RESERVOIR OPERATING RULES FOR URBAN WATER SUPPLY SYSTEMS

BY

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Specially Dedicated to My Parents for their Love and Encouragement in all my Endeavours

DECLARATION

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

(Nelum Piyasena)
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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

SUMMARY

In recent times, a significant shift has emerged throughout the world from planning and construction of water resource projects to the efficient operation of existing systems due to many reasons. The reasons may include the non-availability of water resources for further development, the limited availability of funds for capital works and the spirited lobbying of environmental groups against construction of major water resource projects. Therefore, it is necessary to determine the optimum operating rules for water resource systems.

The generalised water supply simulation model (REALM) is been currently used by many water authorities around Australia for planning and operation of urban water supply systems. The operating rules used in REALM are the restriction rules and target storage curves. These operating rules currently in use do not produce the optimum operation and are based on the subjective operator experience. Therefore, the need to determine optimum operating rules in the form of restriction rules and target reservoir curves was important.

A general approach was used to produce the 'optimum' operating rules for an urban water supply system. Melbourne water supply system is considered as the case study. An objective methodology and computer software (namely Restrictions and Targets) were developed to derive the operating rules in terms of restriction rules and target storage curves.

The restriction rules were derived using a direct search method known as the Hookes and Jeeves method. The objective function used was the maximisation of releases to demand zones. The constraints of current security criteria were considered. A lumped single reservoir and single demand centre approach was used in the study, however, the effects of multi-reservoir interactions such as reservoir evaporation losses, spills from the system, effect of carrier capacity on releases and demand shortfalls were considered implicitly in the approach.

The target storage curves were derived using Discrete Differential Dynamic Programming (DDDP), with the objective function of maximisation of releases to demand zones. REALM system data of the Melbourne system was used and therefore all system details incorporated in a planning study of the system were included in DDDP. Water allocation

among various parts of the water supply system was done through network linear programming (NLP). REALM is used by Melbourne Water in their planning studies. The Restrictions and Targets software were developed for the Melbourne water system in this study.

Both Restrictions and Targets software were used for the Melbourne system using system, streamflow and demand data provided by Melbourne Water (MW) in early 1994. The restriction rules and target storage curves were derived for both static and dynamic demands. The behaviour of the Melbourne system was analysed under the derived and current MW rules using a REALM simulation model of system for the planning period of 1994 to 2026, and a comparison study was performed. The restriction rules derived under both static and dynamic demand analysis performed better than the current MW restriction rules. It was also found that the restriction rules derived from the static demand analysis were consistently better than those of the dynamic demand analysis while the target storage curves derived from DDDP slightly under-performed the MW current target storage curves. Finally, the target curves derived were fine-tuned using simulation results and expert knowledge, and the system behaviour improved significantly.

It is recommended that the operating rules (both restriction rule curves and target storage curves) derived from the static demand analysis be used for the Melbourne system for long term operation as Melbourne system cannot be augmented by constructing reservoirs in the MW catchments due to lack of suitable hydrologic sites.

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1. INTRODUCTION

1.1 BACKGROUND

In recent times there has been a significant shift from planning and construction of water resource projects to the efficient operation of existing systems due to many reasons. The reasons include the growing demand for water due to increase in population and per capita consumption, the non-availability of water resources for further development, the limited availability of funds for capital works and the spirited lobbying of environmental groups against construction of major water resource projects. Therefore, it is necessary to determine the optimum operating rules for existing and new water resource systems to achieve the efficient operation.

The operating rules specify how the demand should be met with available supply of water in the water resource system. They specify rules on how the demand should be restricted during periods of low inflow or droughts, how the demand should be met with different sources of supply in the system etc. Various operating rules are used in planning and operation of water supply systems. They include the restriction rules, the target storage curves, the rule curves, the releases as a function of storage volume and inflow to the reservoirs, and the environmental flows.

REALM (**RE**source **AL**location **M**odel) which was developed by the Water Bureau of the Department of Conservation and Natural Resources (Victoria) is currently being widely used in Victoria for planning and operation of both urban and irrigation water resource systems (Diment, 1991). REALM is a mass balance quasi-simulation computer model developed to facilitate analysis of performance of the headworks and transfer components of both urban and irrigation water supply systems under different operating policies and changes to system configuration. The operating rules used in REALM are the restriction rules, the target storage curves, the environmental flows and other priority releases. The operating rules on environmental flows and other priority releases are derived from considerations such as requirements for flora and fauna, sustainability of river and channel systems etc. However, the operating rules such as restriction rules and target storage curves should produce the 'optimum' outputs based on certain performance measures such as maximising releases.

The operating rules currently used for planning and operation of urban water supply systems are based mainly on the operator experience of the system. Often these operating rules provide satisfactory or near-optimum operation. These operating rules in some cases were verified by system simulation models such as REALM with historical streamflow data. Although the operating rules based on operator experience had produced the satisfactory operation, there is no guarantee that they would produce the 'optimum' operation due to the reasons outlined below.

(a) The system may not have been operated optimally and hence the operating rules based on historical operation will not produce the optimum operating rules.

(b) In order to meet the growing urban water demand, the system has to be augmented from time to time by constructing reservoirs and/or by importing water from elsewhere. With these considerations, the system becomes different to the system for which the operating rules were available from operator experience. However, no operator experience exists for new or augmented systems to determine the operating rules.

(c) Due to growing environmental concerns on water supply systems and catchments, and new water sharing arrangement among competing users under new water legislation (eg. Parliament of Victoria Water Act, 1989), the operating rules are certain to change from the past operating rules. The past operator experience offers little help in these situations.

For these reasons, it is necessary to determine the optimum operating rules by developing systematic and objective methods.

1.2 OBJECTIVES

The objectives of this study are as follows:

(i) Development of an objective methodology to derive the 'optimum' operating rules based on systems analysis methods which include simulation models, optimisation methods, and spreadsheet software.

(ii) Development of a general computer program suite which can be applied to any system configuration of the urban water supply systems and also is compatible with REALM software.

(iii) Derivation of 'optimum' operating rules for the Melbourne water supply system, using the computer program suite developed in (ii).

(iv) Investigation and comparison of the performance of the Melbourne System under derived and current operating rules.

1.3 METHODOLOGY ADOPTED IN THE STUDY

A direct search method commonly known as the Hookes and Jeeves algorithm (Dixon, 1972) was used to develop the restriction rule curves, since the derivation of restriction rules was formulated in this study as an constrained optimisation problem. The details of the method are given in Chapter 3.

A Dynamic Programming method known as Discrete Differential Dynamic Programming (DDDP) was used to determine the 'optimal' storage trajectory for the urban water supply system, from which the target storage curves were derived. Since the reservoir operation is a sequential decision process, Dynamic Programming is well suited to optimise the operation of reservoir systems. The details of the method are found in Chapter 4.

The methodology developed to determine the restriction rules and the target storage curves were applied to the Melbourne Water supply system. The derived operating rules were compared with the current operating rules used by Melbourne Water (MW) by performing several simulation runs with REALM. The results are discussed in detail in Chapter 6.

In brief, the study uses simulation models (REALM), optimisation algorithms (such as linear programming and dynamic programming) and other tools such as spreadsheet software, in deriving the operating rules for the urban water supply systems. Maximisation of releases to demand zones was considered as the objective function in determining both restriction rule curves and target storage curves. Performance measures related to security criteria of the urban water supply systems were considered as the constraints in optimising restriction rules.

1.4 SUMMARY OF MAJOR CONCLUSIONS

Several objective methods and computer software (Restrictions and Targets) were developed to derive the restriction rules and target storage curves for urban water supply systems.

The restriction rules were derived using a direct search method known as the Hookes and Jeeves method. The objective function used was the maximisation of releases to demand zones and the constraints of current security criteria used for the Melbourne system were considered. A lumped single reservoir and single demand centre approach was used in the study, however, the effects such as reservoir evaporation losses, water wastage from the system, effect of carrier capacity on releases and demand shortfalls were considered implicitly in the approach. The Restrictions software produces only the restriction triggers, and not the percentage restrictable demand (which is an input to the model) for various restriction levels.

The target storage curves were derived using DDDP, with the objective function of maximisation of releases to demand zones. REALM system data which represents the Melbourne system were used and therefore all system details were included in DDDP. Water allocation among various parts of the water supply system was done through network linear programming (NLP). An innovative scheme was devised to improve the computer execution time of DDDP. The optimum storage trajectory obtained from the Targets software was later analysed through MS EXCEL to produce the target storage curves.

These operating rules in terms of restriction rules and target storage curves were derived for the Melbourne system based on supplied data on system, demand and streamflow by MW in early 1994. These were compared with the current MW rules using a simulation model of the system. The restriction rules derived under both static and dynamic demand analysis performed better than the current MW restriction rules. Further, it was also found that the restriction rules derived from the static demand analysis were consistently better than those of the dynamic demand analysis. The target storage curves derived from DDDP slightly under-performed the MW target storage curves. One of the reasons for this under performance was the system simplifications and assumptions that were used in

DDDP. However, when fine-tuned using simulation results and expert knowledge, the system behaviour improved significantly.

There is a possibility that the Melbourne system cannot be augmented by constructing reservoirs in the MW catchments due to lack of suitable hydrologic sites. However, regulated water can be imported from nearby catchments to augment the supply. If this scenario is assumed, then it is recommended that the operating rules (both restriction rule curves and target storage curves) derived from the static demand analysis be used for the Melbourne system for the long term operation, once the augmentation is done through water imports. The static demand analysis uses the annual demand level equal to the 'sustainable yield' of the system (as defined later in this thesis) and represents the 2017 annual demand level. The current system will then be fully committed and a constant demand will be provided by the current system, while the growth in demand will be compensated by water imports.

It is also recommended that the restriction rules derived from the dynamic demand analysis be used for the current system until further augmentation, since the restriction triggers were developed based on percentage average annual demand (AAD). Ideally for the Melbourne system, (or other systems with significant growth in annual demand) the target storage curves should be determined considering different levels of annual demands, producing different sets of target storage curves. However, if a single set of target storage curves is to be used for the entire planning period of the simulation, then it is recommended that the target storage curves derived from the dynamic demand analysis be used for the current system (i.e. until further augmentation). These curves reflect the average conditions for the entire planning period.

1.5 RECOMMENDATIONS FOR FUTURE WORK

Four projects were identified for further detailed investigations based on the current study related to methodology and in particular application to the Melbourne system are discussed in detail in Chapter 7. These projects are listed as follows:

- Robust operating rules
- Streamflow modelling
- Urban demand modelling
- Holistic modelling of the Melbourne system

The operating rules described in this thesis were based on a single streamflow/demand scenario and a single objective function, therefore, the operating rules are optimum only for the selected objective function and streamflow/demand scenario used. Therefore, there is a need to develop robust operating rules which multi-criterion decision analysis can be used to determine the robust operating rules derived considering many objective functions and many different streamflow/demand scenarios. This project is an extension of the work described in this Thesis. In this project currently undergoing the operating rules are derived from many objective functions and many streamflow/demand scenarios.

Stoshastically generated streamflow data are commonly used in water supply planning studies. Generally the stochastic data generation models preserve 'standard' statistical parameters. Since the Melbourne system has a large carryover storage, it is necessary to consider 'long future persistence' in the data generation model, in addition to the preservation of other 'standard' statistical parameters. This aspect should be studied.

The demand reduction due to various restriction levels is an important factor in water resources planning studies. A physically based demand model which could model various processes of urban demand should be developed to model the demand reduction.

Once the streamflow and demand inputs are developed as outlined earlier, it is preferred to investigate the Melbourne system in a holistic sense with new inputs and to redefine the security criteria issues such as preferred monthly time reliability of the system, duration and magnitude of restrictions, and other criteria.

1.6 LAYOUT OF THE THESIS

Chapter 2 presents the literature review giving emphasis to the simulation and optimisation methods used in reservoir operation and justifying the system analysis application methods.

The methodology used to derive the restriction rule curves and the restrictions computer software are discussed in detail in Chapter 3. Chapter 4 explains the methodology used to derive the target storage curves and the Targets computer software.

Chapter 5 presents the details of the Melbourne water supply system. The general system details and the information on other data supplied by the Melbourne Water are also presented in this chapter. The application of the Restrictions and Target Software to the Melbourne system is presented in the Chapter 6, together with the comparison of the derived operating rules against the current operating rules used by MW.

Finally, Chapter 7 presents the overall conclusions from the study and some recommendations for future work, especially for planning studies of the Melbourne system.

2. SYSTEM ANALYSIS APPLICATION FOR RESERVOIR PLANNING

2.1 INTRODUCTION

The problem of allocating a resource such as water stored in a reservoir system is a complex task, especially due to the stochastic nature of inflows into the system. As water supply systems build up in complexity, from run-of-the river systems to single reservoirs then to multiple storages, the number of alternative ways of operating the system increases and the "rule of thumb" operation approach becomes less applicable. The operation of most multiple reservoir systems reflects the fact that there are sometimes conflicting and sometimes complementary multiple purposes served by the water stored in and released from reservoirs. For a complex system with a large number of reservoirs and aqueducts, attempts to determine best operating policies by search (i.e. trial and error), with a simulation model made to run on digital computers have been found to require an inordinate amount of computing time. Therefore, the decision makers need tools to operate their reservoir systems in an optimum, or rather, in the best manner. During the past two decades, one of the most important advances made in the field of water resources engineering is the development and adoption of system analysis application methods for planning, design and management of complex water resource systems. The rapid evolution of computers together with their frequent use in management and control also contributed to the growth of system analysis applications in the field.

System analysis cannot be defined with a single phrase as it involves several disciplines and a large number of actions. Ossenbruggen (1984) defines system analysis in brief as follows. "*System analysis is a coordinated set of procedures that can be used to address issues of project planning, engineering design, and management. System analysis is a decision making tool. An engineer can use it for determining how resources can be used most effectively to achieve a specified goal or objective. For successful decision making, both technological and economic considerations must be employed in the analysis.*" Further, this text book illustrates the application of system analysis to a broad range of problems; in structural, geotechnical, environmental, transportation, water resources and construction engineering, to achieve 'optimum' solutions. In the fields of economics, mathematics and business, system analysis is commonly referred to as "*operations*

research" (Ossenbruggen, 1984). The common system analysis techniques that have been used in the past in relation to reservoir operation are based on simulation and mathematical programming methods such as linear programming (LP) and dynamic programming (DP) (Yeh, 1985). Simulation, optimisation and associated stochastic analysis methods are essential tools in developing a quantitative analysis of a variety of water resource problems for both systems planning and operation.

A simulation model in general simulates the physical system and can be used to study the response of the system under a given set of input scenarios. Improvement to the operation of a water supply system can be achieved through a simulation model of the system by observing the consequences of operating rules on the system performance. REALM (Diment, 1991) is one such simulation model that can be applied to analyse the system performance of both urban and irrigation water supply systems. Although simulation is a powerful tool in analysing large and complex water resource systems, it does not provide the optimum operation explicitly, and generally requires numerous simulations under different operating rules to achieve the optimum operation, especially when stochasticity of streamflow is incorporated (Codner, 1979 ; Wurbs, 1993).

Mathematical programming techniques, on the other hand, yield the optimum solution explicitly and are very powerful analytical tools. However the real system usually needs to be simplified before applying these methods (Wurbs, 1993). LP is a mathematical programming technique in which the objective function and the constraints are either linear or can be considered to be piecewise linear. This method is best suited for optimum system design in space rather than in time (Simonovic, 1992). The main advantage in using LP is the availability of standard computer programming packages. Since the operation of water resource systems is a sequential decision process, DP is well suited to optimise the operation of these systems compared to the other optimisation methods (Codner, 1979; Perera, 1985). Further, nonlinear objective functions and constraints can be directly handled by DP which cannot be incorporated explicitly with LP models. The major disadvantage of DP in relation to the reservoir operation is the excessive requirement of computer time and memory, especially when there is a large number of reservoirs in the system. However, Heidari et al (1971) introduced a variation of deterministic dynamic programming (DDP) called discrete differential dynamic

programming (DDDP) to reduce the computer memory requirements in optimising water resource systems.

It is important to note that the simulation and mathematical programming methods are not competitive in the analysis of water resource systems, but they can be of mutual benefit to each other. The mathematical programming methods produce the optimum solution out of all possibilities for a simplified system in case of a large complex system. The derived optimum solution can then be refined using an overall simulation analysis of the actual system to account for the simplifications made in the mathematical programming methods. The combined use of these methods can be very useful in the analysis of water resource systems to exploit the advantages of both methods (Wurbs, 1993).

This chapter deals with systems analysis applications in water resources with emphasis on reservoir operation. First, simulation is discussed. Then, the mathematical programming methods, both LP and DP are reviewed. The chapter then, presents the objective functions used in systems analysis application of reservoir operation in general and the objective functions used for urban water supply systems. Next, the literature on operating rules, used in reservoir operation are reviewed. Finally, the chapter deals with the measures of system performance used for analysis of water resource systems.

2.2 SIMULATION

A simulation model is usually characterised as a representation of a physical system used to predict the response of the system under a given set of conditions. A multiple-reservoir system is such a physical system, which can be analysed by simulation models. Simulation models may not be able to generate an 'optimal' solution to a reservoir problem directly. However, with numerous simulations using alternative decision policies, these models can detect an 'optimal' solution or a near-optimal solution (Simonovic, 1992).

Typical simulation models associated with reservoir operation include a mass-balance computation of reservoir inflows, outflows and changes in storage. They may also include economic evaluation of flood damages, hydroelectric power benefits, irrigation

benefits and other similar characteristics. Simulation models often use historical data. In some cases, simulation models are used only for the period for which streamflows are low. This analysis is known as the critical period analysis. The critical period analysis, which uses low flow sequences, is discussed in detail in McMahon and Mein (1986).

Simulation analysis using historical streamflow data is a simple procedure and displays the behaviour of water storages in a system clearly. The behaviour diagram can be readily understood even by non-technical persons. The procedure can be applied to data based on any time interval. The method takes into account the auto-correlation, the seasonality and other flow parameters as long as they exist in the historical flows used in the analysis. However, when an analysis is based only on historical streamflow records, it is, quite clear that the historical sequence of inflows will not be repeated exactly in the future, and the historical inflows may not be representative of the statistical population of flows. Further, the noncontinuous records cannot be handled because of the difficulties of assigning the initial reservoir condition after a break in the streamflow data (McMahon and Mein, 1986).

The above problem (i.e. historical sequence not being representative of future streamflows) can be overcome by using generated streamflow data in reservoir simulation models. Stochastic data generation provides analysts of reservoir systems with alternative sequences of streamflow having the same statistical properties as the historical record. Using generated data in simulation models provides an unlimited number of synthetic streamflow sequences, all as equally likely to occur in the future as a repetition of the historical flow record. It also provides the opportunity to examine the influence of different flow patterns on the estimates of the parameters of interest. Further, the use of generated data overcome the behavior analysis problems associated with a broken historical record, since the data generation methods do not produce broken sequences (McMahon and Mein, 1986).

Simulation models are widely used by the water authorities around the world in planning of multireservoir water supply systems. Generally they are preferred to the mathematical programming models (commonly known as optimisation models), because of the simplicity and transparentness of the models. Simulation models permit very detailed and realistic representation of the complex physical, economic and social characteristics

of a reservoir system compared to the optimisation models, which require certain system simplifications. The concept inherent in the simulation approach are easier to understand and communicate than other modeling concepts (Simonovic, 1992). The main disadvantage of the simulation approach is that it does not produce the optimum operation, since optimal operating rules are not used.

In the past, simulation models were developed to model specific systems. However, during the last two decades, emphasis has shifted from the development of site specific water supply simulation models to generalised models, which can be applied to any system configuration with any form of operating rules. Several models considered to be representative of the state-of-the-art simulation models are cited in Yeh (1985), Wurbs et al. (1985) and Wurbs (1993).

Site-specific models are developed to simulate specific systems. Many site specific reservoir models are cited in published literature. However, numerous other models successfully used in many offices throughout the world have simply not been reported in literature (Wurbs, 1993). The Colorado River Simulation System (CRSS) and the Potomac River Interactive Simulation Model (PRISM) described below are two typical examples of simulation models developed for particular reservoir/river systems. Wurbs (1993) also states that 20 other site-specific simulation models have been used at specific, United States Bureau of Reclamation projects.

The CRSS, originally developed by the United States Bureau of Reclamation during 1970s and subsequently revised and updated, simulates the operation of the major reservoirs in the Colorado Basin for water supply, low flow augmentation, hydroelectric power and flood control. The CRSS is a set of computer programs and data bases used in long term planning (Wurbs, 1993). The PRISM was originally developed by a research team at John Hopkins University, U.S.A. A number of water management agencies in Potomac river basin participated in drought simulation exercises using PRISM during development and implementation of a regional water supply plan for the Washington metropolitan area (Wurbs, 1993).

The major disadvantage of site specific simulation models is that they are strictly designed for a particular system, and when using for a different system configuration the

actual computer code has to be developed or modified accordingly. This may require expertise and time. On the other hand, the generalised simulation models are extremely user friendly and readily applied to a variety of reservoir/river systems. Therefore, when using a generalised simulation model, the user has to develop only the input data for the particular system of interest and execute the model (Wurbs, 1993). There are several readily available, well documented, generalised computer models which can be used for reservoir system simulation; they include HEC-3 (Hydrologic Engineering Centre, 1971), HEC-5 (Hydrologic Engineering Centre, 1979), WASP (Kuczera and Diment, 1988), IRIS (Loucks et al., 1987, 1989, 1990), WATHNET (Kuczera, 1990), and REALM (Diment, 1991).

Although the simulation models do not provide the 'optimal' operation of the water supply system over the planning period, they may attempt to provide an optimal solution through 'optimal' operating rules. Therefore, it is very important to use 'optimal' and realistic operating rules in simulation models to adequately capture system behaviour (Perera and Codner, 1996). A simulation model with realistic and 'optimal' operating rules may provide the near-optimal operation of the system, while producing important simulation results for the planner.

Recognising the capabilities of both simulation and mathematical programming methods, several studies have been conducted or proposed to exploit the advantages of both methods. This has been done in two ways. The first method is to incorporate optimisation routines nested in simulation models (Yeh, 1985). For example, WASP (Kuczera and Diment, 1988), WATHNET (Kuczera, 1990) and REALM (Diment, 1991) simulation models incorporate network linear programming (NLP) such as NETFLO (Kennington and Helgason, 1980) and RELAX (Bertsekas and Tseng, 1987), to determine the optimum allocation of water within the simulation time step. The use of NLP provides the optimum operation for the simulation time step, but does not give the optimum operation over the planning period. However, a near-optimal solution over the planning period can be achieved by selecting the 'optimal' operating rules.

The second method is the conjunctive use of simulation and mathematical programming methods. The common approach here is to use a mathematical programming method to determine the 'optimum' operation, and operating rules for a simplified system of the

real system and then to use a simulation model to study the behaviour of the system under these 'optimum' operating rules, and to refine the operating rules. Codner (1979) stated that a DP model could be used first to determine the 'optimum' operating rules for the system considering a simplified system (because of the computational difficulties). The 'optimum' operating rules can then be refined by a detailed simulation model, which includes the system details, which have not been included in the previous DP model.

2.3 MATHEMATICAL PROGRAMMING METHODS

Mathematical programming methods are covered in general in the standard text books of operations research and mathematics, while the application of these methods to water resource systems are described in text books such as Loucks et al. (1981), Esogbue (1989) and Mays and Tung (1992). Yakowitz (1982) discussed in detail the role and suitability of DP in reservoir operation. Yeh (1985) presents a comprehensive in-depth state-of-the-art review of reservoir operation models, with a strong emphasis on optimisation techniques (i.e. mathematical programming methods). Since then, there have been many advances in this area which are included in a review of Wurbs (1993), which describes reservoir system simulation and optimisation models. In the above references and many other research papers on system analysis applications to water resource problems, the term "optimisation" is commonly used synonymously with mathematical programming methods. However, in this thesis, the methods, such as pattern search methods are referred to as optimisation methods while the methods that are used to develop time-based patterns of decisions (so that total benefits over time is maximised), through techniques such as LP and DP are referred to as mathematical programming methods.

Most applications of reservoir systems analysis involve either LP and/or DP. Various other non-linear programming methods particularly search algorithms, have also been used in the past. Each of these techniques can be applied in a deterministic or stochastic environment, characterising the streamflow process. The deterministic models use a specific sequence of streamflows either historical or synthetically generated. The stochastic models use a statistical description of the streamflow process instead of a specific streamflow sequence (Karamouz and Houck, 1987). An extensive lists of

references on the use of LP, DP and non-linear programming methods in reservoir system analysis is given in Yakowitz (1982), Yeh (1985) and Wurbs et al. (1985).

Mathematical programming models are formulated to define a set of decision variables that will maximise or minimise an objective function subject to constraints. The objective function and the constraints are represented by mathematical expressions of the decision variables. For a reservoir operation problem, the decision variables are typically the reservoir release rates and/or the end-of-period reservoir storage volumes. Volume of water that is supplied to demand zones and/or reliability can be defined as the objective functions. Constraints include the maximum and minimum capacities of reservoirs, carriers and mass balance at various locations (eg. at reservoirs, pipe junctions and stream junctions) of the reservoir system (Wurbs, 1993).

Mathematical programming methods provide useful capabilities for analysing problems characterised by a need to consider an extremely large number of combinations of decision variables. The other advantage is that they provide more systematic and efficient computational algorithms. However, representing the objectives, performance criteria, operating rules, and physical and hydrological characteristics of the system in the real form without unrealistic simplifications is a difficult aspect of the modelling process which limits the application of optimisation techniques (Simonovic, 1992).

2.3.1 Linear Programming

Linear programming (LP) is considered as one of the most widely used techniques in water resources and one of the most important scientific advances in recent history. LP has the advantage of the availability of well-defined, easy to understand and readily applicable algorithms. Numerous generalised computer programs are available for solving LP problems. LP can be used to solve problems of many disciplines, although the method is limited to solving only linear problems, i.e. problems with linear objective function and constraints (Wurbs, 1993). Many water resource problems can be represented realistically by a linear objective function and a set of linear constraints. In other cases, various linearisation techniques have been used successfully to deal with nonlinearities, but these techniques add another step of approximation and tend to increase the number of constraints on the problem. As stated in Wurbs (1993), the

Tennessee Valley Authority (TVA) hydro scheduling model called HYDROSIM falls into this category. TVA-HYDROSIM is used to simulate the 42 reservoir Tennessee Valley Authority system based on an established set of operating priorities. A series of operating constraints were formulated to represent the various objectives. This model uses LP to compute reservoir releases, storages, and hydro electric-power generation for each week of a 52 week period beginning at present, based on the alternative sequence of historical streamflows. A search procedure is used to handle a nonlinear hydro-power cost function.

The first LP application in deterministic reservoir operation dates back to 1962 (Dorfman, 1962) when linear programming was used for a simplified reservoir problem without considering over-year storage. Loucks et al. (1981), presented a number of LP reservoir problem formulations for deterministic problems based on maximising reservoir yield. Yakowitz (1982) and Yeh (1985) reviewed many different types of LP models and their successful applications in reservoir operation. Simonovic (1992) reviews some important applications of LP in reservoir operation along with additional techniques that have extended and amplified the usefulness of LP. One of them is the method described by Loucks et al. (1981) in determining the capacity of a reservoir by using the continuity equation and the incorporation of storage-dependent losses in a linear programming formulation. The above reviews (Yakowitz, 1982; Yeh, 1985; Simonovic, 1992; Wurbs, 1993) and textbooks such as Loucks et al. (1981), Esogbue (1989) and Mays and Tung (1992) describe some important applications of LP in reservoir operation. Some recent LP applications are described in the following paragraphs.

Crawley and Dandy (1993) developed a monthly planning model that uses linear goal programming to aid in the identification of optimum operating policies for the Adelaide headworks system in South Australia. The planning and operational policies obtained were aimed at achieving maximum yield for a given level of reliability. The reliability was defined as the ratio of the number of years in which no monthly reservoir failure events occur to the total number of years simulated. In this particular system where a significant fraction of the supply was pumped from a distant river, the objective function used was to minimise the cost of pumping while maintaining the operational reliability requirements (storage levels at or above the specified target storage levels) subject to the

physical limitations of the system. Using this model the operation of southern Adelaide water supply headworks system was simulated and the results of the model showed that savings of between 5% and 10% of total pumping cost can be achieved. This model was subsequently implemented by the Engineering and Water Supply Department of Adelaide.

Lund and Israel (1995) presented applications of two stage and multistage linear programming for the preliminary estimation of least-cost integration of several water marketing opportunities with water conservation and traditional water supplies. The author stated that the main problem in the LP formulation was the increase of the size of the problem with the parameters that need to be estimated in situations such as water transfers in urban water supply. The depletion of storage in drought management was another limitation and adding a reservoir to the system increased the operational dimensions of the LP formulation. Uncertainty in parameter values can be represented, by enlarging the number of events considered, to reflect joint hydrological and parameter value events, which may also result in increasing computer time. The author suggested that many of these limitations can be handled through modifications or extensions of the formulation presented, by using a multistage linear and dynamic programming formulations (Lund and Israel, 1995).

Network Flow Programming (NFP), a special type of LP has been frequently applied for simulation and optimisation of water resource systems. Similar to other LP models, the NFP technique can be used to solve models that are characterised by linear objective functions and constraints although the nonlinear systems may also be solved iteratively using NFP in conjunction with linearisation methods. Most systems may be innovatively translated to a network model, but some aspects of the system may have to be approximated by a network model solved iteratively (Wurbs, 1993). These iterative solutions were used in REALM (Diment, 1991) in modelling carrier capacities which were functions of flow in other carriers, in solving the optimum water allocation for a simulation time step through NFP. Often in most recent literature, NFP is described as Network Linear Programming (NLP).

Kuczera (1989) developed a multiperiod linear programming model using NLP to obtain the optimum operation of a multiple reservoir system with greatly reduced computer

time. He applied this model to a 3-reservoir and 2-demand zone system, over 324 periods. The case study illustrated the computational performances of the NLP model.

2.3.2 Dynamic Programming

Dynamic programming (DP) is a mathematical programming technique that can be used to solve a variety of problems involving sequential decisions such as a release policy of a multipurpose reservoir system. Nonlinear objective functions and constraints can be used in DP formulations directly and therefore DP is well suited to determine the optimum operation of water resource systems (Codner, 1979). Dynamic programming is a multistage sequential decision making process based on the theory that, *"An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision."* This is known as Bellman's Principle of Optimality (Bellman, 1957). Detailed reviews of DP applications to water resource problems are given in Yakowitz (1982), Yeh (1985) and Wurbs (1993). The main difficulty in applying DP to practical multi-dimensional problems (e.g. the operation of a system of multiple reservoirs), is the excessive computational requirements of the procedure. This is generally known as the " curse of dimensionality" in DP (Codner, 1979). In an effort to eliminate some of the limitations of DP, a number of improvements have been made by various authors.

- Aggregation or composite reservoir approach (Arananitidis and Rosing, 1970a,1970b and Terry et al. 1986). In this method, the reservoirs are lumped into a single storage so that a representation does not consider all constraints of the reservoirs and links, which may be critical for the system operation.
- Partitioning into smaller problems. (Turgeon, 1980 and Braga et al. 1991) and aggregation/decomposition (Turgeon, 1980,1981). With these methods, the problem is partitioned into managable problems of less state variables. These methods are referred in Yeh (1985) as successive approximation methods.
- Reduction in number of states in DP formulation (Saad and Turgeon, 1988). "Corridor" approach (Codner 1979).

These mathematical manipulations were necessary to solve the optimisation of large multiple reservoir systems, exploiting certain characteristics of the system as these mathematical manipulations and/or simplifications reduced the computational requirements. However, these approaches have utility in those studies. For example, Turgeon (1980) reports that the composite reservoir approach has great utility in supplying the user with a rule curve for reservoir operation.

In literature, DP methods as applicable to reservoir operation have been broadly classified into two categories:

- Stochastic Dynamic Programming (SDP)
- Deterministic Dynamic Programming (DDP)

SDP considers the stochastic nature of streamflow explicitly by employing a probability function for streamflow. DDP uses either the historical sequence of streamflow or a generated sequence of streamflow to implicitly account for the stochasticity of streamflow.

DP methods can be further classified into two classes known as backward looking DP and forward looking DP based on how the recursive relation is used. These formulations can be for both SDP and DDP formulations. In backward looking DP, the last stage is considered first in the optimisation study. The results from this stage are stored for the use of subsequent calculations. Next, the one before the last stage is considered. The calculation step is repeated stage by stage until the first stage is reached. Then a forward search is carried out to determine the 'optimal' policy from the first stage to the last stage. Le Bat (1981) and Perera (1985) used backward looking SDP in their optimisation studies. Forward looking DP starts with the first stage and computes the values of the states in a similar manner to backward looking DP, but marches forward with time. Codner (1979) and Karamouz and Houck (1982) have used forward looking DP for reservoir applications. Where there is no special reason for choosing either the backward or the forward formulation, the backward recurrence is normally used. The procedure of using backward DP and then a forward search for 'optimal' policy is convenient and meaningful especially in problems involving time, as it gives the 'optimal' policy in chronological order. Forward recurrence is advantageous when a deterministic problem

has to be solved several times with different planning horizons. This may occur because a plan is periodically reviewed or where the appropriate planning horizon is unknown. The evaluations can be extended forward in time without repeating previous calculations by adding extra stages into the end, if required (Yeh, 1985).

2.3.2.1 Stochastic dynamic programming (SDP)

SDP considers the stochasticity of streamflow by considering a probability distribution for streamflow. It produces a set of 'optimal' operating rules (i.e. optimum operation) for combinations of storage volumes and streamflow intervals, not requiring 'averaging' out the optimal operating rules over streamflow replicates. Therefore, the method theoretically yields the global optimal operation of the system for all streamflow and storage volume combinations (Perera, 1985). However, in determining the optimum operation of a system of multiple storages, the complex correlations of streamflow and the number of storages prohibit the application of this method to larger systems because of the excessive computer requirements.

Although SDP has been successfully used in determining the optimum operation of single reservoir systems (Loucks and Falkson, 1970; Mawer and Thorn, 1974; Le Bat, 1981), a limited number of studies have been done on multiple reservoir systems (Perera and Codner, 1996). In most of these cases, the problems were simplified by neglecting the cross correlation of streamflow at the storages (Yakowitz, 1982) and in certain cases by lumping storages (Valde's et al 1992). A review of the early SDP studies done in relation to reservoir operation were reported in Codner (1979), Yakowitz (1982), Yeh (1985) and Perera (1985). The general conclusion from these reviews was that the computational requirements increase with increase in the number of reservoirs and streamflow inputs, and therefore it is necessary to simplify large systems into manageable systems for use in SDP. Some recent applications of SDP in reservoir operation are reviewed below.

Karamouz and Houck (1987) compared deterministic dynamic programming with regression (DPR) and SDP for reservoir operating rule generation. To compare the models 12 single-reservoir, monthly operation test cases in four different reservoir sizes ranging from small (20% of the mean annual flow) to very large (upto 170% of the mean

annual flow) at three different hydrological sites were used. For each case, the DPR and SDP models were constructed. They showed that DPR generated rules were more effective for medium to large reservoirs, whereas SDP gives better results for the operation of smaller reservoirs. The authors described the reason for this behaviour is that SDP was more sensitive to the number of characteristic storages (NS) and usually required a much higher NS value to function properly, especially when the reservoir is fairly large. However, DPR forced the rule to perform within a limited range in several iterations.

Valde's et al. (1992) used an aggregation-disaggregation procedure that combines SDP and LP techniques to operate a multireservoir system in order to overcome the dimensionality problems usually found in DP. The reservoirs in a hydropower system were aggregated to represent a single reservoir in power units rather than in water units, and the optimal operating rules for the equivalent aggregated reservoir derived using SDP. The objective function used was the minimisation of the total cost of energy production of the system. The aggregated policy obtained was then used in the real time operation of the system to determine the daily releases for power production from each reservoir of the system. The LP algorithm was used in this approach. The method was applied to the Lower Caroni hydropower system in Venezuela, which consisted of four reservoirs in series. The authors stated that the methodology was computationally efficient although it was partially obtained at the expense of being suboptimal (Valde's et al., 1992).

Vasiliadis and Karamouz (1994) presented a concept of demand driven stochastic dynamic programming (DDSP) model that allows the use of actual variable monthly demand in generating the operating policies. In DDSP, the uncertainties of streamflow process and the forecasts were captured using Bayesian decision theory. Probabilities were continuously updated for each month. Monthly demand along with inflow, storage and flow forecast were included as hydrologic state variables in the algorithm. The operating policies were compared and tested in a hydrologic real-time simulation model and in a real-life operational model. The reliability of the operating policies was measured in terms of meeting the required demand when the operating policies were applied in a simulation/operational model. The inclusion of forecasts as well as the

inclusion of monthly variable demand as state variables allowed the development of a more efficient, realistic and robust operating policies (Vasiliadis and Karamouz, 1994).

Tejada-Guibert et al. (1995) presented several SDP models of Shasta-Trinity system in Northern California with different hydrologic state variables. The authors stated that the inclusion of a hydrologic state variable (such as current period flow, previous flow or seasonal forecasts) in an SDP model allowed the inclusion of temporal persistence found in most hydrologic time series. They compared the use of seasonal and one-period-ahead flow forecasts with use of the flow in the current period as a hydrologic state variable. The performance of each formulation was examined with three different objective functions, which place different penalties on shortfalls associated with firm power and water targets of different magnitudes. Performance was measured in terms of reliability and average annual benefits. It was stated that for an objective function stressing the energy maximisation, all policies performed well, and the choice of hydrologic state variable mattered very little. For a benefit function with larger water and firm power targets and severe penalties on corresponding storages, the predicted performance significantly overestimated simulated performance, and policies that employed more complete hydrologic information performed significantly better (Tejada-Guibert et al, 1995).

Perera and Codner (1986 and 1996) used stochastic dynamic programming (SDP) to derive the 'optimum' target storage curves for the Melbourne water supply system. Because of the computational problems associated with SDP, a system of four storages (by lumping storages without losing the reality of the system operation) were considered in the analysis instead of eight storages.

Raman and Chandramouli (1996) derived the reservoir operating policies to improve the operation and efficient management of available water of the Aliyar Dam in Tamil Nadu, India, using a SDP model. The objective function used was to minimise the squared deficit of the release from the irrigation demand. From the DP algorithm, general operating policies were derived using a neutral network procedure (DPN model) and using a multiple linear regression procedure (DPR model). The DP functional equation was solved for 20 years of fortnightly historic data. The field irrigation demand was computed for this study using Penman method with daily meteorological data. To assess

the ability and performance of the DPN model, a more sophisticated stochastic model was constructed using the same objective function. The performance of DPR, DPN and SDP models were compared for three years of historical data, using the same objective function. The authors concluded that both models based on DP (DPN and DPR models) resulted in better operating policies than the SDP model in this case study, where both use a simple rule to release inter-basin water transfer. They also stated that the finer volumetric discretisation of storage and release improved the performance of both DPN and DPR models but marginally (Raman and Chandramouli, 1996).

2.3.2.2 Deterministic Dynamic Programming (DDP)

DDP requires the streamflow sequences to be known in advance for the study period. DDP has been extensively used in reservoir operation in two different forms. The first method uses the historical sequence of streamflow to determine the optimum operation of the system. The optimal decisions (or releases) thus derived are only relevant to the historical streamflow sequence. That is, the policies derived indicate how the system should be operated given that the historical stremflow sequence occurs again. The second method is to consider the stochastic nature of streamflow by considering multiple sequences of streamflow generated from the historical sequence. This method gives an operating policy for each streamflow sequence. It is then necessary to combine these operating policies to yield a single policy. A review of these methods is given by Codner (1979), Yakowitz (1982) and Yeh (1985).

Generally, when DP is applied to the operation of reservoir systems, it is necessary to consider all possible storage volume combinations of the reservoir systems. This causes computational problems in terms of excessive computer time and memory (Yakowitz, 1982; Yeh 1985). This has become the major disadvantage of DDP in the past, although the method has been applied to many single and multiple reservoir problems. Heidari et al. (1971) introduced a method called "Discrete Differential Dynamic Programming" (DDDP) to reduce the computer memory problems associated with multiple reservoir systems. DDDP is a specific type of DDP in which the number of possible states at any one stage is reduced by placing a corridor about a trial initial storage trajectory and optimisation carried out within the corridor. To obtain the 'optimal' solution, several

iterations with successively improved storage trajectories are considered (Codner, 1979). DDDP method is described in Section 4.4.1 in detail, since it is used in this study.

Nopmongool and Askew (1976) introduced multilevel incremental dynamic programming (MIDP) to the optimisation of multiple reservoir systems. The system was decomposed to its smallest unit (that is a single storage), which was then optimised. Each level of the analysis then consisted of one additional storage using the previously attained optimal release policies. Eventually the total system was optimised, the final pass involving all storages but with a smaller number of iterations than would have occurred through the application of conventional DP. This was because faster lower levels act as screens which eliminate progressively undesirable solutions and left the higher levels a decreasing region of alternatives. Further, the authors stated that their experience indicated that it may not be necessary to go up to the n th level of MIDP in order to solve an n-dimensional problem. Also in MIDP, the choice of the initial trial trajectory was negligible unlike in DDDP, and the responsibility for obtaining a good initial trajectory was totally relieved. The authors stated that the approach resulted in marked reduction in computer execution time attributable to the DDDP global approach of Heidari et al. (1971) due to less number of iterations. However, Codner (1979) stated that in this approach, the higher level analysis involving all storages has to be considered at least once and this may cause problems of high dimensionality.

Codner (1979) used DDDP to determine the optimum operation of the Melbourne water supply system as at December 1970. He used heuristic operating rules to allocate water within the system during a time step in DDDP, and therefore the model was system dependent. He outlined the following advantages and disadvantages in using DDDP in multiple reservoir operations.

- Computer memory requirements are substantially reduced compared to conventional DP.
- As the system is not decomposed the problem of matching decisions (releases) from subsystems does not occur. Generally system decomposition is not used with DDDP.

- Various degree of solution refinement can be achieved through changing the width of the corridor about the trial trajectory.
- The concept is easier to comprehend and apply than many of the methods dealing with decomposition theories.
- The method may converge slowly and require a large number of iterations depending on the accuracy of the initial trajectory.
- If the corridor values are not chosen properly (eg. if they are too wide), it is possible for the approach to converge to a local optimum rather than the global optimum.

Turgeon (1982) illustrated with two examples, that incremental dynamic programming may converge to a non-optimal solution, if the same state increment was used for every stage and then showed how to adjust the increment sizes in each stage so that the solution will converge to the optimum. Although the idea of using different state increments in every stage was first proposed by Heidari et al. (1971), they never described why, when and how the state increments should be varied. In their example, they have used the same state increment for all stages.

