil type classified according to unified soil classification system (Wagner 1957).

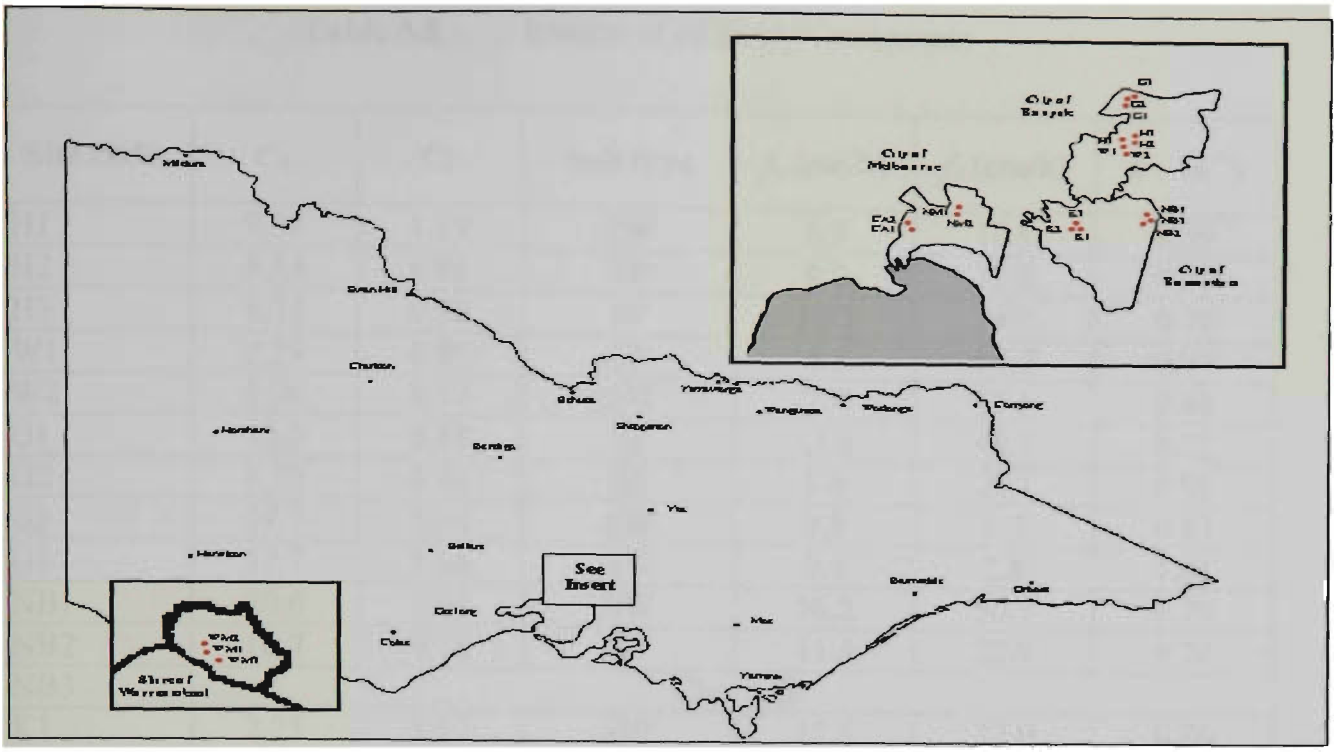


Figure 5.10 Location of Study Sites

Table 5.7 Details of Study Catchments

Council name	Catchment name and site codes	Area (ha)
Banyule	Heidelberg H1, H2, H3	45
	Warringal W 1, W2	29
	Greensborough G1, G2, G3	43
Boroondara	North Balwyn NB1, NB2, NB3	16
	Kew K 1, K2, K3	18
Melbourne	Carlton CA 1, CA2	60
	North Melbourne NM1, NM2	24
Warrnambool	Warrnambool WB1, WB2, WB3	105

Table 5.8 Results of all Study Catchments

Site code	C_U	C_C	Soil type	f_c (cm/h)	f_o (cm/h)	k (h^{-1})
H1	9.33	1.19	SW	6.5	16.9	0.59
H2	9.33	0.96	SP	9.0	15.8	0.29
H3	9.33	0.83	SP	10.5	34.7	0.76
W1	2.29	0.89	GP	4.5	14.7	0.97
W2	1.70	0.97	GW	7.9	15.1	0.82
G1	12.0	0.48	SP	13.5	48.3	0.72
G2	8.75	0.40	SP	5.0	21.1	0.90
G3	17.7	1.64	SW	0.8	5.7	0.83
G3	17.7	1.64	SW	0.4	2.8	1.41
NB1	20.6	1.08	SW	16.2	50.3	0.79
NB2	10.7	0.75	SP	11.4	22.9	0.74
NB3	Clay soil					
K1	2.25	1.17	GP	12.5	22.0	0.86
K2	2.50	1.04	GP	13.0	29.4	0.65
K3	Clay soil					
CA1	4.00	1.00	GW	12.6	30.2	0.90
CA2	17.7	0.71	SP	1.9	6.1	0.78
NM1	5.50	1.64	GW	13.3	38.2	1.08
NM2	13.0	0.94	SP	6.4	14.3	0.60
WM1	2.43	0.94	GP	2.9	9.5	1.08
WM2	12.6	0.98	GW	13.1	30.1	1.02
WM3	3.4	0.93	GP	3.9	24.6	1.20

Note: Fine particles were less than 5% at all sites
GW is well-graded gravels and gravel sand mixtures, little or no fines
GP is poorly graded gravels and gravel sand mixtures, little or no fine
SW is well graded sands and gravely sands, little or fines
SP is poorly graded sands and gravely sands, little or no fines

The five-day rainfall recorded at the study sites were less than 5 mm (and greater than zero), except at the sites H1, W1 and W2. The recorded five-day rainfall at sites H1, W1 and W2 were 25.4, 26.67 and 26.67 mm respectively.

