Real-Time Operation of Reservoir Systems :
Information Uncertainty, System Representation and Computational Intractability

By

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A Thesis
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REAL-TIME OPERATION OF RESERVOIR SYSTEMS: INFORMATION UNCERTAINTY, SYSTEM REPRESENTATION AND COMPUTATIONAL INTRACTABILITY

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RAMESH S. V. TEEGAVARAPU

A Thesis/Practicum submitted to the Faculty of Graduate Studies of The University of Manitoba in partial fulfillment of the requirements of the degree

of

DOCTOR OF PHILOSOPHY

To

My Parents

Who always helped me find the best

- in my life's solution space.

Abstract

Modeling real-time reservoir operations and developing optimal rules are formidable tasks considering a number of issues that need to be addressed within optimization and simulation models. The issues range from uncertain system inputs to implementation of operating rules in real-time. This dissertation addresses some of these issues that are relevant at different stages of real-time reservoir operation process. These issues are: (i) information uncertainty; (ii) system representation; and (iii) computational intractability. Real-time operation models are developed in the present research for single and multiple reservoir systems while addressing these issues in that order.

Uncertainty generally associated with system variables in a variety of forms is a main hurdle in developing approaches for optimizing reservoir operations. Explicit and implicit stochastic approaches based on traditional probability theory concepts cannot always handle all the uncertain elements of reservoir operation. Approaches to handle imprecise information are required as much as methodologies to address the issue of lack of information. The former issue described as information uncertainty in this thesis is addressed using fuzzy set theory. Mathematical programming models are developed under fuzzy environment to handle imprecise and uncertain components of reservoir operation problem dominated by an economic objective. The concept of *compromise operating polices* is proposed and its utility is proved.

Representation of physical system in mathematical programming formulations affects the extent to which the physics of the problem is captured and nature of the solutions that can be obtained. Tradeoffs between exhaustive representation and optimal solutions can be identified. Operation of a multiple reservoir system is considered to develop formulations

of varying degree of system representation. A Mixed Integer Non-Linear Programming (MINLP) Model with binary variables is developed to a specific case of coupled hydropower reservoirs. The model is considered to be innovative in handling the issue of hydraulic coupling. In addition to this, a new model is also proposed for the same problem based on a spatial decomposition approach. These formulations can be superior to the already existing approaches in the literature.

Classical optimization techniques fail to provide solutions to mathematical programming formulations whenever an exhaustive representation of the physical systems is considered. This is due to large number of variables often part of formulations at finer time scales, special conditions and variables. This problem is referred to as computational intractability. To handle this issue, an optimization model based on a stochastic search technique (*Simulated Annealing*) is proposed. The approach with few conceptual improvements is applied to multiple reservoir operation problems plagued by dimensionality and computational intractability issues. Application to standard benchmark and real-life problems confirms the immense potential this approach holds for intractable reservoir operation problems.

Simulation models and a support system that aid the decision making process of reservoir operators in real-time are also developed as a part of research work. The simulation models are developed using an Object-Oriented simulation environment that is based on the principles of System Dynamics. A Decision Support System (DSS) encompassing all the simulation and optimization models developed in the present research is designed and implemented. Some features of these approaches are considered innovative and practical. These approaches can help address the issues of actual implementation of operating rules and bridge the gap between theory and practice.

Acknowledgments

Every day, I remind myself, that my life, both inner and outer, depends on the efforts of other men, and I must strive to give back in same measure as I receive.

- Albert Einstien

A number of fine minds have helped me in my life and career. I wish I could thank all of them in a short note like this. However, I will try my best in doing so. First-of-all, I would like to thank Prof. S.P. Simonovic, my research supervisor, for being an incredible advisor, mentor and the ideal *Guru* to me. Without him I would have never escaped this flood of research and reached a higher ground. I owe a lot to him for defining and reshaping my career. I have learnt a lot from him and will continue to learn more in future. He was always there for me when I was depressed, disorganized and needed help. He provided me with opportunities at times when I badly needed them and encouraged me in all the other activities that I attempted to improve myself. I have really enjoyed working with such a fine advisor like him. Thank you Dr. Simonovic for everything.

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Notation

AX	constraint matrix in Linear programming formulation.
a_1, a_2	lengths in storage loss function.
b	constant on right hand side of LP formulation.
$b_{j,t}$	benefit in any time interval.
$b_{j,max}$	maximum benefit.
$b'_{j,t}$	normalized benefit value.
b_o	original zone length for release.
b_d	decreased zone length for release.
c_{man}	maximum cost of hourly energy production, monetary units.
c_{min}	minimum cost of hourly energy production, monetary units.
CX	objective function matrix
DO_t	cost of energy production.
e_o, e_n	energy (performance measure) at two successive states.
E_{tar}	weekly target energy demand.
f_o	objective function value from Step I.
f_1	objective function value from Step II.
$Fst_{j,T}$	final target storage.
$f(k_j)$	function relating storage and stage.