Ozden (1984) presented another DP-based procedure called binary state DP for the operation of multi-reservoir systems. Binary state DP is a new algorithm which starts from a nominal trajectory as DDDP, but seeks the objective function improvement with minimum number of evaluations at each combination formed by only two values from every coordinate of the state space. The author stated that the computational time savings of this algorithm became more pronounced as the dimension of the problem increased. Further, the method required a minimal amount of high-speed memory. A major disadvantage of the approach was that as in the case of DDDP, it is not possible to predict the number of iterations the algorithm would require to reach the optimal solution for a given problem. However, it was proved that each iteration of the algorithm required only a small fraction (0.67^{2n}) of the computational time required by the DDDP approach for a n-dimensional problem (Ozden, 1984).

Kuo et al. (1990) used DDDP to determine the optimal release policies from Shihmen and Feitsui reservoirs in the Tanshui river basin in Taiwan. A simulation model was first used to determine the initial storage trajectory. DDDP was then used to determine an improved operating policy. At the end of each 10-day period, the streamflow forecast

was updated and the simulation and optimisation models were rerun for the remaining period of the year. The cycle repeated until the last period was reached. The models were evaluated with an actual operational record and tested with several hypothetical conditions. The results showed the models performed effectively for both normal and abnormal years.

2.4 OBJECTIVE FUNCTION

The objective function is an essential element in a mathematical programming model. It is the relationship used to determine the optimal policy from different decisions when system moves from one state to another (or to the same) through various stages. It is a measure of performance through which different policies are compared. Typical objective functions include the minimisation of total economic costs, the maximisation of net benefits and the minimisation of system spills. The objective functions used in water supply simulation and optimisation models were discussed in Codner (1979) and Perera (1985).

Optimisation models generally include one objective function, but sometimes with several objectives. It is not possible to have a single objective function to maximise irrigation releases and hydropower simultaneously, if these are expressed in different units. However, if they are expressed in commensurate units (such as in monetary terms), a single objective function can then be considered.

Where the objectives cannot be expressed in terms of a single objective function, two alternative approaches are typically adopted to analyse trade-offs between objectives. One approach is to execute the optimisation model several times with one objective reflected in the objective function and the other objectives treated as constraints at different fixed user-specified levels and to perform a trade-off analysis. For example, the model might maximise average annual energy, subject to the constraints of user-specified water supply release, and generate a curve of average annual energy versus water supply release. A trade-off analysis is then made between water supply release and annual energy. In the literature this method is known as the constraint method. The other approach for analysing trade-offs between noncommensurate objectives involves treating each objective as a weighted component of the objective function. This method is

commonly known as the weighting method in the literature. The objective function is the sum of each component multiplied by a weighting factor reflecting the relative importance of each objective. The weighing factors can be arbitrary, with no physical significance but translate non-commensurate units into commensurate units. The model can be executed iteratively with different sets of weighting factors to analyse the trade-offs between the objectives (Wurbs, 1993).

Although numerous studies have done on the optimisation of reservoir systems, most of these deal with hypothetical examples. Most studies in the past have employed economic objective functions such as the maximisation of net benefits or minimisation of costs. These are satisfactory in case of projects which involve readily measured real costs and benefits, such as hydropower and irrigation. Harboe et al,(1970), Fults and Hancock (1972) and Meredith (1975) used the maximisation of net benefits, while Aron and Scott (1971), Su and Deninger (1974) and McKerchar (1975) used minimisation of costs as the objective function. The probability of failure of the system was not considered in any of these studies.

The optimum operating rules found by considering only the economic objective function could result in a high degree of failure of the system. It is more desirable to have a system with relatively lower target release (or yield), but with a higher degree of reliability especially for urban water supply (Perera, 1985). Askew (1973) was one of the first to suggest that the probability of failure of the system should be addressed in optimisation of water resources as well as the economic objective functions.

Most reservoirs are designed to serve more than one purpose such as power generation, flood control and water supply, and therefore the need for multiobjective operation has become eminent. Hence the most recent applications deal with multi-objective planning and operation.

Tauxe et al. (1980) formulated a multiobjective DP model to determine the monthly releases for a single reservoir. The trade-offs between excess energy and evaporation losses were generated by considering the objective functions with one state variable and the other as a constraint.

Mohammadi and Marino (1984) presented a generalised model that uses a combination of LP and DP for the operation of a single multipurpose reservoir in maximisation of both municipal and industrial (M&I) water release and power generation. The LP portion of the reservoir operation model determined the optimum set of monthly releases for power generation, M&I requirements, and downstream requirements such that the total monthly releases were minimised for a given contract levels of water and energy. The constraints were demands (contract levels) for water and energy, minimum reservoir storage (set by recreation or power plant minimum requirements or both), maximum reservoir storage (set by flood control considerations), power plant capacity and other system characteristics such as the capacity of a canal for M&I water delivery. Since LP yielded several end reservoir storages for each month, a forward DP solution procedure is used to select one end-storage for the given contrast levels (Mohammadi and Marino, 1984).

Simonovic (1988) studied the long-term planning of the operation of a single multipurpose reservoir using a chance constrained model. Apart from the direct multi-purpose use of water from the reservoir for downstream users, releases were available for other uses, which can be diverted. Therefore, the influence of downstream users was taken into account by a special form of an objective function in this study. Releases were also bounded by the capacity of the diversion outlet works above and by the guaranteed minimum from below (i.e. flow necessary to protect aquatic life in the river downstream). These two bounds were considered as constraints on the control space. The objective function was to maximise the downstream discharge. Three types of downstream releases were considered, based on estimated needs for irrigation of a certain area, production of electric power and water supply. Assuming a particular mix of downstream users of water released, the objective function was modified with weighting coefficients. The weighting coefficients were assigned in the objective function (on three different type of releases) on a priority basis.

Harboe (1992) illustrated six applications of multiobjective decision making techniques for finding optimal or satisfying operating rules for reservoir systems. The examples include situations with hydropower versus water supply (for irrigation), flood control versus low flow augmentations, selection of an operating rule, low flow versus reliability, low flow versus water quality and finally recreation versus water quality.

Several methods including the weighting and constraint methods were used in multi-objective planning and the operating rules derived. The models were applied to Shasta and Folsom Reservoirs in Northern California and to the Wupper River system in Germany. Several alternative operating rules were obtained, and a selection for the derived operating rules were performed by assigning weights and making sensivity analysis.

Laabs and Schultz (1992) presented a three-step multiobjective decision making (MODM), technique for reservoir management. In the first step of the method, a weighting method which allowed the combination of various objectives into one objective function was used. By systematically varying the weights for objectives, a number of pareto optimum reservoir operating rules were developed. In the second step, these operating rules were tested by using a simulation model. The results were statistically analysed and the reliabilities computed for attaining various objectives. In the third step of the model, two alternative MODM techniques were offered namely compromise programming and sequential multiobjective problem solving Technique (SEMOPS). Here, the decision maker in a computer dialogue was allowed to select the optimum reservoir operating rule from the large number of generated rules in the first step by specifying the preference for various objectives. Multiobjective Wupper reservoir system in Germany was chosen as the case study (Laabs and Schultz, 1992).

2.4.1 Urban Water Supply

Codner (1974) analysed the operation of the Melbourne water supply system using a simulation model and employed two different objective functions. The first objective function was the maximisation of volumetric reliability which was based on the concept of Frecker (1969), that at the optimum volumetric reliability, the present value of net benefits from a system were maximised. The volumetric reliability was defined as the ratio of the total volume of water supplied over a given length of time to the total volume of water demanded over the same period. This objective function did not require the evaluation of monetary benefits of water and system costs and can be considered as a pseudo economic objective function (Codner, 1974). The second objective function was a direct economic objective function which maximised the net benefits. Codner (1974) showed the difficulties in computing costs and benefits associated with the second

method and concluded that the volumetric reliability concept was a satisfactory objective function for urban water supply systems.

In the later study of the Melbourne system, Codner (1979) used the volumetric reliability and a loss function to optimise the operation of the system using DP. He reviewed the previous optimisation studies in relation to the objective function used in urban water supply systems and made the following conclusions.

- Volumetric reliability should be used as the objective function to try to maximise the reliability (yield) of the system.
- A loss function index need should be included to differentiate between release policies that deliver equal volumetric reliability.
- Although not in the objective function, the time reliability of the system should be determined within the DP algorithm as it represents an important parameter.

Perera (1985) and Perera and Codner (1996) used maximising the annual volumetric reliability as the objective function for determining the optimal operation of the Melbourne water supply system. Maximising the volumetric reliability is equivalent to maximising the water supply yield constrained by the demand. In urban water supply systems, demand deficits play an important role, which is related to volumetric reliability. Maximising the volumetric reliability increases the overall reliability of the system and reduces demand deficits. In these studies, the minimisation of system spills (total spill from the multiple reservoir system) was considered as a secondary objective function to differentiate between release policies that deliver equal volumetric reliability.

In recent decades, water transfers have been increasingly sought as a source of additional water supplies for urban systems. Lund and Israel (1995) presented a study on optimisation of transfers in urban water supply planning. The objective function considered in this study was to minimise the expected value of all costs.

2.5 OPERATING RULES

The operating rules specify how the demand should be met with available supply of water in the water resource system. Therefore, they provide rules on how the demand

should be restricted during periods of low inflow or droughts, how the demand should be met with different sources of supply in the system etc. Various operating rules are used in planning and operation of urban water supply systems and these operating rules can be defined explicitly or implicitly.

An explicit operating rule defines exactly what kind of action has to be taken for given inflows, demands and system states. Fig. 2.1 illustrates two simple explicit operating rules. The normal rule meets demands where possible, while the hedging rule requires the imposition of restrictions on demand even though water is available to meet demand (Kuczera, 1988). Hedging rule considers some conservation in imposition of restrictions providing considerable protection against possible severe droughts. Examples of site-specific multireservoir simulation models which use explicit rules are found in Collinge (1978) and Daniell and Fitzgerald (1982).

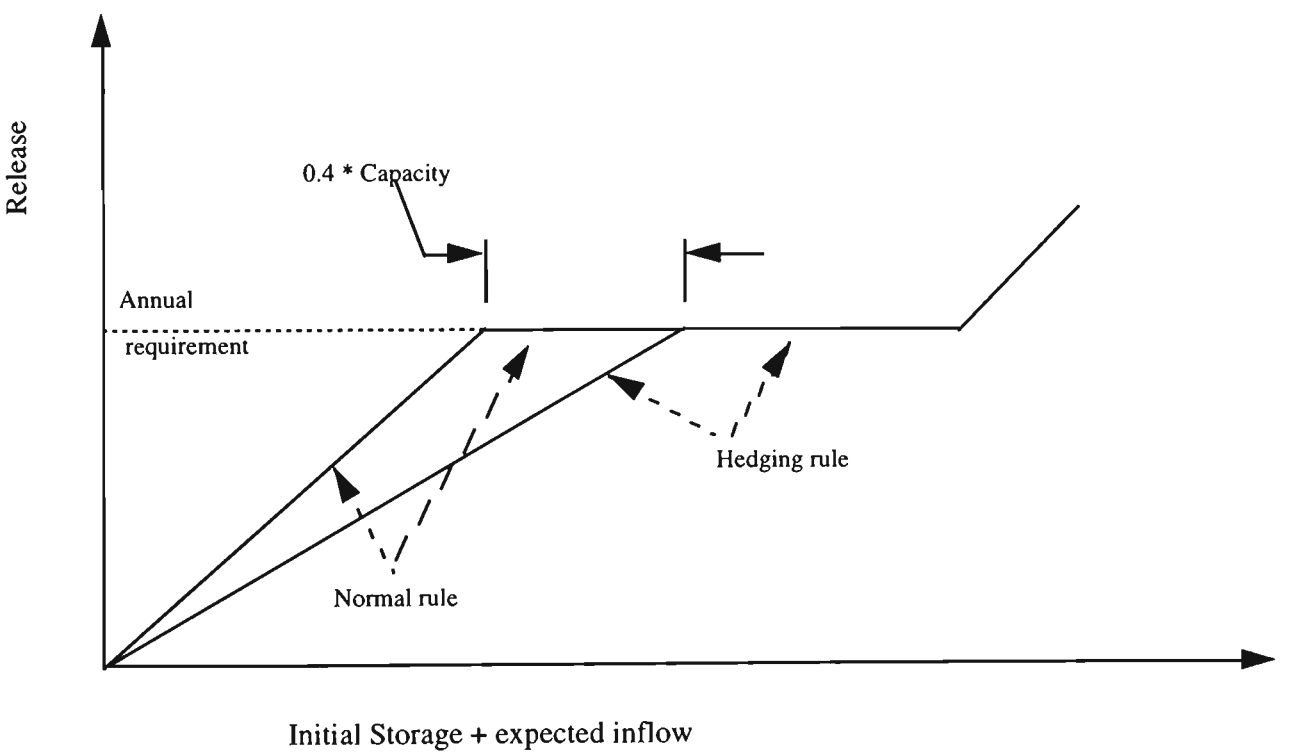


Fig. 2.1 Normal and Headging Operating Rules (extracted from Kuczera 1988)

Implicit operating rules guide an optimisation algorithm which is given the task of deciding actual releases and transfers over a given time interval. The main practical benefit implicit rule models offer is that they streamline the search for better operating policies and the identification of augmentation strategies (Kuczera, 1988). Implicit

operating rules are used in HEC 3 (HEC, 1971), WASP (Kuczera and Diment, 1988), HOMA (Crawley and Dandy, 1993) and REALM (Diment, 1991).

The operating rules that are considered in this thesis are the restriction rules and the target storage curves in relation to urban water supply systems. They are described in detail in Chapters 3 and 4 respectively, together with a review of previous studies.

2.5.1 Restriction Rules

Most water supply authorities follow a multistage restriction program where successive stages are implemented sequentially as the risk of running out of water increases. A survey of water rationing policies for major urban headworks systems in Australia highlighted the widespread use of both voluntary and mandatory multistage water restrictions (Sheedy and Kesari, 1988). These are discussed in detail in Chapter 3.

2.5.2. Target Storage Curves

The term 'target storage curves' is a relatively new term in water supply planning models. The target storage curves are used in a family of simulation models developed in Australia; these models are WASP (Kuczera and Diment, 1988), WATHNET (Kuczera, 1990) and REALM (Diment, 1991). The target storage curves determine the preferred spatial distribution of storage volume of individual storages in a multiple reservoir system for given total system storages. The previous work in relation to target storage curves are discussed in detail in Chapter 4.

2.6 MEASURES OF SYSTEM PERFORMANCE

The common use of simulation models of water supply systems has led to the development of performance measures, which quantify the characteristics of system behaviour. These performance measures include measures of frequency, severity and duration of restrictions, the recoverability of a water resource system from periods of shortfall, the time of system drawdown and variations in the system drawdown (Rhodes, 1992). Simple and frequently used measures of system performance are the mean and

variance of system outputs and performance indices. The outputs of simulation models are used to compute these system performance measures.

System performance measures in relation to reservoir operation were first studied by Hashimoto et al. (1982). They describe the system performance from three different view points:

- How often the system fails (reliability),
- How quickly the system returns to a satisfactory state once a failure has occurred (resiliency), and
- How significant the likely consequences of failure may be (vulnerability).

They formulated the definition of these criteria assuming that the performance of the water resource system can be described by a stationary stochastic process. That is, the probability distributions that describe the output time series do not change with time. The reliability of the system was defined as the frequency or probability that the system was in a satisfactory state. They also stated reliability as the opposite of risk. That is, the risk (or the probability of failure) is simply one minus the reliability. Both reliability and risk do not describe the severity of failure. Therefore, the severity of failure was described by other criteria such as resiliency and vulnerability by Hashimoto et al. (1982). Resiliency describes how quickly a system is likely to recover or bounce back from failure once a failure is occurred. If failures are prolonged, the system recovery is slow and may have serious implications for system design. Vulnerability refers to the likely magnitude of a failure, if one occurs. Maximising system efficiency and reliability can increase system vulnerability to a costly failure, should a failure occurs (Hashimoto et al. 1982).

Use of reliability, resiliency and vulnerability concepts has been illustrated in Hashimoto et al. (1982) with a single reservoir problem. They stated that a high system reliability can be normally accompanied by a high system vulnerability. However, they further stated that in order to achieve the best performance, the engineers and planners need to develop appropriate quantitative risk criteria that describe the undesirable events that may experience as a consequence of a particular operating policy decisions.

Beshay and Howell (1986) used resiliency, insensitivity, invulnerability, stability and robustness as additional measures of hydrologic performance with reliability to assist in making better choices about storage sites, sizes and operating procedures. Their use has been demonstrated on a simplified version of a case study in the central tablelands of New South Wales. They defined reliability as the proportion of time in which the storage is in the satisfactory state, (i.e. when the consumers are allowed unrestricted use). The resiliency was defined as a measure of the average time taken from the hydrologic end of the drought to the end of unsatisfactory state. Invulnerability was defined as a measure of the system resistance to drought conditions. Stability is defined as the measure of the degree of fluctuation between satisfactory and unsatisfactory states within a short time. Here, a short period of time has been arbitrarily defined as a period of less than or equal to six months of satisfactory state. They stated that different water authorities may adopt longer or shorter periods to suit their management policies or their requirements. Insensitivity was defined as the measure of how insensitive a storage was to dry conditions in terms of how the storage contents are volumetrically affected; this is a measure of average time from when the storage was last full to the beginning of the unsatisfactory state (Beshay and Howell, 1986).

Since reliability has been categorised as the most commonly practiced performance measure in defining the probability of failing to achieve some target release, Moy et al. (1986) presented two additional descriptions of reservoir performance. They are:

- The maximum shortfall from the target (system vulnerability), and
- The maximum number of consecutive periods of deficit during a record (system resilience).

A multiobjective, mixed-integer, linear programming model, incorporating reliability, resilience and vulnerability as objectives, was formulated by Moy et al. (1986) to investigate the release policy of a reservoir used for the single purpose of water supply. The three risk objectives are to minimise the maximum deficit, minimise the maximum number of consecutive deficits, and minimise the total number of deficit periods. They stated that an understanding of the trade-offs between these objectives may lead to improved formulation of reservoir operating rules. They found that when the reliability was increased or the maximum length of consecutive shortfalls was decreased (i.e.

resilience increases), the vulnerability of the water system to larger deficits increased (Moy et al, 1986).

2.7 SUMMARY

The following conclusions are drawn from the literature review presented in this chapter. Some of these conclusions are used in the subsequent chapters in formulating the methodology for deriving the operating rules for urban water supply systems.

Simulation models play an important role in water supply planning and management. They do not optimise the operation of water supply systems, but evaluate the consequences of the operating rules on the system performance. The simulation models can be used refine the operating rules to reflect the optimum operation.

Mathematical programming methods, on the other hand, optimise the operation of water supply systems. The commonly used mathematical programming methods in water supply planning are LP and DP. LP has the advantage that well-defined, easy to understand and readily applicable algorithms are available for use. However, in most water resource planning studies, the objective functions and constraints are non-linear and therefore, linearisation techniques have to be used in LP. The linearisation techniques require iterative solutions, which increases dimensions in the LP problem and the computer time required.

Water resource optimisation problems are sequential decision processes, and therefore, DP is ideally suited to solve these problems. Non-linear objective functions and constraints can be handled explicitly with DP. DDP accounts for the stochastic nature of streamflows implicitly through multiple replicates of generated streamflow data sequences, while SDP accounts for the stochastic nature through a probability distribution of streamflow. The general opinion from the literature is that SDP provides the global optimum for the operation of water resource systems, since it considers the stochastic nature of streamflow through probability distribution and that 'averaging' out is not required for the 'optimal' operating rules. However, the 'curse of dimensionality' prohibits the use of this method for systems with a large number of reservoirs.

DDDP provides an alternative approach to determine the optimal operation of a system with a large number of reservoirs by reducing the computer memory requirements of the conventional DDP approach. The stochasticity of streamflow can be handled through multiple replicates of generated streamflow data. Water allocation within the multiple reservoir system can be determined through NLP, thus eliminating the use the heuristic operating rules in the system. Therefore, DDDP with NLP can be used to develop a generalised computer program, which can be used in any system configuration with any form of operating rule.

Once the operating rules are derived from the optimisation methods such as DDDP, they should be refined through a simulation model. Further the simulation model can be used to study the behaviour of the system under derived operating rules and to compute various performance measures of the system operation. Performance measures such as reliability, duration and severity restrictions, resiliency etc. should be considered in evaluating the operating rules.

An Objective function is necessary in mathematical programming methods to measure the system performance under different operating policies and to select the optimal policy from different decisions. Maximisation of the sum of releases to demand zones (or volumetric reliability) is a satisfactory objective function to determine the 'optimal' operating rules for urban water supply systems. A secondary objective function of minimising system spills can be used to differentiate between solutions, which deliver equal volumetric reliability.

3. RESTRICTION RULES

3.1 INTRODUCTION

The **RE**source **AL**location **M**odel (REALM) which was developed by the (former) Department of Conservation and Natural Resources (Victoria) is currently being widely used in Australia for planning and operation of both urban and irrigation water resource systems. The operating rules used in REALM are the restriction rules, the target storage curves, the environmental flows and other priority releases (Diment, 1991).

REALM does not optimise the operating rules; rather it evaluates the consequences of the specified operating rules. The operating rules currently used for planning and operation of urban water supply systems are derived by adhoc methods based on operator experience of the system. Sometimes these operating rules provide satisfactory or near optimum operation. In most cases they have been tested and fine-tuned by system simulation models using historic streamflow data through trial and error analysis. However, they may not provide the 'optimum' operation based on certain performance criteria. The 'optimal' operating rules will provide more water to demand zones, still satisfying the required performance criteria.

The restriction rules and target storage curves are independent of each other. The restriction rules depend on the total available storage for release while the target storage curves determine the preferred spatial distribution of individual reservoir volumes for an expected total system storage volume. Therefore they can be derived separately. In this chapter, only the restriction rules are considered.

The restriction rules are generally expressed in terms of either total system storage or percentage average annual demand (AAD), and certainly this is the case in WASP (Kuczera and Diment, 1988), WATHNET (Kuczera, 1990) and REALM (Diment, 1991). Typical restriction rule curves are shown in Fig. 3.1, which describe the current restriction rule curves (as at 1994) used by Melbourne Water (MW) for Melbourne water supply system. In modelling urban water supply systems for planning studies, the user has to input the details of restriction rules. They are the upper rule curve, lower rule curve, number of intermediate zones and percentage restrictable demand for these zones.

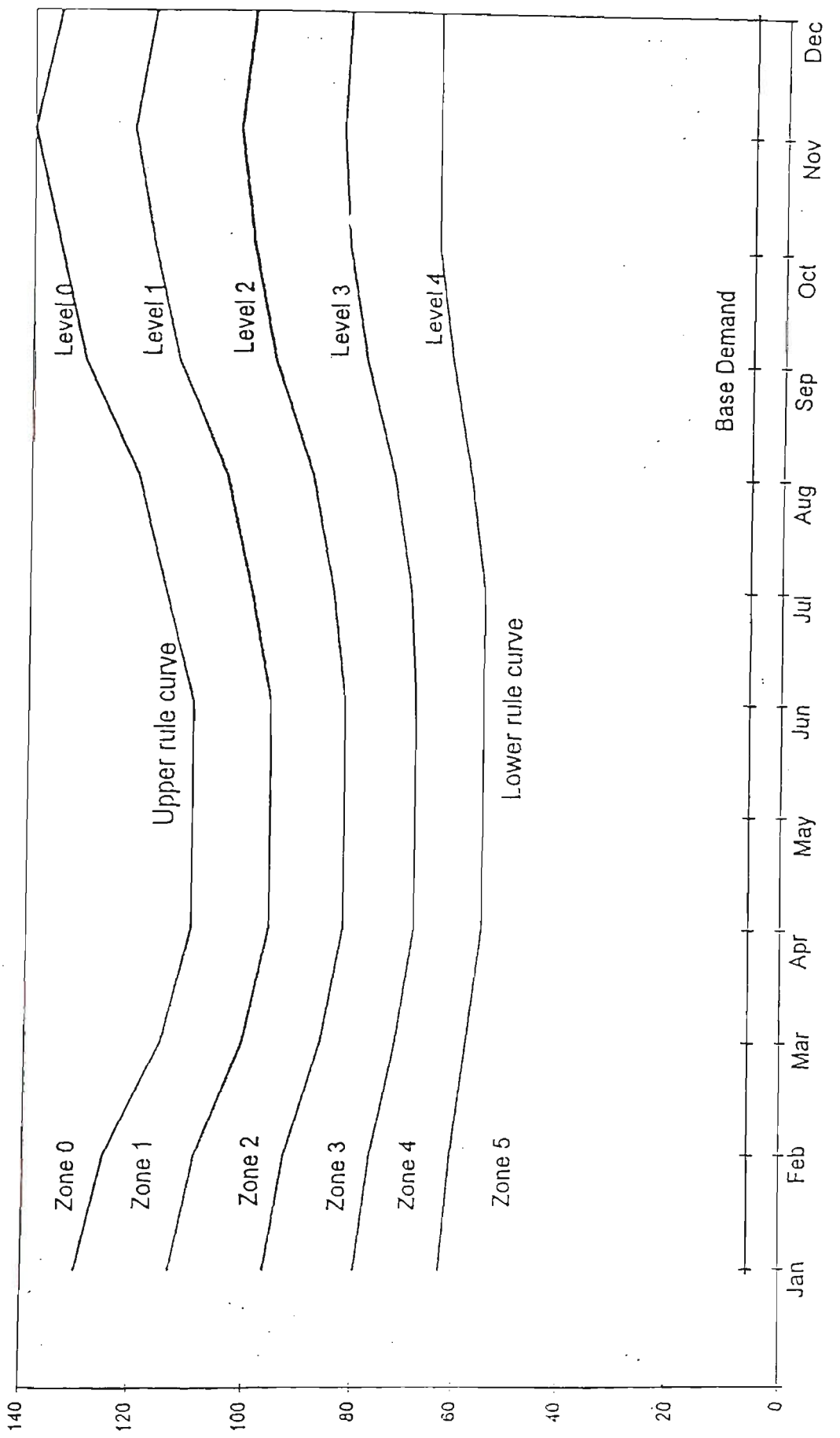


Fig 3.1 Current Restriction Rules (as at 1994) used by Melbourne Water

When the storage level at a particular month is above the values defined by the upper rule curve, then no restrictions are imposed on water demand. If the storage volume is below the values defined by the lower rule curve, then water demand is restricted to the base demand (ie. household demand). If the storage volume is in an intermediate zone, the demand is then restricted by the corresponding percentage (ie. percentage restrictable demand) of the zone; in this case only the demand above the base demand is restricted.

When working out the percentage restrictable demand, first a number of zones is identified for which restrictions are to be imposed. For each zone, actions are identified to impose restrictions. Some of these actions may include measures such as prohibiting of garden sprinklers, and prohibiting of hand held hoses and cans for watering public gardens and parks. Demand models which account for the processes of urban water demand can be employed to compute the percentage restrictable demand corresponding to these actions, which in turn can be used to produce the percentage restrictable demand for these zones. The percentage restrictable demand used by MW for different restriction zones are given in Table 3.1.

Table 3.1 Percentage Restrictable Demand Used by MW

Restriction Zone	Restriction Level	Relative Position (%)	% Restrictable Demand
0	above 0	0	0
1	0-1	25	25
2	1-2	50	50
3	2-3	75	80
4	3-4	100	95
5	below 4	-	100

Note:

- Levels 0 and 4 are the upper and lower restriction rule curves respectively.
- Relative position refers to the restriction level (rather than restriction zone); eg. relative position of 50%indicates the position of level 2 with respect to level 0 (relative position of 0%) and level 4 (relative position of 100%).
- Percentage restrictable demand refers to a zone and it is the percentage restrictable above the base demand.

Very few studies have been done on the derivation of restriction rules. Collinge (1978) determined restriction rules based on simulation of Melbourne water supply system over a period of three years. During this period, three repetitions of streamflow of worst 12 months on record were considered together with the corresponding demands.

The criterion for determining the restriction rules was that the storages would have emptied by the end of three year period with the above streamflows and demands in spite of restrictions. These restriction rules with slight modifications are used by MW for the current system. However these restriction rules do not consider the current security criteria of the Melbourne water supply system.

The Sydney Water Board has had no formal restriction policy because of the fairly conservative design drought adopted in its headworks planning. However, the imposition of restrictions is considered if available storage falls below 50% of full capacity with the possibility of more severe restrictions for lower storage levels (Sheedy and Kesari ,1988).

The Hunter District Water Board, Newcastle, adopted an eight-stage restriction policy during the drought of 1979-1982. The effect of these restrictions was an average reduction of 16% in consumption with respect to expected unrestricted consumption. Later, it was found that the same reduction could have been achieved with a two level restriction policy. The initiation of these restrictions was set at 80% of total system storage capacity. Subsequent levels of restrictions were determined on an ad-hoc basis (Sheedy and Kesari, 1988).

The Western Australia metropolitan water supply system has experienced a number of restrictions since 1950, either due to inadequate distribution capacity or due to insufficient storage. A three class restrictions policy ranging from partial sprinkler restrictions which would reduce the average annual demand by 14% to total sprinkler restrictions which reduces the annual demand by 46% is used for modelling purposes. The policy is based on an annual reliability of 90 % (Sheedy and Kesari, 1988).

The water consumers of The Engineering and Water Supply Department, Adelaide, have enjoyed a relatively restrictions free supply of water since 1967. Before this, restrictions were imposed by decree or on a voluntary basis (Sheedy and Kesari, 1988).

Crawley and Dandy (1996), in their work on the impact of water restriction cost on the selection of operating rules for water supply systems, state that the implementation of water restrictions, either voluntary or mandatory, will normally result in economic loss to both consumers and the water supply authority. The case study selected (Southern Adelaide

water supply system) highlighted that the selection of a more conservative operating rule set is economically preferable to a less conservative operating rule set in conjunction with a water restriction policy, to attain a specified level of system reliability. In this paper, the economic costs associated with the implementation of water restrictions were considered in the examination of reliability-cost trade-offs for the operation of the Southern Adelaide water supply system. The inflow variability, the demand variability, the pumping system reliability and the implementation of water restrictions were identified as the major factors that were associated with reliability-cost trade-offs for the Adelaide water supply headworks system (Crawley and Dandy, 1996).

When developing the restriction rules, it is necessary to consider the security criteria used by the water Authority. Security criteria measures the ability to supply the demands requested from the system through certain performance measures such as magnitude, duration and frequency of restrictions, and reliability of supply.

Different performance measures and security criteria are used by different water authorities. For example, MW uses security criteria related to monthly time reliabiity, worst restriction level and maximum duration of consecutive water restrictions.

The performance measures related to security criteria used for MW are as follows.

- Monthly time reliability should not be less than 95%.
- The worst restriction level is level 3 (Fig. 3.1)
- Maximum duration of any form of restrictions is 12 months.

The security criteria for the Melbourne water supply system does not consider the frequency of restrictions explicitly. Frequency of restrictions defines how often restrictions are imposed (eg. one in twenty yeras etc.).

3.2 OBJECTIVES

The main objective of this part of the study is to develop 'optimal' restriction rules that maximise releases to demand zones without violating the security criteria. The security criteria used in this study are represented by the performance measures of monthly time reliability, worst restriction level and maximum consecutive duration of restrictions. Major

water authorities in Victoria, Australia, use this form of security criteria. The restriction rules developed in this study are similar to the restriction rules shown in Fig. 3.1.

Two specific objectives are considered and they are:

- To develop a methodology and a resulting computer program (known as the Restrictions Software in this thesis) that is applicable to any system configuration of urban water supply systems with any number of restriction levels.

- To develop restriction rules which are compatible with REALM software (Diment,1991), so that these rules can be entered as input data for REALM. Most water authorities use REALM as the simulation model in water resources planning and operation in Victoria.

Although the resulting computer program is developed for dealing with the security criteria with performance measures of monthly time reliability, worst restriction level and consecutive duration of restrictions, the computer program can be easily modified to allow any other form of security criteria.

One other important assumption is made in the derivation of restriction rules. It is assumed that the number of restriction levels (or zones) and the percentage restrictable demand corresponding to each zone are known. The evaluation of number of restriction zones, actions that should be undertaken in these zones and percentage restrictable demand corresponding to these zones is outside the scope of this study.

3.3 METHODOLOGY

As stated in the Section 3.2, the objective of this part of the study is to determine the restriction rules that maximise the releases to demand zones subject to the constraints of security criteria in terms of monthly time reliability, worst restriction level and maximum consecutive duration of restrictions. This is an optimisation problem. A direct search algorithm known as Hookes and Jeeves algorithm (Dixon, 1972) is used for this optimisation problem. The justification for using the Hookes and Jeeves algorithm is explained in Section 3.3.2. Optimisation is carried out on a multi-dimensional grid of

restriction triggers (defined in the next paragraph) between the upper rule curve and worst restriction level, by systematically changing the values of restriction triggers.

The restriction triggers are the values on the restriction rule curves (including intermediate curves) which triggers different levels of restrictions. The restriction triggers between upper rule curve and worst restriction levels are considered because restrictions cannot be imposed below the worst restriction level. The detail of the optimisation algorithm is described in Section 3.3.2.

A simulation model of the water supply system considering a grid point, which represents a restriction policy, was used to produce the releases to demand zones. These are then used to compute the objective function of the optimisation problem. The simulation of complex urban water supply systems (such as Melbourne system which is described in Chapter 5) consumes a large amount of computer time and many simulations have to be carried out in the optimisation even with the Hookes and Jeeves algorithm. Therefore, a lumped storage system is used in this study instead of the simulation of the complex system.

The urban water supply reservoir system is lumped into a single reservoir single demand centre system. The sum of releases is computed from the simulation of the lumped system for the planning period. The constraints are computed from the results of simulations. Although in theory the lumped system does not consider the capacities of carriers, reservoir spills, reservoir evaporations, and wastage of water from the system, they are implicitly modelled in the lumped system in this study. This is explained in Section 3.3.1.

Mathematically, the problem is formulated as follows.

$$\underset{\underline{v}}{Max}\left[\sum_{n=1}^{N} d_n\right] \tag{3.1}$$

subject to the constraints of

$$d_n \leq D_n \quad (3.2)$$

$$S_{n+1} = S_n + I_n - d_n - E_n - W_n + SF_n \quad (3.3)$$

$$S_{n+1} \leq C_{max} \quad (3.4)$$

$$S_{n+1} \geq C_{min} \quad (3.5)$$

$$TR \approx tr \quad (3.6)$$

$$MD \geq md \quad (3.7)$$

$$WL \geq wl \quad (3.8)$$

where d_n is the release from the lumped reservoir to lumped demand centre during time step n,

D_n is the demand (sometimes restricted) to be supplied from the lumped reservoir during time step n,

N is the number of monthly time steps of the simulation,

$\underline{v}$ is the restriction policy,

S_n is the storage volume of the lumped reservoir at the beginning of time step n,

I_n is the inflow to the lumped reservoir during time step n,

E_n is the evaporation loss that should be considered from the lumped reservoir during time step n, (Section 3.3.1)

W_n is the water wastage that should be considered from the lumped system during time step n, (Section 3.3.1)

SF_n is the component of demand that should not be supplied from the lumped system during time step n, (Section 3.3.1)

C_{max} is the maximum capacity of the lumped reservoir,

C_{min} is the minimum capacity of the lumped reservoir,

TR is the performance measure of the security criteria related to monthly time reliability,

tr is required value of TR,

MD is the performance measure of the security criteria related to maximum duration of continuous restrictions of any form,

md is required value of MD,

WL is the performance measure of the security criteria related to worst restriction level,

wl is required value of WL, and

$\approx$ refers to approximately equal (just above or below).

Several numerical experiments were conducted on the Melbourne water supply system, using different restriction rules. In all cases it was found that the performance measure on monthly time reliability is first reached compared to the other two performance measures. Therefore the constraint on monthly time reliability was expressed as an equality constraint in Equation. (3.6) to model just reaching (or violating) the required time reliability. It was also found that restriction rules with extremely low values were obtained when Equation (3.6) was set as an inequality constraint (ie TR >=tr), in addition to Equations (3.7) and (3.8). These restriction rules with extremely low values had low resilience in system recovery, once failure was started or even could lead into short but severe restrictions. Low resiliency in system recovery, and short and severe restrictions are not acceptable from operational point of view.

3.3.1 Lumped System Model

As stated earlier, the reservoirs and demand zones in the multiple reservoir urban water supply system are lumped into a system of single reservoir and single demand zone. A schematic representation of lumped storage system is shown in Fig. 3.2.

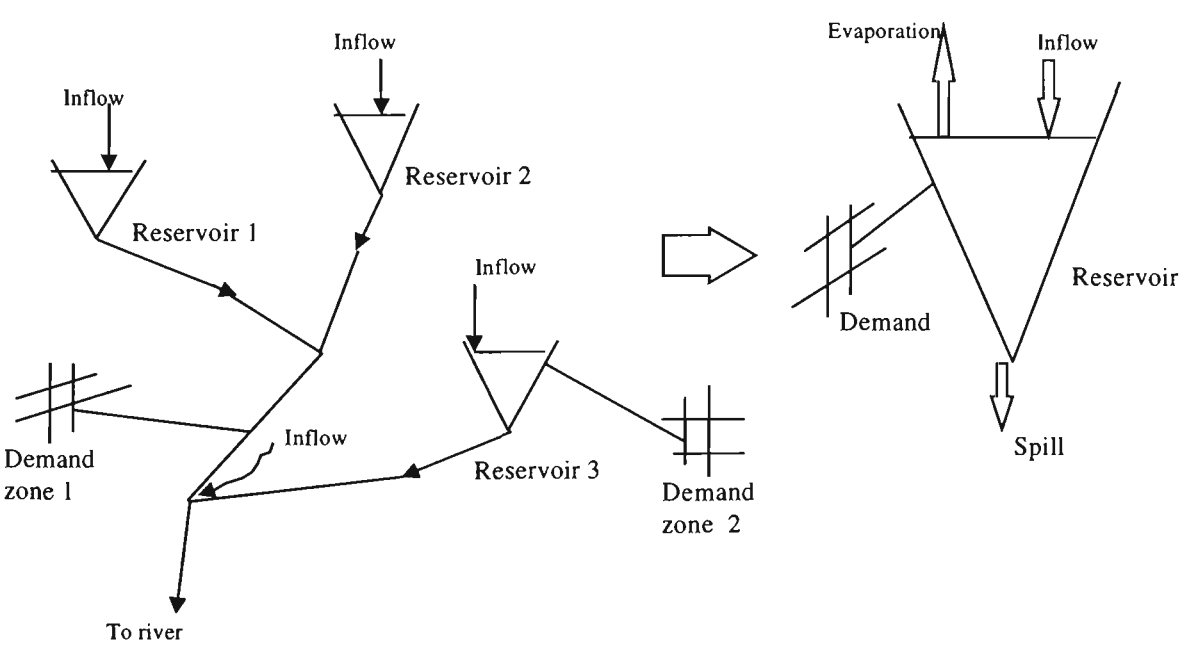


Fig. 3.2 Schematic Representation of Lumped System

The lumped storage system stores the (actual) spills from storages if capacity permits, while in the real system, some of these spills cannot be stored. Similarly, the evaporation losses cannot be explicitly modelled because of the relationship between surface area and storage volume cannot be satisfactorily defined for the lumped storage to simulate the evaporation

losses of individual storages. Further, the lumped streamflows at the downstream locations such as the most downstream junction in Fig. 3.2 are stored in the lumped storage system. They are lost as wastage or unused water in the real system. The wastage or unused water comprises of water that cannot be used by demand zones and courted from the bottom ends of the catchments. Furthermore, the capacity constraints of carriers are not considered in the lumped system. This is particularly important in some cases when the (restricted) demand cannot be supplied because of the bottlenecks in the carriers (i.e. capacity is insufficient), causing shortfalls. Shortfalls also could occur due to non-availability of water resources at certain reservoirs. If these effects are ignored in the derivation of restriction rules, the analysis will provide an erroneous solution. Therefore, these effects were included in this study and the procedures of including these effects are explained below.

REALM was used to simulate the operation of the real urban water supply system to compute the reservoir evaporation and wastage of water from the system, under the current operating rules. Further, the demand shortfalls were computed from REALM results. This simulation also considers the effect of the capacities of the carriers. The simulation was performed for the same period as the simulation of the lumped system in the optimisation of restriction rules. The reservoir evaporation and wastage of water were considered as outflows from the lumped system, in deriving the restriction rules. Shortfalls should not be supplied as demand in the lumped system, and hence, shortfalls were considered as an inflow to the lumped system. That is, the restricted demand in the optimisation run was reduced by the corresponding shortfalls. These inflows to and outflows from the lumped system (which are computed from the simulation of the real water supply system under its current operating rules) indirectly allows evaporation losses at reservoirs, total spill from the system, demand shortfalls and other effects due to carrier capacity constraints. The total spill from the system allows for uneven storage levels in the real system during spilling. Once the 'optimal' restriction rules were derived through the Hookes and Jeeves method (Section 3.3.2), the reservoir evaporation, wastage of water and demand shortfalls should be computed under new restriction rules to investigate whether they have changed. Generally, they do not change. If they are changed significantly, then the optimisation procedure should be repeated with these new reservoir evaporations, wastage of water and demand shortfalls for the lumped system and the restriction rules derived.

3.3.2 Hookes and Jeeves Method

The problem considered in this chapter is to determine the restriction trigger points which maximise the releases, subject to the constraints of security criteria. This is a constrained optimisation problem. Direct search method (Dixon, 1972) can be effectively used for this problem, since it was decided to carry out the optimisation on a fixed grid of restriction triggers because of simplicity. The pattern search method known as the Hookes and Jeeves method is used in the study.

The optimisation is carried out on a multi-dimensional grid, dimensions (or variables) being restriction triggers between the upper rule curve and the worst restriction level of each month. Consider the restriction rule curves shown in Fig. 3.1. There are 5 curves including upper and lower rule curves. If the worst restriction level is defined by level 3 curve, then there are 48 variables that should be considered in the optimisation. The security criteria specify that the storage level cannot fall below the storage volume corresponding to the worst restriction level. Since it is difficult to illustrate the Hookes and Jeeves method for multi-dimensions (in the example above, there are 48 dimensions), the method is illustrated in Fig. 3.3 for an optimisation problem with two variables (variables A and B).