The tests made at different times at the same site (eg. G3) did not give similar results, as infiltration depends on many factors. Furthermore, field tests could not be completed at NB3 (similar to K3) sites, where water barely penetrated through the clay soils. These observations are consistent with ASTM (1994).

There were some problems in using the double-ring infiltrometer at certain sites such as difficulty in setting up in hard soils, requirement of undisturbed flat surface to perform the test and the length of time required for the test. Furthermore, it was necessary to refill the rings to maintain the constant water level at the start of each observation, which disturbed the experiment, as it required time to fill water.

The ranges of f_c and f_o values found in this study were 0.4-16.2 cm/h (with a mean of 8.3) and 2.8-50.3 cm/h respectively. The average value of k was found to be 0.85 h^{-1}. Since most soils of the study sites were observed to be of course grains, the above parameter values were compared against the published values in DRAINS (O'Loughlin and Stack 1998) and XP-UDD (XP-Software 1997) user manuals.

According to DRAINS user manual, the soil types given in Table 5.8 can be classified as Type B soil (which has moderate infiltration rates and moderately well-drained). This type of soil is assigned a single value of 1.3 cm/h for f_c and depending on the initial soil moisture conditions, f_o can have any value between 1.3–20 cm/h. The parameter k is listed as 2 h^{-1}.

Similarly, XP-UDD manual suggests the values of f_c between 0.38 and 0.76 cm/h for Type B soil. Furthermore, it states that most reported values for k were in the range of 3–6 h^{-1} and if no field data are available, an approximate value of 4.14 h^{-1} could be used. The range of f_o has given in XP-UDD user manual can be considered as 3.3–20 cm/h.

As can be seen from above comparisons, f_c and f_o obtained from the field studies are higher than the published values in DRAINS and XP-UDD user manuals. Also, k obtained from field studies is lower than the above published values.

5.7 Summary and Conclusions

Urban drainage models are widely used in urban stormwater planning and management, especially in design and analysis of urban drainage systems. In order to use these models effectively, it is necessary to input accurate parameter values. The soil infiltration parameters can be estimated through field experiments. With these parameters estimated external to the model calibration, the other parameters of the urban drainage model can be estimated through model calibration reasonably well, since there are less parameters to be estimated. Thus, this process will improve the reliability of the model. If necessary, the values obtained from field experiments can also be refined through calibration, since the calibration can now consider only a narrow band of values for these parameters obtained from field measurements.

Field infiltrometer tests were conducted at two sites of the Kew catchment, in order to estimate the infiltration parameters related to Horton's infiltration model. Double-ring infiltrometer was used for this purpose and the tests were conducted for approximately 6 hours. Double–ring infiltrometer test encourages only vertical flow in the inner ring due to the presence of the outer ring, thus not overestimating the infiltration rate.

In order to understand different soil types and to determine the soil infiltration rates in different urban catchments, double-ring infiltrometer tests were conducted at another nineteen sites of seven urban catchments in four city councils in Victoria. Most of f_o and f_c values found in this study were significantly different to the values published in XP-UDD and DRAINS urban drainage software user manuals. Therefore, it is recommended that care should be exercised in using the values published in these user manuals for Victorian urban catchments.

CHAPTER 6

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

6.1 Aims and Tasks

The basic objective of this research study was to estimate the model parameter values of urban drainage catchment models. This was done through the use of genetic algorithms (GAs) and soil infiltration tests. The methods were used to estimate the model parameters related to the Kew urban drainage catchment in Victoria (Australia). The following studies and tasks were carried out to achieve the above objective in this research study.

- Review of literature related to urban drainage processes and modelling, and selection of an urban stormwater drainage software tool for the study.
- Literature review of currently available optimisation methods and a detailed review of GAs optimisation method, its operators and the use of GAs for various applications. Available GENESIS GA software tools were also reviewed.
- Development of a computer program to link urban stormwater drainage and GAs software tools.
- Selection of optimum GAs operator set for urban stormwater drainage model calibration using two urban catchments including the Kew catchment.
- Calibration of impervious area model parameters of the Kew urban drainage model using GAs, and validation.
- Estimation of infiltration parameter values of pervious areas of the Kew urban drainage catchment using soil infiltrometer tests. This study was extended to determine infiltration characteristic of several other urban drainage catchments in Victoria.

6.2 Summary and Conclusions

The summary and conclusions made under literature review, XP-UDD and GENESIS, GAs operator study, calibration and validation of impervious area parameters of the Kew urban drainage catchment and estimation of pervious area parameters of the Kew catchment using double-ring infiltrometer tests are presented below.