$f_m(x)$ objective function in general MINLP formulation.

$h_{j,t}$ average forebay level.

$h_{j+1,t}$ average level of the downstream reservoir.

H the amount by which penalty zone is decreased.

H_o the amount by which penalty coefficient is increased.

$h_{j+1,t}$ average level of the downstream reservoir.

I_t inflow in time period, t.

$Ist_{j,1}$ initial storage.

$k^i_{j,t}$ initial forebay level.

$k^f_{j,t}$ final forebay level.

l_b total number of binary variables in general MINLP formulation.

L_c number of transitions (length of markov chain).

M_s performance measure.

m_{j+1} number of tailwater curves.

$\mathbf{M}$ large integer.

n_c number of continuous variables.

n total number of reservoirs.

P_j maximum allowable spillway discharge.

$Pcap_j$ maximum power production capacity.

$Q_{j,t}$ plant discharge.

RTR target release.

R_t release in time period, t.

R_{max} maximum release.

R_{min} minimum release.

$R_{j,t}$ total flow from the reservoir (spill and plant discharge).

S_j reservoir storage.

$SP_{j,t}$ spill from the reservoir.

STR target storage.

S_t storage in time period, t.

S_{max} maximum allowable storage.

S_{min} minimum storage.

T final time interval.

T^e temperature of the system.

$T_{j,t}$ tailwater elevation.

T_o^e initial temperature.

T last time period of simulation.

X matrix of decision variables.

t time period.

t_o tolerance value for the right hand side of constraint.

$T_{j,t}$ tailwater elevation.

$\mathbf{V}$ vector of variable values.

$\mathbf{V}_{range}$ vector of allowable range for variable.

$v'_{j,t}$ specific value of the variable.

X matrix of decision variables.

$Y_{l,m_{j+1},t}$ binary variables.

γ_o, γ_1 constants.

τ time delay.

t_o tolerance value for the right hand side of constraint.

λ, L level of satisfaction.

α, β unit slopes for the storage loss function.

$\beta_{j,t}$ overall plant efficiency for generating station.

$\boldsymbol{\Delta}$ vector of decrements or increments.

$\epsilon_{j,t}$ normalized benefit value for the reservoir.

SUBSCRIPTS

j reservpor or hydropower plant.

l number of tailwater elevation curves.

t time index.

f_o objective function.

Chapter 1

Introduction

It isn't that they can't see the solution.

It is that they can't see the problem.

- G. K. Chesterton

The Scandal of Father Brown, 'The Point of a Pin'

1.1 Problem Domain

Optimal operation of water resource systems, especially reservoirs, through the application of systems analysis techniques has gained enormous attention in the past few decades. This is evident from the large number of operation models (Yeh, 1985; Yakowitz, 1992; Wurbs, 1993) already developed and being used for planning and operation of reservoir systems. Research is still continued in the areas where the complexities associated with the operation of the multiple reservoir systems overwhelm the capabilities of existing state-of-the-art optimization tools in finding solutions. Better management of existing reservoir systems in a sustainable way is also a motivation to develop improved and innovative approaches.

Real-time operation of reservoir systems is a complex and challenging task. The main hardships in developing optimal or near-optimal operation rules for reservoirs lie in dealing with the complexity of typical systems, the uncertainty of the future inflows, demands and multi-objective nature of the operation itself. Real-time or short-term operation in general relies on forecasted information about various inputs to the system. These inputs are not always realized in real-life situations, and therefore there is need for updating the system status as and when information about the variables becomes available. Also, the models should consider a realistic representation of the physical system, and be solvable in a *time frame acceptable for actual implementation* of the operating policies.

A variety of optimization and simulation models have been developed in the past for long-, short-term and real-time operation of single and multiple reservoir systems. Deterministic and stochastic approaches were used to handle various issues arising out of the modeling process. Real-time operation has always received maximum attention of the researchers, as it relates to the actual implementation of operation rules. Various issues relevant to reservoir operation still exist that are needed to be addressed in some framework or the other. These issues include : (i) uncertainty in the estimation of system variables (inflows, demands, etc.); (ii) representation of the system (hydraulic and hydrologic) within the optimization models; (iii) imprecision in the definition of economic objectives (through loss functions); (iv) computational resources and time required for solution; (v) multi-period and multiple reservoir operation problems and (vi) real-time implementation of operation rules and scenario generation (policy analysis). While some of the existing models in literature consider one or more issues indicated, research is still continued in the areas where limitations due to the available optimization tools, methodologies and computational resources exist. The present research work addresses some of these issues in the context of real-time operation of single and multiple reservoir systems.