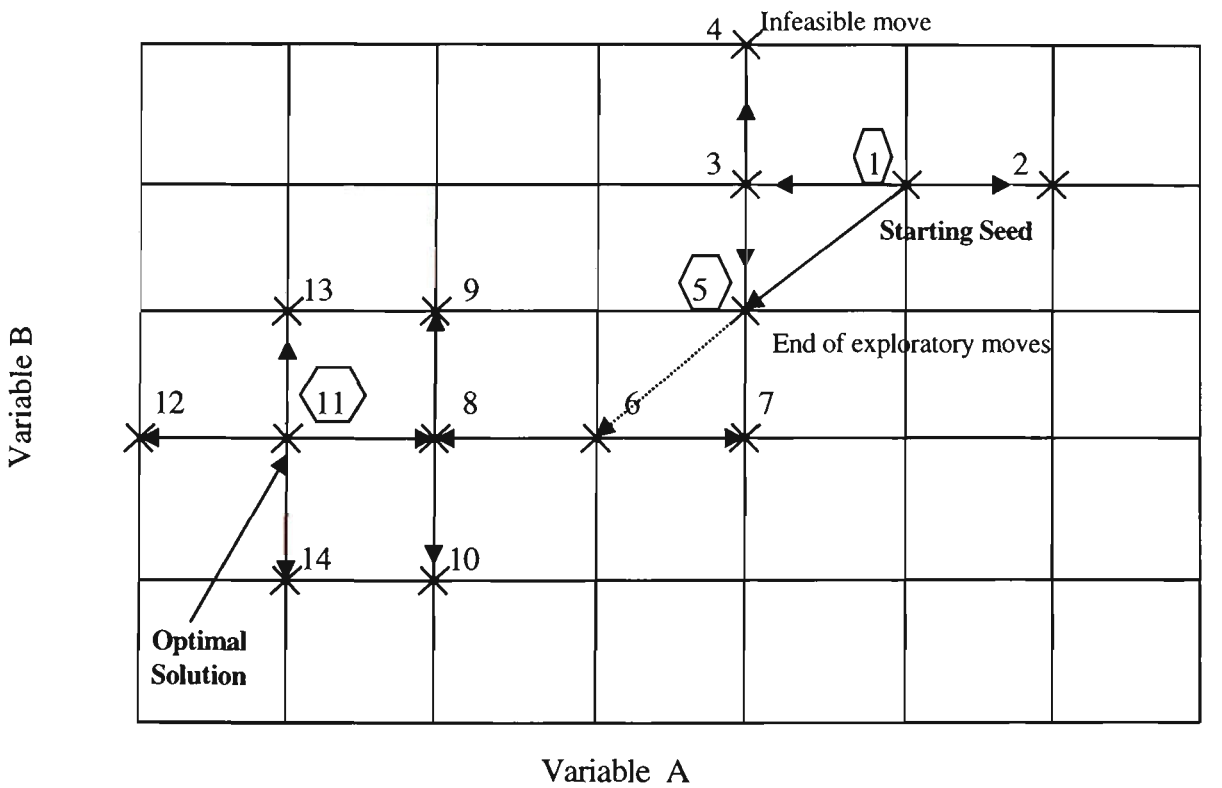


Fig. 3.3 Use of Search Technique for a Hypothetical Optimisation Problem

An arbitrary objective function and constraints are considered for this example. Suppose the starting seed used for the search technique (which has to be provided to initiate the optimisation process) is point 1 in the grid which represents certain values of variables A and B. The objective function and the constraints are computed for this point. Keeping the variable B constant, the variable A is increased by one increment to produce the point 2 in the grid. The objective function and constraints are computed for this point. Point 3 is considered then by reducing the variable A by one increment from its original position, but still keeping the variable B constant, and the objective function and constraints computed. These two points (points 2 and 3) are checked for feasibility in terms of constraints and optimality with respect to the objective functions against each other. If both points 2 and 3 are infeasible, then point 1 is considered as the best solution. Otherwise, the best feasible solution out of points 2 and 3 is compared with point 1. If either point 2 or 3 (whichever is the best in terms of the objective function) produces a better solution than point 1 in terms of the objective function, this is accepted as the best solution. Otherwise point 1 is still considered as the best solution. In this example, point 3 produces a better solution. Next, the variable B is considered around point 3 keeping variable A constant, which gives points 4 and 5. The above procedure is repeated for points 4 and 5. Point 5 produces a better solution than points 3 and 4 in this example. This is the end of the exploratory moves.

During the exploratory moves, the best solution has moved from point 1 to 5. A pattern search is then made to produce point 6 which is an extrapolation from point 1 through point 5. The objective function and constraints are computed for this move (i.e. point 6) and checked for feasibility in terms of constraints and optimality in terms of the objective function of point 5. If this point is superior compared to point 5 in terms of optimality, then point 6 becomes the current best solution, or otherwise the previous point (i.e. point 5) remains as the current best solution. In this example, point 6 provides a better solution. Exploratory moves are again conducted for the current best solution (point 6) as described earlier. The exploratory moves can be seen in Fig. 3.3. In this set of exploratory moves, point 8 has become the better solution. A pattern search is then made to produce point 11. Point 11 is feasible and better in terms of the objective function compared to point 8. Further exploratory moves are then considered around point 11. Point 11 is still the better solution after these exploratory moves. Therefore, point 11 is considered as the 'optimal' solution which satisfies the required constraints. With this method, the exploratory moves

and pattern searches are performed until no better solution is reached compared to the previous solutions.

For the problem considered in this study, it is necessary to optimise the restriction rules without violating the security criteria. Figure 3.1 is reproduced as Fig 3.4 to illustrate the optimisation procedure for optimising the restriction rules. Suppose the worst restriction level is level 3, then there are 48 variables for the optimisation problem. These are the restriction triggers on restriction rule curves between the upper rule curve and the worst restriction level for each month. The restrictable demand amounts are known for each zone defined by levels and these amounts can be used to compute the restricted demand during the simulation, in case when the storage volume falls below the upper rule curve. A storage increment (i.e. in terms of percentage of AAD in Fig. 3.4) is used to define the exploratory moves.

Maximising releases to the demand zone is considered as the objective function, while the monthly time reliability, the maximum duration of restrictions and the worst level of restrictions are considered as constraints in the optimisation. The constraint on time reliability is expressed as an equality constraint, to model just reaching (or violating) the time reliability constraint in the optimisation.

Suppose the starting seed used for the search technique is the restriction policy shown in Fig. 3.4 (defined by solid lines). The seed is similar to point 1 in Fig. 3.3, only difference being point 1 in Fig. 3.3 had only two variables to describe the seed, whereas there are 48 variables (which are shown by symbols on the restriction rule curves) to describe the seed in Fig. 3.4. The objective function and constraints are computed from the simulation of the lumped system for this restriction policy, considering evaporation losses, wastage of water and demand shortfalls as in the real system (Section 3.3.1). Then the first variable defined by point A (Fig. 3.4) is increased by the storage increment to define point A1 keeping all other 47 variables at the original positions. This is a new restriction policy, and the objective function and constraints are computed for this new restriction policy. Similarly, a new restriction policy considering point A2 is considered. The results related to these two restriction policies are checked for feasibility in terms of the constraints. If both are infeasible, then the restriction policy considering point A is the best so far. If both or any of the above restriction policies (defined by points A1 and A2) are feasible, then the better

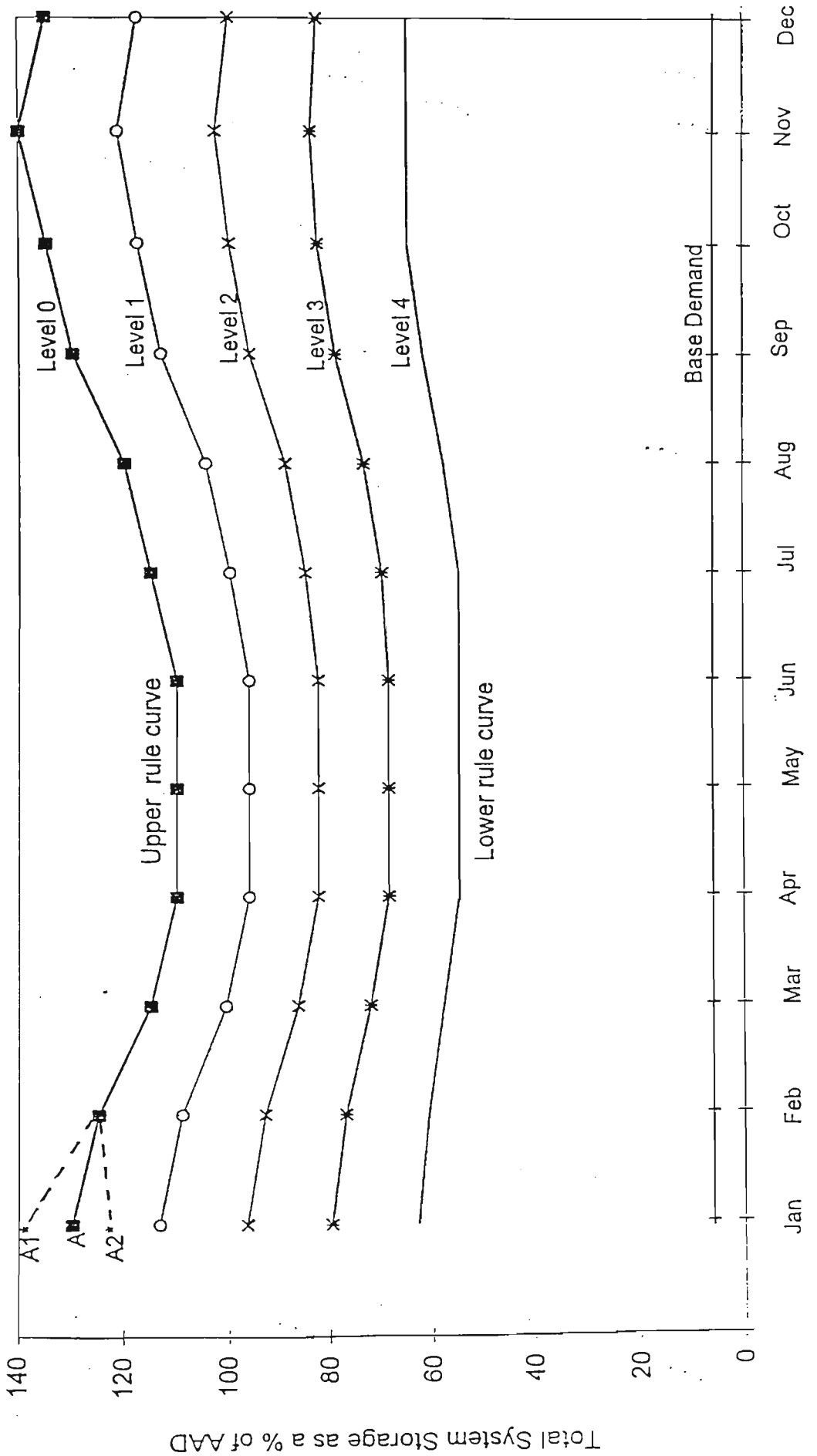


Fig 3.4 Use of Search Technique for Optimising Restriction Rules

solution in terms of the objective function is checked against the objective function of the restriction policy defined by point A. The restriction policy which gives the best objective function out of these is considered as the current best. Suppose the restriction policy defined by point A2 produces the best solution.

Then the search moves to the next month (i.e. next variable), keeping the restriction trigger of previous month at point A2. This procedure repeated until all exploratory moves are completed. Exploratory moves are conducted first for all monthly triggers on the upper rule curve, then the next level down and so on until it completes all triggers of the worst restriction level. Then the pattern search is performed as in the simplified example and then the exploratory moves again. This procedure is repeated until no further improvements to the objective function, which produces the best (or 'optimal') set of restriction rule curves for the system.

In general, the restriction policy obtained from the optimisation is different to the seed used to initiate the optimisation process. The evaporation losses, wastage of water and demand shortfalls are computed (Section 3.3.1) for the seed and used in the optimisation for all restriction policies considered in the optimisation. In theory, the evaporation losses, wastage of water and demand shortfalls should be different from one restriction policy to another. Once the 'optimal' solution is obtained from the optimisation, the evaporation losses, wastage of water and demand shortfalls should be recomputed using the 'optimal' restriction policy and checked against those of the seed. If they are different, the optimisation should be carried out again with the 'optimal' solution as the seed with corresponding evaporation losses, wastage of water and demand shortfalls. However, it was found that these evaporation losses, wastage of water and demand shortfalls were not different and another optimisation run was not required, when the Restrictions software was used to derive the restriction rules for the Melbourne system.

The Hookes and Jeeves algorithm, like any other direct search method, suffers from the problem of converging to a local optimum. Theoretically, the convergence to a global optimum may be achieved by considering different seeds in the optimisation and selecting the optimum from all these solutions. However, because of the nature of the optimisation problem considered here, there will not be a single optimum solution, which produces the

optimum value of the objective function, satisfying the constraints. Instead, there will be a narrow band. This is explained below.

The objective function and constraints are computed by considering the releases to the demand centre. These releases supply the unrestricted or restricted demand depending on the storage volume of the system at the beginning of time step. In most cases, if restrictions are to be imposed, for many restriction policies in the optimisation, (a grid point represents a restriction policy) restricted demand is the same, which produces the same value of objective function and constraints. This is because the storage volume at the beginning of the month falls into the same restriction zone although the restriction level triggers are slightly different and the restricted demand is function the restriction zone. For some restriction policies, however, restricted demand will be different since the storage volume at the beginning of the month may be in a different restriction zone, which produces a different objective function and constraints. Because of this process, there will be a narrow band for the 'optimal' restriction rules, which produces the required objective function and constraints.

3.3.3 Usage of Restrictions Software

The Restrictions computer software was developed using the theoretical considerations described in Sections 3.3, 3.3.1 and 3.3.2. The details such as input data files required in the software and output processing required to obtain REALM compatible restriction rules are given in Appendix A. The output data, which produces an average restriction policy, is also discussed in Appendix A. The application of the restrictions software to the Melbourne system is described in Section 6.3.

REALM has two options to model restrictions. One method is to express the restriction rule curves in terms of absolute total system storage and the other in terms of storage volume as a function of the average annual demand (AAD). The former method is suitable for systems where the average annual demand is constant (or the growth is insignificant), while the latter method is suitable for systems with growth in annual demand, such as urban water supply systems. The latter method produces progressively higher restriction rule curves from year to year in terms of absolute storage volume, if there is a growth in annual

demand. The developed methodology and the Restrictions computer software can be used to derive the restriction rules under both static and dynamic annual demands.

When the computer software is used with the static annual demand, it is necessary to determine the appropriate level of annual demand that should be used in the derivation of restriction rules. For systems with no or insignificant growth in annual demand, the demand sequence is known and this sequence can be used in the derivation of restriction rules. The static demand considers insignificant growth in annual demand, while the dynamic demand considers a significant growth.

For systems with significant growth in annual demand, the computer software can be used with a static annual demand sequence. In this case, it is recommended that the average demand corresponding to the 'ultimate sustainable development' be used in the derivation of restriction rules. This average annual demand is referred to as the 'sustainable yield' of the system in this thesis. It is assumed then that further augmentations are not possible to the water supply system due to reasons such as non-availability of suitable hydrologic sites. Generally, the systems with growth in annual demand are fairly large with significant carry-over storage. The Melbourne system is such an example. Therefore, the initial storage conditions affect the yield of these systems. The 'sustainable yield' can be computed for these systems as follows. A simulation model such as REALM is run several times considering different levels of forecast annual demands for the planning period with the appropriate initial storage volumes of the reservoirs. The choice of initial storage volumes for the Melbourne system is discussed in Section 6.3.1.2. Same annual demand is considered for each year of the planning period, disaggregated into monthly demands and seasonally adjusted for the climatic conditions, if necessary (by correlating demands with either rainfall, temperature and streamflows, and a combination of these variables). The annual demand levels are increased systematically from one simulation to the other, until the security criteria is just reached; this annual demand then is the 'sustainable yield' of the system.

The computer software can be used with dynamic demands (i.e. projected demands in most cases). In this case, the dynamic demand sequences are used in the derivation of restriction rules. As previously, the annual dynamic demands should be disaggregated to produce monthly demands. These monthly demands can be seasonally adjusted, if necessary.

Once the demand sequences are established, the same procedure is used to determine the restriction rules using both static and dynamic demands. Input data files are prepared as in Section 3.4.2. The output analysis is made as in Section 3.4.3 (to generate information on restriction rules for use in REALM). Any initial storage volume can be used in the computer software. However, it is recommended that the most likely storage volume (such as mean/median value of storage volume over the planning period, or half-full storage) be used as the initial storage volume for the static demand analysis case. For dynamic (or projected) demand case, the available data on storage volumes should be used for initial storage volumes.

The storage increment dictates the step size in redefining restriction triggers in the optimisation, when moves are made from one exploratory move to another or to a pattern search move. If the user requires that changes to restriction rules be made with finer steps, then a smaller storage increment should be used. In the computer software, the storage increment is expressed as a percentage of AAD.

3.4 SUMMARY

This chapter describes the importance and the necessity for deriving the 'optimal' restriction rule curves for urban water supply systems (Section 3.1). A direct search technique (Section 3.3.2) was used to optimise the restriction rules, by considering a multi-reservoir multi-demand urban water supply system as a lumped single reservoir single demand zone system. However, a method was introduced to account for reservoir evaporation losses, wastage of water from down-stream ends of the system and the effect of carrier capacities on supply in the lumped system. An objective function of maximising releases was considered in the optimisation, while the constraints of monthly time reliability, worst restriction level and duration of any form of consecutive restrictions were considered to define the security criteria of the water supply system. A computer program known as Restrictions Software was developed considering the above objective function and constraints. Restrictions Software can be used with any system configuration of urban water supply systems. The optimisation provides restriction triggers between the upper rule curve and the worst restriction level for different months.

4. TARGET STORAGE CURVES

4.1 INTRODUCTION

REALM, the **R**esource **AL**location **M**odel, is currently being widely used in Australia for planning and operation of water resource systems. REALM is designed to simulate the behavior of storages of water supply reservoir systems under user-defined operating rules. The operating rules consist of target storage curves and a restriction policy, among other operating rules such as environmental flows (Diment, 1991). Similar operating rules are used in other simulation models developed in Australia such as WASP (Kuczera and Diment, 1988) and WATHNET (Kuczera, 1990).

The target storage curves determine the preferred distribution of storage volume among individual reservoirs in a multiple reservoir system with respect to the total system storage. These curves can be specified in REALM for different seasons. It is possible to have different sets of curves for different months, a set of curves for all months of the year or different sets of curves for different groups of months such as Summer and Winter. The above references give a detailed description of the definition of target storage curves with some examples.

Figure 4.1 illustrates the concept of target storage curves for an example of a two storage reservoir system. For a given total system storage S_T at a given season, the target storage curves specify the storage volumes at reservoirs *1* and *2* as S_1^* and S_2^* respectively, where the sum of S_1^* and S_2^* equals S_T. The target storage curves are defined for the whole range of total system storage giving preferred storage volumes of individual storages. They can be optimal or otherwise. The characteristics of target storage curves in relation to where water should be stored and where water should be drawn from, are described in Perera and Codner (1996), by considering the slope of these curves as explained in Section 4.2.

REALM (or any other simulation model) does not optimise the operating rules; rather it evaluates the consequences of the specified operating rules. The optimal operation of the reservoir system is achieved by proper selection of 'optimal' operating rules. In REALM, this process occurs through specification of the 'optimal' target storage curves.

For a given total system storage, there can be many combinations of storage volumes of individual reservoirs in the multiple reservoir system. Out of all these possible combinations, there is one set which produces the 'optimal' target storage curves for a given objective function and constraints. However, it is not an easy task to determine the 'optimal' target storage curves due to the complexities of multiple reservoir systems, stochastic nature of streamflows, uncertainty in forecast demands etc. Because of these complexities, almost all planning studies of multiple reservoir water supply systems use target storage curves which are derived from the calibration of operation of the water supply system (Kuczera and Diment, 1988 and Perera et al., 1993). This is done by systematic trial and error analysis by adjusting the target storage curves to produce the historical behavior under historic conditions such as system details, inflows to the system and demands from the system. The major problem with this approach is that these target storage curves may not be 'optimal', since it is assumed that the operators have operated the system optimally in the past. The other problem with this approach is that the system and the operational criteria change with time, such that no operator experience exists to define the target storage curves. Therefore, it is necessary to develop the target storage curves based on an objective method considering the system details, the inflows to the system, the demand from the system and the other operational criteria. Mathematical programming methods can be used to derive the 'optimal' target storage curves, considering the above aspects.

The target storage curves and restriction rule curves are independent of each other. The target storage curves defines the preferred spatial distribution of individual storage volumes for an expected total system storage while the restriction rules depend on the total available storage for release. Therefore, they can be derived separately. In this chapter the target storage curves are considered.

Very few studies have been done in determining the 'optimum' operating rules in terms of target storage curves for urban water supply systems. Perera and Codner (1996) used stochastic dynamic programming (SDP) to derive the 'optimum' target storage curves for the Melbourne water supply system. Because of the computational problems associated with SDP, a lumped system of four storages (instead of the nine storages in the system) was considered in the analysis. Although an attempt was made not to loose the reality of the system operation by lumping the storages, the model may not have adequately represented the real Melbourne system. Further, the restriction rules were not considered

in the study. An objective function of maximising volumetric reliability was used in the study. Although the study gave an insight into the target storage curves of large storages, the lumped target storage curves had to be disaggregated to produce the individual curves for small and moderately large storages in the system.

This chapter first gives a brief account of the characteristics of the target curves. The objectives of this part of study is presented followed by the methodology adopted in developing the target curves. Finally, the computer program which was developed to derive the target storage curves, is presented.

4.2 CHARACTERISTICS OF TARGET STORAGE CURVES

As stated earlier, the target storage curves define the spatial distribution of reservoir storage volumes within a multiple reservoir system for given total system storages. REALM attempts to achieve these target storage volumes at the end of each simulation time step. The interpretation of target curves is an important factor to understand how water can be stored in a multireservoir system. When the inflow during a simulation time step is greater than the demand, the total system storage at the end of simulation time step increases and the target curves determine where this excess water should be stored (Perera and Codner, 1996). This can be explained by comparing the gradient of the target storage curve of a reservoir to that of the total storage line (45^0 line in Fig 4.1). Perera and Codner (1996) give the following description to explain where this excess water should be stored.

- If the gradient of target storage curve of a reservoir is equal to that of the total storage line for a given total system storage, then the excess water is stored only in this reservoir.
- If the gradient of the target storage curve is less than that of the total storage line, then the excess water is partly stored in this reservoir, with the remainder being stored in at least one other reservoir.
- If the gradient of the target storage curve is greater than that of the total storage line, then the excess water is stored only in this reservoir. In addition, water is transferred from at least one other reservoir to this reservoir.
- If the target curve is horizontal, then the excess water is not stored in this reservoir.

When the demand is greater than the inflow during a simulation time step, then the target curves specify which reservoir(s) release water to supply the demand. Similar descriptions to the above can be made then in relation to where water should come from, to meet the demand. In this case the total system storage reduces. The sum of target storage curve gradients for a given total system storage must equal one. This is because of the definition of the target curves,(Section 4.1) and can be seen from Fig. 4.1.

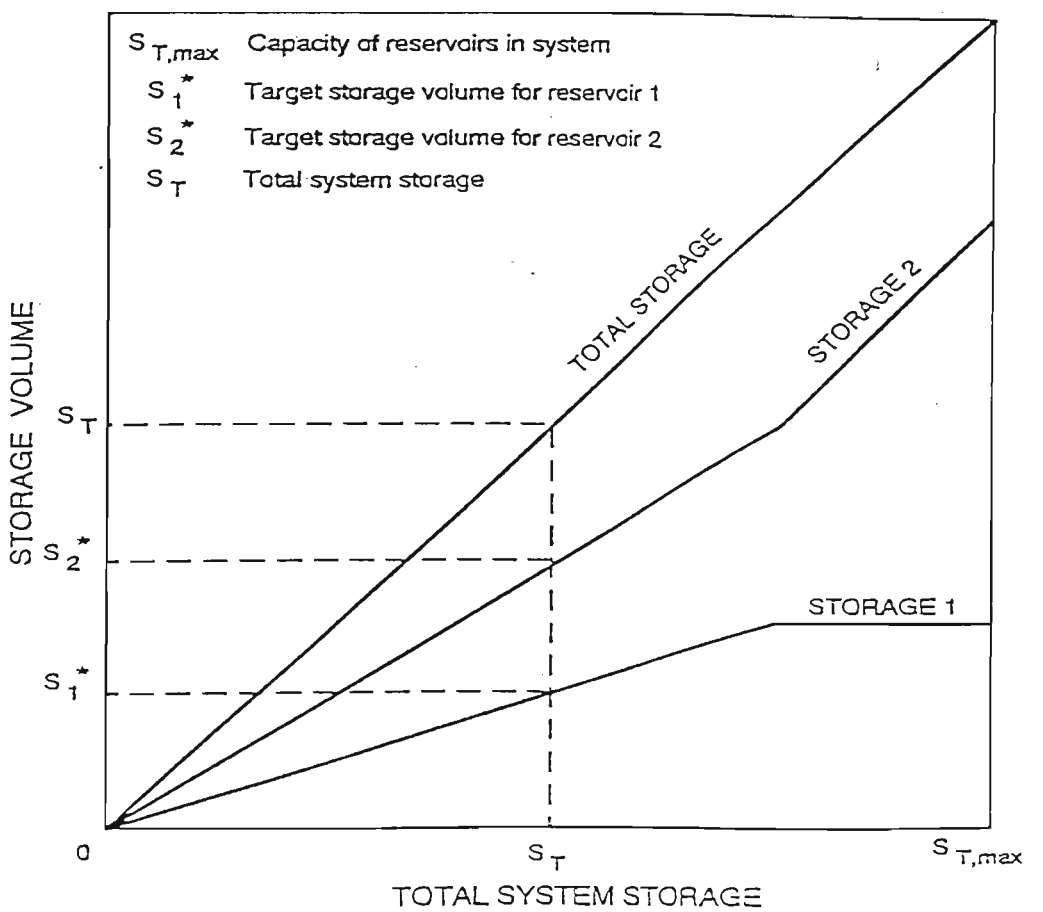


Fig. 4.1 Target Storage Curves for a Two Reservoir System

4.3 OBJECTIVES

As summarised in Section 2.7, the reservoir operation involves sequential decision making, and Dynamic Programming (DP) is ideally suited to solve these problems. Non linear objective functions and constraints can be handled explicitly with DP. Although Stochastic Dynamic Programming (SDP) is well suited to handle the stochastic nature of the streamflows, the commonly known 'curse of dimensionality' prevents the use of SDP for large multiple reservoir systems. However, Discrete Differential Dynamic Programming (DDDP) provides an alternative approach to determine the optimal operation of water supply systems with large number of reservoirs by reducing the computer memory requirements of conventional DP methods.

Network Linear Programming (NLP) can be used within DDDP to allocate water among various elements of the water supply system, thus eliminating the use of heuristic operating rules. NLP has been successfully used in generalised computer simulation models such as WASP (Kuczera and Diment, 1988), WATHNET (Kuczera, 1990), and REALM (Diment, 1991), in allocating water within the network in a simulation time step. The use of NLP makes the methodology applicable to any system configuration of water supply systems as in those simulation models. Therefore, it was considered to use DDDP and NLP in this study to optimise the operation of any system configuration of urban water supply systems. The objective function was considered as the maximisation of releases to demand zones.

Therefore, the main objective of this part of the study was to develop the 'optimal' target storage curves for urban water supply systems using DDDP, by considering the objective function of maximising releases to demand zones. Although DDDP reduces the problem of computer memory required to model the reservoir operation, the computer execution time is still a problem especially if all system complexities are to be modeled. It was considered necessary in this study to include all system details, which are generally used in a planning simulation model of the water supply system.

Two specific objectives were considered in this study as follows:

- To develop a methodology and a computer program (known as the Targets computer software in this Thesis) to derive the target storage curves that are applicable to any system configuration of urban water supply systems, considering all system details, restriction rule curves, and environmental and other priority releases of the system used for planning studies.

- To develop target storage curves, which are compatible with REALM software, so that these rules can be, entered as input data for REALM.

4.4 METHODOLOGY ADOPTED

DDDP was used to determine the 'optimum' operation of the water supply reservoir system, which is explained in detail in Section 4.4.1. A monthly model was considered in the DDDP formulation, since the target storage curves are based on a monthly time step.

The REALM input data files which are used for planning studies of urban water supply systems were used in this study. Allocation of water within the time step was done through Network Linear Programming (NLP) using the penalties in the carriers specified in the REALM system file. This is explained in detail in Section 4.4.2. An innovative scheme, which is explained in Section 4.4.3, was devised to reduce the computer execution time.

4.4.1 DDDP approach

As stated earlier, the objective function of maximising releases to the demand zones was considered in the DDDP formulation of this study. All system constraints such as reservoir capacity constraints, carrier capacity constraints and continuity equation at reservoirs, stream and pipe junctions were also considered. Storage level was considered as the state variable to describe the configuration of the system at each stage. Backward DDDP was used in the study.

Mathematically, the optimisation problem is formulated as follows.

$$f_n(\underline{S}_n) = \underset{\underline{S}_{n-1}}{Max}\left[\sum_{k,l} d_{k,l} + f_{n-1}(\underline{S}_{n-1})\right] \tag{4.1}$$

subject to the following constraints

$$0 \le d_{k,l} \le D_{k,l,\max} \tag{4.2}$$

$$0 \le r_{j,k} \le R_{j,k,\max} \tag{4.3}$$

$$0 \le \sum_{l} d_{k,l} + \sum_{j} r_{k,j} \le I_k + S_{k,n} + \sum_{j} r_{j,k} \tag{4.4}$$

$$0 \le \sum_{k,l} d_{k,l} \le DS(n) \tag{4.5}$$

$$0 \le S_{k,n} + I_k + \sum_{j} r_{j,k} - \sum_{l} d_{k,l} - \sum_{j} r_{k,j} \le S_{k,\max} \tag{4.6}$$

and the basic continuity equation (for storage k) is

$$S_{k,n-1} = S_{k,n} + I_k + \sum_{j} r_{j,k} - \sum_{l} d_{k,l} - \sum_{j} r_{k,j} \tag{4.7}$$

where $f_n(\underline{S}_n)$ is the sum of releases supplied to the demand zones from the optimal operation of a system having storage volume combination

($\underline{S}_n$) at the beginning of time step (i.e. stage n), where there are n stages to the end of the planning period,

$d_{k,l}$ is the release at stage n from storage k to the water demand zone l, this can be a release to supply the restricted demand,

$D_{k,l,max}$ is the maximum value of the release $d_{k,l}$,

$r_{j,k}$ is the release at stage n from storage j to storage k,

$R_{j,k,max}$ is the maximum value of the release $r_{j,k}$ (or the capacity of the carrier representing $r_{j,k}$ release),

$S_{k,n}$ is the content of storage k at the beginning of stage n,

$S_{k,max}$ is the maximum capacity of storage k,

I_k is the natural inflow to storage k at stage n and

$DS(n)$ is the total demand for stage n.

Equations (4.4), (4.6) and (4.7) are for storage k. Equations (4.1)-(4.7) describe a general DP formulation for a multiple water supply reservoir system, with multiple demand zones, as shown in Fig. 4.2. However, in this study, DDDP (i.e. DP within a storage "corridor") was used which is explained later in this section; DDDP uses Equations (4.1)-(4.7) within a storage "corridor". Also it was assumed that the initial storage volumes of reservoirs at the beginning of the planning period were known. These initial storage volumes are required to trace back the 'optimal' storage trajectory for the iterations of DDDP.

It is not easy to explain the DDDP approach to problems with many reservoirs, since the "corridor" cannot be shown in many dimensions. Therefore, the computations of DDDP are explained for a single storage. Figure 4.3 shows the approach for a single storage. First, an initial storage trajectory is considered and a "corridor" defined by a storage increment is placed around the initial trajectory. The optimisation is then carried out within the "corridor" using Equations (4.1)-(4.7) for the planning period and the 'optimal' storage trajectory selected within this "corridor". This is known as an iteration. This optimal trajectory is then used as the initial storage trajectory for the next iteration and the procedure repeated. Several iterations are considered until the optimal trajectory between two consecutive iterations do not change. This is the final 'optimal' storage trajectory.

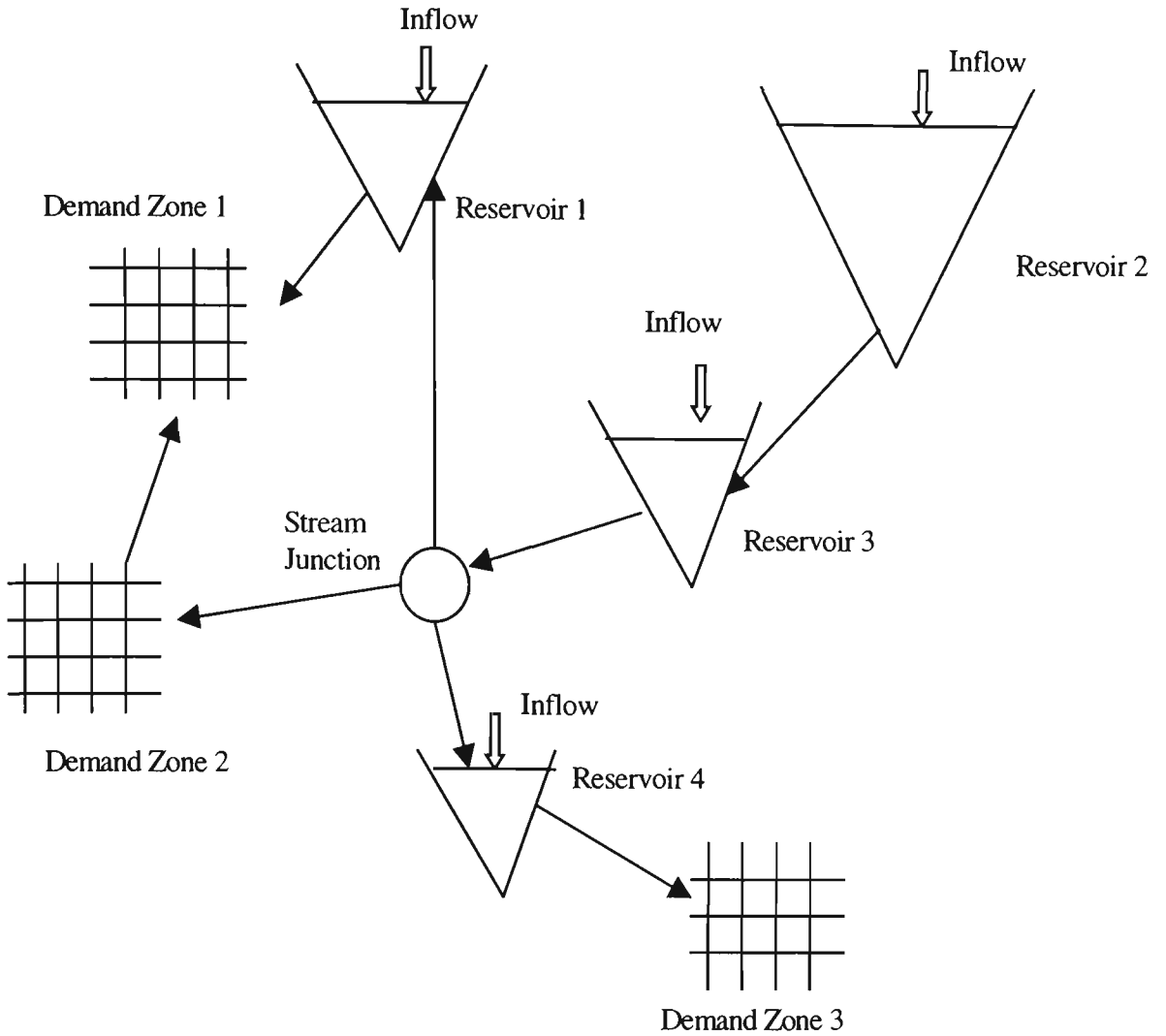


Fig.4.2 Multiple Reservoir System with Multiple Demand Zones

Although the explanation is given for a single storage, the method can be easily extended for multiple reservoirs. In the case of multiple reservoir, storage volume is represented by a storage volume combination of reservoirs and the corridor is multi-dimension "corridor" defined by storage volume combinations. Convergence is achieved in the Targets software once there are no changes to the optimal storage trajectory over two consecutive iterations or the objective function corresponding to storage volume combination at the start of the planning period (this storage combination is known; see previous paragraph) does not change over two iterations, whichever is reached first.

Since the optimisation algorithm starts with an initial storage trajectory, there is a possibility that the solution converges to a local optimum rather than the global optimum. Known or assumed initial storage volumes at the beginning of the planning period are considered in this study in deriving the optimal storage trajectories.

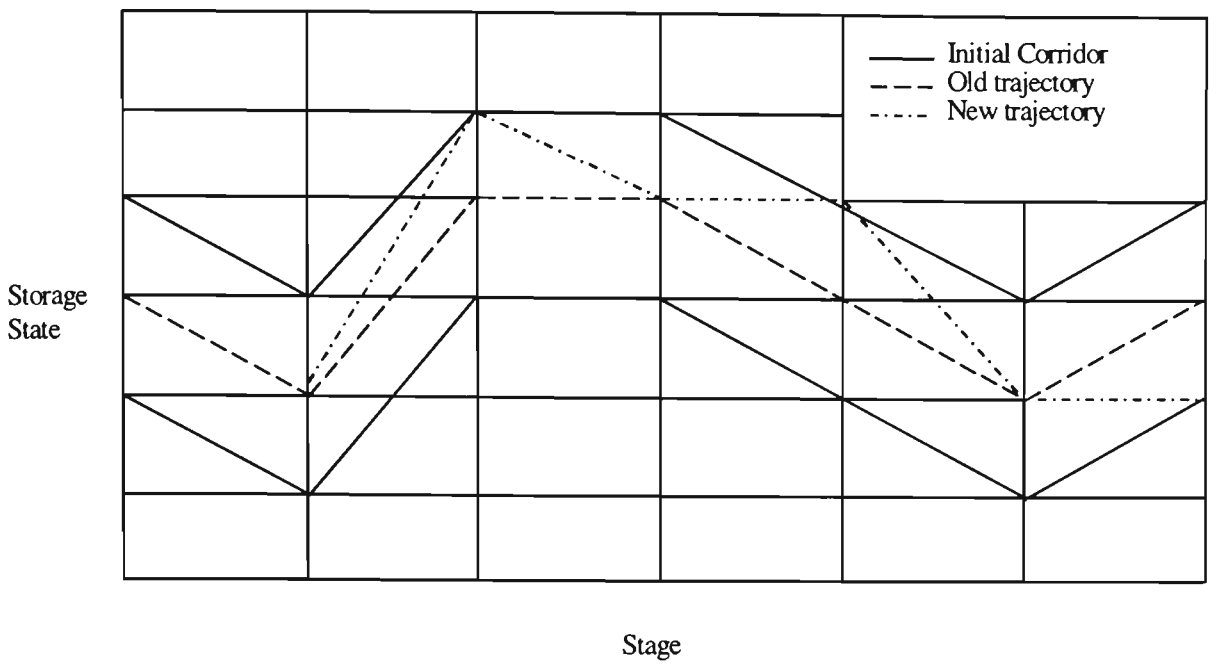


Fig. 4.3 Use of DDDP for a Single Reservoir System (Extracted from Codner,1979)

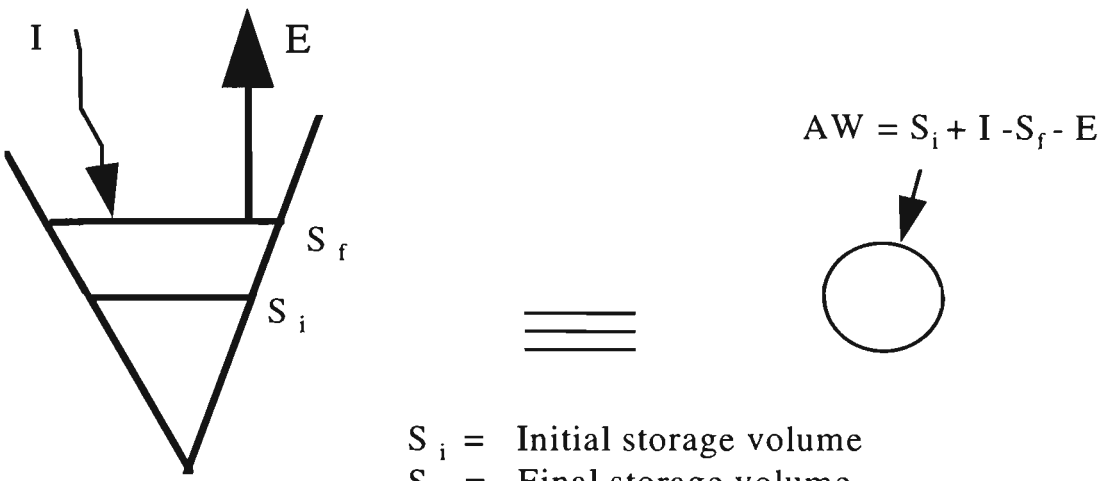
4.4.2 Optimal Allocation within the Time Step

As stated in Section 4.4, it was considered necessary to include all system details that were used in a simulation model (such as REALM) for planning studies of urban water supply systems. Further, one of the secondary objectives of this part of the study was to derive the target storage curves which are compatible with REALM software. These objectives were achieved by using the data files used by REALM for planning studies of systems. The REALM system data file contains data related to reservoirs (minimum and maximum capacity, and details on reservoir evaporation loss), demands, stream and pipe junctions, and gravity diversions. It also contains data related to carriers such as minimum and maximum capacities (minimum capacity can be considered as minimum flow that should be supplied as a priority release), losses in the carriers and penalties of the carriers which are used to allocate releases to different parts of the water supply system.

NLP was used to allocate water within the water supply system during a time step, after converting the water supply system to a system of nodes and arcs. This is the same approach that was used in WASP (Kuczera and Diment, 1988), WATHNET (Kuczera, 1990 and 1992) and REALM (Diment, 1991). In converting the water supply system to a system of nodes and arcs, each node is assigned an 'inflow to the node or outflow from the

node'. This 'inflow to the node or outflow from the node' is referred to as 'available water' (AW) in this thesis. AW is positive when it is 'inflow to the node' and negative when it is 'outflow from the node'. For example, a demand node is assigned a negative AW equal to the demand (if necessary, restricted) during the time step. Similarly, AW is computed for a reservoir considering initial storage volume, final storage volume, inflow to the reservoir and evaporation losses from the reservoir. Simply, this quantity is the difference of sum of initial storage volume and inflow to the reservoir, and the sum of final storage volume and evaporation loss of the reservoir. DDDP specifies the initial and final storage volume combinations which are used in AW computation for reservoirs. Similar AWs are computed for the other types of nodes. AW computations are shown in Fig. 4.4 for reservoirs, demand zones, stream junctions and gravity diversions. For pipe junctions, AW is zero, since there are no external inflows or outflows.

Modeling gravity diversions (Fig. 4.4d) are different to the other nodes. Gravity diversions divert a certain amount of flow to the water supply system depending on receiving flow (through unregulated streamflow and/or upstream carriers) and intake capacity, and remainder being spilled. Gravity diversions can be used to model weirs in a water supply system. An factor called 'ideal spill factor' is used to model the daily operation of the system in a monthly model, such as the one considered in this study. This factor implicitly allows for daily high flows that cannot be captured for use in the water supply system in daily operation, since the intake capacity of gravity diversion is small. Gravity diversions are modeled in this study using an additional ECN node, and two additional ECN arcs (i.e. ecn capacity arc and ecn spill arc). ECN stands for Equivalent Component Networks and used by Diment (1990) in modeling reservoirs, gravity diversions and demands. AW is computed at the ecn node and is equal to the unregulated inflow (not through the upstream carriers) to the gravity diversion node.