6.2.1 Literature review

In the literature review, the differences of non-urban and urban drainage processes were studied. The past and current practices of stormwater management in urban areas were also investigated. The currently available design methods of stormwater drainage systems were reviewed and identified the merits of using computer software tools for urban drainage design and analysis. Even though the current stormwater management considers the urban water cycle holistically, still urban drainage is an important component of urban stormwater management.

Methods available for model calibration ranging from trial and error method to automatic methods were reviewed. The automatic optimisation methods can be divided into two main methods, namely deterministic and stochastic optimisation methods. It was found from the literature that the stochastic optimisation methods were more superior to other optimisation methods for water resource applications. Genetic algorithms (GAs) are one of the stochastic optimisation methods, which have proven to be successful in optimising model parameters in the water resource applications, and therefore considered in this study.

The following conclusions were drawn from the literature review conducted in this study.

- Continual urban development is contributing more runoff mainly due to the increase of impervious areas. Stormwater management practices have changed over time to reduce the environment impacts in disposing stormwater and to (re)use of stormwater as an alternative water supply source.

- Stormwater drainage systems are required to minimise urban flooding. The most practical and efficient way of designing and analysing these systems is by the use of urban drainage software tools. However, they need to be calibrated for the urban drainage system under consideration. Therefore, genetic algorithms optimisation technique was selected for the study, as it is a robust and automatic stochastic optimisation methods.
- The literature reviewed also showed that there is no *optimum* GAs operator set for urban drainage model applications or other water resource applications. It also revealed that *optimum* GAs operator set depend on the application.

6.2.2 XP-UDD and GENESIS

The XP-UDD stormwater drainage software tool is an enhanced and user-friendly version of SWMM and its input and output files are in ASCII format, which can be accessed by the external software tools, which was necessary in this study, and therefore it was used in this study. Seven model parameters of the XP-UDD software were identified for calibration, two related to the impervious areas (i.e. percentage of the impervious area - $\%A$ and the depression storage - DS_i) and the other five related to the pervious areas (i.e. depression storage - DS_p, overland flow roughness of the pervious areas - n_p and the three Horton's soil infiltration parameters - f_o, f_c and k).

The GENESIS GAs software was used for this study, since has been successfully used in the past by many researchers. Since XP-UDD and GENESIS are two separate software tools, a computer program was developed by the candidate to link the two software tools, to obtain *optimum* GAs operators and then to perform automatic calibration of model parameters of the study catchment.

6.2.3 GAs operator study

In GAs, several operators are available, which required to be selected prior to optimise model parameters in any application. These GAs operators include parameter representation, population size, selection, crossover and mutation. Each GAs operator has many options (or methods) and therefore, it was required to select the proper GAs operators for the application to achieve the GAs efficiency. The literature review revealed that there is no specific study conducted for selecting GAs operators for urban drainage models, as GAs have not been widely used for these applications. Although several researchers studied the effect of GAs operators for other applications these findings are inconclusive. Therefore, a detailed study was conducted in investigating the *optimum* GAs operator set for urban stormwater drainage models.

The *optimum* GAs operator investigation was conducted considering two urban catchments, representing a *small* (i.e. Kew urban drainage catchment) and a *medium* catchment for investigation of GAs operators and validation of the study results respectively. The existing stormwater drainage networks of these two catchments were assembled in XP-UDD urban drainage software. Two separate studies were conducted with each catchment to determine the appropriate GAs operators related to impervious and pervious area model parameters, as the runoff generation mechanism is deferent in these two areas. Two design storms (i.e. *small* and *large*) were modelled in these different runoff mechanisms. The *small* design storm with Annual Recurrence Interval (ARI) of 1 year and storm duration of 30 minutes (which produced runoff only from the impervious areas) was considered for the impervious area model parameter study. The *large* design storm with an ARI of 100 years and 30 minutes duration (which generated runoff from both impervious and pervious areas) were used for the pervious area study. Typical parameter values were assumed to produce the hydrographs corresponding to these two design storms and these hydrographs were considered in the integrated GENESIS/XP-UDD as the observed hydrographs in optimising GAs operators, and the above typical parameter values as the actual parameter values for these catchments. To study the effects of GA operators in the XP-UDD drainage model, population size, selection type, crossover and mutation rates were varied one at a time, keeping all other operators constant.

It was found in this study that GA operators were sensitive to the number of model parameters that needs to be optimised in the urban drainage model. If the number of parameters to be optimised was small (i.e. less than or equal to 2), GAs operators did not play an important role in converging to the optimum model parameter set and therefore general GAs operators recommended in literature can be used. Furthermore, it was observed that small population sizes (eg. between 25 – 50) were efficient in converging to the *optimum* model parameter values for urban drainage modelling with a small number of model parameters.

For models with large number of parameters (experimented with 5 parameters), GAs operators played an important role in converging to the *optimum* parameter set. In this study, Gray coding, a population size of 100, proportionate selection method, a crossover rate of 0.6 and a mutation rate of 0.001 had given the best results and therefore they are recommended for urban drainage models with a large number model parameters. Furthermore, it was found that the efficiency of the parameter convergence could be improved by limiting the parameter range and precision of the coding to the required level.