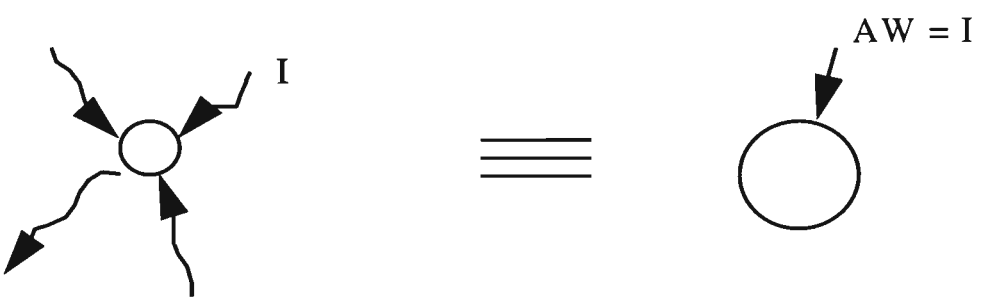


S_i = Initial storage volume
S_f = Final storage volume
I = Inflow to reservoir
E = Evaporation loss from reservoir

(a) Reservoir

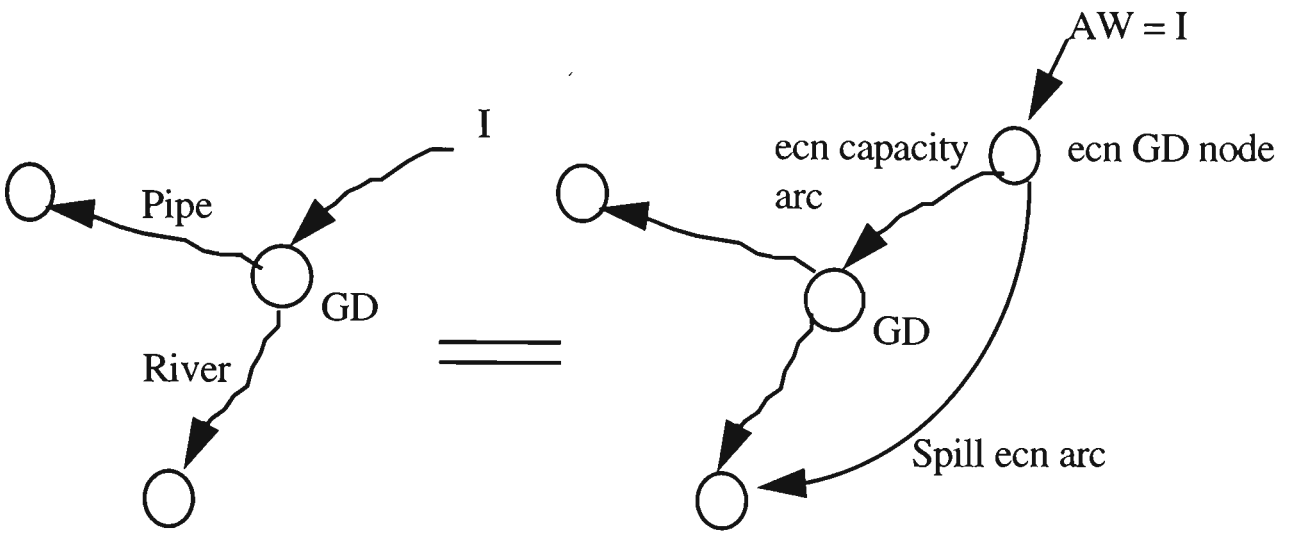
- D = Demand

(b) Demand zone

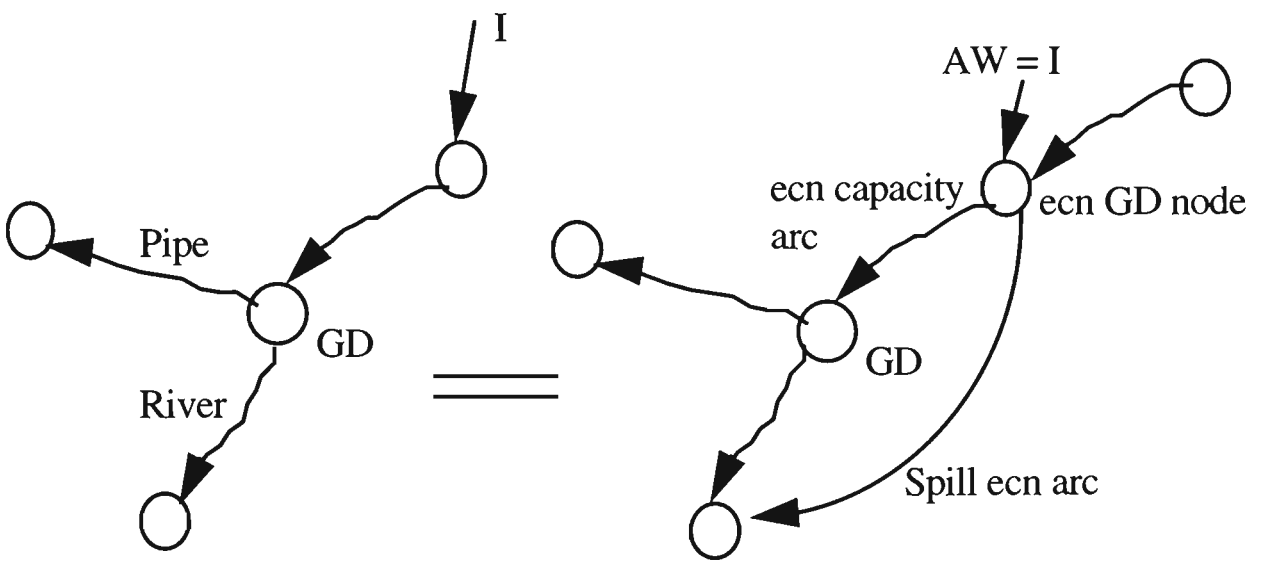


(c) Stream Junction

Fig. 4.4 AW Computations for Various Nodes



Gravity Diversion node with no upstream carrier



Gravity Diversion node with upstream carrier

(d) Gravity Diversion Node

Fig. 4.4 AW Computations for Various Nodes contd....

The spill ecn arc has an unlimited capacity, while the capacity of the ecn capacity arc is computed as below (Diment, 1990).

$$GD\_CAP = \frac{Q+C}{2f} - \sqrt{\left(\frac{Q+C}{2f}\right)^2 - \frac{QC}{f}} \qquad (4.8)$$

where GD_CAP is the capacity of ecn capacity arc,

Q is the unregulated streamflow received by the GD node,

C is the intake capacity, and

f is the ideal spill factor.

WASP (Kuczera and Diment, 1988) and REALM (Diment, 1991) simulation models use the same approach in modeling the gravity diversions.

The carriers in the water supply system are converted to arcs in the system of nodes and arcs. The arcs are represented by a maximum capacity in the system of nodes and arcs while the minimum capacity is always zero. The actual minimum capacity in the water supply system is represented indirectly in the system of nodes and arcs by modifying AW in the nodes upstream and downstream of the carrier containing minimum flows. AW is increased in the downstream node by the minimum capacity, while AW of the upstream node is decreased by the minimum capacity. This process ensures that the minimum capacity release is always supplied. As stated earlier, the minimum capacity represents the minimum flows that should be supplied as priority releases (eg. environmental flows) in simulation models such as REALM. The maximum capacity of the carrier containing minimum flows is then reduced by the minimum carrier capacity.

To use NLP for a system of nodes and arcs, it is necessary that AW of the system should be balanced out. That is, the sum of negative and positive AW should be zero. Generally, they do not balance out. Therefore, it is necessary to introduce a 'balancing node' (BN) with AW so as to balance out the AWs in the system. This balancing node has other advantages in performing computations, as described in Sections 4.4.3.

A further requirement of NLP to use in a system of nodes and arcs is that there should not be 'bottlenecks' in the system. Bottlenecks cause infeasible solutions in NLP, since there

are more inflows at certain nodes than is permitted through the carriers downstream because of capacity constraints. Therefore, additional arcs with indefinite capacity are created from nodes which receive streamflow as input (eg. reservoirs, stream junctions and gravity diversions) to the BN. Figure 4.5 shows these additional arcs to BN. There are two arcs from reservoirs to BN. The second arc connecting the reservoirs to BN (which is known as the 'limited capacity arc' in this thesis) is explained in Section 4.4.3.

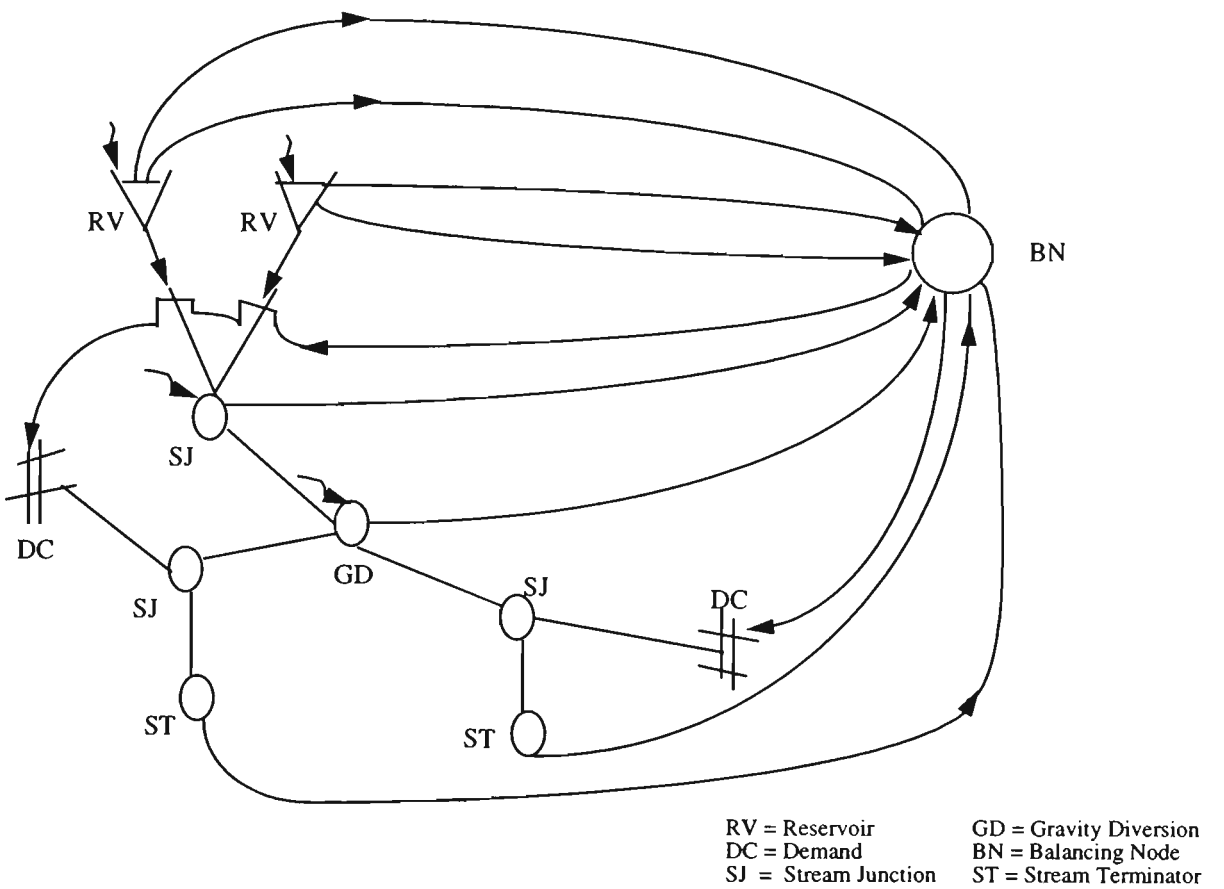


Fig. 4.5 System of Nodes and Arcs for Use in NLP

In some cases, it is not possible to supply the demand in certain demand zones because of non-availability of water. This produces infeasible solutions in NLP. These infeasible solutions are alleviated by having additional arcs from BN to the nodes representing the demand zones, with indefinite capacity.

Similarly, the stream terminators (i.e. end of rivers or streams of the catchments, where water leaving the catchments cannot be harvested) should have an arc connecting BN. This is necessary because the system of nodes and arcs should be a closed network to use NLP. Large penalties are assigned for these additional arcs so that water flows in these arcs as the last resort. Arc penalties are used in NLP to assign water within the network.

The system of nodes and arcs thus created should not produce any infeasible solutions when solving with NLP. The penalties of these additional arcs (from reservoirs, stream junctions, gravity diversions and stream terminators and to demand zones) depend on the penalties (user specified) of the physical carriers of the water supply system. As stated earlier, the penalties of the physical carriers are specified in REALM system data files. The penalties used for these additional arcs in modeling the Melbourne water supply system is given in Chapter 6 (Fig. 6.5).

Water allocations in water supply simulation models such as REALM are made using user specified carrier penalties. The same carrier penalties are used to determine the water allocation in the system in the DDDP model and hence the water allocation does not use any heuristic operating rules. Therefore, the methodology and the Targets computer software can be used to determine the optimum storage trajectory for any system configuration of urban water supply systems.

4.4.3 Improvement of Computational Efficiency

The conventional DDP in relation to reservoir operation requires the consideration all storage combinations of reservoirs in the system and storing different variables related to these storage combinations. The storage combinations depend on the storage increment used to discretise the maximum storage capacity. The smaller the storage increment, the higher the number of storage combinations, but with better accuracy of results from the DDP and vice versa. It should be noted that the storage combinations increase exponentially with the increase in number of reservoirs.

DDDP considers the storage volume combinations within a storage "corridor". However, the storage combinations still increase exponentially with the increase in number of reservoirs in the system, but at a lesser rate compared to conventional DDP, since the whole storage domain is not considered. For example, a single storage system requires the consideration of only 3 storage states. For a two storage system, the storage combinations increase to 9. In general, if there are N reservoirs in the system, then it is necessary to consider 3^N storage combinations. Sometimes it is not required to consider all 3^N storage combinations, because the storage capacity bounds (both minimum and maximum) limit the combinations that should be considered. The Melbourne system, as considered in this

study, has 8 reservoirs and therefore, 6561 storage combinations should be considered in DDDP, without considering the storage capacity bounds.

In general, for a DDDP time step, water allocation should be carried out (Section 4.4.2) for 3^N start storage combinations of the system producing 3^N end storage combinations, thus necessitating solving 3^{2N} water allocation problems. All time steps should be considered in the planning period for one iteration, and then a number of iterations has to be carried out to obtain the optimum storage trajectory. It is not computationally feasible to use NLP to solve all these water allocation problems, since they use a considerable amount of computer time. Therefore, it is necessary to improve the computational effort of DDDP in solving these water allocation problems.

Although there are many water allocation problems to be solved to compute the required objective functions at one time step, these water allocation problems are similar. Solution from one water allocation problem can be used to generate the solutions for the other water allocation problems, without solving NLP for each problem. This will then reduce the problem of computer execution time in DDDP.

The storage increment is used to define the "corridor" in DDDP. The storage increment is also used as one unit in DDDP modeling of the system. For example, if a reservoir has a maximum capacity of 40,000 ML and the storage increment is 1,000 ML, then the capacity of this reservoir is considered as 40 units in DDDP. Similarly, the other system details such as carrier capacities, reservoir evaporation losses, streamflow and demand are expressed in terms of the storage increment. In most cases, they have to be rounded off to the nearest unit (in terms of storage increment). Finer storage increment models the above details accurately, however, at the expense of more iterations to converge to the optimum solution in DDDP.

As stated earlier, Fig. 4.5 shows the equivalent system of nodes and arcs of the water supply system, which is used in NLP. An additional arc with capacity of 2 units (subsequently modified as discussed later in this Section) is created for each reservoir in the system. This is the second arc connecting a reservoir to BN, previously referred in Section 4.4.2 as the 'limited capacity arc'. Penalties are selected for these 'limited capacity arcs' by considering the other user-specified penalties in the system. These penalties allow

water to flow in these arcs, before being wasted through stream terminators and other arcs from reservoirs to BN, but after supplying the required demand.

Two water allocation problems are solved using NLP for a DDDP time step in the Targets computer software. First problem considers the storage volumes at the beginning and end of the time step at the feasible minimum and maximum values of the "corridor" respectively. The second problem considers the storage volumes at the beginning and end of the time step at the feasible maximum and minimum values of the corridor respectively. The former (AW is lowest at reservoir nodes) produces the maximum possible shortfalls of the supply and generally considers the shortfalls due to non-availability of water resources in certain reservoirs. The latter (AW is highest at reservoir nodes) produces the minimum shortfalls and generally considers the shortfalls due to carrier capacity constraints. However in some cases, both types of shortfalls could occur in these two water allocation problems. If there are no shortfalls when solving the first problem, certainly there will not be shortfalls due to the second problem and also there will not be any shortfall due any combination of feasible start and end storages within the "corridor" for this time step.

The solutions of the above two water allocation problems are used to compute the objective function for all feasible storage combinations (within the "corridor") at the start of the time step. The procedure uses the flow in the 'limited capacity arcs' from reservoirs to BN to compute the required objective functions in DDDP, without repetitive use of NLP; the procedure is described below in steps with a numerical example in Table 4.1. The example considered here is a two storage system with a "corridor" that is not affected by the storage capacity bounds. That is, all possible 9-storage combinations are feasible for both start and end storage combinations. Table 4.1 explains the computation of additional shortfalls for each feasible of start and end storage combination. The total shortfalls (see Note 5 in Table 4.1) are then computed and are later used with the objective functions of respective end storage combinations to produce the objective functions of start storage combinations.

1. Water allocation for the first problem is solved using NLP for the time step and the flows in "the limited capacity arcs" from reservoirs to BN noted. The capacities of these arcs (which are previously set at 2 units) are then modified to the sum of flow in these arcs from the solution of the first problem and the difference in AW of the

Table. 4.1 Example of Supply Shortfall Computations for Storage Combinations Without Repetitive Use of NLP

Step	ID of start storage combination	ID of end storage combination	Capacity of limited capacity carrier	Flow in limited capacity carrier	Supply shortfall	Comments
1	(-1,-1) (+1,+1)	(+1,+1) (-1,-1)	(2,2) (4,4)	(0,0) (3,3)	2 0	First problem Second problem
			Flow bank	Not used	Additional shortfalls	
2	(+1,+1)	(-1,-1) (-1,0) (-1,+1) (0,-1) (0,0) (0,+1) (+1,-1) (+1,0) (+1,+1)	(3,3) (3,2) (3,1) (2,3) (2,2) (2,1) (1,3) (1,2) (1,1)		0 0 0 0 0 0 0 0 0	Highest start storage combination
3	(+1,0)	(-1,-1) (-1,0) (-1,+1) (0,-1) (0,0) (0,+1) (+1,-1) (+1,0) (+1,+1)	(3,2) (3,1) (3,0) (2,2) (2,1) (2,0) (1,2) (1,1) (1,0)		0 0 0 0 0 0 0 0 0	Second highest start storage combination
	(+1,-1)	.....	.....		.....	
	.....	.....	.....		.....	
	(-1,-1)	(-1,-1) (-1,0) (-1,+1) (0,-1)	(1,1) (1,0) (1,0) (0,1)		0 0 1 0	

		(0,0)	(0,0)		0	Lowest start storage combination
		(0,+1)	(0,0)		1	
		(+1,-1)	(0,1)		1	
		(+1,0)	(0,0)		1	
		(+1,+1)	(0,0)		2	

Note: (1) This example considers only shortfalls due to non-availability of water resources, but not due to capacity constraints. Similar example can be devised to account for both types of shortfalls.

(2) The values within brackets refer to reservoir 1 and 2 respectively.

(3) All computations are in DDDP units.

(4) Identification numbers (ID) of storage combinations are given

(0,0): values corresponding to initial storage trajectory

(1,1): maximum storage combination with the corridor

(-1,-1): minimum storage combination within the corridor

(1 unit = storage increment)

The storage corridor width is 2 units.

(5) Additional shortfalls refer to the shortfalls in addition to the shortfalls in the second problem. Total shortfalls therefore should be the sum of additional shortfalls and minimum shortfall (i.e. from

corresponding reservoirs of these two problems. In this example, flows in 'limited capacity arcs' are (0,0), while the differences in AW of reservoirs for two problems are (4,4). This is the maximum flow that could occur in these arcs due to the second problem. NLP is then solved for the second problem and the flows in the limited capacity arcs from reservoirs to BN noted. These flows are stored in a 'flow bank' for use in later steps. (The value is referred to Step 1 of Table 4.1)

2. The objective function for the highest feasible storage volume combination at the start of the time step is considered first. The flow in the 'flow bank' is used to define the feasible end storage combinations. If flow in the 'flow bank' is above or equal to the difference of corresponding feasible maximum and minimum end storage volume of a reservoir, then any end storage volume between feasible maximum and minimum is possible without having additional shortfalls to supply. Otherwise, higher storage volumes are only possible with corresponding additional shortfalls to supply. Flow in the 'flow bank' is reduced to define the end storage combination. Flow in the 'flow bank' cannot go below zero, thus producing shortfalls. (The value is referred to Step 2 of Table 4.1)

3. Next storage combination at the start of the time step is then considered and the objective function computed. In this case, the storage 2 has a storage volume 1 unit less than in Step 2. Considering the end storage combination at the minimum feasible storage combination, the NLP solution is simulated by reducing the corresponding flow in the 'flow bank' by 1 unit. The reason for this flow adjustment is that if the reservoir volume is less by 1 unit compared to Step 2, then the flow in the corresponding 'limited capacity arc' has to be less by 1 unit. If the flow becomes negative in this arc with this flow adjustment, then this start storage combination is not feasible. Additional shortfalls are computed as in Step 2 for all end storage volume combinations. (The value is referred to Step 3 in Table 4.1)

4. The procedure is repeated for all feasible start storage combinations. The lowest start storage combination had produced additional shortfalls. As explained in Step 3, flow in 'flow bank' becomes (1,1) due to start and end combinations of (-1,-1) and (-1,-1). Then if end storage combination of (-1,+1) is considered, this is possible with an additional unit of shortfalls. (The value is referred to Step 3 of Table 4.1)

These steps explain how the additional shortfalls are computed for each start and end storage combinations. The total shortfalls for each start and end storage combination are computed as the sum of shortfalls due to second problem and the additional shortfalls. The total supply to demand zones are then computed as the difference of demand and the total shortfalls for each start and end storage combination. The supply to demand zones is added to the objective function of each end storage volume combination to produce the objective function for storage combinations at the start of the time step (Equation 4.1).

The scheme described above was tested with several hypothetical examples of water supply systems, including a three reservoir system with two demand zones having interstorage links. The results were compared with the conventional DDDP and found to produce exactly the same results as the conventional DDDP approach.

4.4.4 Usage of Targets Computer Software

Similar to the Restrictions software, the Targets software can be run with static and dynamic demands. The procedure for running Targets software is exactly the same for both static and dynamic demands, the only difference being the demand sequences used. The demands sequences that are used in these analyses are described in Section 3.3.3. The details such as input data files required to use the targets software and the output processing required to obtain REALM compatible target storage curves are given in Appendix B. The application of the Targets software to the Melbourne system is described in the Section 6.4.

4.5 SUMMARY

This chapter describes the importance and the need for the derivation of target storage curves for urban water supply systems. DDDP was used to determine the 'optimum' operation of the water supply reservoir system in terms of the 'optimal' storage trajectories. An objective function of maximising releases to demand zones was considered in this study. Although this objective function was hard-coded in the software, it is relatively easy to modify the software to allow for different objective functions. A monthly model was considered in this optimisation since the target storage concept is for months. NLP was used to allocate water within the water supply system during a time step, after converting the water supply system to a system of nodes and arcs.

The optimisation produces the 'optimal' storage trajectories for individual storages in the multiple reservoir urban water supply system. These optimal storage trajectories are used to produce the target storage curves using an Excel spreadsheet. Several macros were developed to group the storage volume data to generate scatter plots for the required target storage curves. The target storage curves can then be drawn manually on the scatter plots.

The Targets software can be used with any system configuration of urban water supply systems. This was achieved through the use of NLP with user-specified penalties for carriers in the water supply system. The data files used in the Targets software are similar to the REALM data files and therefore also compatible with REALM software. Furthermore, it uses all system details that are generally used in a planning simulation model of urban water supply systems.

5. MELBOURNE WATER SUPPLY SYSTEM

5.1 GENERAL

The Melbourne water supply system is the major system in Victoria and is one of the major water resource systems in Australia. Melbourne Water (MW) is the authority responsible for management and operation of the Melbourne system. The system is nearly hundred and fifty years old. The first of the major works was the Yan Yean reservoir which was constructed in 1857. It is an off stream storage located just north of the metropolitan area, with a maximum capacity of 30,000 ML which is in use today. The Maroondah reservoir located on Watts river was completed in 1927. During the next five years, the Silvan and O'Shannassy reservoirs were added to the Melbourne system. The Upper Yarra reservoir in the far-east is the largest reservoir in the Yarra River basin and was completed in 1958. The Cardinia reservoir, was constructed in 1973 and it is supplied with water from Silvan and Upper Yarra reservoirs. This reservoir, located 43 km south of Melbourne, primarily serves the Melbourne and metropolitan area as well as supplementing supplies to the Mornington Peninsula.

The most recent major augmentations of Melbourne's supply were triggered by the extended drought of the late 1960s. The construction of major headworks such as Greenvale, Sugarloaf and Thomson dams added the drought security to the current system. The Thomson reservoir, the largest storage serving Melbourne, also supplies urban demands of Mornington Peninsula, and irrigators and other domestic and industrial consumers in the Thomson and Latrobe valleys downstream of the dam.

To date, (according to the information supplied by MW in early 1994) nine major surface water storages, a major treatment plant, 164 pumping stations, 157 service storages and approximately 23,000 kilometres of transfer, distribution and reticulation mains have been constructed to convey water for urban, industrial and minor irrigation uses. A schematic diagram of the Melbourne system is shown in Fig. 5.1, showing all reservoirs and some major links but avoiding demand zones as a single demand centre. The capacity of the total system storage is about 1,773 gigalitres, Most of water to the reservoirs come from the forested catchments to the north and east of Melbourne. The system supplies to 1.2

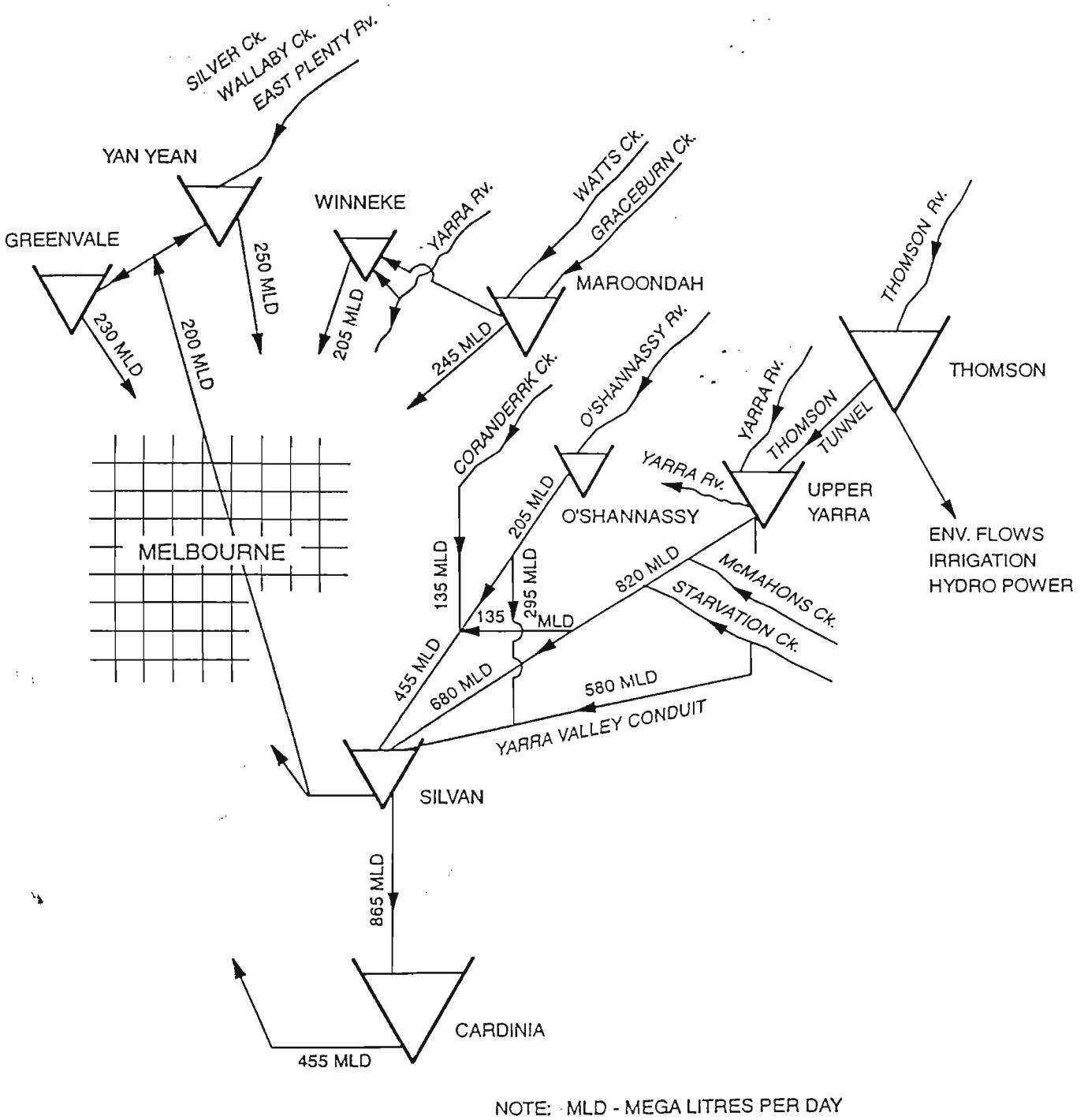


Fig 5.1 Schematic Representation of a Multiple Reservoir Water Supply System

million properties and to about 3.1 million people in the supply area. (Melbourne Metropolitan Board of Works, 1992).

There are three principle components of the Melbourne water supply system and they are as follows:

- Headworks
- Seasonal transfer system
- Regional distribution system

The water supply headworks include all major reservoirs in the system, excluding seasonal storages which are part of the seasonal transfer system. The headworks reservoirs such as Thomson and Upper Yarra harvest water from water supply catchments.

The seasonal transfer system transfers water to the Melbourne Metropolitan area, and consists of seasonal storage reservoirs and pipelines which are used to balance out the differences between seasonal and annual consumption. The seasonal storages include Yan Yean, Silvan, Cardinia and Greenvale. The principle pipelines are the Yarra-Silvan conduit in the Yarra valley and the Silvan-Preston Main across the metropolitan area to the northern and western suburbs.

The regional distribution system distributes water within Melbourne. This transports water from the seasonal storages to the major water supply zones throughout the metropolitan area, to satisfy varying daily demands for industrial and domestic needs. The system consists of pipelines, pumping stations and service reservoirs such as those at Preston, Mitcham, Mount Waverley, Notting Hill and Somerton.

5.2 WATER CONSUMPTION

Continuing growth of Melbourne's water consumption is the principle factor in dictating the development of the Melbourne water supply system. Before 1970, the total annual water consumption, including industrial and commercial use was approximately constant at 475 kl/household. Since 1970, this has increased to reach 525 kl/household in 1980/1981. Projections of water consumption in to the future were prepared by MW on the basis that the increasing trend in water consumption per household will continue but at a

reduced rate. On this basis the average annual consumption was computed as 550 kl/household during 1990-91 and 580 kl/household during 2000-01. This implies a 0.5% average annual growth in water consumption per household or about 10 per cent over the 20-year period. (Melbourne Metropolitan Board of Works, 1992).

Water consumption data relate to all uses of water; domestic, industrial, commercial and other uses such as flushing mains and firefighting operations. Domestic consumers use slightly more than half of all water supplied, and about one third of their consumption is used outdoors, the major part being on the gardens. About one and a half times more water is used in Summer than in Winter, the additional water use being mainly on gardens. The Melbourne Water Resources Review (Melbourne Metropolitan Board of Works, 1992) states that the highest daily consumption since the 1982-83 drought has been 3,040 megalitres, recorded on 24 January 1990. The current system is capable of delivering about 3,500 megalitres a day.

Between 1985-1990, the average increase in total consumption was about 2.2% p.a. This increase is due to population increase and per capita water consumption increase. Industrial and commercial consumption is continuing to decline at a rate of about 1.7% annually. The amount of water used by various levels of government, hospitals, churches, sports grounds, and as supply to shipping increased at an annual rate of 9%. Approximately, 18% of all water leaving the reservoirs was unaccounted for, either because it was supplied to unmetered properties, was used for fire-fighting or flushing mains, was not registered on meters due to low flows, or leakages of the supply system (Melbourne Metropolitan Board of Works, 1992).

5.3 DATA USED IN THIS STUDY

Melbourne Water provided required data for this study in early 1994. They include system, streamflow and demand data. Additionally, the recorded storage volumes at the beginning of January 1994 were supplied for use in the planning period for this study. They are given in Table 5.1, together with maximum and minimum capacity of reservoirs.

Table 5.1 Storage Data of Melbourne Supply System

Reservoir Name	Starting Volumes as At Jan 1994 (ML)	Maximum Capacity (ML)	Minimum Capacity (ML)
Greenvale	26,519	27,000	5000
Yan Yean	23,863	30,000	5000
Silvan	36,216	40,000	23,500
Cardinia	273,666	287,000	58,000
Sugarloaf	94,840	96,000	18,500
Maroondah	22,000	22,000	2000
O'Shannassy	1581	3123	1204
Upper Yarra	43,209	200,000	30,000
Thomson	1,050,165	1,068,000	170,000

5.3.1 System Details

The system details are provided by MW in the form of a REALM system file. The system file describes the water supply headworks, the seasonal transfer system and (to a lesser degree) the regional distribution system. Although the regional distribution system deals with the daily operation of the system, the REALM system file considers the monthly effects of the regional distribution system through demand zones. Therefore, the system details provided by MW reflect the system details on a monthly time scale. These system data are used by MW for the planning studies of the Melbourne water supply system and are also used in this study.

As can be seen from Table 5.1, the Melbourne water supply system is out of balance in terms of storage capacity, the Thomson storage dominating the whole system. The Thomson storage is about twice the capacity of the Melbourne system, prior to the construction of Thomson.

5.3.2 Streamflow

Streamflow is a necessary input for any planning study of a water supply system. Streamflow can be at a reservoir, which can be regulated, and/or at a confluence where tributaries join major rivers. Both these types of streamflow should be included in planning studies of water supply systems, since they are used to supply the demand. Melbourne Water uses historical streamflow data from January 1955 to December 1988

(34 years) in their planning studies as streamflow to reservoirs and stream junctions. These streamflow data which were supplied by the MW are used in this study.

5.7.3 Demand

Similar to streamflow (Section 5.7.2), the demands to be supplied from the system are an important data input to water supply planning models. Future water demands have been projected by MW for use in planning studies of the Melbourne system. These demands were supplied by MW for use in this study. The projected average annual demands are shown in Fig. 5.4. The projected water demands were estimated by MW considering the annual household water consumption at 450 kl/household (based on 1993/94 water usage), but allowing for increase in population.

As can be seen from Fig. 5.1, the current (1997) annual demand of the Melbourne water supply system is about 500 gigalitres as was estimated prior to 1994. There are two kinks in Fig. 5.2, one in 1997 and the other in 2002. These are due to proposed demand management programs to reduce the consumption by 30 ML/day after 1997 and a further reduction of 65 ML/day for the period after 2002. It is also seen form Fig. 5.4 that by year 2024, the average annual demand for the Melbourne water supply system will reach approximately 650 gigalitres. The annual demands are disaggregated to monthly demands using the monthly disaggregation factors, supplied by MW for each demand centre. These monthly demands are then adjusted for climatic conditions. MW also supplied the monthly demand disaggregation factors and the information on how to adjust monthly-disaggregated demand to account for climatic conditions.

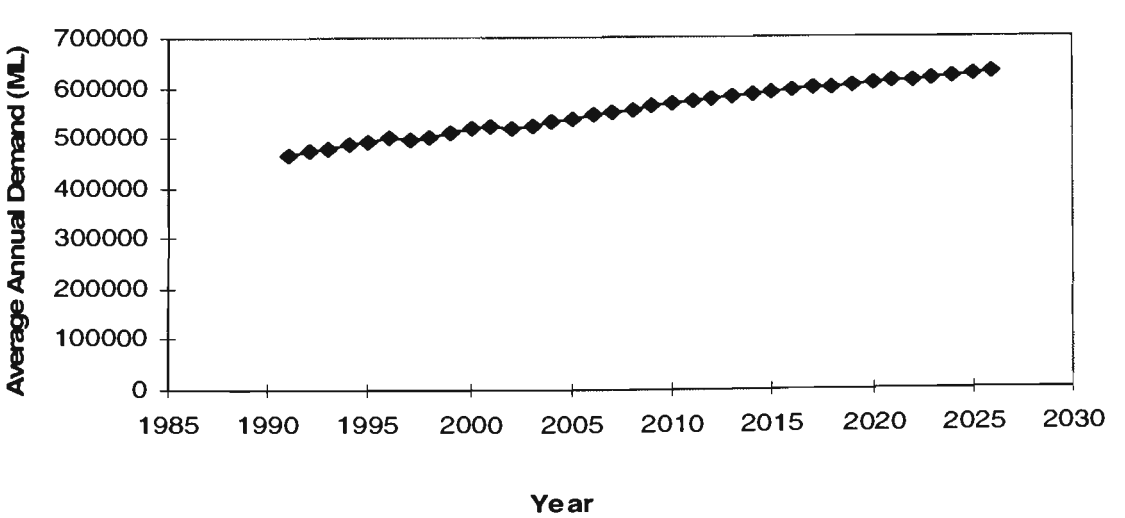


Fig. 5.2 Melbourne Water Projected Demand Curve

5.8 SUMMARY

This chapter discribs the relevant details of the Melbourne water supply system in relation to this study. The sequential development of the system is first presented. System details in terms of the data provided by MW are then discussed. Finally the streamflow data and demand projections used by MW for planning studies of the Melbourne system are explained. These system details, streamflow and demand data were used in this study, in deriving the operating rules for the Melbourne system in terms of the restriction rules and target storage curves.

6. OPERATING RULES FOR THE MELBOURNE WATER SUPPLY SYSTEM

6.1 GENERAL

Chapters 3 and 4 described the development of Restrictions and Targets computer software packages respectively. Chapter 5 presented the details of the Melbourne Water supply system and data used in this study, which were supplied by Melbourne Water (MW). This chapter discusses the application of Restrictions and Target software packages to the Melbourne Water supply system to derive the operating rules in terms of restriction rules and target storage curves. Once the operating rules were derived a study was conducted to investigate the performance of the Melbourne system under current and derived operating rules. These results are also discussed in this chapter.

6.2 OBJECTIVES

The objectives of this part of the study are to determine the 'optimum' operating rules for the Melbourne water supply system in terms of restriction rule curves and target storage curves and to compare these operating rules with those that are currently used. The comparison is done by studying the system behavior under derived and current operating rules.

6.3 RESTRICTION RULES

As described in Chapter 3, the Restrictions computer software can be used to derive the restriction rules under both static and dynamic annual demands. In this chapter, the Restriction Software was used with both static and dynamic annual demands separately to derive the restriction rules for the Melbourne system.

6.3.1 Restrictions Using Static Demands

When the Restrictions software is used with the static annual demand, it is necessary to determine the appropriate level of annual demand that should be used in the derivation of restriction rules. For systems with no or insignificant growth in annual demand, the demand

sequence is known and this sequence can be used in the derivation of restriction rules. However, for Melbourne system, which has a significant growth in annual demand, it is suggested that the average demand corresponding to the 'sustainable yield' be used in the derivation of restriction rules. A discussion on the 'sustainable yield' is given in Section 3.3.3. With the 'sustainable yield' scenario it is assumed that further augmentations are not possible to the water supply system due to reasons such as non-availability of suitable hydrologic sites. This may become the case for Melbourne system in future. This is discussed in detail in Section 6.3.1.1.

Generally, the systems with growth in annual demand are fairly large with significant carry-over storage. Certainly this is the case with Melbourne system. The initial storage conditions affect the computation of yield of these systems. However, it is suggested that the most likely storage volume (such as mean/median value of storage volume over the planning period, or half-full storage) be used as the initial storage volume for the static demand analysis.

6.3.1.1 Sustainable yield

The procedure discussed in Section 3.3.3 was used to determine the 'sustainable yield' for the Melbourne system. Several annual static demands corresponding to the years of 2010, 2015, 2016, 2017, 2018, 2019, 2020 and 2026 were considered in determining the 'sustainable yield' of the system. These annual demands were obtained from Fig. 5.2. REALM simulation runs were performed for each of these demand scenarios using system and streamflow files supplied by MW, but with a demand file prepared using the static annual demand corresponding to each year. The contents of the demand file are different from one REALM run to the next and reflect the respective annual demand. The monthly demand disaggregation factors and the information required to adjust the monthly demands, to allow for climatic conditions were supplied by MW through streamflow and system files. The system file also contains the current restriction policy and target storage curves. The planning period for each simulation was considered as 1994-2026 (33 years) and the recorded January 1994 initial storage levels (Table 5.1) were considered as initial storage volumes for the simulation. The 'recycled' streamflow sequences (McMahon and Mein, 1986) were used to account for the stochasticity of streamflow of the system; MW uses this approach in planning studies of the Melbourne System.

Results of each simulation run were analysed to determine the performance indices (monthly time reliability, worst restriction level and maximum duration of any form of restrictions) of the security criteria adopted by MW. These indices were computed by analysing the REALM restrictions levels output file. This file consists of 33 years of data each year having 33 replicates. This means, 396 data lines exist for each year representing 33 replicates and 12 months. The monthly time reliability for each year was computed as the percentage of the number of months which did not have any form of restrictions to the total number of months (396) within that year. The minimum monthly time reliability was noted considering all years. To obtain the maximum duration of continuous restrictions, the restriction levels output file was analysed for each replicate but for the whole planning period, and the number of months that had continuous restrictions for each replicate computed. The maximum duration of continuous restrictions considering all replicates was noted. The worst restriction level (ie. maximum restriction level) is extracted from the file considering all years and replicates, and noted. These performance indices computed for different static annual demands are presented in Table 6.1.

Table 6.1 Performance Indices for Different Levels of Static Annual Demand

Static Annual Demand (ML)	Corresponding Year	Performance Indices		
		Supply reliability %	Worst level of Restrictions	Maximum duration of Rest.
567346	2010	100%	No rest	-
589528	2015	98.2%	level1	2 months
593670	2016	95.5%	level 2	3 months
596819	2017	93.0%	level 2	3 months
599974	2018	90.6%	level 2	5 months
603143	2019	88.2%	level 3	6 months
606312	2020	85.7%	level 3	> 12 months
627656	2026	83.1%	level 4	> 12 months

The acceptable limits of performance indices by MW for the security of supply of the Melbourne system are as follows:

- Minimum monthly time reliability of 95%,
- Maximum duration of consecutive restrictions of 12 months,
- Worst restriction level of 3.