6.2.4 Calibration of impervious area parameters of Kew catchment

Model calibration of the Kew urban drainage catchment was conducted using the selected optimum GAs operators. For model calibration, observed *small* and *large* flow events are required. However, *large* flow events, which are large enough to produce pervious area runoff, were not available for this catchment and therefore only the impervious area parameter values were calibrated using GAs with the available observed *small* storms. Five observed *small* rainfall/runoff events were used in this study. Of these five events, three were used for calibration and the other two were used for validation of the results obtained from the calibration study.

Results of the calibration and validation showed that the shape, peak discharge, time to peak and multi peaks were modelled with a reasonable accuracy. It was found in this study that GAs could be used to estimate the model parameter values successfully in urban stormwater models.

6.2.5 Estimation of pervious area parameters of Kew catchment

Field infiltrometer tests were conducted at two sites of the Kew catchment in order to estimate the infiltration parameters related to the Horton's infiltration model of pervious areas, since they could not be estimated through model calibration, due to unavailability of observed data related to *large* storms. Double-ring infiltrometer was used for this purpose and the each test was conducted for approximately 6 hours. Furthermore, soil samples at a depth between 30-45 cm were taken to determine the particle size distribution at each site using sieve analysis, and then the soil type.

In order to understand different soil types and to determine the soil infiltration rates in different urban catchments, soil infiltrometer field tests were conducted at another nineteen sites at several selected urban catchments (which were monitored for rainfall/runoff data) within in Victoria. The minimum infiltration rate (i.e. f_c) and the initial infiltration rate (i.e. f_o) values found in this study were significantly different to the values in XP-UDD and DRAINS urban drainage software user manuals. Therefore, care should be exercised in using the values published in these user manuals for Victorian urban catchments.

6.2.6 Additional remark

Most urban drainage models adopt similar methods for modelling hydrologic and hydraulic processes such as modelling rainfall losses, runoff routing, pit inlet modelling and catchment sub division. Although the XP-UDD software tool was used to demonstrate the use of GAs for urban drainage model calibration, the results obtained from this study can be considered as valid for other urban drainage models, which use the similar methods to model hydrologic and hydraulic process. However this needs to be tested.

6.3 Recommendations

Based on the findings of this research project, several recommendations are made for future studies, as listed below.

- The investigation of optimum GAs operator set was conducted in this study using limited numerical experiments with two catchments. It is recommended that further studies should be conducted with several other urban catchments to generalise the findings of the GAs operators study of this thesis, and also to study the effect of scaling (preferably by applying the model to catchments of at least a couple of orders of magnitudes larger).
- It is also recommended that further studies of model calibration using GAs should be conducted using different urban drainage modelling software.
- Furthermore, further studies should be conducted to establish a relationship with string length and population size in bit string representation to use the genetic algorithm efficiently for the large parameter optimisation problems in urban drainage modelling.
- It is also recommended to study the effect of other GAs operators (i.e. real value representation, tournament selection method and single or uniform crossover methods) on convergence of urban stormwater drainage model parameters, as these operators were not investigated in this study due to the limited capability of GENESIS software.
- The objective function used in this study was the minimization of sum of the squares of flow residuals between observed and computed hydrographs. However, it may be worthwhile to consider the other forms of objective functions to assess their appropriateness and also to include constraints that force the maximum deviation

between observed and simulated flow values to be within a pre-specified (acceptable) tolerance.

- It is also suggested to establish a database of soil infiltration rates for Melbourne Metropolitan area urban catchments, since the standard infiltration rates published in DRAINS and XP-UDD urban drainage software manuals are significantly different to the values found in this research. Soil infiltrometer tests can be used for this purpose.

REFERENCES

1. Akram M. and Kemper W. D. (1979), *Infiltration of soils as affected by the pressure and water content at the time of compaction*, Journal of Soil Science Society of America, 43, pp. 1080-1086.

2. Al-Qinna M. I. and Abu-Awwad A. M. (1998), *Infiltration rate measurements in arid soils with surface crust*, Journal of Irrigation Science, 18(2), pp. 83-89.

3. American Society for Testing and Materials - ASTM (1994), Standard test methods for infiltration rate of soils in field using double-ring infiltrometer, ASTM Subcommittee D-18.04 on Hydrologic Properties of Soil and Rock.

4. Anikow C. Z. and Michalewicz Z. (1991), *Comparison of real and binary codings*, Proceedings of the Fourth International Conference on Genetic Algorithms, University of California, San Diego, California, 13-16 July, pp. 31-36.

5. Antonisse H. J. (1989), *Theory of real coded GAs*, Proceedings of the Third International Conference on Genetic Algorithms, George Mason University, California, 4-7 June, pp. 86-91.

6. Back T. (1992), *A User's Guide to GENEsYs 1.0*, Department of Computer Science, University of Dortmund, USA.

7. Back T., Hammel U. and Schwefel H. (1997), *Evolutionary computation: comments on the history and current state*, IEEE Transaction on Evolutionary Computation, pp. 3-17.

8. Back T. and Schwefel H. (1993), *An overview of evolutionary algorithms for parameter optimisation*, Journal of Evolutionary Computation, 1(1), pp. 1-23.

9. Baker J. E (1987), *Reducing bias and inefficiency in the selection algorithm*, Proceedings of the Second International Conference on Genetic Algorithm, Massachusetts Institute of Technology, Massachusetts, USA, pp. 14-21.

10. Balascio C. C., Palmeri D. J. and Gao H. (1998), *Use of genetic algorithm and multi-objective programming for calibration of a hydrologic model*, Journal of American Society of Agricultural Engineers, 41(3), pp. 615-619.

11. Biethahn J. and Nissen V. (1995), *Evolutionary algorithms in management applications*, Springer-Verlag Berlin Heidelberg, Germany.

12. Blickle T. and Thiele L. (1997), *A comparison of selection schemes used in evolutionary algorithms*- Book Section, Evolutionary Computation, pp. 361-394.

13. Boyd M. J., Bufill M. C. and Knee R. M. (1993), *Pervious and impervious runoff in urban catchments*, Journal of Hydrological Sciences, 38(6), pp. 463-478.

14. Bufill M. C. and Boyd M. J. (1992), *A sample flood hydrograph model for urban catchment*, Proceedings of the International Symposium on Urban Management, Sydney, Australia, pp. 98.103.

15. Caruana R. and David S. J. (1987), *Gray vs. binary coding for genetic algorithm function optimizers*, Philips Laboratories, North American Philips Corporation, New York, USA.

16. Caruana R. A. and Schaffer J. D. (1989), *Using Multiple Representations to Control Inductive Bias: Gray and Binary Codes for Genetic Algorithms*, Proceedings of the 6th International Conference on Machine Learning.

17. Commonwealth Environment Protection Agency (1993), *Urban Stormwater: A resource too valuable to waste*, Discussion paper, Canberra, Australia.

18. Coombes P. (2003), *Integrated urban water management*, Proceedings of IUWM and WSUD Conference, Lismore City Council, NSW, Australia.

19. Craig R. F. (1975), *Soil Mechanics*, Van Nostrand Reinhold Company, Australia.

20. Cui L. (2003), *Optimisation of urban water supply head works systems using probabilistic search methods and parallel computing*, PhD Thesis, University of Newcastle, Australia.

21. Cullino C. (1995), *Urban stormwater management in search of best practice*, The Second International Symposium on Urban Stormwater Management, Melbourne, Australia, pp. 49-53.

22. Dandy G. C., Simpson A. R. and Murphy L. J. (1996), *An improved genetic algorithm for pipe network optimisation*, Water Resources Research, 32(2), pp. 449-458.

23. Danish Hydraulic Institute (1993), *Modelling of urban sewer systems on microcomputers,* MOUSE V3.0, User's Guide and Technical Reference, Lawson and Treloar Pty Ltd, Australia.

24. Davis L. (1991), *Handbook of genetic algorithms*, Van Nostrand Reinhold, New York, USA.

25. Dayaratne S. T. (2000), *Modelling of urban stormwater drainage system using ILSAX*, PhD Thesis, Victoria University of Technology, Australia.

26. De Jong K. A. (1975), *Analysis of the behaviour of a class of genetic adaptive systems*, PhD Thesis, University of Michigan, Ann Arbor, Michigan, USA.

27. De Jong K. A., Fogel D. and Schwefel H. (1997), *A history of computation- Book Section*, Handbook on Evolutionary computation, Institute of Physics Publishing, Oxford University Press, New York, USA. pp. 1-12.

28. De Jong K. A. and Sarma J. (1995), *On decentralizing selection algorithms*, Proceedings of the 6th International Conference on Genetic Algorithms, pp. 17-23.

29. Deletic A. (2001), *Modelling of water and sediment transport over grassed areas*. Journal of Hydrology, 248(4), pp. 168-182.

30. Department of Primary Industries and Energy (1992), *Floodplain management in Australia,* Australian Water Resources Council, Water Management Series No.21, Australia.

31. Duan Q., Sorooshian S. and Gupta V. (1992), *Effective and efficient global optimisation for conceptual rainfall-runoff models*, Water Resources Research, 28(4), pp. 1015-1031.

32. Eshelman L. J. (1997), *Genetic algorithm- Book Section*, Handbook on evolutionary computation, Institute of Physics Publishing, Oxford University, New York, USA, pp. 1-11.

33. Eshelman L. J. and Schaffer J. D. (1992), *Foundations of Genetic Algorithms 2- Book Section*, Morgan Kaufman Publishers, San Mateo, California, USA. pp. 5-17.

34. Ferguson B. K. (1998), *Introduction to stormwater*, John Wiley & Sons Inc., USA.

35. Fogel D. B. (1997), *Real valued vectors- Book Section*, Handbook on evolutionary computation, Institute of Physics Publishing, Oxford University, New York, USA, pp. 1-2.

36. Franchini M. (1996), *Use of a genetic algorithm combined with a local search method for the automatic calibration of conceptual rainfall-runoff models*, Journal of Hydrological Sciences, 41(1), pp. 21-39.

37. Franchini M. and Galeati M. (1997), *Comparing several genetic algorithm scheme for the calibration of conceptual rainfall-runoff models*, Journal of Hydrological Sciences, 42(3), pp. 357-379.