If at least one criteria of the above performance indices fails, the system is considered to fail in supplying the required demand. As can be seen from Table 6.1, the system first failed in 2017. The 'sustainable yield' in this study is defined as the least static annual demand, which fails under one or more performances indices of the security criteria. Therefore, the 'sustainable yield' corresponds to the year 2017, with the average annual demand of 596,819 ML.

6.3.1.2 Input data

Since the Restrictions software uses a lumped single reservoir and single demand centre approach, several input files (streamflow, demand, reservoir evaporation, demand shortfalls and spills) are required to represent the lumped system. In addition, a starting condition file which gives the initial storage volume of the lumped system and other run time parameters, and a restriction data file which produces the initial seed for the optimisation, are required to use the Restrictions Software. The preparation of these files are described below. They were prepared using streamflow, demand, and system files supplied by MW and the results of a REALM run considering the static annual demand corresponding to the year 2017 (ie. sustainable yield). The lumped streamflow, demand, reservoir evaporations, demand shortfall and spills files were prepared for the planning (or study) period of this study, which is from January 1994 to December 2026.

(a) Streamflow file

The monthly streamflows that were used in a REALM simulation model of the Melbourne system were added for each month of the year of the study period to produce the lumped streamflow file.

(b) Demand file

The demand data file provides the unrestricted demand for the total system. This file was prepared from the unrestricted demand output file created from REALM. The monthly unrestricted demands were summed to obtain the monthly total demand for each month of the year of the study period.

(c) Reservoir evaporation file

This file was prepared from the reservoir evaporation losses output file created from REALM. The reservoir evaporation losses were summed to obtain a monthly total evaporation loss. The MW system file considers only the evaporation losses of the main reservoirs and therefore only those reservoir evaporation losses were considered in this study.

(d) Demand shortfall file

This file was prepared from restricted demand and supplied demand output files extracted from the REALM run. The monthly demand shortfalls were computed by subtracting the demand supplied from the restricted demand for each month.

(e) Spills file

The spills file contains the unused or wastage of water leaving the most downstream locations of the system. This file was prepared from output file of carrier flows created from REALM. The flow reaching the stream terminators were summed up to obtain a monthly total spill from the system.

(f) Restriction data file

The restriction data file consists of the 'seed' restriction rule curves for the system to initiate the optimisation. As discussed in Section 3.3.2, there is a narrow band for the 'optimal' restriction rules, which satisfies the required objective function and the constraints. It is necessary to obtain the upper and lower bounds of these restrictions. This can be achieved by considering two seeds (one with higher set of restriction rule curves and the other with a lower set of restriction rule curves) for restrictions. Table 6.2 gives the starting seeds used, in terms of upper and lower restriction rule curves. The restriction rule curves are expressed as percentages of Average Annual Demand (AAD). The amount of restrictable demand for each zone is also given in the Restrictions data file.

Table 6.2 Restriction Seeds Used

Month	Higher set of seed		Lower set of seed	
	Lower (%AAD)	Upper (% AAD)	Lower (% AAD)	Upper (% AAD)
Jan	63	130	68.9	112
Feb	61	125	66.3	109
Mar	58	115	60.8	106.
Apr	55	110	56.3	106
May	55	110	56.3	106
Jun	55	110	56.3	106
Jul	55	110	58.0	106
Aug	58	120	62.6	106
Sep	62	130	70.0	106
Oct	65	135	74.3	107
Nov	65	140	75.6	108
Dec	65	135	71.6	115

(g) Start condition file

The January 1994 recorded storage volumes of reservoirs were added and used as the initial storage volume for use in Restrictions computer software. This storage volume was considered satisfactory for use in the Restrictions Software for static demand analysis, as this initial storage volume is exceeded for more than 45% of months of the planning period. The allowable levels of the performance measures currently used by MW were considered as discussed in Section 6.3.1.1.

- Monthly time reliability 95% (MW addresses this as the supply reliability)
- Worst level of restrictions of level 3
- Maximum duration of continuous restrictions of 12 months.

A storage increment of 1% AAD was used. This storage increment defines restriction triggers in the optimisation, when moves are made from one exploratory move to another or to a pattern search move. A tolerance limit of 0.01% was used for both objective function of volumetric reliability and constraint of monthly time reliability when determining the 'optimum' restriction policy. This means, the new policy was accepted in optimisation as the better solution; if it is at least better than by 0.01% of the previous 'optimal' solution.

6.3.1.3 Derivation of restriction rules

The evaporation, spills and demand shortfall files were created using a REALM simulation run of the actual Melbourne system (i.e. not the lumped system) considering the above higher seed. The Restrictions software was then run with the appropriate input data files, which gives the restriction rule triggers between the upper rule curve and worst restriction level (level 3). The lower seed was considered then and the same procedure followed to derive the restriction rules. Finally, a third seed was considered as the average of the restriction policies obtained from the earlier two seeds and the same procedure repeated to derive an average restriction policy. This is an average 'optimal' restriction policy within a narrow band of 'optimal' restriction rules which produce the same objective function and constraints. These results are used to produce the REALM compatible restriction rules.

REALM requires only the upper and lower restriction rule curves and the relative position of intermediate levels, which have to be derived from the results of the optimisation. The relative positions in REALM should be the same for each month. Three restriction zones exist between upper rule curve and worst restriction level. The Restrictions software produces 48 restriction trigger points in terms of percentage of AAD for different restriction levels between upper rule curve and worst restriction level for different months. That is, the trigger points define the upper rule curve and the levels 1, 2 and 3. Figure 6.1 shows the results obtained from the Restrictions software and the variables used to define the restriction rules as input to REALM.

The average height of restriction zones for each month was computed. For example, for month of February, the average height is (A+B+C)/3. The lower restriction rule curve was then computed by subtracting (4/3) of the average height of restriction zones from the upper rule curve for each month. The factor (4/3) was used because there were 4 restrictions zones between upper and lower rules curves, and 3 zones between upper rule curve and worst restriction level. This procedure determines the lower restriction rule curve.

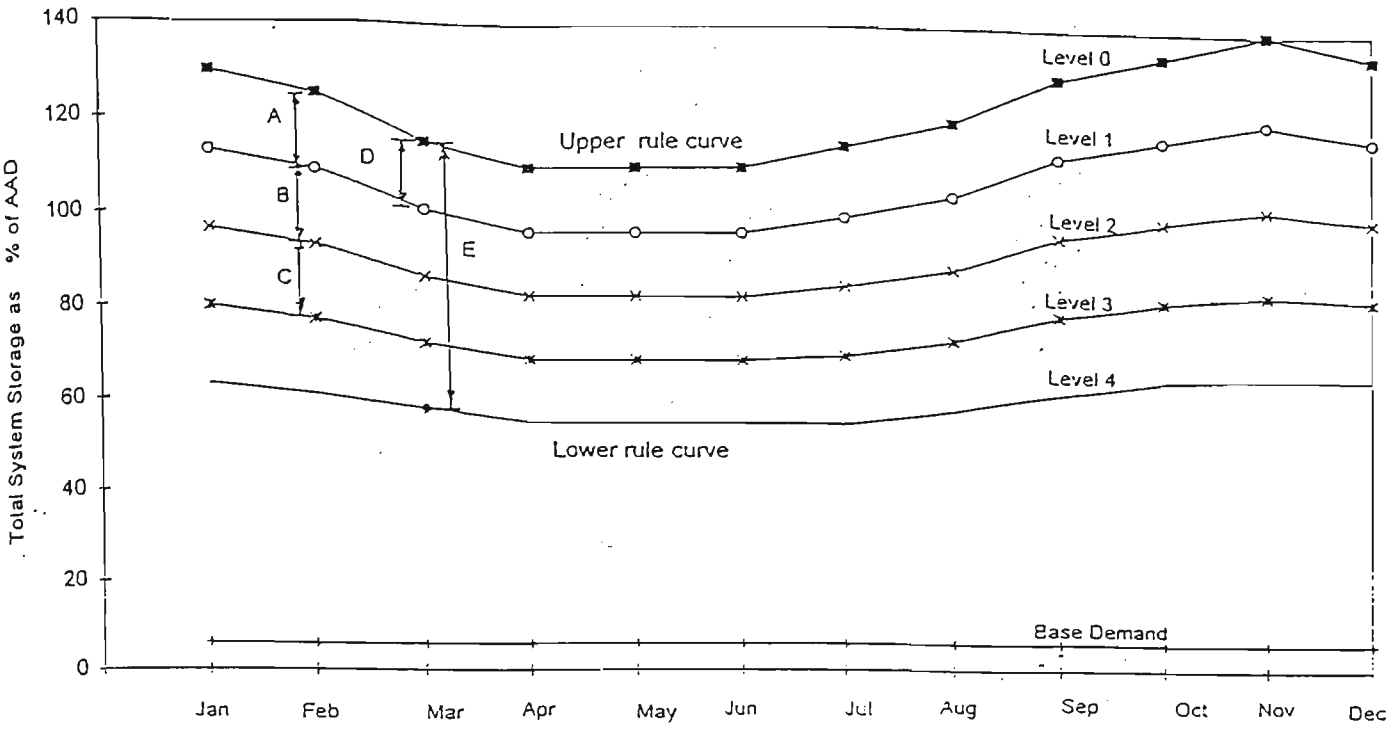


Fig. 6.1 Variables Used to Define Restriction Rules as Input to REALM

The relative position was computed for each intermediate level by averaging out the height of each zone with respect to upper rule curve as a percentage of the height between upper and lower rule curves and expressing the ratio as a percentage over all months. For example, for month of March, the relative position of zone 1 is D/E expressed as a percentage. Similar relative positions are computed for zone 1 for each month and the average across all months computed as the relative position for zone 1. Similar computations are carried out for all restriction zones. This procedure determines the relative position of each intermediate restriction level, which are input to REALM.

Figure 6.2 shows the average upper and lower restriction rules derived from the optimisation using static demands. This figure also shows the results using dynamic demands (Section 6.3.2) and the current restriction policy used by MW. Table 6.3 shows the values of derived average restriction policies (including results of dynamic demand analysis) and current MW restriction rule curve details corresponding to Fig. 6.2. Figure 6.3 shows the details of derived restriction policies (including dynamic demand analysis) with intermediate restriction zones. The computed relative positions of the intermediate restriction levels are quite similar to the values in Table 3.1 (which are the values currently used by MW) and therefore they are not reproduced as a separate table.

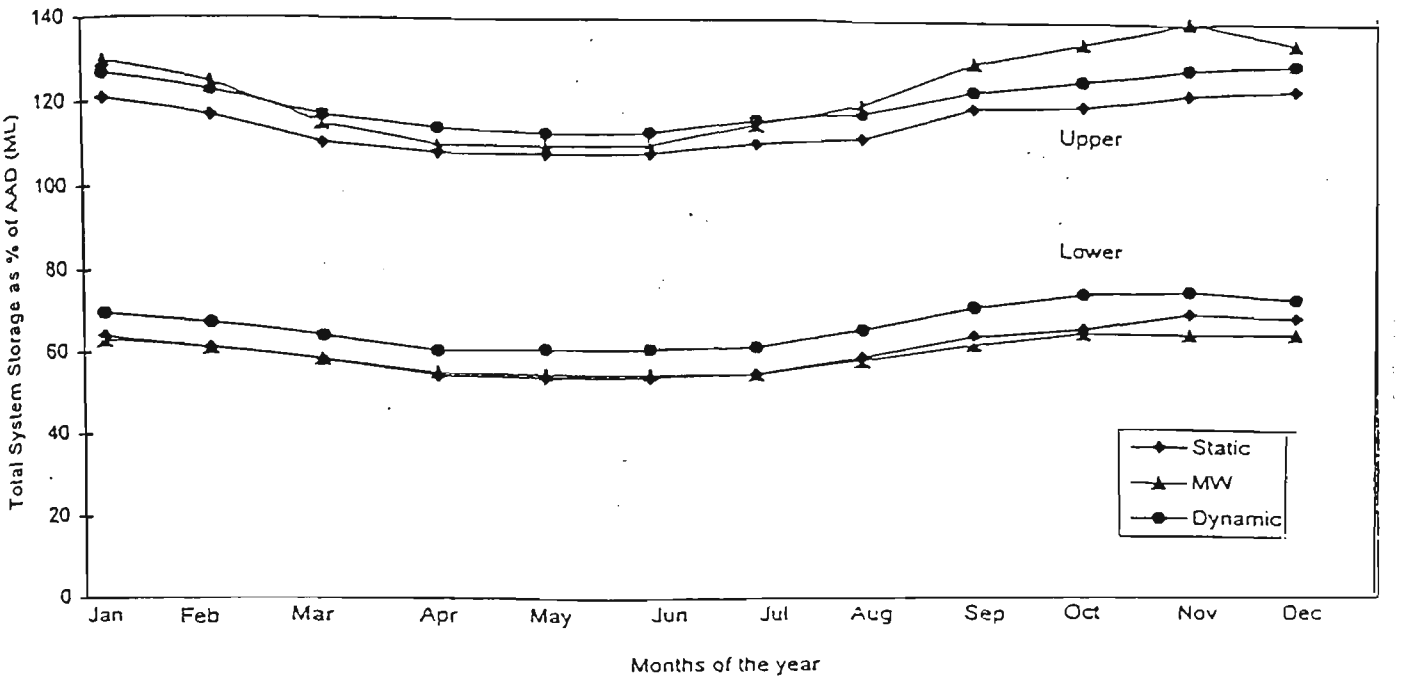


Fig. 6.2 Upper and Lower Restriction Rule Curves for Melbourne System

Table 6.3 Derived and Current MW Restriction Rule Curves

Month	Static Demand Analysis		Dynamic Demand Analysis		Current MW Rules	
	Lower (% AAD)	Upper (% AAD)	Lower (% AAD)	Upper (% AAD)	Lower (% AAD)	Upper (%AAD)
Jan	64.0	121.0	69.6	127.0	63	130
Feb	61.0	117.0	67.0	123.0	61	125
Mar	57.8	110.5	63.8	117.0	58	115
Apr	54.0	108.0	60.4	113.5	55	110
May	54.0	108.0	61.0	113.0	55	110
Jun	54.0	108.0	61.0	113.0	55	110
Jul	55.0	110.5	61.5	115.5	55	115
Aug	59.0	112.0	65.6	118.0	58	120
Sep	64.0	119.0	71.0	123.0	62	130
Oct	66.0	120.0	74.5	126.0	65	135
Nov	70.0	123.0	75.5	129.0	65	140
Dec	69.0	124.0	73.6	130.0	65	135

6.3.2 Restrictions Using Dynamic Demands

Similar to the static demand analysis, the Restrictions software was run for the dynamic demand analysis, but with the dynamic (or projected) demands supplied by MW. The monthly demand file was created using annual projected demands and the monthly demand disaggregation factors supplied by MW, adjusted for climatic conditions. This was done by running REALM with annual projected demand. The planning period was considered as January 1994 to December 2026, and the recorded January 1994 storage volumes were used as the initial storage volumes, as in the static demand analysis case. The reservoir evaporation, demand shortfalls and spills files were created as in Section 6.3.1.2 from REALM results but using dynamic demands. The other input data files remains as in Section 6.3.1.2. The Restrictions software was then run and restriction rule curves derived as in Section 6.3.1.3. The derived restriction rules are shown in Table 6.3 and Figs. 6.2 and 6.3. Similar to the static demand analysis, these restriction rules were the average 'optimal' restriction rules in a nearer band of 'optimal' restriction rules, which provide the same objective function and constraints. The procedure for deriving restriction rules is exactly the same for both static and dynamic demands, the only difference being the different demand sequences used in different analyses.

6.3.3 Comparison of System Behavior

A study was then conducted to investigate the performance of the Melbourne system under current and derived restriction rules. Three different REALM simulation runs were carried out using MW system data files, streamflow and dynamic (projected) demand files. All three simulation runs used the target storage curves currently employed by MW. First run uses the MW current restriction rule curves, while the second and third runs use the restriction rule curves derived from the static and dynamic demand analyses respectively. The study period was considered as January 1994 to December 2026, and the recorded 1994 January storage volume of reservoirs were used as initial starting storage volumes. The 'recycled streamflow sequences' (McMahon and Mein, 1986) were used to account for the stochasticity of streamflow of the system, since this approach is currently used by MW.

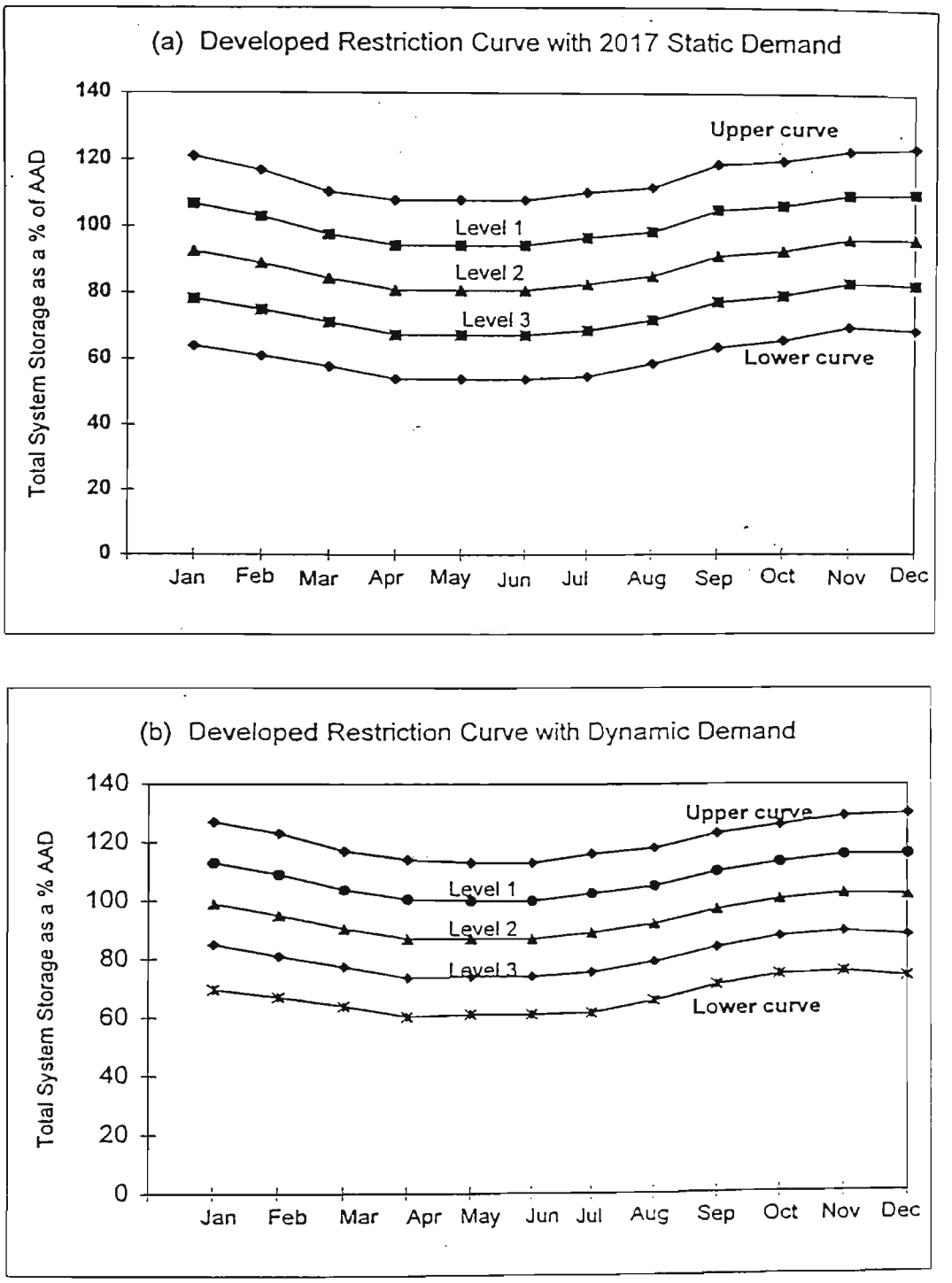


Fig. 6.3 Derived Restriction Rule Curves

Results from these three REALM runs were analysed and presented in Table 6.4. As can be seen from Table 6.4, the restriction rules derived using static demands are consistently better than the current operating rules with respect to all indicators. The performance measures related to the security criteria is better with the developed restriction rules and more water can be supplied to demand zones. The only indicator which is worse under static demands is the average number of shortfalls which is higher than those of the current

restriction rules. However, the restricted demand under the restriction rules derived from the static demand analysis is higher corresponding to that under the current MW rules. If there are shortfalls under the current rules (due to bottlenecks in the system and/or non-availability of water resources in certain reservoirs), the chances are that the shortfalls will be higher when the restricted demand is higher.

Table 6.4 Comparison of System Behavior under MW and Derived Restriction Rules

Performance Indicator	MW Rules	Derived Rules with	
		Static Demand	Dynamic Demand
Year of start of restrictions	2016	2019	2017
Year of failure	2021	2022	2021
Monthly time reliability at failure	93.1%	94.2%	93.2%
Restriction level at failure	2	2	2
Duration of consecutive restrictions at failure (levels)	4 months (1/2)	3 months (1/2)	4 months (1/2)
Minimum monthly time reliability	85.8%	90.4%	88.4%
Year of minimum monthly time reliability	2026	2026	2026
Worst level of restrictions	2	2	3
Duration of consecutive restrictions for the simulation period (levels)	6 (2)	3 (2)	4 (3)
Average monthly unrestricted demand (ML)	46786	46786	46786
Average monthly restricted demand (ML)	46746	46766	46749
Average monthly supplied demand (ML)	46604	46621	46607
Average monthly shortfalls (ML)	143	146	140
Average total system storage (ML)	1393481	1391933	1393088
End of simulation total system storage (ML)	874809	858167	861764

The overall performance of the system under the derived restriction rules based on dynamic demands is again better than those of the current restriction rules. There was one occasion (i.e. the worst restriction level during the simulation period) where the system performs worse under the derived dynamic demand restriction rules compared to MW rules. However, this worst restriction level was after the system has failed in terms of the security criteria and therefore is not important as a performance index.

Figure 6.4 shows how the monthly time reliability varies with the years in the planning period with respect to derived (both under static and dynamic demands) and current restriction rules. It can be seen from Fig. 6.4 that the system behaves best with the derived restriction rules using static demands in terms of year of failure. The reliability curve with

respect to static demand analysis shows a sharp drop after the system has failed. The reliability curve in dynamic demand analysis more or less follows the curve corresponding to the current MW rules. As can be seen from Table 6.4 and Fig. 6.4, the Melbourne system performs better under both sets of derived restriction rules (i.e. using static and dynamic demands) compared to the current MW restriction rules. It is also seen that the rules derived from the static demands are consistently better than the rules derived from the dynamic demands.

When the restriction rules were derived using the Restrictions software, the restriction triggers were computed as a percentage of AAD. Therefore, the derived restriction rules under the dynamic demand analysis considers the effect of dynamic (or projected) demand. Therefore, it is recommended that the restriction rules derived from the dynamic demand analysis be used for the current system until further augmentation by water imports. Under this scenario, it is considered that the Melbourne system cannot be augmented by constructing reservoirs in the MW catchments due to lack of suitable hydraulic sites, but regulated water can be imported from the nearby catchments. Once the system is augmented by water imports, the restriction rules derived by static demand analysis should be used for the system for long term operation. The current system will then be fully committed and a constant demand can be provided by the current system, while the growth in demand could be accommodated by water imports.

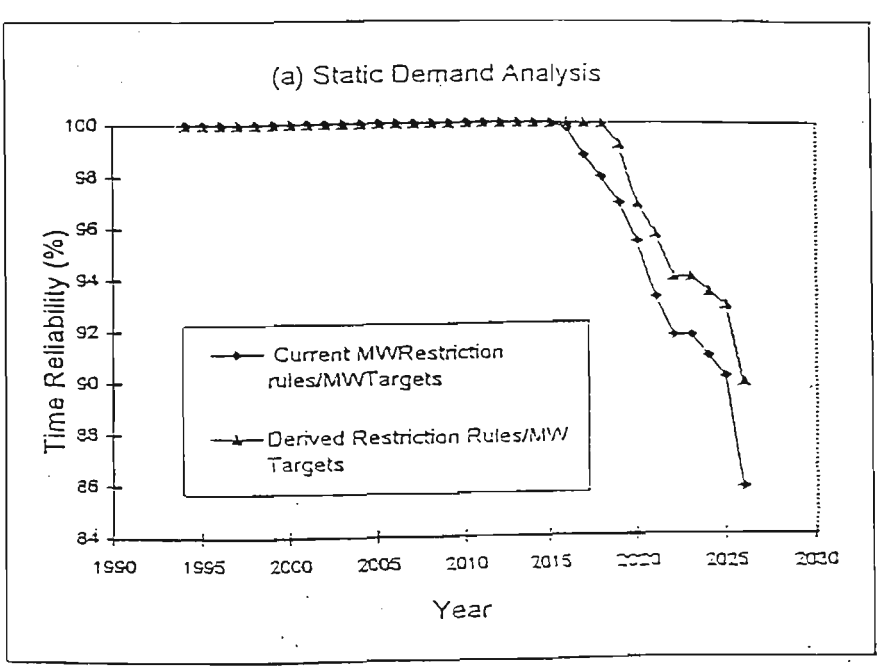


Fig. 6.4 Time Reliability versus Year for Different Restriction Rules

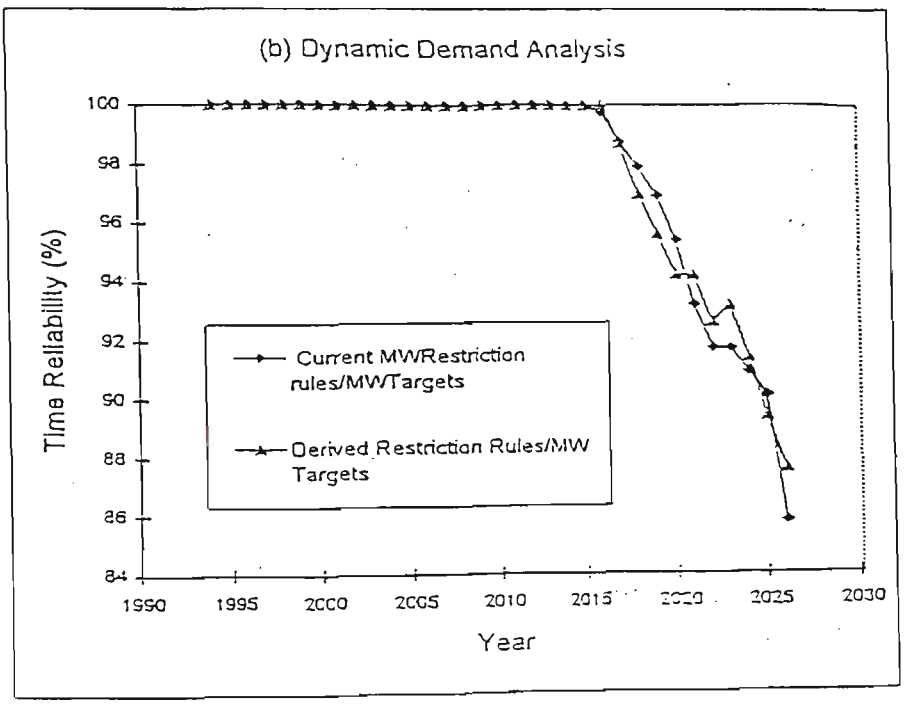


Fig. 6.4 Time Reliability versus Year for Different Restriction Rules.(contd..)

6.4 TARGET STORAGE CURVES

Similar to the Restrictions software, the Targets software was run with both static and dynamic demands for the Melbourne system. The procedure for running the Targets software is exactly the same for both static and dynamic demands, the only difference being the demand sequences used. Since different demand sequences are used, the initial storage volume trajectory file used in static demand analysis is different to that used by the dynamic demand analysis. The initial storage trajectories were obtained by running REALM with the corressponding demand sequence.

Several input data files (system file, streamflow file, demand file, initial storage volume trajectory file, restrictions file and starting conditions file) are required to run the Targets software. Preparation of these files and their contents were discussed previously in the Section 4.5.1 in detail.

The REALM system, streamflow and demand data files supplied by MW in early 1994 were used in this study, with slight modifications to the system file. The information on restriction rules and target storage curves were deleted from the REALM system file; this is a necessary requirement to use the REALM system files in the Targets software. Further, O'Shannassy reservoir was replaced with a stream junction, since the storage capacity of O'Shannassy was 3,123 ML and very small compared to the other storages in the system. Modelling O'Shannassy as a separate storage does not improve the accuracy of DDDP results, but increases the computer time in DDDP significantly, because of an additional storage in the system. This is not a necessary requirement to run the Targets software, but was done to improve the computer time without losing the accuracy of results. O'Shannassy storage capacity was added to the Upper Yarra storage capacity because of close proximity of two storages. No changes were made to the REALM streamflow file supplied by MW for use in the Targets software.

As mentioned earlier, the demand files were prepared separately for static and dynamic demand analyses. The static demand analysis used a constant annual demand for each demand zone for the entire planning period, which was then disaggregated into monthly demands and adjusted for seasonal climatic conditions. In this study, the annual demand corresponding to year 2017 which represents the 'sustainable yield' of the system (Section 6.3.1.1) was used for static demand analysis. The dynamic demand analysis uses the projected demands supplied by MW. In both cases, the demand files required to run the Targets software were created by running REALM with corresponding static and dynamic annual demands, with MW supplied system and streamflow files. The unrestricted demand file created by REALM for each case was used as the demand file in running the Targets software. This process converts the annual demands into monthly demands, adjusts them to account for seasonal climatic conditions and produces monthly demands at each demand zone for the planning period. The initial starting storage volumes are not important in this case, since the purpose of this REALM run is to get the unrestricted demand.

The restrictions file was created using the restriction rule curves derived from the static demand analysis (Section 6.3.1.3) and used in both static and dynamic demand analyses in deriving the target storage curves. Alternatively the restriction rules derived using the dynamic demand analysis could have been used in the restrictions file in deriving the target storage curves. However, this was not done in this study since the purpose of this part of

the study is to illustrate the Targets software for the Melbourne system. The procedure is the same for both analyses the only difference being the contents of the restrictions file.
The initial storage trajectory files were created for both static and dynamic demand analyses by running REALM with (MW supplied) system and streamflow files, but with corresponding static and dynamic demand sequences that were used for the two analyses. The recorded January 1994 total storage volume was used as the initial total system storage. The justification for using the 1994 storage conditions for the initial storage volume is given in Section 6.3.3.1. The recorded January 1994 individual storage volumes were not used in developing the initial storage trajectory, since it was found that Upper Yarra had an unusually low storage volume corresponding to the total system storage; this was because of the repairs to Upper Yarra reservoir at the time. Therefore, the total system storage was disaggregated using current MW target storage curves to generate the initial storage volumes of individual reservoirs for use in this study. These storage volumes were used in developing the initial storage trajectories and were also used in the Targets software for both static and dynamic demand analyses.

A storage increment 1,000 ML was considered in the study to discretise the storage capacity of the reservoir system and to round off the variables such as streamflow, demand, carrier capacities etc. It is acknowledged that a finer storage increment models the system more accurately, but at the expense of more iterations being required to converge to the optimum solution, causing significant increases in computer time.

It is necessary to provide the correct penalties for the additional arcs described in the Section 4.4.2 and 4.4.3 to achieve the intended purposes. These arcs are two arcs from each reservoir to balancing node (BN), one arc from each stream-junction (SJ) and gravity diversion (GD) which receive streamflow to BN, one arc from each stream-terminator (ST) to BN and one arc from BN to each demand centre (DC). These penalties depend on the user-defined penalties in the system. Figure 6.5 shows the penalties of these additional arcs used for the Melbourne system.

6.4.1 Static Demand Analysis

The Targets software was run with the static demand sequence and other inputs as described in Sections 4.5.1 and 6.4. The Targets software produces one output file, which

contains the 'optimal' storage trajectories of all reservoirs for the whole planning period. The output file was then analysed as described in Section 4.5.2 to produce the target storage curves. This output analysis produced eight target storage curves corresponding to eight storages considered in the analysis. Two sets of curves were prepared, one for Summer (Dec-Mar) and the other one for Winter (Apr-Nov). MW currently uses Summer and Winter target storage curves. The Upper Yarra target storage curve was then disaggregated into Upper Yarra and O'Shannassy curves by assigning the current MW O'Shannassy values to the O'Shannassy target storage curve.

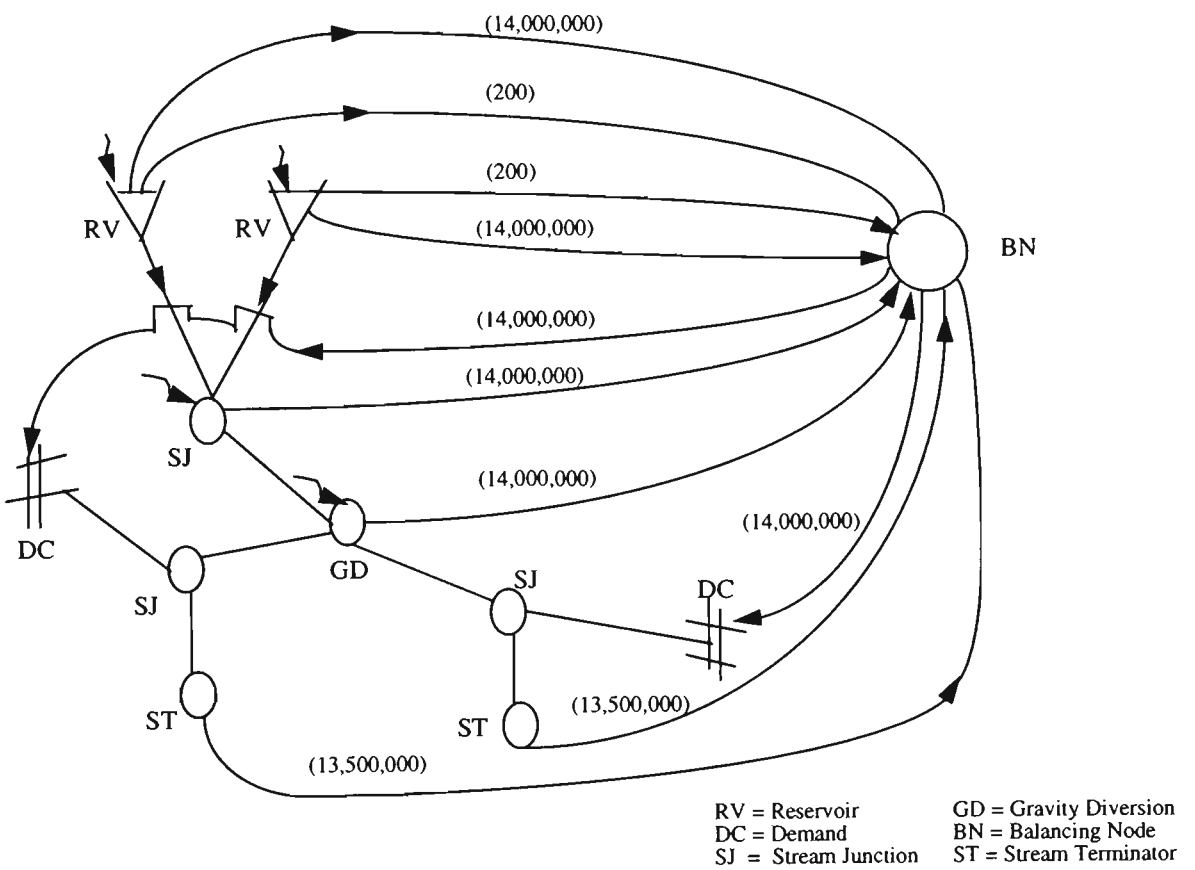


Fig. 6.5 System of Nodes and Arcs for use in NLP with Penalties used for Additional Arcs

The optimal storage trajectory file obtained from the Targets software was imported into MS EXCEL. The MACRO which was developed to group the storage volume data according to seasons (i.e. Summer and Winter) was used then. The total system storage volume was computed for all months of each season and a scatter plot of reservoir volume versus total system storage was plotted for each reservoir for each season. The target storage curve for each reservoir was then plotted manually considering the following rules.

- The curve should be plotted to coincide with the mode (which has the highest relative frequency of points) of individual storage volumes corresponding to the total system storages.
- The target storage curve should not decrease with increase in total system storage.

The target storage curves thus obtained using static demand analysis are tabulated in Table 6.5, and shown in Fig. 6.6. In addition, the MW current target storage curves are shown in Fig. 6.7. Raw data (i.e. 'Optimal' storage trajectories obtained from DDDP) used to derive the target storage curves and the corresponding derived curves are shown in Fig, 6.8. The solid symbols in Fig. 6.8 are the raw data, while shaded symbols define target storage curve.

6.4.2 Dynamic Demand analysis

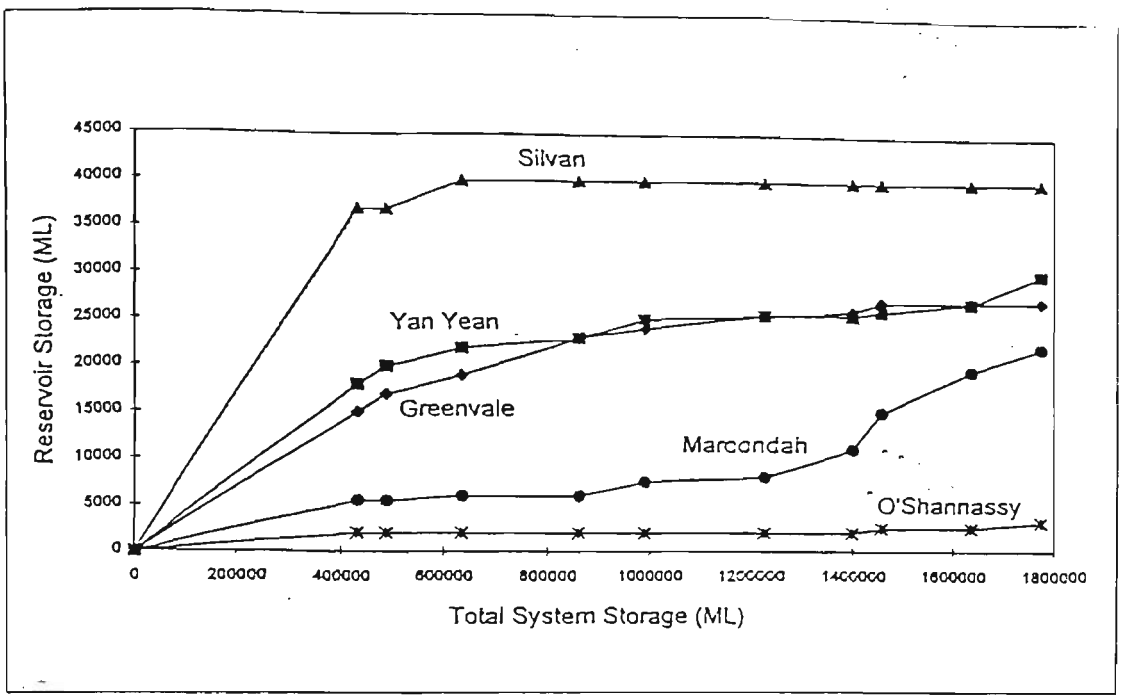
The Targets software was run with inputs as described in Sections 4.5.1 and 6.4, but with the demand and initial storage trajectory files representing dynamic (or projected) demand sequence (Section 6.4). The target storage curves were then derived as described in Section 6.4.1. They are tabulated in Table 6.6 and are also shown in Fig. 6.9. Raw data (i.e. Optimal' storage trajectories obtained from DDDP) used to derive the target storage curves using dynamic demand analysis and the corresponding derived curves are shown in Fig. 6.10. The solid symbols in Fig. 6.10 are the raw data, while shaded symbols define target storage curve.

6.4.3 Comparison of System Behaviour

A study was then conducted to investigate the performance of the Melbourne system under current and derived (both from static and dynamic demand analyses) target storage curves. Three different REALM simulation runs were carried out using MW supplied system, streamflow and dynamic (projected) demand files. However, the system file was slightly modified to replace the current MW restriction rules with derived restriction rule curves based on the static demand analysis. The justification for using the restriction rules of the static demand analysis is discussed in Section 6.4. Already the base simulation run, which uses the current MW restriction rules and target storage curves, but with above system, streamflow and demand files have been performed in Section 6.3.3.