38. Gardner W. H. (1979), *How water moves in the soils*, Journal of Crops and Soils, 32, pp. 13-18.

39. Goldberg D. E. (1985), *Optimal initial population size for binary-coded genetic algorithms*, Department of Engineering Mechanics, University of Alabama, USA.

40. Goldberg D. E. (1989a), *Genetic algorithm in search, optimization and machine learning*, Addison-Wesley Publishing Company, Inc., Reading, Massachusetts, USA.

41. Goldberg D. E. (1989b), *Sizing population for serial and parallel genetic algorithms*, Proceedings of the Third International Conference on Genetic Algorithms, George Mason University, California, 4-7 June, pp. 70-79.

42. Goldberg D. E. and Deb K. (1991), *A Comparative analysis of selection schemes used in genetic algorithms- Book Section*, Foundations of Genetic Algorithms, Morgan Kaufman Publishers, San Mateo, California, pp. 69-93.

43. Goldberg D. E. and Guo C. H. (1987), *Genetic algorithm in pipe optimisation*, Journal of Computing in Civil Engineering, 1(2).

44. Goonrey C. (2003), *Use of stormwater as an alternative supply source*, Internal Report, School of Architectural, Civil and Mechanical Engineering, Victoria University of Technology, Australia.

45. Gray F. (1953), *Pulse code communication*, U.S Patent 2, March 17.

46. Green W. H. and Ampt G. A. (1911), *The flow of air and water through soils*, Journal of Agriculture Science, 4, pp. 1-24.

47. Grefenstette J. J. (1986), *Optimisation of control parameter for Genetic algorithms,* IEEE Transaction on Systems, Man and Cybernetics SMC, 16 (1), pp. 122-128.

48. Grefenstette J. J. (1987), *A user's guide to GENESIS*, Technical Report, Navy Center for Applied Research in Artificial Intelligence, Navy Research Laboratory, Washington DC, USA.

49. Grefenstette J. J. (1995), *A users guide to GENESIS (Version 5.0)*, http://www.aic.nrl.navy.mil/pub/galist/src/genesis.tar.z

50. Grefenstette J. J (1997), *Proportional selection and sampling algorithms*-Book section- *Book Section*, Handbook of Evolutionary Computation (Part C, Section 2.2), Institute of Physics Publishing, Oxford University Press, New York, USA, pp. 1-6.

51. Hendrickson J. D., Sorooshian S. and Brazil L. E. (1998), *Comparison of Newton-type and direct search algorithms for calibration of conceptual rainfall-runoff models*, Water Resources Research, 24, pp. 691-700.

52. Hessner J. and Männer R. (1991), *Choosing optimal mutation rates*, Proceedings of the First Workshop on Parallel Problem Solving from Nature, Berlin, pp. 23-31.

53. Holland J. (1975), *Adaptation in natural and artificial systems*, The University of Michigan Press, Ann Arbor, Michigan, USA.

54. Hollstien R. B. (1971), *Artificial genetic adaptation in computer control systems*, PhD Thesis, University of Michigan, Ann Arbor, Michigan, USA.

55. Horton R. E. (1940), *An approach towards a physical interpretation of infiltration capacity*, Journal of Soil Science Society of America, 5, pp. 399-417.

56. Huber W. C. and Dickinson R. E. (1988), *SWMM user's manual version 4*. U.S Environmental Protection Agency, Environmental Research Laboratory, Athens, Georgia, USA.

57. Hunt J. (2000), *Learning Classifier Systems*, JayDee Technology Ltd, http://www.jaydeetechnology.co.uk.

58. Ishaq M. and Khan A. A. (1999), *Modeling infiltration for an urban runoff model in Saudi Arabia*, The Arabian Journal for Science and Engineering, 24(2b), pp. 203-216.

59. Janikow C. Z. and Michalewicz Z. (1991), *An experimental comparison of binary and floating point representations in genetic algorithms*, Proceedings of the Fourth international conference on genetic algorithms, University of California, San Diego, California, 13-16 July, pp. 31-36.

60. Kostiakov, A.N. (1932), *On the dynamics of the coefficient of water percolation in soils and on the necessity of studying it from a dynamic point of view fro purposes of amelioration.* Transaction of 6th Congress of International Soil Science Society, Moscow, Part A, pp. 17-21.

61. Laurenson E. M. and Mein R. G. (1995), *RORB-Version 4,* Runoff Routing Program User Manual, Department of Civil Engineering, Monash University, Australia.

62. Liong S. Y., Chan W. T. and Shreeram J. (1995), *Peak-flow forecasting with genetic algorithm and SWMM*, Journal of Hydrologic Engineering, 121(8), pp. 613-617.

63. Maheepala U. K. (1999), *Data acquisition and modelling of urban drainage catchments in the City of Knox*, Masters Thesis, Monash University, Australia.

64. Maheepala U. K. and Perera B., J. C. (1999), *Quality assurance checks for a hydrologic data acquisition program for urban stormwater drainage systems*, Proceedings of the 8th International Conference on Urban Stormwater Drainage, Australia, pp. 2115-2122.

65. Maheepala U. K., Perera B., J. C. and Dayaratne S. T. (1999), *Diagnostic checking and analysis of hydrological data of urban drainage systems*, Proceedings of the 25th Hydrology and Water Resource Symposium and 2nd International Conference on Water Resource and Environment Research, Queensland, Australia, pp. 813-818.

66. Maheepala U.K., A.K. Takyi and B.J.C. Perera (2001), "Hydrological Data Monitoring for Urban Stormwater Drainage Systems", Journal of Hydrology, 245, pp. 32-47.

67. Mardle S. and Pascoe S. (1999), *An overview of genetic algorithms for the solution of optimisation problems,* Computers in Higher Education Economics Review, 13 (1).

68. Marquardt D. W. (1963), *An algorithm for least-squares estimation of nonlinear parameters*, Journal of Social Industrial and Applied Mathematics, 11(2), pp. 431-441.

69. Mayer D. G., Belward J. A. and Burrage K. (1999a), *Robust parameter settings of evolutionary algorithms for the optimisation of agricultural system models*, Journal of Agricultural systems, 69(3), pp. 199-213.

70. Mayer D. G., Belward J. A., Widell H. and Burrage K. (1999b), *Survival of the fittes- genetic algorithms versus evolution strategies in the optimisation of system models*, Journal of Agricultural Systems, 60(2), pp. 113-122.

71. Mbagwu J. S. C. (1997), *Soil physical properties influencing the fitting parameters in Philip and Kostiakov infiltration models*, Journal of Discovery and Innovation, 9(4), pp. 179-187.

72. Mein R. G. and Larson C. L. (1971), *Modelling infiltration during steady rain*, Water Resources Research, 9(2), pp. 384-394.

73. Melbourne Water (2000), *Amendment C1 Bayside planning*, Melbourne Water Waterways and Drainage, East Richmond, Victoria, Australia.

74. Metcalf and Eddy Engineers (1971), *Inc. Storm Water Management Model, volume 1, final report*, U.S. Environmental Protection Agency, Washington DC, USA.

75. Michalewicz Z. (1996), *Genetic Algorithm + Data Structures = Evolution Programs*, 3rd Edition, Springer- Verlag Berlin Heidelberg, Germany.

76. Mohan S. (1997), *Parameter estimation of non-linear muskingum models using genetic algorithm*, Journal of Hydraulic Engineering ASCE, 123(2), pp. 137-142.

77. Mohan S. and Loucks D. P. (1995), *Genetic algorithms for estimating model parameters*, Proceedings of the 22nd Annual Conference, Cambridge, Massachusetts, USA.

78. Mulligan A. E. (1995), *Genetic algorithms for calibrating water quality models*, Masters Thesis, Tufts University, Medford, Massachusetts, USA.

79. Mulligan A. E. and Brown L. C. (1998), *Genetic algorithm for calibrating water quality models*, Journal of Environmental Engineering, 124(2), pp. 104-110.

80. Ndiritu J. G. and Daniell T. M. (2001), *An improved genetic algorithm for rainfall-runoff model calibration and function optimization*, Journal of Mathematical and Computer Modelling, 33(6), pp. 695-706.

81. Ng A. W. (2001), *Parameter optimisation of river water quality models using genetic algorithms*, PhD Thesis, Victoria University of Technology, Australia.

82. O'Loughlin G. (1993), *The ILSAX program for urban storm water drainage and analysis*, User's Manual for Microcomputers, Version 2.13, School of Civil Engineering, University of Technology, Sydney, Australia.

83. O'Loughlin G. and Stack B. (1998), *DRAINS User's Manual,* Watercom Pty Ltd, Sydney, Australia.

84. Peck C. C. and Dhawan A. P. (1995), *Genetic algorithms as global random search methods*, Evolutionary Computation 3, pp. 39-80.

85. Philip J. R. (1957), *The theory of infiltration*, Journal of Soil Sciences, 83, pp. 435-448.

86. Pilgrim D. H. (1987), *Australian rainfall and runoff - A guide to flood estimation*, The Institution of Engineers, Australia.

87. Pitt R., Lilburn M., Durrans S. R., Burian S., Nix S., Voorhees J. and Martinson J. (2002), *Guidance Manual for Integrated Wet Weather Flow (WWF) Collection and Treatment Systems for Newly Urbanized Areas (New WWF Systems)*, http://civil.eng.ua.edu/~rpitt/Publications/BooksandReports.

88. Roesner L. A., Aldrich J. S. and Dickinson R. E., (1988), *SWMM User's manual, Version 4:EXTRAN*, U. S. Environmental Protection Agency, Athens, Georgia, USA.

89. Savic D. and Walters G. A. (1997), *Genetic algorithms for least-cost design of water distribution networks*, Journal of Water Resources Planning and Management ASCE, 123(3), pp. 67-77.

90. Schaffer J. D., Caruana R. A., Eshelamn L. J. and Das R. (1989), *A study of control parameter affecting online performance of genetic algorithms for function optimisation,* Proceedings of the Third International Conference on Genetic Algorithms, George Mason University, California, 4--7 June, pp. 51-60.

91. Schwefel H. (1981), *Numerical optimisation of computer models*, Wiley, Chichester, UK.

92. Schwefel H. (1997), *Advantages and disadvantages of evolutionary computation over other approaches- Book Section*, Handbook on evolutionary computation, Institute of Physics Publishing, Oxford University Press, New York, USA, pp. 1-2.