Table 6.5 Target Storage Curves Derived from Static Demand Analysis

Summer (ML)									
Total system storage	Greenvale	Yan Yean	Silvan	Cardinia	Sugarloaf	Maroondah	O'Shanassy	Upper Yarra	Thomson
0	0	0	0	0	0	0	0	0	0
430,000	15,000	18,000	37,000	117,000	30,000	5,500	2,000	35,500	170,000
486,500	17,000	20,000	37,000	130,000	35,000	5,500	2,000	40,000	200,000
634,000	19,000	22,000	40,000	175,000	50,000	6,000	2,000	100,000	220,000
859,000	23,000	23,000	40,000	185,000	80,000	6,000	2,000	130,000	370,000
988,850	24,000	25,000	40,000	195,000	90,000	7,500	2,000	135,000	470,000
1,226,000	25,500	25,500	40,000	200,000	90,000	8,000	2,000	135,000	700,000
1,397,000	26,000	25,500	40,000	230,000	93,000	11,000	2,000	145,000	825,000
1,455,500	27,000	26,000	40,000	250,000	95,000	15,000	2,000	150,500	850,000
1,636,000	27,000	27,000	40,000	270,000	95,000	19,500	2,000	160,500	995,000
1,773,123	27,000	30,000	40,000	287,000	96,000	22,000	3,123	200,000	1,068,000
Winter (ML)									
Total system storage	Greenvale	Yan Yean	Silvan	Cardinia	Sugarloaf	Maroondah	O'Shanassy	Upper Yarra	Thomson
0	0	0	0	0	0	0	0	0	0
430,000	15,000	18,000	37,000	117,000	30,000	5,500	2,000	35,500	170,000
500,000	18,000	20,000	37,000	140,000	32,000	6,000	2,000	45,000	200,000
633,000	20,000	23,500	38,000	200,000	45,000	8,500	2,000	96,000	230,000
835,500	24,000	24,000	40,000	230,000	85,000	10,500	2,000	110,000	310,000
997,000	26,000	24,000	40,000	235,000	95,000	15,000	2,000	130,000	430,000
1,187,000	26,000	24,000	40,000	235,000	95,000	20,000	2,000	145,000	600,000
1,279,000	27,000	25,000	40,000	240,000	95,000	20,000	2,000	150,000	680,000
1,505,500	27,000	25,000	40,000	240,000	95,000	21,000	2,000	155,500	900,000
1,624,700	27,000	28,000	40,000	250,000	95,000	22,000	2,000	160,700	1,000,000



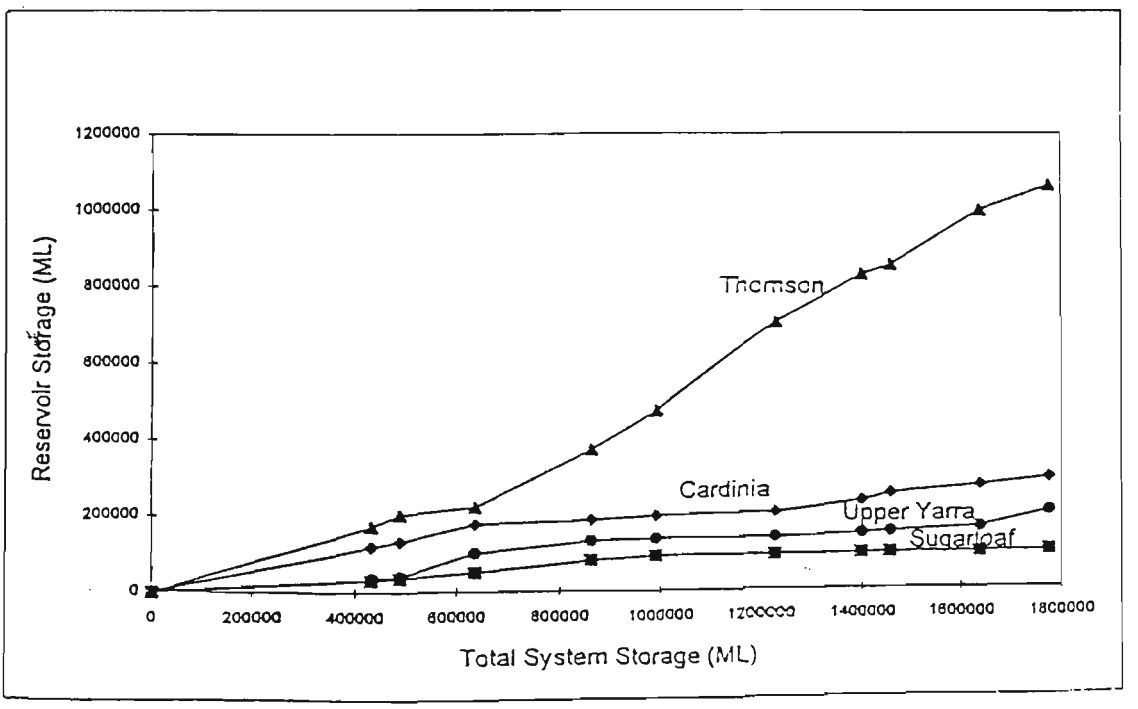
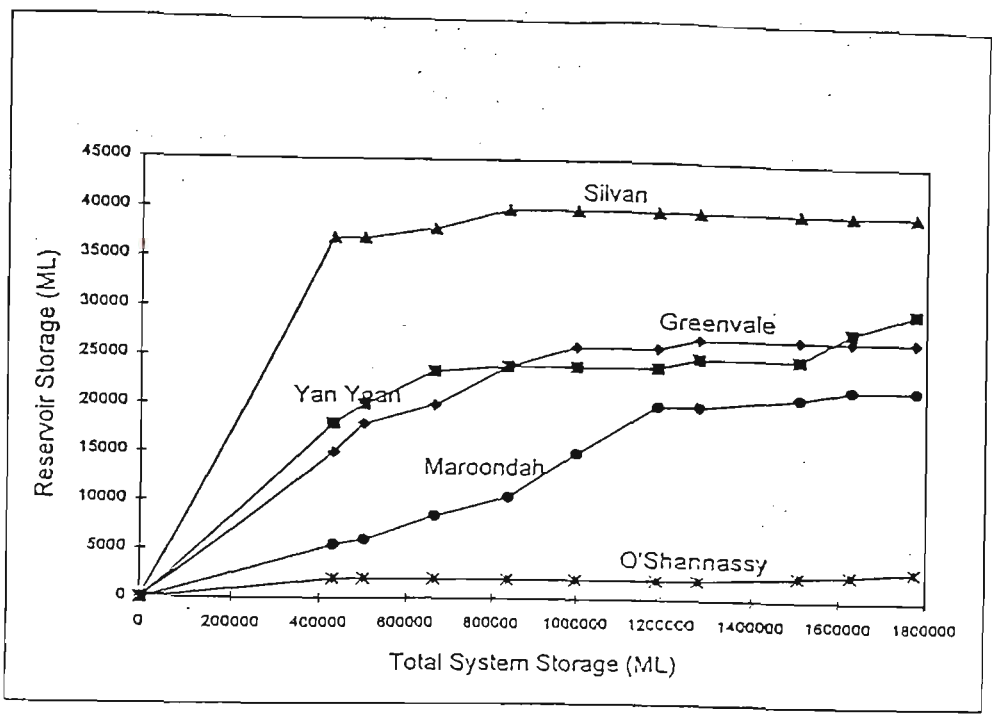


Fig. 6.6(a) Target Storage Curves Derived from Static Demand Analysis- Summer curves



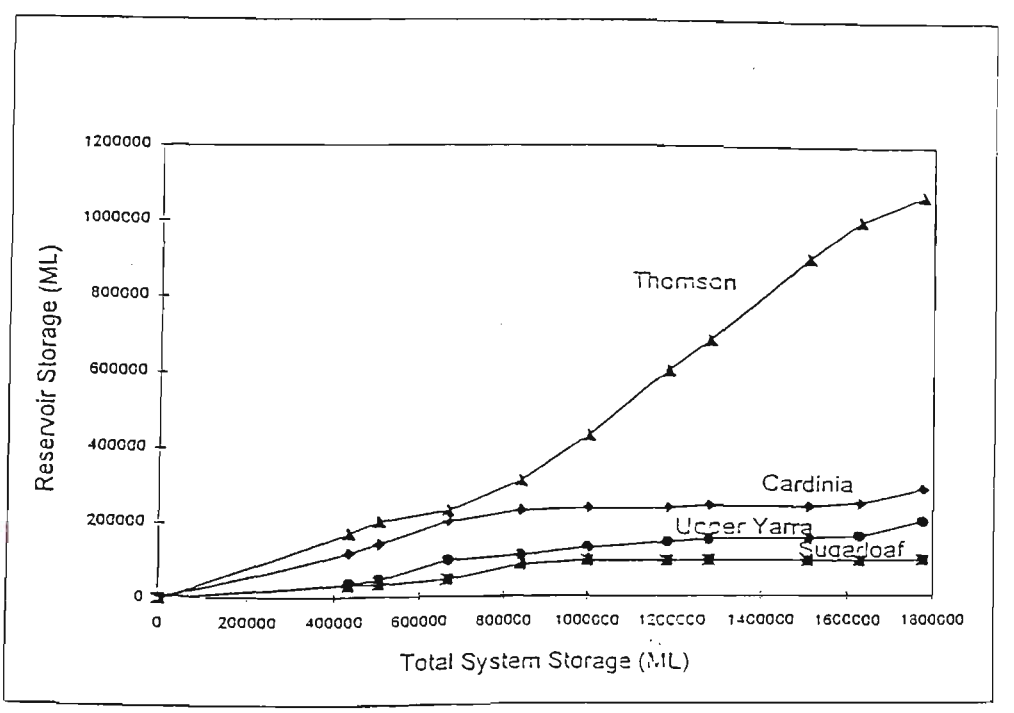
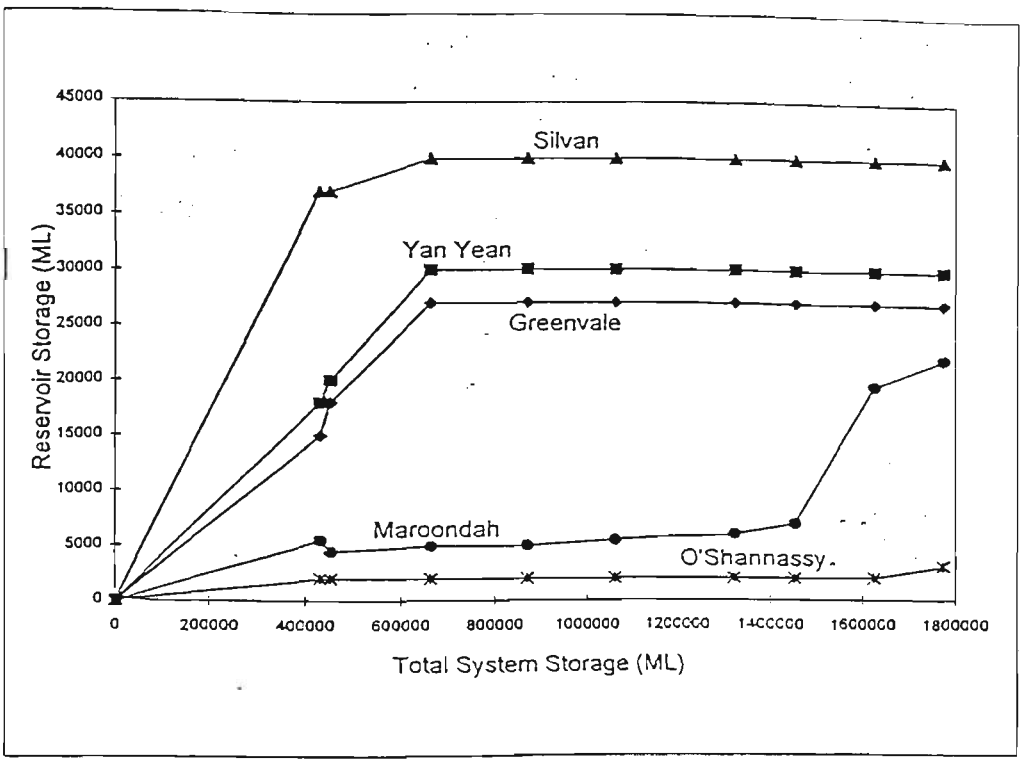


Fig. 6.6(b) Target Storage Curves Derived from Static Demand Analysis-Winter curves



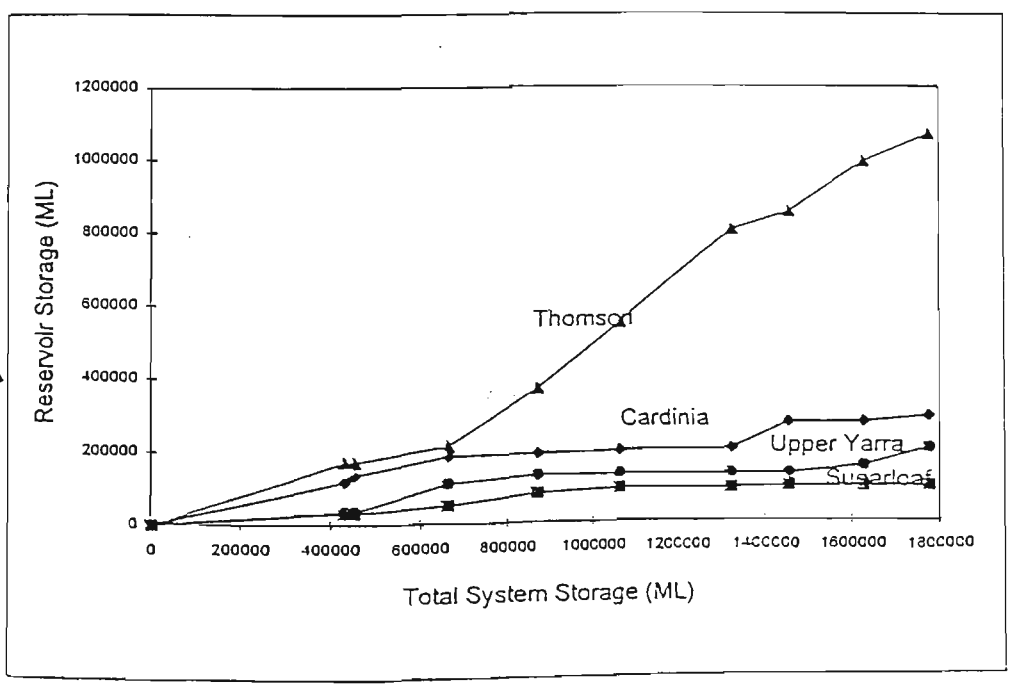
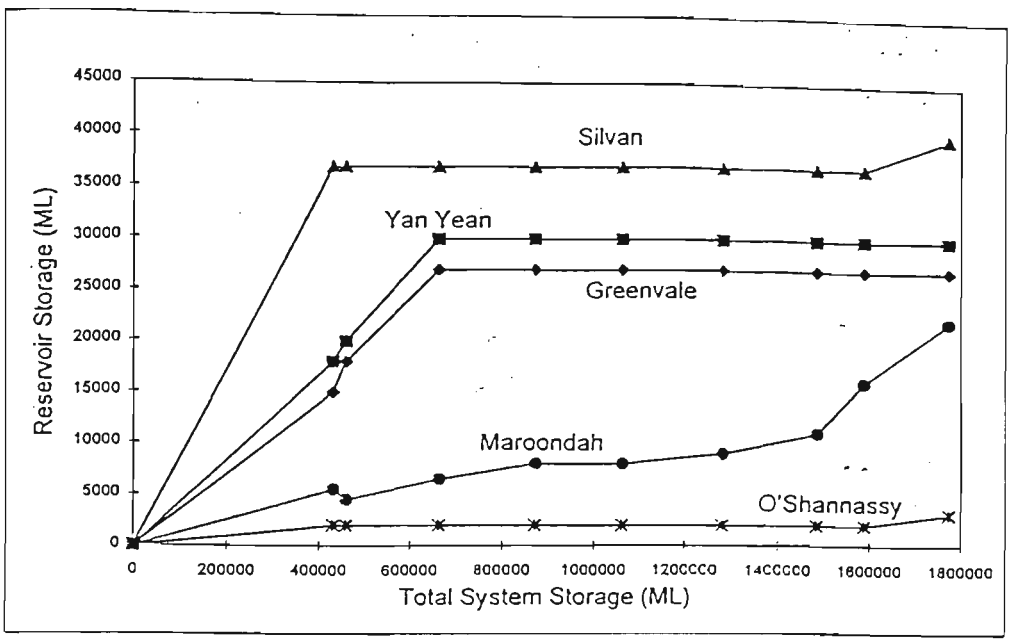


Fig. 6.7(a) MW Current Target Storage Curves-Summer curves



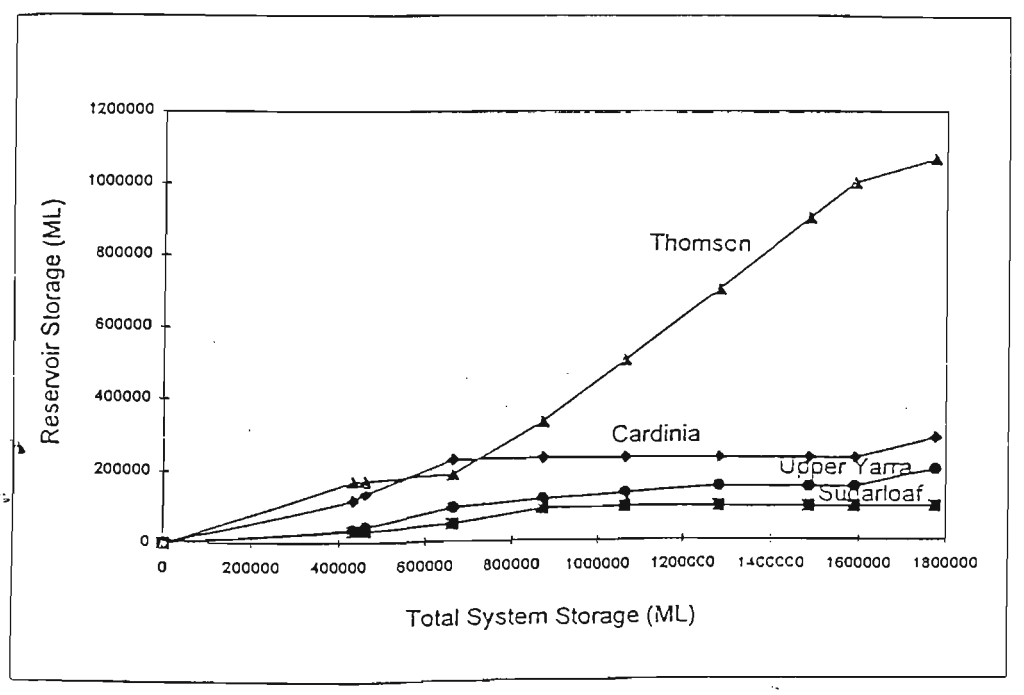


Fig. 6.7(b) MW Current Target Storage Curves-Winter curves

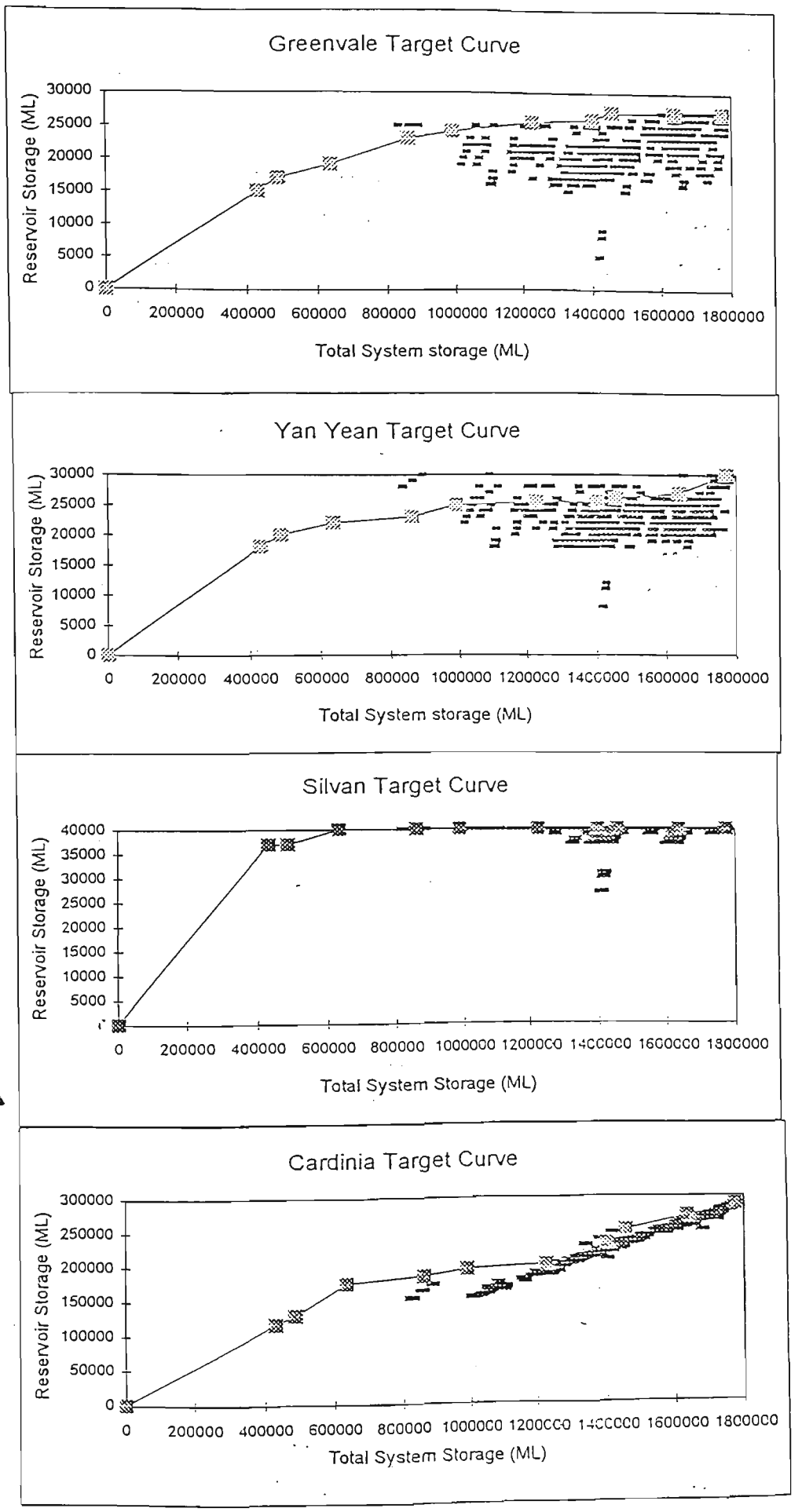


Fig. 6.8(a) Raw Data Used in Deriving Summer Target Storage Curves in Static Demand Analysis

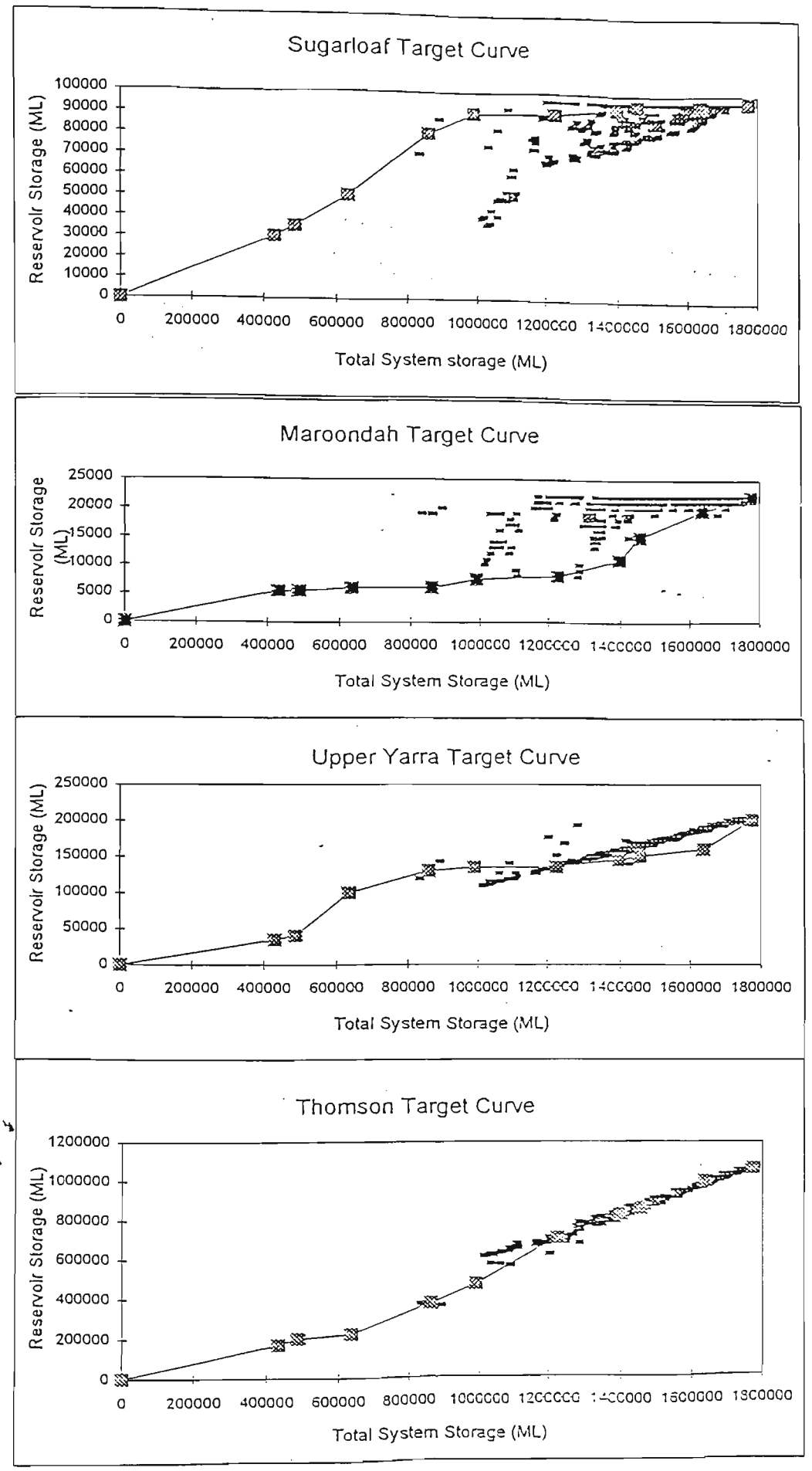


Fig. 6.8(a) Raw Data Used in Deriving Summer Target Storage Curves in Static Demand Analysis (continued...)

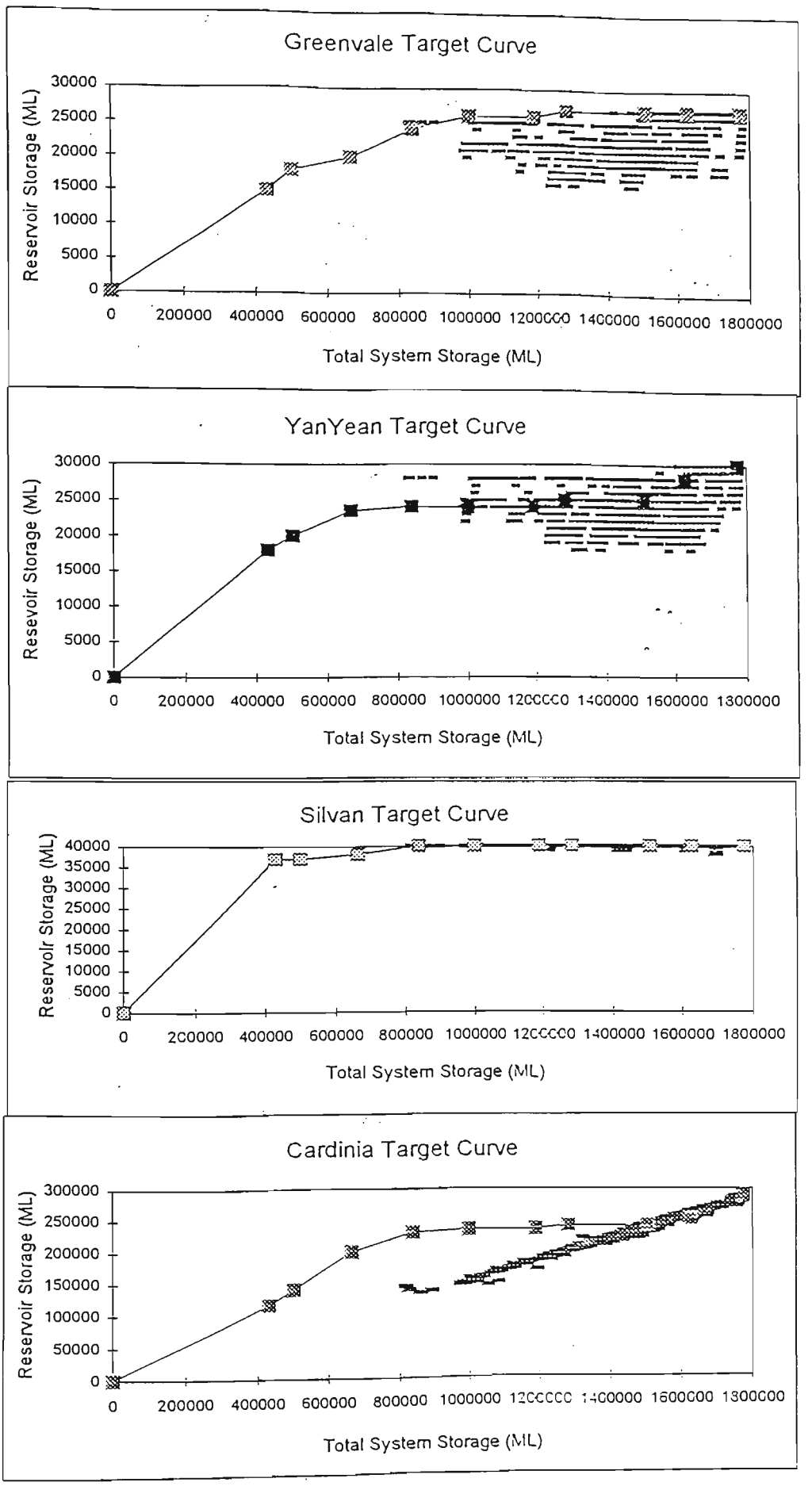
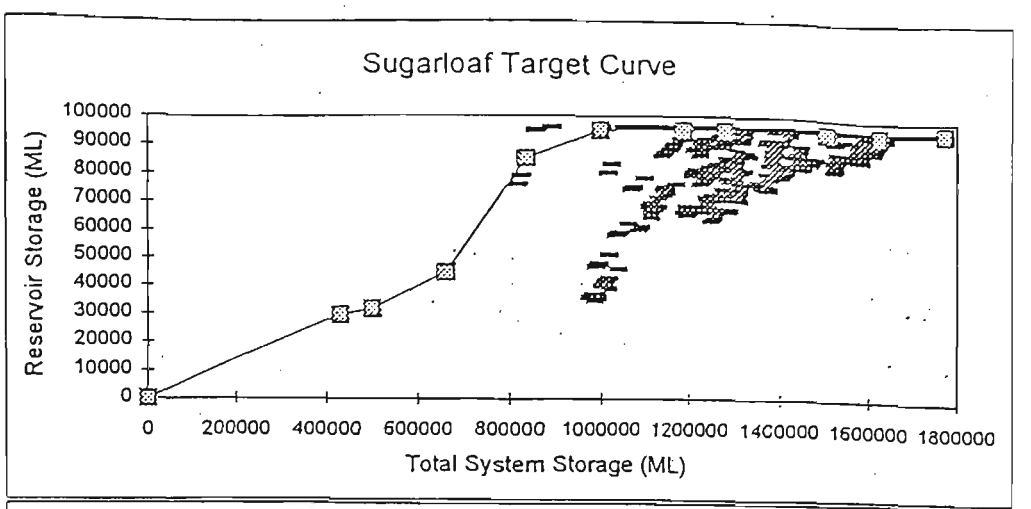
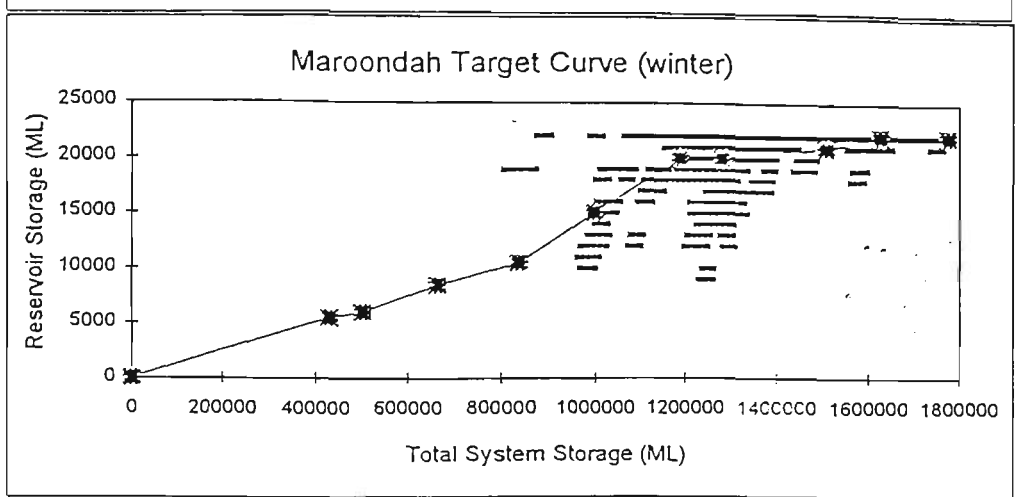
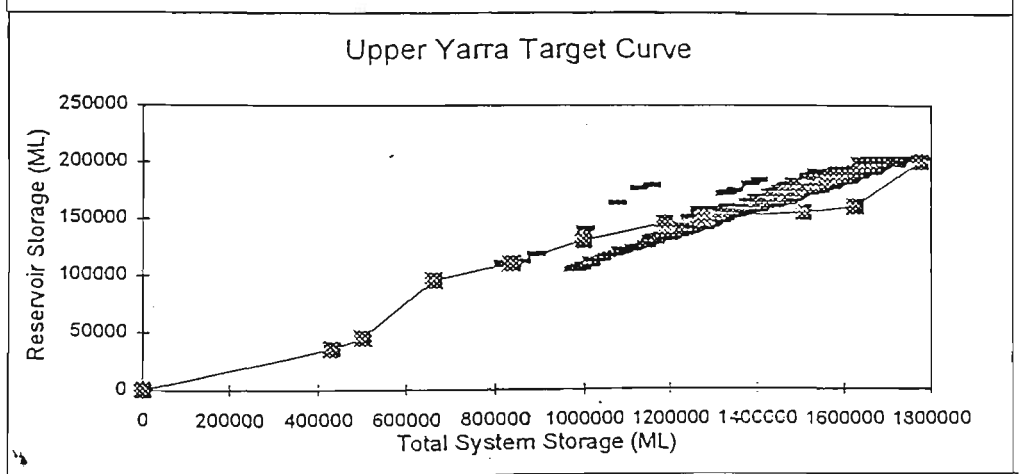


Fig. 6.8(b) Raw Data Used in Deriving Winter Target Storage Curves in Static Demand Analysis







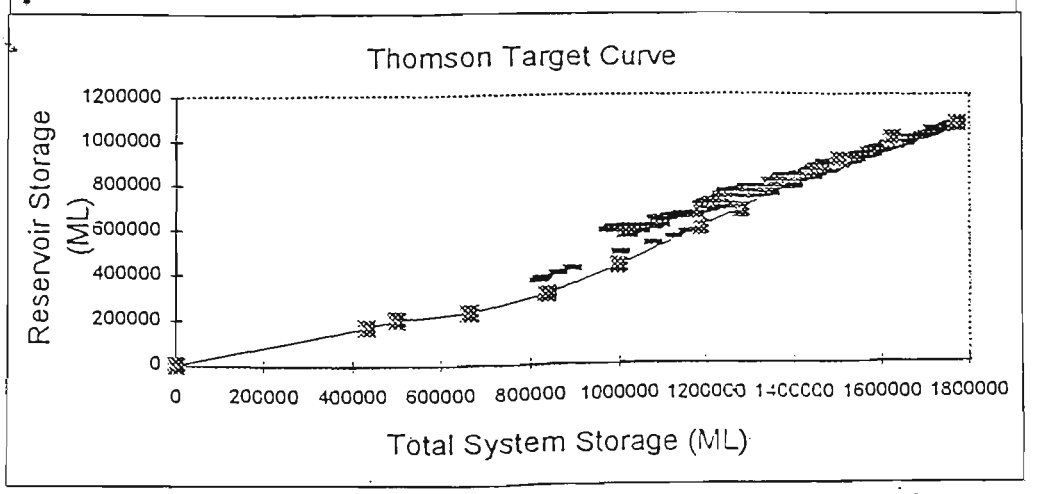
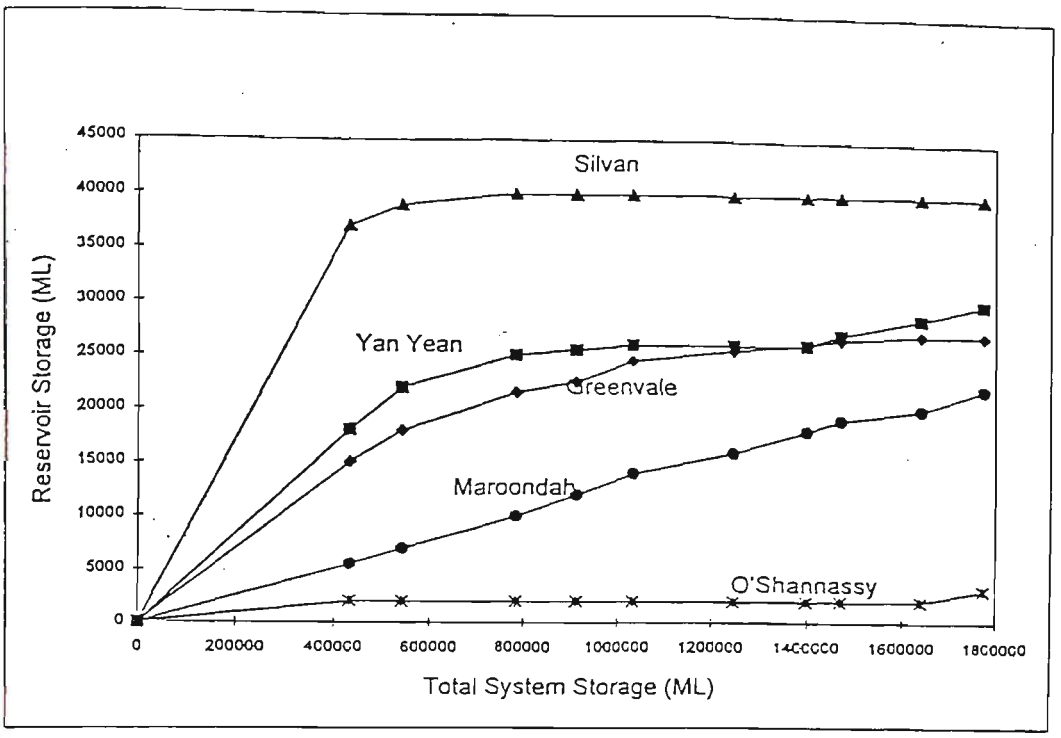


Fig. 6.8(b) Raw Data Used in Deriving Winter Target Storage Curves in Static Demand Analysis (continued..)

Table 6.6 Target Storage Curves Derived from Dynamic Demand Analysis

Summer (ML)									
Total system storage	Greenvale	Yan Yean	Silvan	Cardinia	Sugarloaf	Maroondah	O'Shanassy	Upper Yarra	Thomson
0	0	0	0	0	0	0	0	0	0
430,000	15,000	18,000	37,000	117,000	30,000	5,500	2,000	35,500	170,000
540,000	18,000	22,000	39,000	135,000	47,000	7,000	2,000	70,000	200,000
783,500	21,500	25,000	40,000	180,000	75,000	10,000	2,000	120,000	310,000
911,000	22,500	25,500	40,000	195,000	84,000	12,000	2,000	130,000	400,000
1,031,500	24,500	26,000	40,000	200,000	90,000	14,000	2,000	135,000	500,000
1,246,500	25,500	26,000	40,000	210,000	92,000	16,000	2,000	135,000	700,000
1,397,000	26,000	26,000	40,000	225,000	95,000	18,000	2,000	145,000	820,000
1,469,500	26,500	27,000	40,000	250,000	95,000	19,000	2,000	150,000	860,000
1,638,500	27,000	28,500	40,000	270,000	96,000	20,000	2,000	160,000	995,000
1,773,123	27,000	30,000	40,000	287,000	96,000	22,000	3,123	200,000	1,068,000
Winter (ML)									
Total system storage	Greenvale	Yan Yean	Silvan	Cardinia	Sugarloaf	Maroondah	O'Shanassy	Upper Yarra	Thomson
0	0	0	0	0	0	0	0	0	0
430,000	15,000	18,000	37,000	117,000	30,000	5,500	2,000	35,500	170,000
565,500	20,000	22,500	39,000	150,000	55,000	7,000	2,000	70,000	200,000
750,000	23,000	25,000	40,000	200,000	80,000	10,000	2,000	110,000	260,000
916,000	25,000	25,000	40,000	230,000	89,000	15,000	2,000	120,000	370,000
1,077,500	26,000	25,500	40,000	240,000	93,000	16,000	2,000	135,000	500,000
1,216,500	26,500	26,000	40,000	242,000	95,000	18,000	2,000	147,000	620,000
1,415,800	26,500	26,000	40,000	248,000	95,000	18,000	2,000	150,000	810,000
1,535,500	27,000	26,000	40,000	250,000	95,000	20,000	2,000	155,500	920,000
1,634,700	27,000	29,000	40,000	260,000	95,000	21,000	2,000	160,700	1,000,000
1,773,123	27,000	30,000	40,000	287,000	96,000	22,000	3,123	200,000	1,068,000



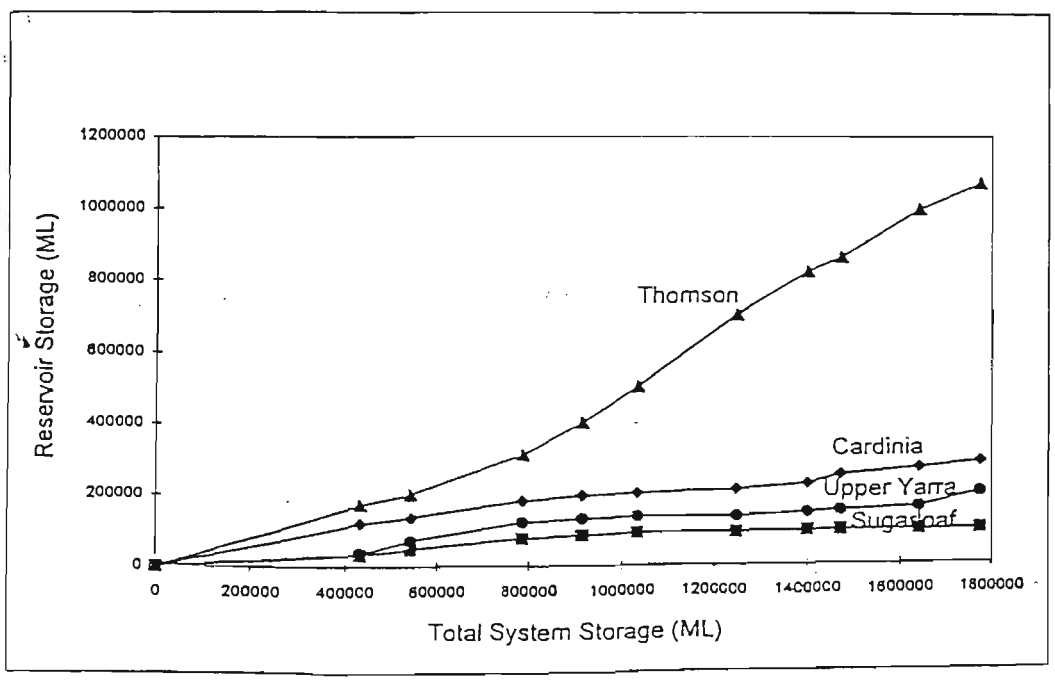
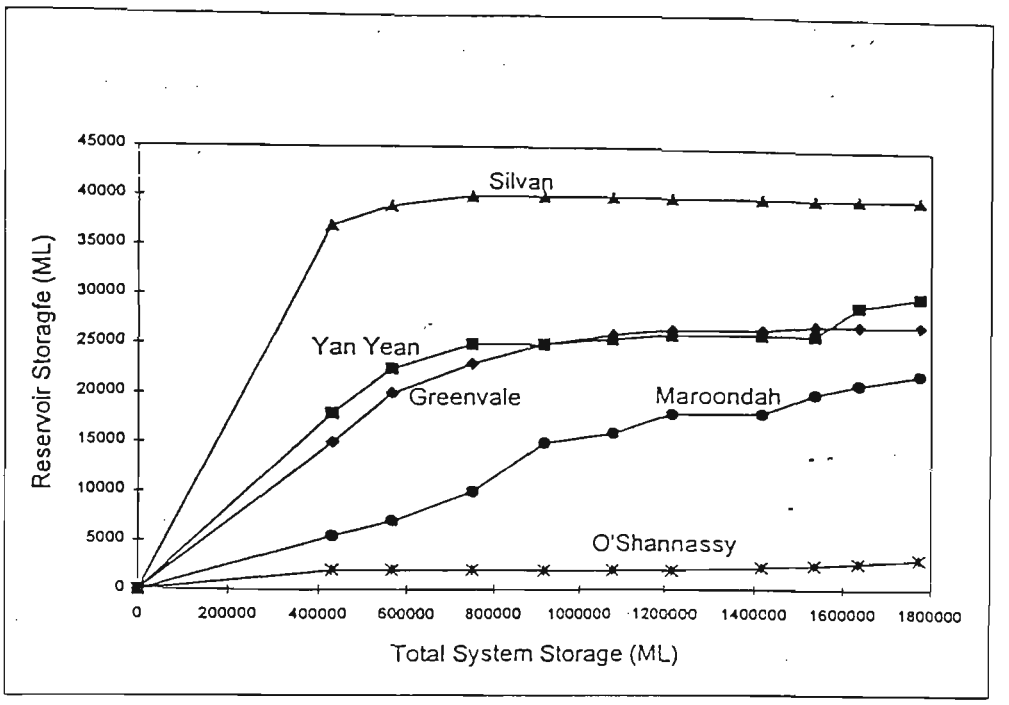


Fig. 6.9(a) Target Storage Curves Derived from Dynamic Demand Analysis-Summer curves



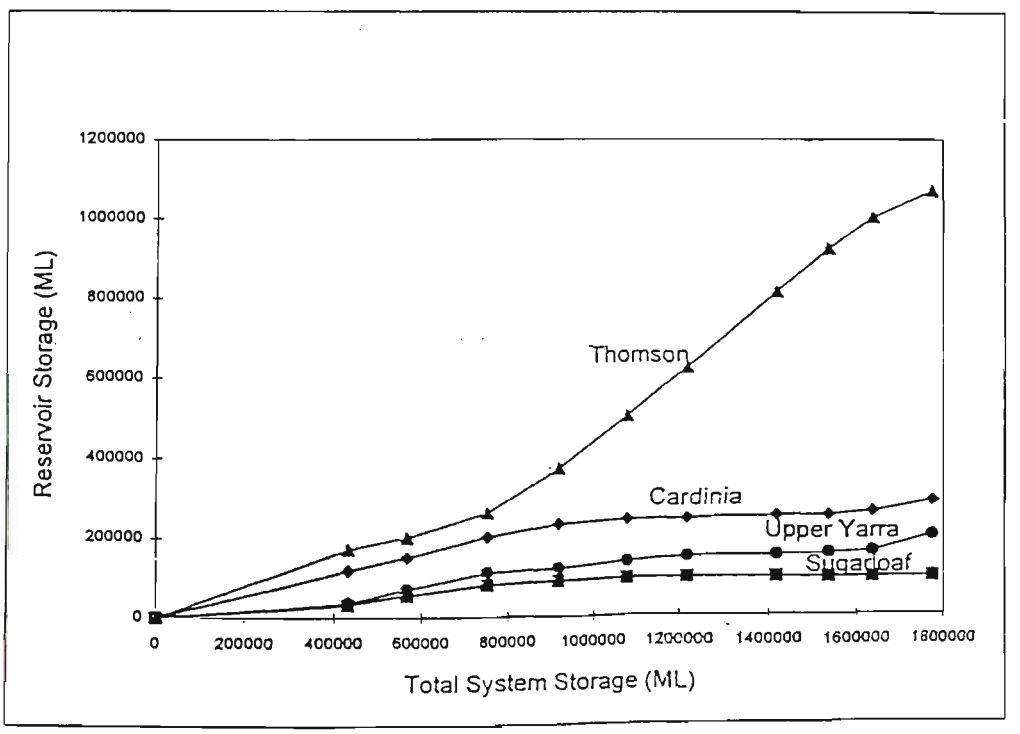


Fig. 6.9(b) Target Storage Curves Derived from Dynamic Demand Analysis-Winter curves

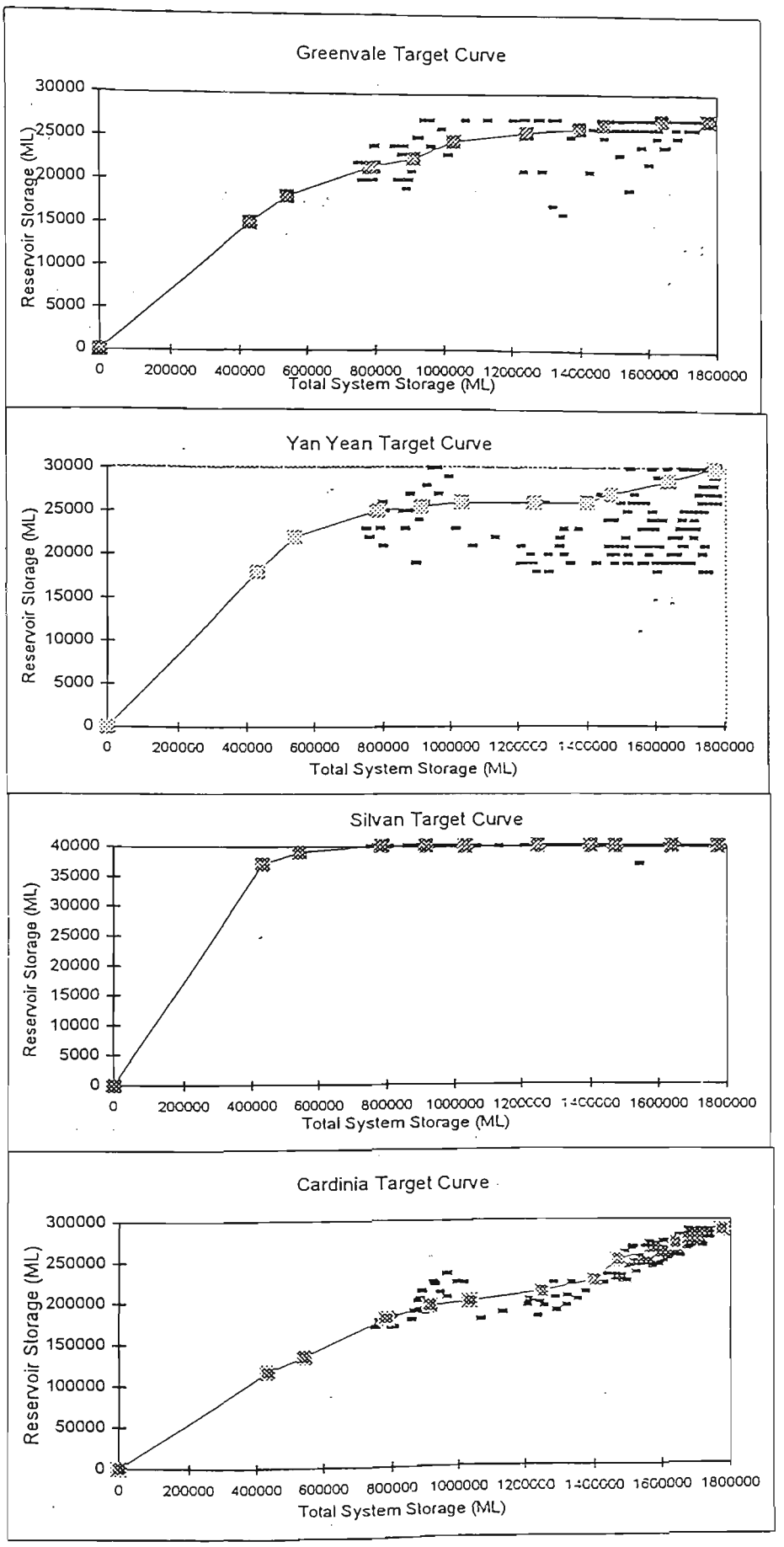


Fig. 6.10(a) Raw Data Used in Deriving Summer Target Storage Curves in Dynamic Demand Analysis

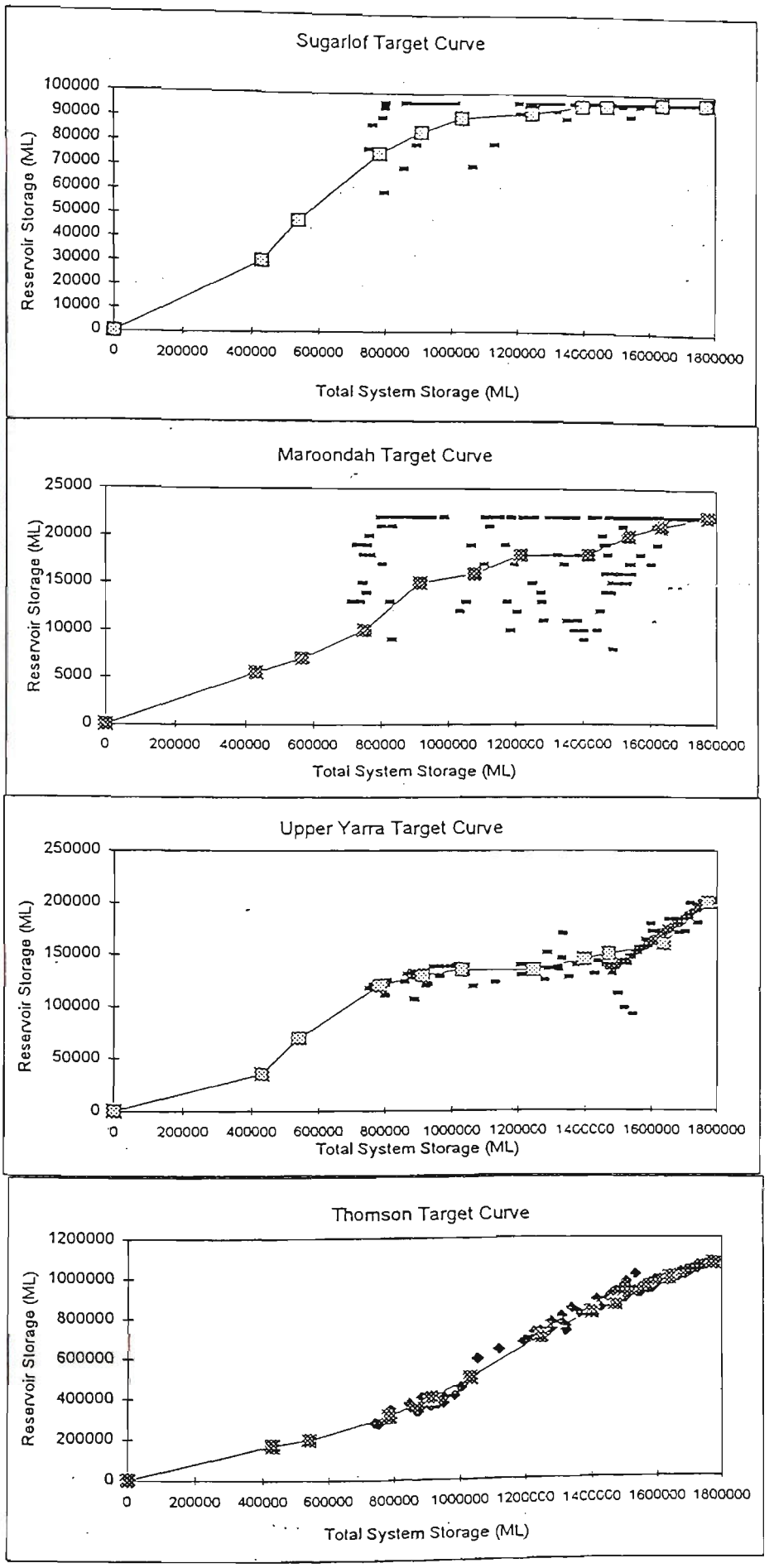


Fig. 6.10(a) Raw Data Used in Deriving Summer Target Storage Curves in Dynamic Demand Analysis (continued..)

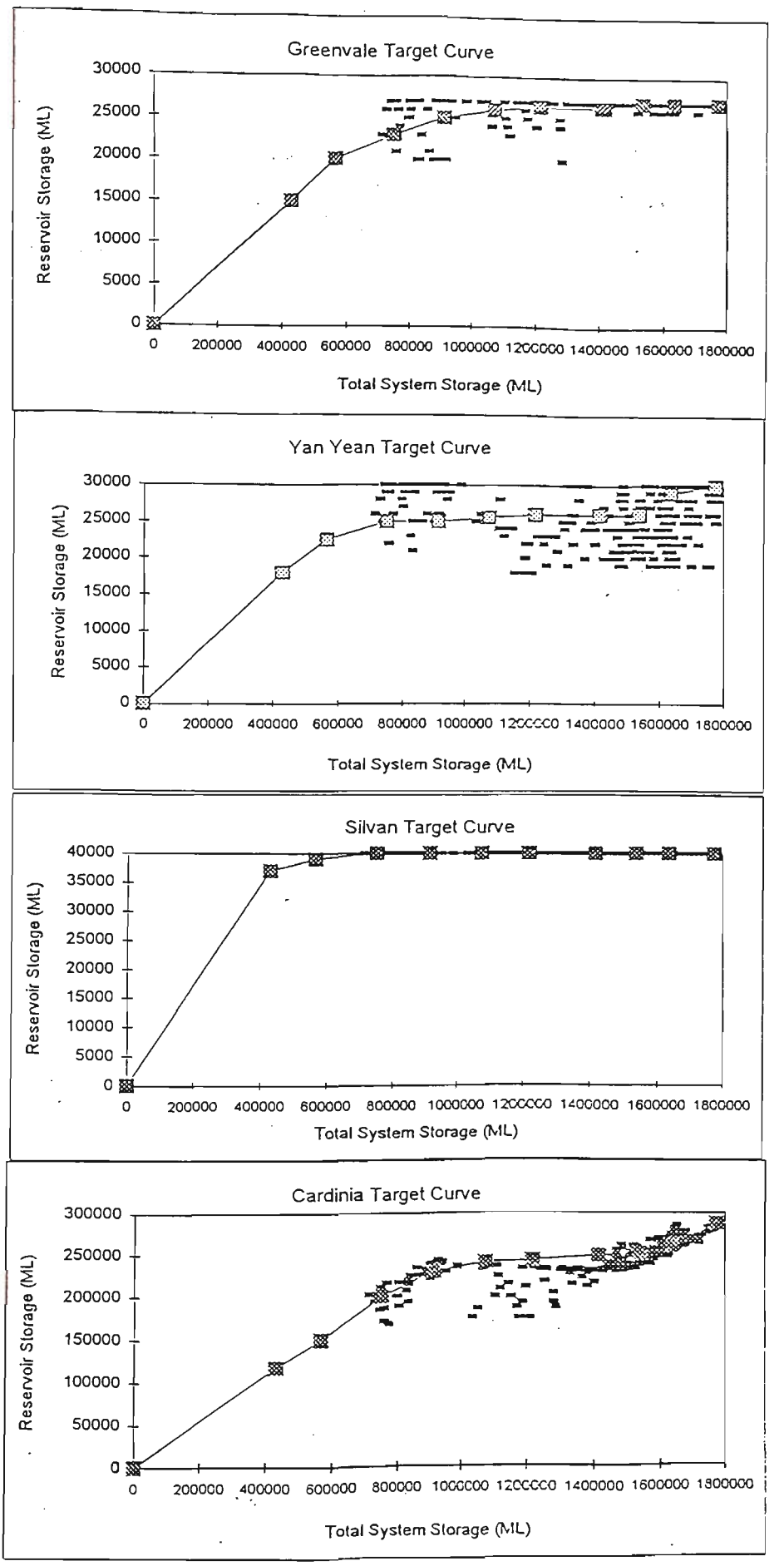


Fig. 6.10(b) Raw Data Used in Deriving Winter Target Storage Curves in Dynamic Demand Analysis

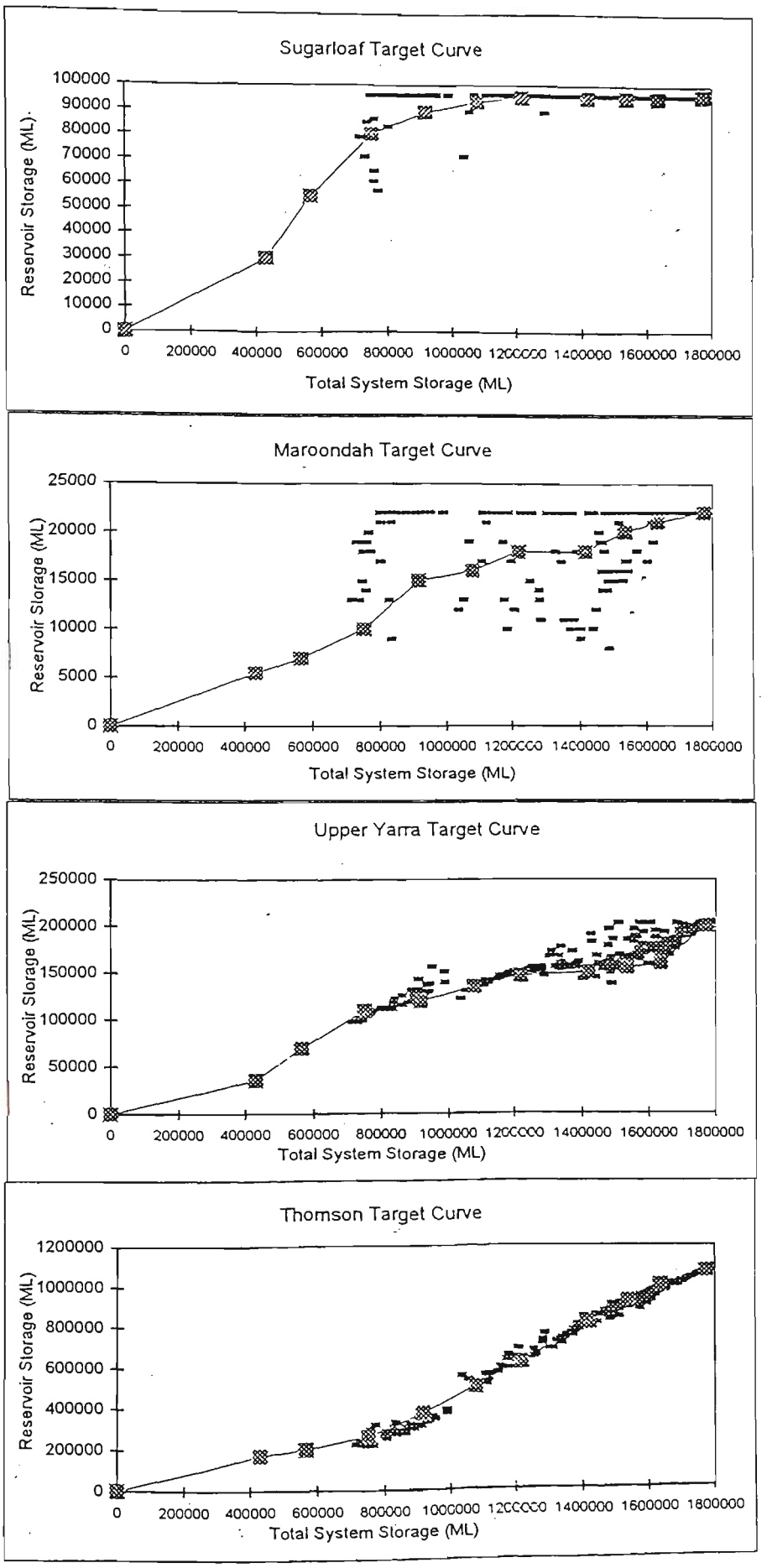


Fig. 6.10(b) Raw Data Used in Deriving Winter Target Storage Curves in Dynamic Demand Analysis (continued..)

The study period was considered as from January 1994 to December 2026, and the recorded 1994, January storage volume of reservoirs were used as the initial storage volumes. The 'recycled streamflow sequences' (McMahon and Mein, 1986) were used to account for the stochasticity of streamflow of the system as in Section 6.3.3.

Results from these three REALM runs were analysed and presented in Table 6.7. In addition, similar information is given in Table 6.7 for MW current operating rules (both restriction rules and target storage curves) and MW current target storage curves but restriction rules derived from the study (using static demand analysis). They are shown in the Table 6.7 in Columns 2 and 6 (last column) respectively. All simulation runs use the restriction rules derived in this study using static deman analysis, except for the last column where both MW restriction and target storage curves are used. Figure 6.11 shows how the supply reliability varies with time with the derived target storage curves. Some discussion on comparison of system behaviour is given in Section 6.4.4.

6.4.4 Fine Tuning of Target Storage Curves

As can be seen from Table 6.7, the Melbourne system has performed best under the derived restriction rules (using the static demand analysis) and MW target storage curves. Although an objective method was used to derive the optimal storage trajectory, some 'averaging' was used to compute the target storage curves from the results of DDDP. Further, two assumptions were made in modelling the system. First, a storage increment of 1,000 ML was used in discretising the storage capacities of the system and rounding off streamflow, demand and other system data. If a finer storage increment had been used, the results could have been improved, but at the expense of computer time. The second assumption was the modelling of O'Shannassy storage; this should not have any effect on the derived target storage curves, because of the size of the storage. There is also one other aspect that should be considered in comparing different operating rules (in this case the target storage curves). The current MW target storage curves were derived by trial and error considering multiple streamflow replicates derived from 'recycled streamflow sequences' approach (McMahon and Mein, 1986); the same approach was also used to derive the performance indicators in Table 6.7.

Table 6.7 Comparison of System Behaviour under MW and Derived Target Storage Curves

Performance Indicator	MW Rules	Derived Rules			MW Original Rules
		with Static Demand	with Dynamic Demand	Fine Tuned	
Year of start of restrictions	2019	2017	2016	2018	2016
Year of failure	2022	2021	2020	2021	2021
Monthly time reliability at failure	94.2%	94.2%	92.6%	94.2%	93.1%
Restriction level at failure	2	2	2	2	2
Duration of consecutive restrictions at failure (levels)	3 months (1/2)	3 months (1/2)	4 months (1/2)	3 months (1/2)	4 months (1/2)
Minimum monthly time reliability	90.4%	88.6%	87.1%	88.6%	85.8%
Year of minimum monthly time reliability	2026	2026	2026	2026	2026
Worst level of restrictions	2	2	3	2	2
Duration of consecutive restrictions for the simulation period (levels)	3 (2)	3 (2)	6 (3)	4 (2)	6 (2)
Average monthly unrestricted demand (ML)	46786	46786	46786	46786	46786
Average monthly restricted demand (ML)	46766	46758	46737	46761	46746
Average monthly supplied demand (ML)	46621	46603	46582	46616	46604
Average monthly shortfalls (ML)	146	156	155	144	143
Average total system storage (ML)	1391933	1376418	1365128	1384734	1393481
End of simulation total system storage (ML)	858167	835677	806121	830986	874809

Note: All simulation runs use the restriction rules derived in this study using the static demand analysis, except for the last column where both MW restriction and target storage curves are used.

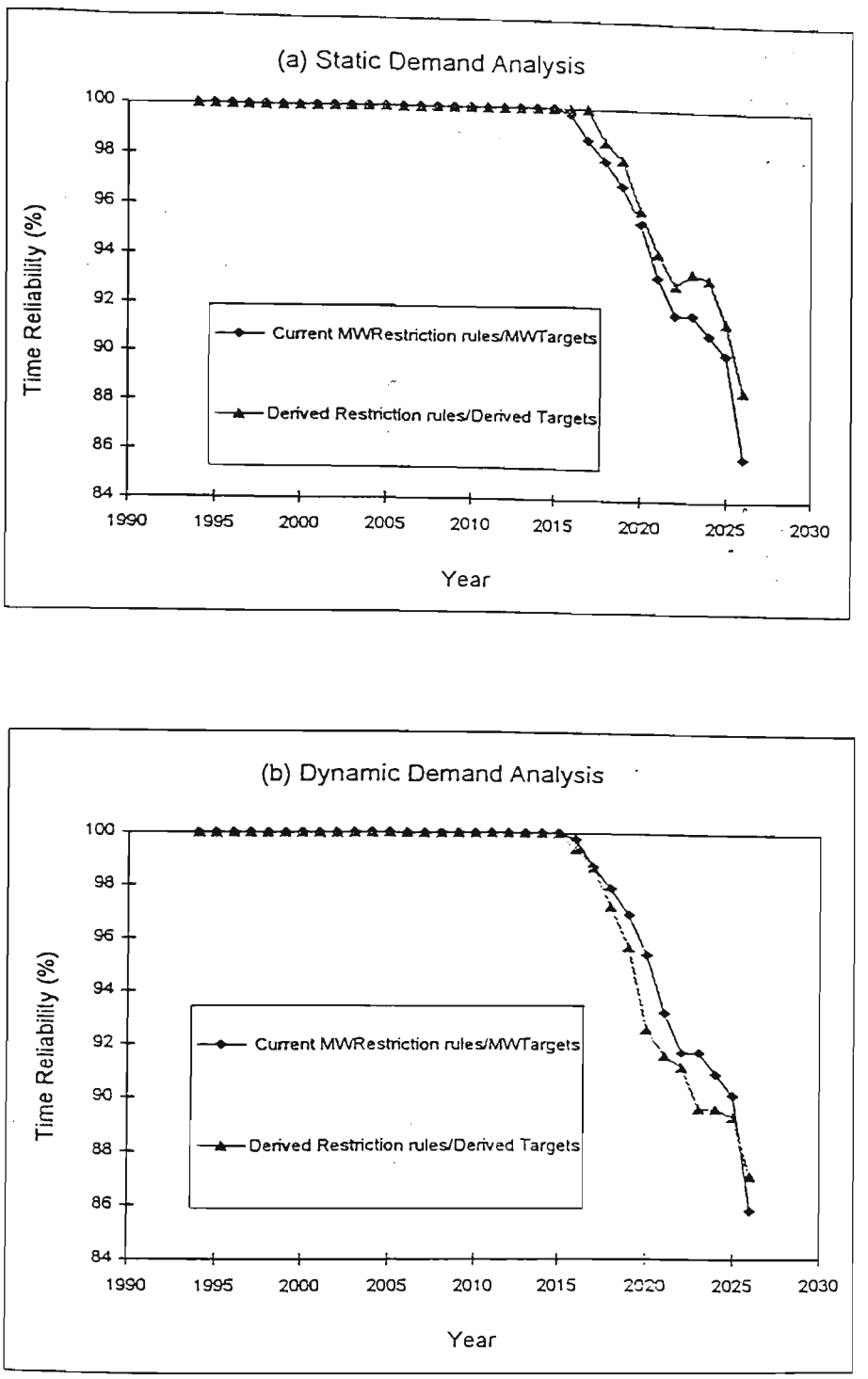


Fig 6.11 Time Reliability versus Year for Different Target Storage Curves

The multiple replicates were not considered in the derivation of the target storage curves and therefore, this could also be a reason for the underperformance of the derived target storage curves. Because of all these reasons (i.e. the 'averaging' out results, the use of

storage increment and the use of multiple replicates of streamflows), it is necessary to fine-tune the operating rules derived from the optimisation through simulation and other expert knowledge. This has been recommended by many researchers in the past (Codner, 1979; Loucks et al., 1981; and Yeh, 1985) and generally referred to as the complementary use of optimisation and simulation models in water resource planning and operation.

In this study, the target storage curves derived from the static demand analysis was fine-tuned using simulation results and other expert knowledge. Although the fine tunning can be done for the target storage curves derived from the dynamic demand analysis, this was not done in this study. This part of the study was done solely to illustrate the complementary use of optimisation and simulation for fine-tuning the target storage curves.

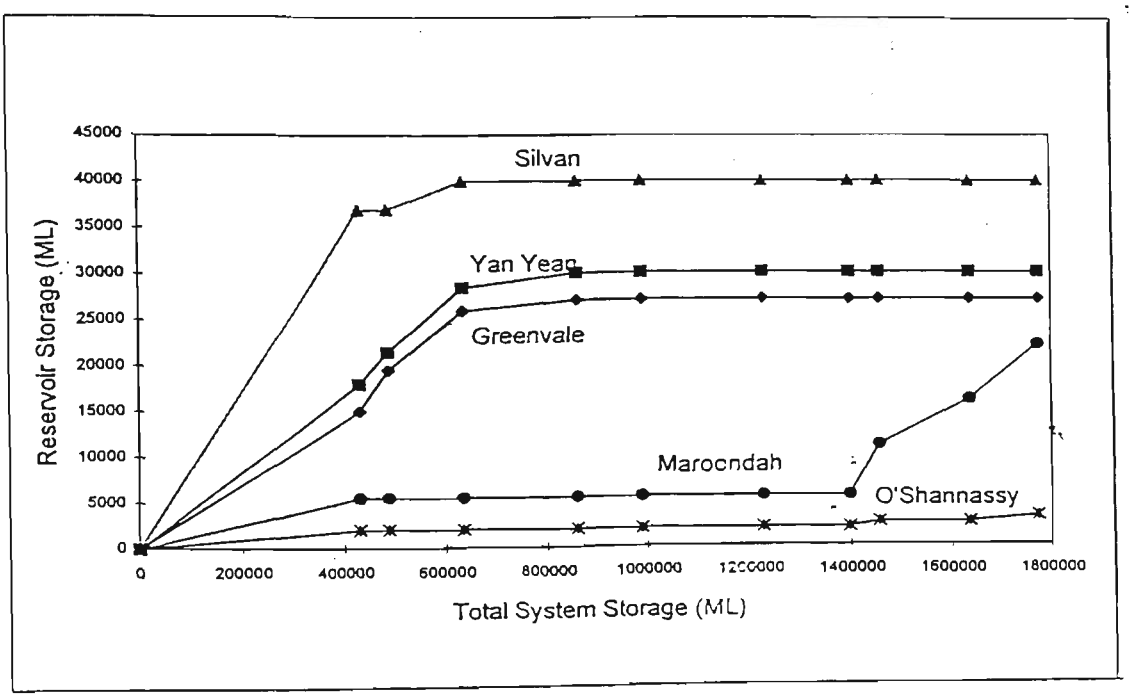
Operationally, it has been found that Greenvale and Yan Yean had have high storage volumes, and Maroondah low volume, for most total system storages. This was also found in the current MW target storage curves, which have been developed from the operational experience and by trial and error simulation of the system. Therefore, the following rules were considered in fine-tuning the target storage curves.

- Greenvale and Yan Yean should be kept as full as possible.
- Any increase in Greenvale and Yan Yean storages should be compensated with a decrease in Maroondah storage for given total system storages in the derived target storage curves. If Maroondah cannot be decreased due to minimum storage, then the reduction is equally shared between the major storages of Cardinia, Upper Yarra and Thomson.

These rules introduce modifications to Greenvale, Yan Yean and Maroondah and (in some occasions) slight changes to Cardinia, Upper Yarra and Thomson. These target storage curves are given in Table 6.8 and Fig. 6.12. After fine-tuning the target storage curves obtained from the static demand analysis based on this approach, these target curves were used in REALM as described in Section 6.4.3 to study the behaviour of the Melbourne system under these operating rules; the results and a comparison are shown in Table 6.7. Fig. 6.13 shows how the monthly reliability varies with time with these target storage curves.

Table 6.8 Fine Tuned Target Storage Curves Derived from Static Demand Analysis

Summer (ML)									
Total system storage	Greenvale	Yan Yean	Silvan	Cardinia	Sugarloaf	Maroondah	O'Shanassy	Upper Yarra	Thomson
0	0	0	0	0	0	0	0	0	0
430,000	15,000	18,000	37,000	117,000	30,000	5,500	2,000	35,500	170,000
486,500	19,500	21,500	37,000	129,000	35,000	5,500	2,000	39,000	198,000
634,000	26,000	28,500	40,000	171,000	50,000	5,500	2,000	96,000	215,000
859,000	27,000	30,000	40,000	182,000	80,000	5,500	2,000	126,500	366,000
988,500	27,000	30,000	40,000	193,000	90,000	5,500	2,000	133,000	468,000
1,226,000	27,000	30,000	40,000	198,000	90,000	5,500	2,000	133,500	698,000
1,397,500	27,000	30,000	40,000	230,000	93,000	5,500	2,000	145,000	825,000
1,455,500	27,000	30,000	40,000	250,000	95,000	11,000	2,000	150,000	850,000
1,635,500	27,000	30,000	40,000	270,000	95,000	16,000	2,500	160,000	995,000
1,773,123	27,000	30,000	40,000	287,000	96,000	22,000	3,123	200,000	1,068,000
Winter (ML)									
Total system storage	Greenvale	Yan Yean	Silvan	Cardinia	Sugarloaf	Maroondah	O'Shanassy	Upper Yarra	Thomson
0	0	0	0	0	0	0	0	0	0
430,000	15,000	18,000	37,000	117,000	30,000	5,500	2,000	35,500	170,000
500,000	18,000	20,000	37,000	140,000	32,000	6,000	2,000	45,000	200,000
663,000	27,000	30,000	38,000	196,000	45,000	6,000	2,000	93,000	226,000
835,500	27,000	30,000	40,000	228,000	85,000	6,000	2,000	109,500	308,000
997,000	27,000	30,000	40,000	235,000	95,000	8,000	2,000	130,000	430,000
1,187,000	27,000	30,000	40,000	235,000	95,000	13,000	2,000	145,000	600,000
1,279,000	27,000	30,000	40,000	240,000	95,000	15,000	2,000	150,000	680,000
1,505,500	27,000	30,000	40,000	240,000	95,000	16,000	2,500	155,000	900,000
1,624,700	27,000	30,000	40,000	250,000	95,000	20,000	2,700	160,000	1,000,000
1,773,123	27,000	30,000	40,000	287,000	96,000	22,000	3,123	200,000	1,068,000



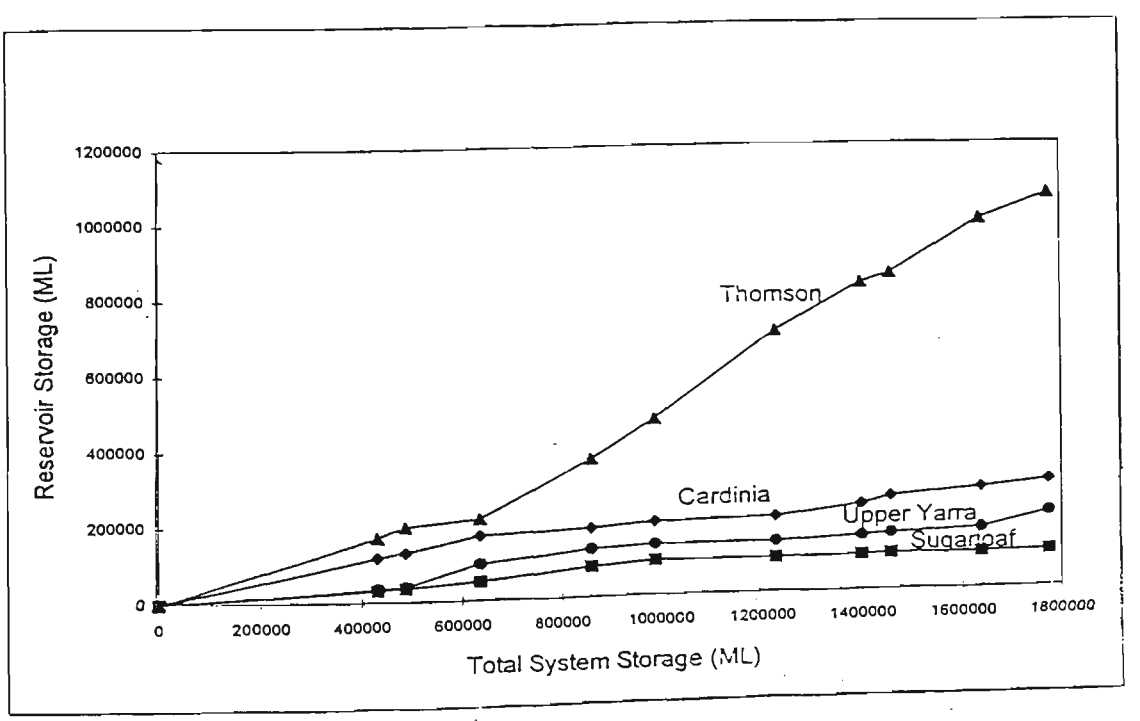
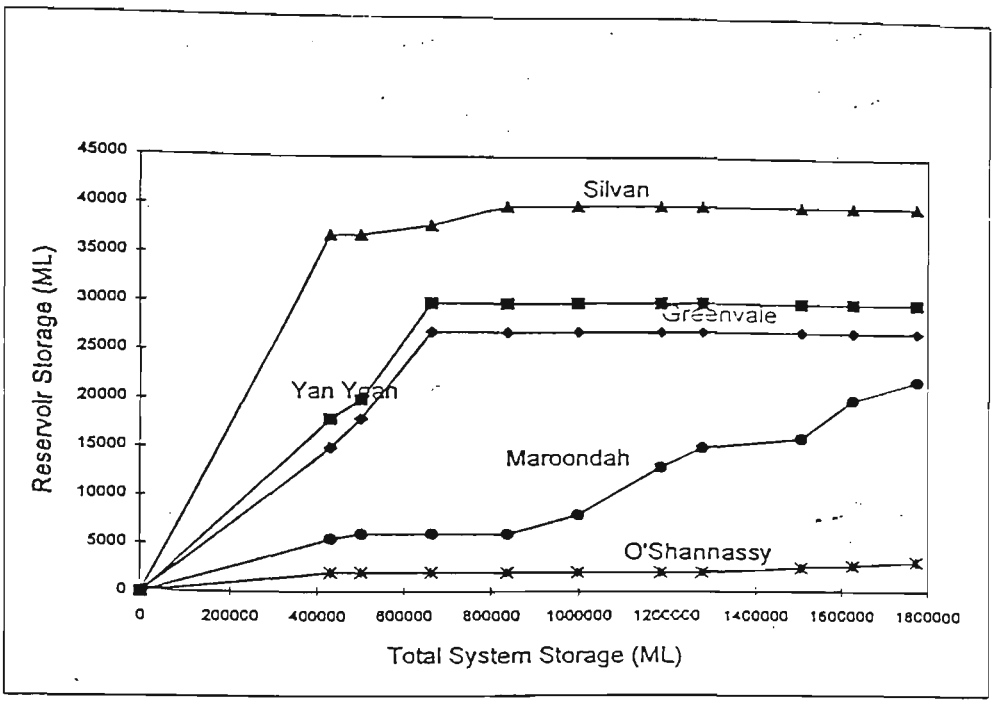


Fig 6.12(a) Fine Tuned Target Curves Derived from Static Demand Analysis-Summer curves



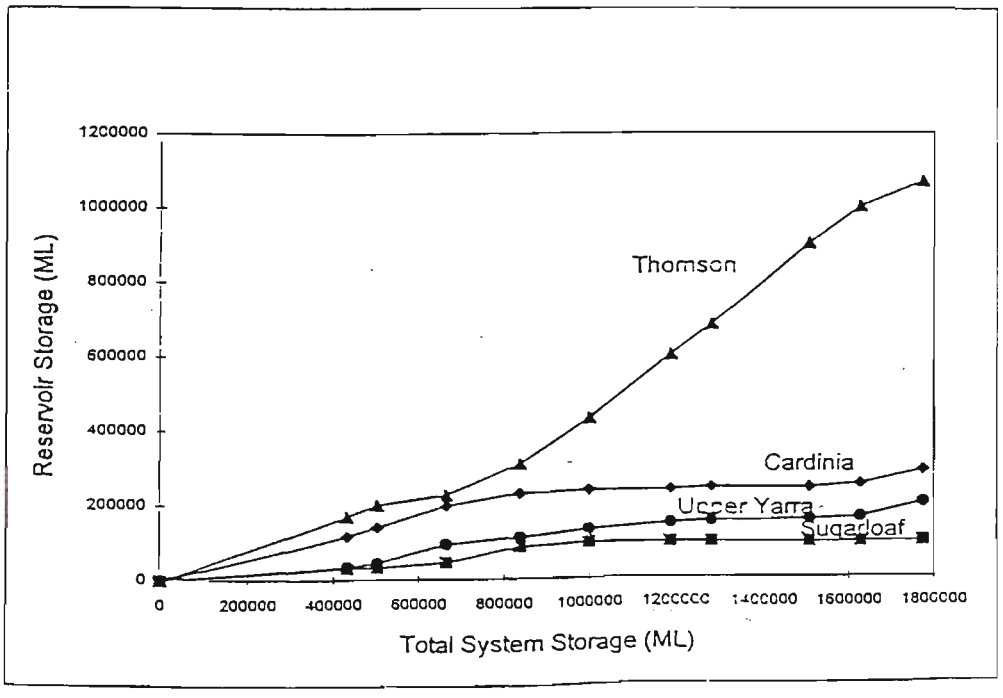


Fig 6.12(b) Fine Tuned Target Curves Derived from Static Demand Analysis-Winter curve

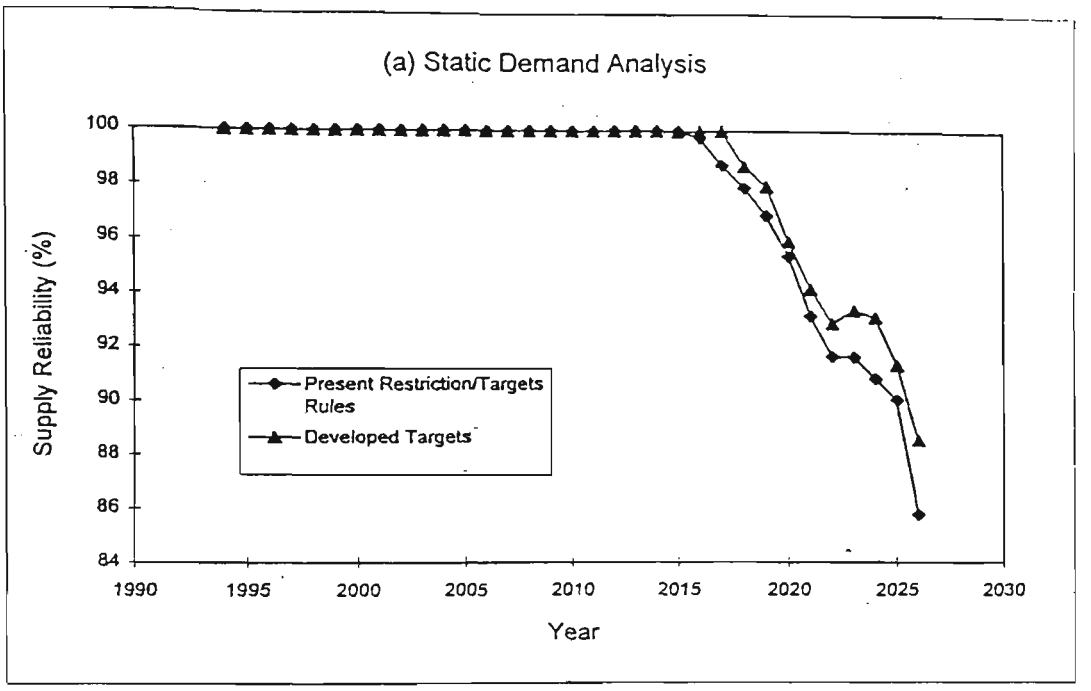


Fig 6.13 Time Reilability versusYear for Fine Tuned Target Storage Curves

Although the results were significantly improved compared with the rules obtained by the static demand analysis, still the combination of restriction rules derived from the static demand analysis and current MW target storage produced the best results. When fine-tuning was done in this study, the target storages were modified only once based on above mentioned rules. However, if target storages curves are fine-tuned several times by trial and error about the 'optimum' obtained from DDDP, the results may be significantly improved.