93. Sen Z. and Oztopal A. (2001), *Genetic algorithms for the classification and prediction of precipitation occurrence*, Journal of Hydrological Sciences, 46(2), pp. 255-265.

94. Simpson A. R., Dandy G. C. and Murphy L. J. (1994), *Genetic algorithms compared to other techniques for pipe optimisation*, Journal of Water Resources Planning and Management ASCE, 120(4), pp. 423-443.

95. Skukla M. K., Lal R. and Unkefer P. (2003), *Experimental evaluation of infiltration models for different land use and soil management systems*, Journal of Soil Science Society of America, 168(3), pp. 178-191.

96. Smedema L. K. and Rycroft D. W. (1983), *Land Drainage*, Cornell University Press, New York, USA.

97. Sorooshian V. and Gupta K. (1995), *Model calibration- Book Section*, Computer models of watershed hydrology, Water Resources Publications, Colorado, pp. 26-68.

98. Speers A. and Mitchell G. (2000), *Integrated urban water cycle*, Proceedings of the National conference on Water Sensitivity Urban Design - Sustainable Drainage Systems for Urban Areas, Melbourne, Australia.

99. Syswerda G. (1989), *Uniform crossover in genetic algorithms*, Proceedings of the Third International Conference on Genetic Algorithms and Applications, George Mason University, California, 4-7 June, pp. 2 -9.

100. Tsihrintzis V. A. and Hamid R. (1998), *Runoff quality prediction from small urban catchments using SWMM*, Journal of Hydrological Processes, 12(2), pp. 311-329.

101. USEPA (1992), *Stormwater management model (Version 4),* User's Manual, U.S. Environmental Protection Agency, Environmental Research Laboratory, Office of Research and Development, Athens, Georgia, USA.

102. Vale D. R., Attwater K. B. and O'Loughlin G. G. (1986), *Application of SWMM to two urban catchment in Sydney*, Proceedings of Hydrology and Water Resources Symposium, The Institution of Engineers, Brisbane, Australia, pp. 268-272.

103. Vasquez J. A., Maier H. R., Lence B. J., Tolson B. A. and Foschi R. O. (2000), *Achieving water quality system reliability using genetic algorithm*, Journal of Environmental Engineering ASCE, 126(10), pp. 954-962.

104. Victoria Stormwater Committee (1999), *Urban stormwater: best practice environmental management guidelines*, CSIRO Publishing, Melbourne, Australia.

105. Wagner A. A. (1957), *The use of the unified soil classification system by the Bureau of reclamation*, Proceedings of Fourth international conference SMFE, London.

106. Wang Q. J. (1991), *The Genetic algorithms and its application to calibrating conceptual rainfall-runoff models*, Water Resources Research, 27(9), pp. 2467-2471.

107. Wang Q. J. (1996), *Using genetic algorithms to optimise model parameters*, Environmental Modelling and Software, 12, pp. 27-34.

108. Wardlaw R. and Sharif M. (1999), *Evaluation of genetic algorithms for optimum reservoir system operation*, Journal of Water Resources Planning and Management ASCE, 125(1), pp. 25-33.

109. Watermark National Computing (1998), *PEST (Parameter ESTimation), User's Manual*, Australia.

110. Whelans and Maunsell H. G. (1994), *Planning and management guidelines for water sensitivity urban (Residential) design*, Consultant Report, Department of Planning and Urban Development, Western Australia, Australia.

111. Whitley D. (1989), *The GENITOR algorithm and selection pressure*, Proceedings of the Third International Conference on Genetic Algorithms, George Mason University, California, 4-7 June, pp. 116-121.

112. Widell H. (1997), *GENIAL 1.1 - A function optimizer based on evolutionary algorithms- Use Manual*, www.hjem.get2net.dk/widell/genial.htm.

113. Wong T. H. F. (2001), *A changing paradigm in Australian urban stormwater management*, Keynote Address, Second South Pacific Stormwater Conference, Auckland, New Zealand, 27-29 June.

114. WP Software and XP Software (1993), *Inc. XP-SWMM model with XP graphical interface, User's Manual*, Tampa, Florida, USA.

115. Wright A. H. (1991), *Foundations of Genetic Algorithms- Book Section*, Theory of real coded GAs, Morgan Kaufman Publishers, San Mateo, California, pp. 205-219.

116. XP-Software (1997), *XP-UDD32 getting started manual*, PO Box 3064, Purdue Street, Belconnnen, ACT, Australia.

117. WP Software (1991), *RAFT-XP (Runoff Analysis and Flow Training simulation)*, Version 2.7, User Manual, Australia.

118. Yang M., Merry C. and Sykes R. (1999), *Integration of water quality modeling, Remote sensing and GIS*, Journal of the American Water Resources Association, 35(2), pp. 253-263.

119. Yoon J. and Padmanabdan G. (1993), *Parameter estimation of linear and non-linear Muskingum models*, Journal of Water Resources Planning and Management ASCE, 119(5), pp. 600-610.

120. Yu B. (1999), A comparison of the Green-Ampt and a spatially variable infiltration model for natural storm events, Journal of the American Society of Agricultural Engineers, 42(1), pp. 89-97.