Similar improvements were found when the target storage curves derived from the dynamic demand analysis were fine-tuned using the above rules.

6.5 CONCLUSIONS

6.5.1 Restriction Rules

After analysing the results it was found that the Melbourne system performed better under both sets of derived restriction rules (i.e. using static and dynamic demands) compared to the current MW restriction rules. Also, it was found that the restriction rules derived from

the static demands were consistently better than the rules derived from the dynamic demands. The performance of the system was measured in terms of performance criteria currently used by MW.

The static demands corresponds to the 'sustainable yield' of the system. There is a possibility that the Melbourne system cannot be augmented by constructing reservoirs in the MW catchments due to lack of suitable hydrologic sites. However, regulated water can be imported from nearby catchments to augment the supply. If this scenario is assumed, then it is recommended that the restriction rules derived using the static demand analysis be used for the Melbourne system for the long term operation, once the augmentation is done through water imports. The current system will then be fully committed and a constant demand will be provided by the current system, while the growth in demand will be accommodated by water imports.

When the restriction rules were derived using the Restrictions software, the restriction triggers were computed as a percentage of AAD. Therefore when the dynamic demands were used, the restriction triggers were also derived as a percentage of AAD. In other words, the developed restriction rule under the dynamic demand analysis considers the effect of dynamic demand. Therefore, it is recommended that the restriction rules derived from the dynamic demand analysis be used for the current system until further augmentation.

6.5.2 Target Storage Curves

As outlined in Section 6.5.1, there is a possibility that the Melbourne system cannot be augmented although regulated water can be imported from nearby catchments to augment the supply. If this scenario is assumed, then it is recommended that the target storage curves derived using the static demand analysis (but fine-tuned) be used for the Melbourne system for the long term operation, once the augmentation is done through water imports.

If a single set of target storage curves is to be used for the entire planning period of the simulation, then it is recommended that the target storage curves derived from the dynamic demand analysis (but fine-tuned) be used for the current system until further augmentation.

These curves reflect the average conditions for the entire planning period. These conclusions are similar to the conclusions related to the restriction rule curves.

Fine-tuning the target storage curves about the 'optimum' obtained from DDDP should improve the results. However, only one such fine-tune was done in this study based on observations of limited simulation runs performed and MW target storage curves. If further fine-tuning was done, the results could have been improved.

7. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

7.1 Summary and General Conclusions

Several objective methods and computer software (Restrictions and Targets) have been developed to derive the restriction rules and target storage curves for the urban water supply system.

The restriction rules were derived using a direct search method known as the Hookes and Jeeves method. The objective function used was the maximisation of releases to demand zones and the constraints of security criteria used for urban water supply systems were considered. These constraints are expressed in terms of monthly time reliability, worst restriction level and the duration of consecutive restrictions. A lumped single reservoir and single demand centre approach was used in the study. However, effects such as reservoir evaporation losses, water wastage from the system, carrier capacity on releases and demand shortfalls were considered implicitly in the approach. The Restrictions software produces the restriction triggers, for various restriction levels between the upper rule curve and the worst restriction level.

The target storage curves were derived using DDDP, with the objective function of maximisation of releases to demand zones. REALM system data, which represents the urban water supply system, were used and therefore all system details generally included in a planning study of the water supply system were included in the DDDP. Water allocation among various parts of the water supply system was done through network linear programming (NLP). An innovative scheme was devised to improve the computer execution time of DDDP. The optimum storage trajectory obtained from the Targets software was later analysed through MS EXCEL to produce the target storage curves.

Objective methods developed in this study were found to be effective in deriving the operating rules (both restriction rule and target storage curves) for the Melbourne system. These methods can be used for the systems where the operator experience does not exist. For example, when a new streamflow scenario (different to the historical sequence) is

considered, the methods developed in this study can be used to determine the operating rules.

The target storage curves obtained from DDDP should be fine-tuned using simulation and expert knowledge (if exists) of the system, because of the assumptions used in DDDP. This can be done with limited number of simulations, since fine-tuning is done around the optimum solution obtained from DDDP.

7.2 Conclusions related to Melbourne System

Both Restrictions and Targets software were used for the Melbourne system using system, streamflow and demand data provided by Melbourne Water (MW) in early 1994. The restriction rules and target storage curves were derived for both static and dynamic demands. The behaviour of the Melbourne system was analysed under derived and current MW rules using a REALM simulation model of system for the planning period of 1994 to 2026, and a comparison made. Further, the derived target storage curves were fine-tuned using the results of simulation and expert knowledge.

The restriction rules derived under both static and dynamic demand analysis performed better than the current MW restriction rules. Further, it was also found that the restriction rules derived from the static demand analysis were consistently better than the rules derived from the dynamic demand analysis. The target storage curves derived from DDDP slightly under-performed the MW target storage curves. However, when fine-tuned using simple rules (Section 3.7.3), the system behaviour improved significantly. Therefore, it is anticipated that with further refinement, the target storage curves obtained from DDDP can be improved.

There is a possibility that the Melbourne system cannot be augmented by constructing reservoirs in the MW catchments due to lack of suitable hydrologic sites. However, regulated water can be imported from nearby catchments to augment the supply. If this scenario is assumed, then it is recommended that the restriction rules derived from the static demand analysis be used for the Melbourne system for the long-term operation, once the augmentation is done through water imports. The current system will then be fully committed and a constant demand will be provided by the current system, while the

growth in demand will be accommodated by water imports. However, it is also recommended that the restriction rules derived from the dynamic demand analysis be used for the current system until further augmentation, since the restriction triggers have been developed based on percentage average annual demand (AAD).

Ideally for the Melbourne system, the target storage curves should be determined considering different levels of annual demand. However, if a single set of target storage curves is to be used for the entire planning period of the simulation, then it is recommended that the target storage curves derived from the dynamic demand analysis be used for the current system (i.e. until further augmentation). These curves reflect the average conditions for the entire planning period. If the augmentation scenario described earlier is assumed, then it is recommended that the target storage curves derived using the static demand analysis be used for the Melbourne system for the long term operation, once the augmentation is done through water imports.

The derived operating rules (both restriction rule curves and target storage curves) depend on the system description, streamflow and demand data supplied by MW in early 1994 and therefore system dependent. These operating rules cannot be used with the current MW system description, which is different to the one, used in this study. Further the robustness of these operating rules to different streamflow and demand scenario has not been investigated in this study.

7.3 Recommendations for Future Work

Based on the findings of this study, the following issues were identified for further analysis.

- The operating rules (both restriction rule curves and target storage curves) should be derived for the current system description with upto date streamflow and demand data.

- Once the operating rules are derived using new system, streamflow and demand files, then the performance of the Melbourne system under these operating rules should be investigated and a comparison made between the operation under these rules and current MW rules.

- The target storage curves obtained from DDDP should be refined through a few number of simulation runs.

In addition, four new projects described below are identified for further detailed investigations. First project is a direct extension of this study, while the other three require detailed investigations. These projects were identified in relation to Melbourne system. However, the projects are generic in nature and the principles can be applied to any urban water supply system.

Robust operating rules: In the current study, the operating rules were derived using a single streamflow/demand scenario and a single objective function. Although the operating rules were derived using objective optimisation methods, they are optimum only for the selected objective function and the streamflow/demand scenario used. They may not be necessarily optimum for the other objective functions and streamflow/demand scenarios. Therefore it is necessary to develop operating rules which are robust for many possible streamflow/demand scenarios and a number of objective functions. These robust operating rules should be studied by further enhancing the software developed in the current study to cater for different objective functions. Further the enhanced software should be used with different streamflow/demand scenarios. A multi-criterion decision analysis can then be used to select the 'most reliable' set of robust operating rules from many sets of operating rules (derived using various objective functions and streamflow/demand scenarios). This project is currently in progress.

Streamflow modelling: MW considers the stochasticity of streamflow only through 'recycled' streamflow (McMahon and Mein, 1986) in planning of the Melbourne system. The major problem with this approach is that the synthesised streamflow data are restricted to those observed in the historical sequence and seriously affect the results of the planning studies. Stochastically generated data eliminates this important weakness, and therefore should be considered in future planning studies. In addition to the preservation of standard statistical parameters of the historical data, it is necessary to preserve the 'persistence or long-term memory' of the streamflow sequence. This is required because of the long carry-over storage of the Melbourne system. Further, the effect of bush fires in streamflow yield should be considered in the above analyses. Since long records of streamflow are necessary for security analysis of water supply systems, it

may also be necessary to extend streamflow records beyond the historical period using long records of rainfall for the Melbourne system.

Urban demand modelling: Demand reduction due to various restriction levels is necessary to model the restrictions of the Melbourne system. No proper models are available currently to model the demand reduction. A physically based demand model (modelling various processes of urban demand) can be developed to model the demand reduction due to various restriction levels. The MW water usage database can be used to develop this model.

Holistic modelling of Melbourne system: Once the streamflow and demand inputs are developed, then it is possible to investigate the Melbourne system in a holistic sense with new inputs and to redefine security criteria issues such as the preferred supply reliability of the system, duration and magnitude of restrictions, and other criteria.

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APPENDIX A

APPENDIX A
THE RESTRICTIONS COMPUTER SOFTWARE

A.1 Input Data Files

The methodology described in Section 3.3 was used to develop the Restriction computer software to determine the restriction rules. The input data files required for the computer program are:

- Streamflow data file
- Demand data file
- Restrictions data file
- Evaporation file
- Spills file
- Demand shortfalls file
- Starting conditions file

The streamflow data file consists of monthly totals of streamflow data to the lumped reservoir for the study period. This file is prepared from the streamflow files used for REALM simulation model of the real system, by summing up the monthly streamflows at various locations of the system.

The demand data file provides the unrestricted demand for the lumped demand centre. This file is prepared from the demand files used for REALM simulation model of the real system, by summing up the monthly demands of demand zones.

The restrictions data file consists of the 'seed' restriction rule curves for the system to initiate the optimisation. They could be the current restriction rules for the system or some reasonable and feasible (in terms of security criteria of the system) restriction rules. The restriction rule curves are expressed in this file as percentages of AAD. The percent restrictable demand of each zone is also given in this data file.

The lumped system does not explicitly consider the reservoir evaporation losses, the loss (or wastage) of water from downstream ends of the river system, demand shortfalls and the effect of capacity constraints. These considerations are accounted through the evaporation

file, spills file and demand shortfalls file. These files are prepared by running REALM for the real system, considering monthly demands at demand zones and monthly streamflows at streamflow locations in the system. These monthly data files should be concurrent with the streamflow and demand files used for the lumped system in the optimisation. The evaporation losses, the wastage of water from the downstream ends of the system and the demand shortfalls are extracted from the results of the simulation of the real system, to produce evaporation, spills and demand shortfalls files respectively. These files describe one column of monthly data for each above variable. For example, the evaporation losses file contains the total evaporation losses from all reservoirs (as one column), which have to be extracted from the relevant REALM output file.

The starting conditions file consists of the simulation period, the names of the streamflow file, demand data file, restrictions data file, evaporation file, spills file, and demand shortfall file, the total starting storage volume of the system, the storage increment and the values of the performance measures of the security criteria.

A.2 Output Analysis

As stated in Section 3.2, one of the objectives of this part of the study is to produce restriction rules that are compatible with REALM software. The input data related to restriction rule curves in REALM are the upper and lower rule curves, the number of intermediate zones, the relative positions of these intermediate curves with respect to upper and lower rule curves, and the percentage restrictable demand for the intermediate zones. Based on this information, REALM calculates the intermediate restriction rule curves. The Restrictions computer software developed in this study however produces the 'optimal' restriction trigger points between the upper rule curve and the worst restriction level. It does not produce the trigger points for the lower rule curve or the relative position of intermediate restriction zones, which are required as, input to REALM software. For example, the Restrictions software produces 48 optimal restrictions trigger points between the upper rule curve and the worst restriction level for the example in Fig. 3.4. In this example, the worst restriction level is considered as level 3.

This upper rule curve defined by the restriction trigger points can be used as input to REALM. However, the lower rule curve and the relative positions of intermediate curves have to be developed from the results of the optimisation (i.e. restriction trigger points

between the upper rule curve and the worst restriction level). The number of restriction zones and the percentage restrictable demand for the intermediate zones are input to the Restrictions computer software. Some form of mathematical extrapolation can be used to generate the lower rule curve, while an averaging technique can be used to compute the relative positions of the intermediate curves. The Restrictions computer software does not perform the mathematical extrapolation and/or the averaging. Section 6.3.1.3 describes how this has been done for the Melbourne system.

APPENDIX B

APPENDIX B
TARGET COMPUTER SOFTWARE

The Targets computer software uses the theoretical considerations described in Section 4.4. It is developed as a generalised computer package, which can be applied to any system configuration of urban water supply systems. It requires a number of input data files and creates an output file, which produces 'optimal' storage trajectories.

B.1 Input Data Files

The input data files required for the Targets software are :

- System data file
- Streamflow data file
- Demand data file
- Initial storage volume trajectory file
- Starting conditions file

The system data file consists of the system description of the water supply system such as details of reservoirs demand zones, carriers etc. This data file is created from the REALM system description file, deleting information on target storage curves and restriction rules.

The streamflow data file consists of monthly streamflow and other climatic data (such as rainfall and evaporation to compute the evaporation losses from reservoirs). The streamflow file considers only one replicate of data. The demand data file provides monthly-unrestricted demand for each demand zone. The streamflow and demand files contain data for the study period. These files are standard REALM streamflow and demand files.

The initial storage trajectory file contains the initial storage trajectories for the reservoirs in the system for the study period. These trajectories can be initially created by running REALM software with existing (or some assumed reasonable) operating rules.

The starting conditions file consists of the start volumes of reservoirs, minimum storage capacities of the reservoirs, the simulation period, the names of the input data files (e.g.

system, streamflow, demand and initial trajectory files), and the storage increment for discretising the maximum storage capacity.

B.2 Output Analysis

The Targets Software produces the 'optimal' storage trajectories for individual storages in the multiple reservoir urban water supply system. These optimal storage trajectories are used to produce the target storage curves using an Excel spreadsheet. Several macros were developed to group the storage volume data to develop the target storage curves. For example, if target storage curves are required only for Summer and Winter seasons, then a macro will group the storage data into these seasons.

Macros were developed to group data to produce sets of target storage curves to represent

- Different target storage curves for different months,
- One set of target storage curves for all months of the year, and
- Two sets of target storage curves for Summer and Winter seasons (Summer from Dec-Mar and Winter from Apr-Nov).

Once the data are grouped according to required set of target storage curves, the total system storage volume is computed for all months of each group and a scatter plot of reservoir volume versus the total system storage is plotted for each reservoir for each season. Using MSExcel chart facilities, the target storage curves are drawn on these scatter plots manually.

B.3 Generalised Nature of the Computer Program

The Targets software was developed as a generalised package, which can be applied to any system configuration of urban water supply systems. This was achieved through the use of NLP, with user-specified penalties for carriers for allocating water within the water supply system. REALM system file is used in the Targets software which specifies these penalties. This allows similar water allocation in Targets and REALM software. However, the objective function of maximising supply to the demand zones was considered in this Targets software. Although this objective function has been hard-coded

in the Targets software, it is relatively an easy matter to incorporate a different objective function such as minimising spills.

APPENDIX C

RESERVOIR OPERATING RULES

FOR

MELBOURNE WATER SUPPLY SYSTEM

B. J. C. PERERA AND N. P. PIYASENA

FOR

MELBOURNE WATER

DEPARTMENT OF CIVIL AND BUILDING ENGINEERING

VICTORIA UNIVERSITY OF TECHNOLOGY

MAY 1997

APPENDIX D

24th Hydrology & Water Resources Symposium Proceedings

Reservoir Operating Rules for Urban Water Supply Systems

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mmary: In recent times there has been a considerable shift throughout the world from continual augmentation of water source systems to the efficient operation of existing systems. As a result, it is prudent to invest considerable effort to determine 'optimal' operating rules for these systems. In this study, 'optimal' operating rules in terms of restriction rules and target rage curves were derived for an urban water supply system. The restriction rules were derived using a direct search method, hile the target storage curves were determined from dynamic programming. The Melbourne water supply system was used as the se study. The behaviour of the Melbourne system was analysed under the derived and current Melbourne Water (MW) rules ing a REALM simulation model of the system. The efficiency of the water supply system has potential to improve under the rived operating rules.

INTRODUCTION

recent times there has been a significant shift from gmentation of water supply systems to the efficient eration of existing systems. Reasons for this include the n-availability of water resources for further development, nited availability of funds for capital works and the spirited bbying of environmental groups against the construction of ajor water resource projects. Therefore, it is necessary to termine optimum operating rules for existing and new ater resource systems to achieve efficient operation and to aximise economic return. The development of optimum erating rules for an urban water supply system is described this study.

EALM (REsource ALlocation Model) is currently being idely used in Victoria, Australia for planning and operation urban water supply systems (Diment, 1991). Although EALM does not explicitly optimise the operation of the stem over the whole planning period, the proper selection 'optimum' operating rules implicitly optimises the long rm operation. The operating rules used in REALM which e relevant to long term optimum operation are the striction rules and the target storage curves.

herefore the primary objective of this study was to develop methodology to derive the 'optimal' restriction rules and rget storage curves for an urban water supply system. velopment of a general computer program suite, mpatible with REALM software, applicable to any system nfiguration was considered as the secondary objective. he final objective was to apply the developed methodology the Melbourne water supply system to demonstrate its plicability.

MELBOURNE WATER SUPPLY SYSTEM

e Melbourne water supply system consists of headworks, easonal transfer system and a regional distribution system. However, in this study, only the headworks and seasonal transfer system are considered as they play a key role in headworks planning. Figure 1 shows the headworks and seasonal transfer components of the current Melbourne system combining all demand zones to a single zone.

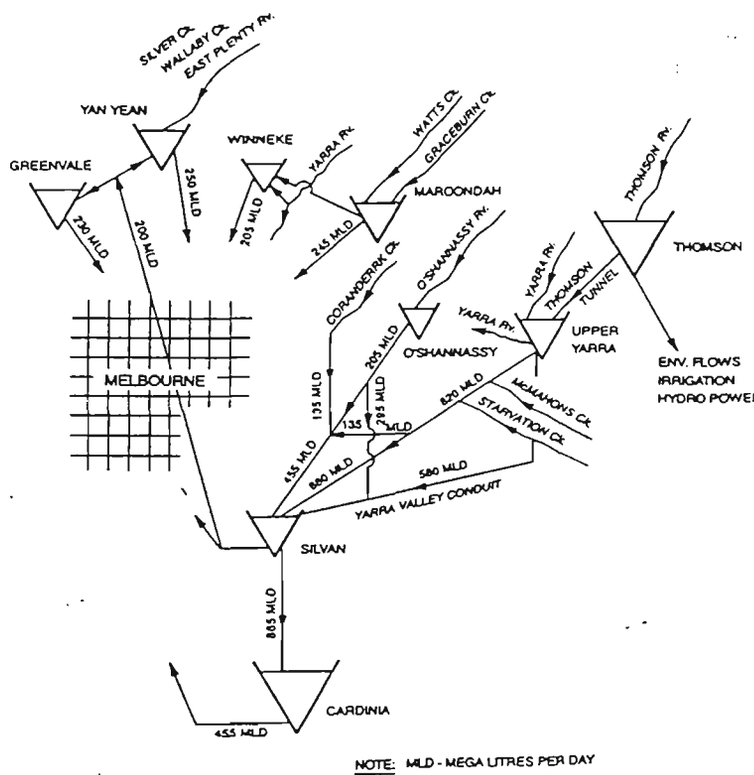

Fig. 1 Melbourne Water Supply System

3 RESTRICTION RULES

Water restrictions are imposed on demand during drought years to reduce pressure on the remaining water resources in the system. The restriction rules set the timing of imposing restrictions and the degree of severity of such restrictions. Typical restriction rule curves are shown in Fig. 2. AAD refers to the Average Annual Demand in Fig. 2. When the

rage level at a particular month is above the values fined by the upper rule curve, no restrictions are imposed the water demand. If the storage volume is below the ues defined by the lower rule curve, the water demand is tricted to the base demand. If the storage volume is in an rmediate zone, the demand is then restricted by the responding percentage restrictable demand of the zone; in case only the demand above the base demand is tricted.

ten developing restriction rules, it is necessary to timise the releases to the demand zones without violating security criteria used for the operation of the water pply system. Security criteria measure the ability of the ter supply system to service the demands, through rformance measures such as monthly supply reliability, ximum duration and severity of any form of restrictions. erefore, the restriction rules were derived in this study ing the objective function of maximising releases to mand zones subject to the constraints of security criteria in ms of the above performance indices. These performance dices are used currently for the Melbourne system. This is constrained optimisation problem. A direct search method own as the Hookes and Jeeves algorithm (Dixon, 1972) as used to solve this problem. The method consists of two jor moves, namely the exploratory and pattern search oves. The exploratory moves search around the previous timal solution in a systematic manner, while the pattern arch generates the next search point immediately after the ploratory moves. The method uses these two moves in ndem until the optimal solution is reached.

timisation was carried out on a multi-dimensional grid of striction triggers between upper rule curve and worst striction level. The restriction triggers are the values on the striction rule curves which trigger different levels of strictions. A grid point in the multi-dimensional grid of striction triggers represents a restriction policy. A simulation model of the water supply system using a grid point as the restriction policy was used to produce the releases to demand zones, which in turn can be used to compute the objective function. However, the simulation of a complex system (such as the Melbourne system) uses a considerable amount of computer time for one such simulation over the planning period. Further, many simulations have to be carried out in the optimisation even with the Hookes and Jeeves algorithm to analyse different restriction policies. Therefore, a simulation of a lumped storage system was used in this study.

The water supply system was lumped into a single reservoir single demand centre system. The sum of releases was computed from the simulation of the lumped system for the planning period. The constraints of the optimisation problem (i.e. performance indices of security criteria) were computed from the results of the simulation. Although in theory, the lumped system does not consider the capacities of carriers, reservoir evaporations, demand shortfalls and water wastage from the system, they were implicitly modelled in the lumped system. In this study, the REALM simulation model (Diment, 1991) was used to simulate the operation of the real water supply system using the current operating rules to compute the above details and enter them as input to the optimisation problem. Once the 'optimal' restriction rules were derived through the optimisation method, these inputs are computed under new restriction rules to investigate whether the inputs have changed. If they change significantly, then the optimisation procedure is repeated with these new inputs and the restriction rules re-derived.

4 TARGET STORAGE CURVES

Target storage curves determine the preferred distribution of storage volume among individual reservoirs in a multiple reservoir system. Figure 3 illustrates the concept of target

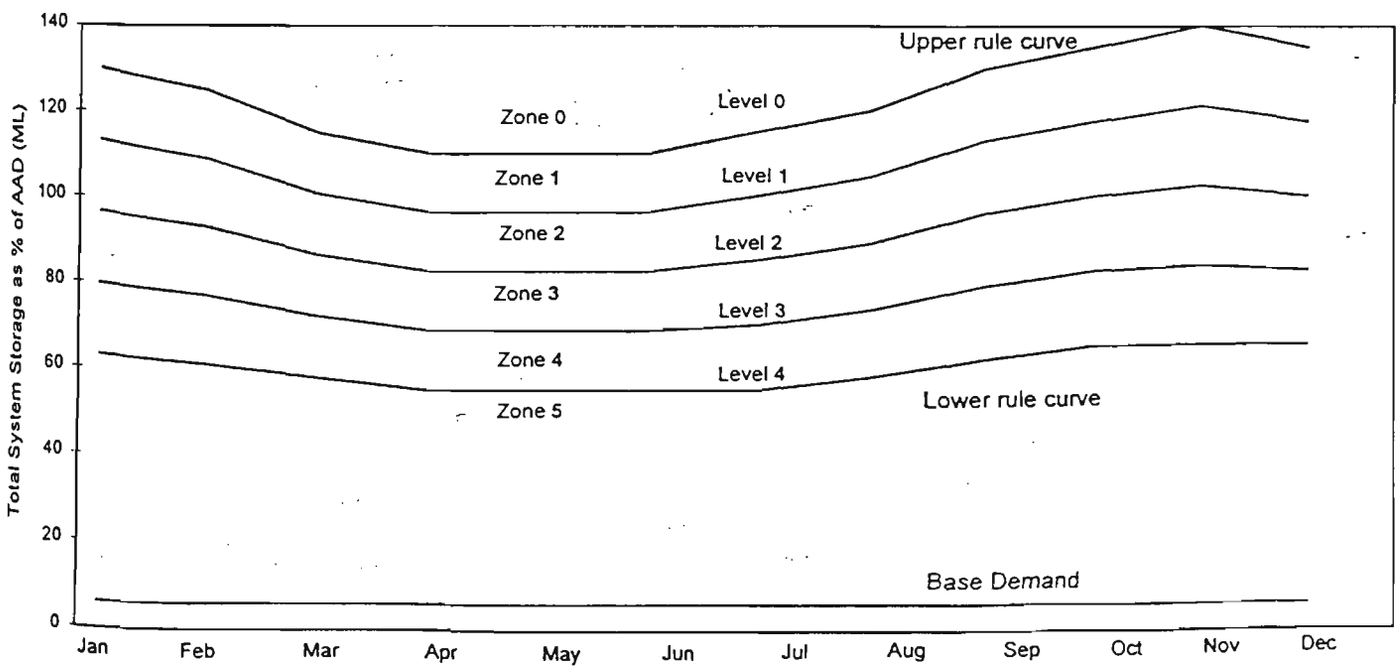

Fig. 2 Typical Restriction Rule Curves

rage curves for an example of a two storage reservoir stem. For a given total system storage S_T at a given ason, the target storage curves specify the storage volumes reservoirs *1* and *2* as S_1^* and S_2^* respectively, where the m of S_1^* and S_2^* equals S_T. They can be optimal and non-timal as the case may be.

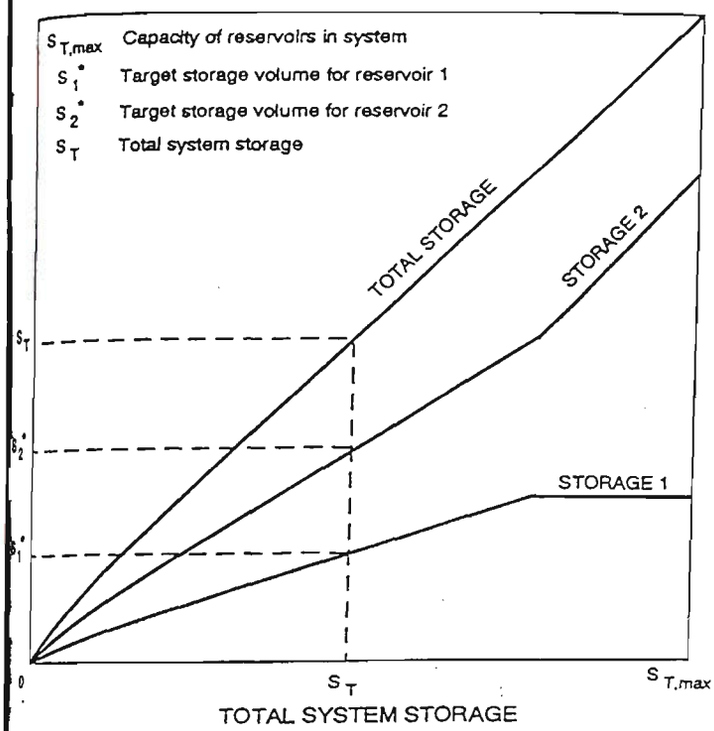

Fig. 3 Target Storage Curves for a Two-Storage System

or a given total system storage, there can be many ombinations of storage volumes of individual reservoirs in a ultiple reservoir system. Out of all these possible ombinations, there could be one set which produces the optimal' target storage curves for a given objective function nd constraints. However, it is not an easy task to determine he 'optimal' target storage curves due to the complexities of ultiple reservoir systems, stochastic nature of streamflows, ncertainty in demand forecasts etc. In most previous udies, the target storage curves were determined by alibrating a simulation model of the system (Kuczera and iment, 1988). The major disadvantages of this approach are hat the target storage curves obtained may not be optimal, ince the system may not have operated optimally and that he method is not applicable to systems where there are no ast operational data. Therefore, it is necessary to develop arget storage curves based on an objective method. System nalysis methods can be used for this purpose. Perera and odner (1996) used stochastic dynamic programming (SDP) o derive the 'optimum' target storage curves for the elbourne system. Because of the computational problems ssociated with SDP, a system of four storages (by lumping torages without losing the reality of the system operation) as considered in the analysis. Although the study had given n insight into the target storage curves of large storages, the umped target storage curves had to be disaggregated to roduce the individual curves for small and moderately sized storages. Further, restriction rules were not considered in the study.

The general opinion of reviews by Yakowitz (1982) and Yeh (1985) on systems analysis applications of water resources systems is that dynamic programming (DP) can be successfully used to determine the optimum operation of reservoir systems. However, the major disadvantage of DP is the excessive computational requirements in terms of memory and execution time, when there is a large number of reservoirs in the system. Heidari et al. (1971) introduced a variation of DP called discrete differential dynamic programming (DDDP) to reduce the computer memory requirements in optimising water resource systems. DDDP is a form of DP where the optimal solution is achieved within a narrow band of operation around the initial solution. This optimal solution is then considered as the initial solution for the next iteration and the procedure repeated until no further improvement to the optimal solution is achieved.

DDDP was used in this study to determine the 'optimum' operation of the water supply system. A monthly model was considered in the DDDP formulation since the target storage curves are based on a monthly time step. The objective function of maximising releases to the demand zones was employed in this study. System constraints on reservoir capacity and carrier capacity, and continuity equations at reservoirs, stream and pipe junctions were also considered. The storage volumes of reservoirs at the beginning of the planning period were assumed known. These initial storage volumes were required to trace back the 'optimal' storage trajectory for each iteration of DDDP.

Secondary objectives of this study were to include all system details used in a headworks planning model of the water supply system and to develop a general computer program which can be applied to any system configuration and be compatible with REALM. Therefore, the REALM system files of the water supply system that were used for planning studies, were used in this study. Restriction rules were also considered in the study. Allocation of water within the time step is done through Network Linear Programming (NLP) using the penalties in the carriers defined in the REALM system file. In this study, NLP computer software known as NETFLO (Kennington and Helgason, 1980) was used to allocate water within the water supply system, once the system is converted to a system of nodes and arcs. NLP has been used in WASP (Kuczera and Diment, 1988) and REALM (Diment, 1991).

DDDP produces the 'optimal' storage trajectories for individual storages in the multiple reservoir system. These optimal storage trajectories are imported into MS EXCEL and analysed to produce the target storage curves for different seasons. A MACRO model was developed to group the storage volume data according to seasons (eg. Summer and Winter) for which target storage curves are to be developed. The total system storage volume is computed for all months of each group and a scatter plot of reservoir

olume versus total system storage plotted for each reservoir r each season. The target storage curve for each reservoir is en plotted manually.

APPLICATION TO MELBOURNE SYSTEM

The developed software (referred to as Restrictions and Targets software in this paper) was used to derive restriction ules and target storage curves for the Melbourne system. The streamflow, demand and system data files used by MW or planning studies of the Melbourne system to reflect 1994 onditions were used in this study.

estrictions and Targets software can be and was used with oth static and dynamic annual demands. When the computer oftware is used with the static annual demand, it is necessary o determine the appropriate level of annual demand that hould be used. For systems with no or insignificant growth in nnual demand, the demand sequence is known. For systems ith even moderate growth in annual demand (such as the Melbourne system), the static annual demand sequence can be enerated from the demand corresponding to the 'ultimate ustainable development'. This average annual demand is eferred to as the 'sustainable yield' of the system in this paper. Under this scenario, further augmentations are not deemed ecessary to the water supply system. The dynamic demand equences can then be generated from the projected annual emands.

5.1 Restriction Rules

The storage increment dictates the step size in redefining estriction triggers in the optimisation. A storage increment of 1% AAD was used for both static and dynamic demand analysis. A seed is required to initiate the optimisation of restriction rules. Two seeds were considered initially and the 'optimal' restriction rule curves derived through optimisation procedure. One seed represents high values for restriction rule curves and the other low values. Finally, a third seed was considered as the average of the restriction policies obtained from the earlier two seeds and the same procedure repeated to derive an average restriction policy. This is an average 'optimal' restriction policy. This approach was necessary since there is a narrow band of 'optimal' restriction rules which results from the same objective function and constraints. For each seeds, the evaporation, spills and demand shortfalls files were created using a REALM simulation run of the actual Melbourne system.

5.1.1 Static and dynamic demand Analysis

For the purpose of this study, the 'sustainable yield' for the Melbourne system was computed as in Section 5. The 'sustainable yield' was used to generate a monthly demand file for use in static demand analysis. The Restrictions software was then run to produce the restriction triggers between upper rule curve and the worst restriction level. The worst restriction level considered in this study was level 3. The Restrictions software was then run for the dynamic demand analysis. The monthly demand file was created using annual projected demands. Figure 4 shows the average upper and lower restriction rules. This figure also shows the corresponding curves of the restriction rules used by MW currently.

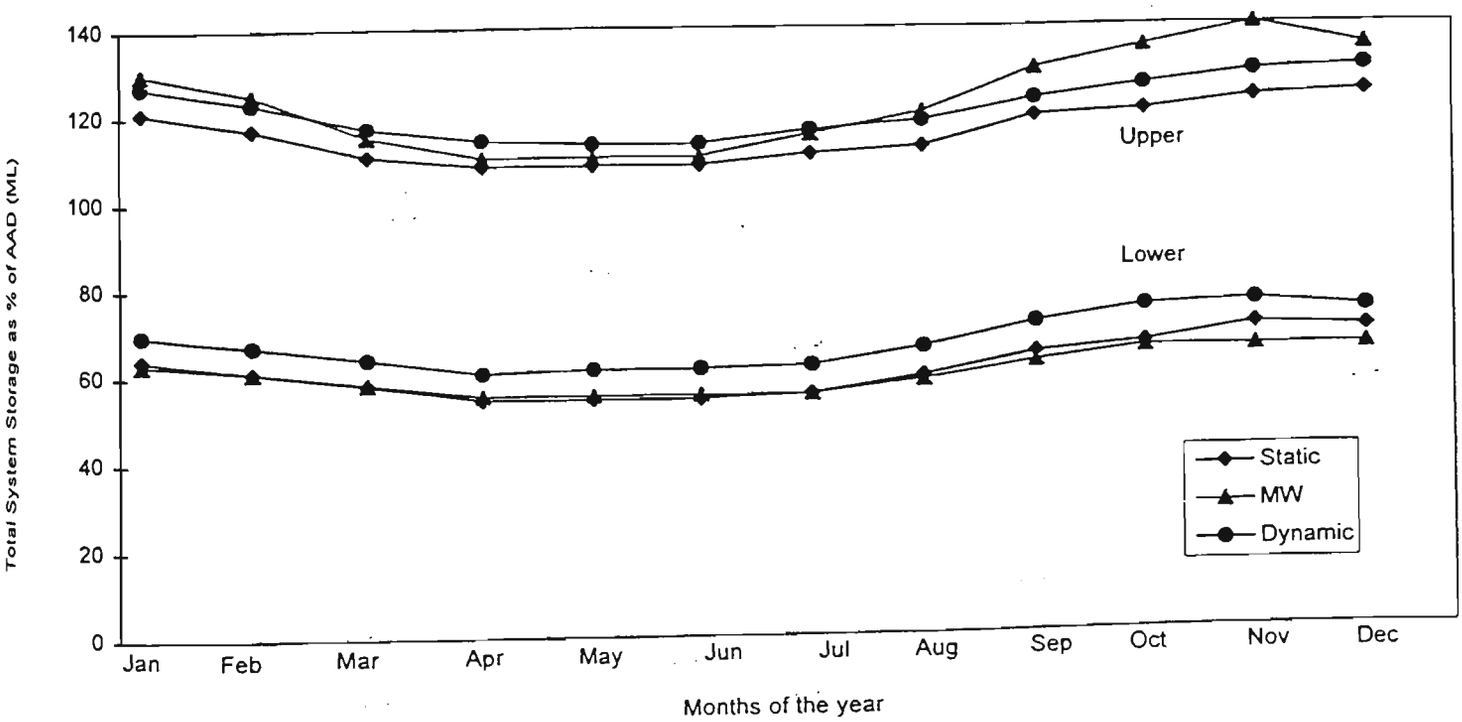

Fig. 4 Upper and Lower Restriction Rule Curves for Melbourne System

Table 1 - Comparison of System Behaviour under Various Operating Rules

Performance Index	MW Targets	MW Targets		Derived Static Targets	Derived Dynamic Targets	Derived Fine-Tuned Targets
	MW Restrictions	Derived Static Restrictions	Derived Dynamic Restrictions	Derived Static Restrictions		
Year of start of restrictions	2016	2019	2017	2017	2016	2018
Year of failure (below 95% supply reliability)	2021	2022	2021	2021	2020	2021
Monthly supply reliability at failure	93.1%	94.2%	93.2%	94.2%	92.6%	94.2%
Restriction level at failure	2	2	2	2	2	2
Duration of consecutive restrictions at failure	4 months	3 months	4 months	3 months	4 months	3 months
Average monthly restricted demand (ML)	46746	46766	46749	46758	46737	46761
Average monthly shortfalls (ML)	143	146	140	156	155	144

Note: Information in this table should be treated as indicative as a number of the model parameters and inputs were based on information at the time of the study. Some of these information including the growth in demand have changed.

5.1.2 Comparison of system behaviour

A study was then conducted to investigate the performance of the Melbourne system under current and derived restriction rules. Three different REALM simulation runs were carried out using MW system data files, streamflow and dynamic (projected) demand files, but with the target storage curves currently used by MW. First run uses the MW restriction rule curves, while the second and third runs use the restriction rule curves derived from the static and dynamic demand analyses respectively. The simulation approach used by MW was used in this comparison study.

Results from these three REALM runs were analysed and presented in Table I. The restriction rules derived using static demands perform better than the current operating rules with respect to all indicators. Only indicator which is worse under static demands is the average number of shortfalls which are higher than those of the current restriction rules. This is to be expected since the average restricted demand under the derived restriction rules are higher that under the current MW rules. The performance of the system under the derived restriction rules from dynamic demands is also better than that of the current restriction rules, with static demand restriction rules better than the dynamic demands.

5.2 Target Storage Curves

Slight modifications were made to the system file provided by MW for use in Targets software. The information on restriction rules and target storage curves were deleted from the REALM system file. Further, O'Shannassy reservoir was replaced with a stream junction, since the storage capacity of O'Shannassy was very small compared to the other storages. O'Shannassy storage capacity is added to the Upper Yarra storage. The restrictions file was created using the restriction rules curves derived from the static demand analysis (Section 5.1.1) and used in both static and demand analysis runs in deriving the target storage curves. A storage increment 1,000 ML was considered in the study to discretise the storage capacity of the reservoir system and to round off the variables such as streamflow, demand, carrier capacities etc. The initial storage trajectories were created for both static and dynamic demand analyses by running REALM with (MW supplied) system and streamflow files, but with corresponding static and dynamic demand sequences (Section 5.1.1).

5.2.1 Static and dynamic demand analysis

The Targets software was run with both static and dynamic demand sequences with corresponding initial storage trajectories and the target storage curves derived for the eight storages for Summer (Dec-Mar) and Winter (Apr-Nov). The Upper Yarra target storage curve was then disaggregated into Upper Yarra and O'Shannassy curves by assigning the current MW O'Shannassy target storage values to the O'Shannassy curve.

A study was then conducted to investigate the performance of the Melbourne system under current and derived target storage curves. Two different REALM simulation runs were carried out similar to Section 5.1.2. The first run used target storage curves derived from static demands, while the second run used those of the dynamic demand analysis; both runs used the restrictions derived from the static demand analysis.. The results from these two REALM runs were analysed and also presented in Table I.

5.2.2 Fine-tuning of target storage curves

As can be seen from Table I, the Melbourne system has performed best under the derived restriction rules (using static demand analysis) and MW current target storage curves. Although an objective method was used to derive the optimal storage trajectory, some 'averaging' was used to compute the target storage curves from the results of DDDP. Further, the storage increment of 1,000 ML was used in discretising the storage capacities of the system and rounding off streamflow, demand and other system data. If a finer storage increment had been used, the results could have been improved, but at the expense of computer time. Because of the above assumptions, it is necessary to fine-tune the

perating rules derived from the optimisation through imulation and other expert knowledge. This has been commended by many researchers in the past (eg. Yeh, 985) and generally referred to as the complimentary use of ptimisation and simulation models in water resources udies.

this study, the target storage curves derived from the static mand analysis were fine-tuned using simulation and expert owledge. It was found that Greenvale and Yan Yean servoirs should have high storage volume, and Maroondah w volume, for most total system storages. This was also und in the current MW target storage curves, which were veloped from the operational experience and trial and error mulation of the system. Therefore, the following rules were nsidered in fine-tuning the target storage curves.

Greenvale and Yan Yean should be kept as full as possible.
Any increase in Greenvale and Yan Yean storages should be compensated with a decrease in Maroondah storage for given total system storages. If Maroondah cannot be decreased, then the reduction is equally shared by the major storages Cardinia, Upper Yarra and Thomson.

fter fine-tuning the target storage curves based on above les, these target curves were used in REALM to study the haviour of the Melbourne system under these operating les; the results are shown in Table I. Although the results ve been significantly improved compared with the rules tained from the static demand analysis, still the mbination of restriction rules derived from the static mand analysis and current MW target storage produced e best results. When fine-tuning was done in this study, the get storages were modified only once based on above les. However, if target storage curves are fine tuned several nes by trial and error about the 'optimum' obtained from DDP, the results can be significantly improved..

SUMMARY AND CONCLUSIONS

bjective methods were developed to determine the perating rules in terms of restriction rules and target storage rves for urban water supply systems. Restriction rules ere derived using a direct search method known as the ookes and Jeeves method. while target storage curves were termined from discrete differential dynamic programming DDP). In both cases, the objective function was nsidered as the maximisation of releases to demand zones. he restriction rules considered the constraints of security iteria generally used for urban water supply systems. The veloped software can be used to derive operating rules nder both static and dynamic demands. Water allocation mong various parts of the water supply system was done rough network linear programming (NLP). An innovative heme was devised to improve the computer execution time f DDDP.

Restriction rules derived under both static and dynamic demand analysis were found to be an improvement to the current restriction rules used by MW. Further, it was also found that the restriction rules derived from the static demand analysis were consistently better than those derived from the dynamic demand analysis. The target storage curves derived from DDDP under-performed the MW current target storage curves. However, when fine-tuned using simple rules, the system behaviour improved significantly. Therefore, it is anticipated that with some refinement, the target storage curves obtained from DDDP can be further improved.

MW has invested in a Headworks Optimisation Model to develop optimum and robust operating rules for the Melbourne system. The results of this study are expected to be available by October 1997.

6 ACKNOWLEDGEMENTS

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