1.2 Problem Statement

Three major issues are discussed in the present thesis, apart from few minor ones relevant to real-time operation of reservoir systems. These are: (i) information uncertainty; (ii) system representation; and (iii) computational intractability. These issues are schematically shown in the Figure 1.1 at various levels of reservoir planning and operation process at which they are relevant and specific areas of concentration are indicated. The arrows represent inflows to the reservoirs in the system and also in one way suggest the direction and the order in which the issues are dealt in the present research. The order also preserves the priority of these issues in any reservoir operation problem. The issues are addressed in the context of real-time operation moving from single to multiple reservoirs. This is because issues relevant to a single reservoir may not be of any significance to the operation of a multiple reservoir system and vice versa. All the issues that are dealt with in the present study are in the context of real-time operation of reservoir systems.

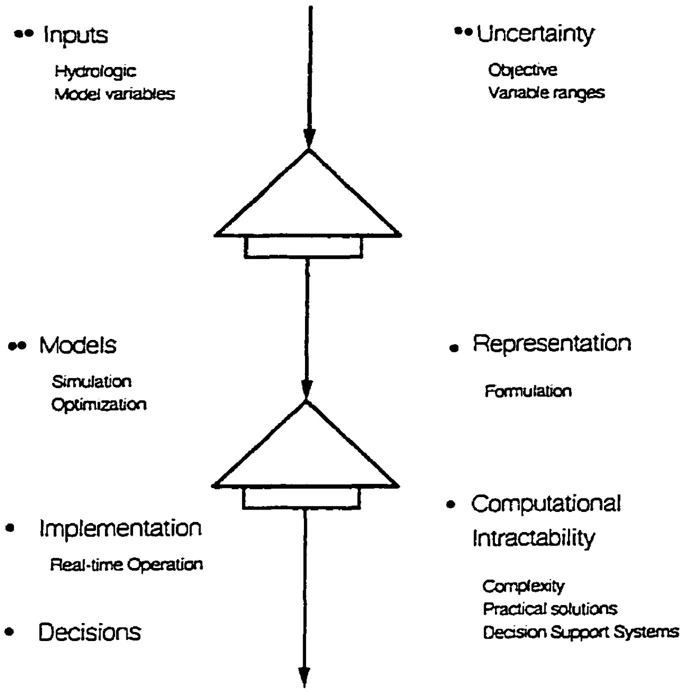


Figure 1.1: Scope of the present research

Issues related to uncertainty in system variables (i.e. inflows, demands, etc.) were addressed using implicit and explicit stochastic approaches in the past. With the increasing attention towards reservoir operation with economic objectives (handled through loss functions), issues related to uncertainty and imprecision in the definition of these objectives have started to surface. This is mainly due to lack of complete information of some of the variables. Recent studies have concentrated on methods to develop realistic loss or penalty functions needed for inclusion of economic objectives within the operation models. However, extensive literature review suggests that issues related to uncertainty and imprecision involved in the derivation of these functions were not addressed before. Uncertainty in the definition of loss functions (models with economic objectives) in the context of single reservoir operation is addressed in this study.

The present research also concentrates on ways to deal with the exhaustive system representation within mathematical programming formulations. In many of the research works reported in the past, use of temporal or spatial decomposition, or both, has been made in optimization models to alleviate the high dimensionality problems associated with operation of multi-period and multiple reservoir systems. This feature has helped in handling many variables at a time. Also, the models developed were linked in such a way that a periodic updating (or re-running) of higher level models is possible.

On the other hand, simplifications in the representation of the physical system can be made to solve the problem using appropriate optimization tools. In case of the former methodology, realistic representation of the physical system is achieved, while the latter ensures optimal solutions. Spatial decomposition methodology that is different from earlier works is proposed in the present work to handle this issue. Issues relevant to realistic representation of physical systems, hydraulic aspects of reservoir systems, computational resources and time required for solution, in the context of multi-period and multiple hydropower reservoir system, are addressed in the present research.

The complexity of mathematical programming models is expected to increase with the increase in the number of variables that are needed to represent the physical system under consideration. The dimensionality of the problem becomes an issue, when the formulations are attempted for finer time scales as in real-time operations or when the system representation is exhaustive. The optimization models developed using traditional techniques are difficult to solve and become computationally intractable when plagued by this problem. Simulation combined with an efficient search technique (Simulated Annealing) is identified as superior approach for solving high dimensional, computer intractable reservoir operation problems. A model based on this search technique proposed in the present study would confirm this.

1.3 Motivation and Research Methodology

The motivation to develop the approaches and real-time operation models in the present research are based on these questions : (i) how to handle uncertainty that cannot be handled by classical probability theory; (ii) what level of system representation is acceptable for some reservoir operation problems in mathematical programming formulations; (iii) when formulations become computationally intractable and (iv) to what extent practical implementation of models is possible. The last two aspects are a consequence of the second issue.

The present research work attempts to address some of the issues that were not considered in the optimization models developed in the past. In all the cases, approaches that are conceptually better (in some way) than existing methodologies are proposed and experimented with. In this process, operation problems relevant to single and multiple reservoirs are handled and appropriate formulations are developed. Through out this research work, the emphasis has been on the exhaustive and realistic representation of the physical system within an optimization framework.

Problems that cannot be addressed by classical probability are increasing as more and more social, economic and ecological factors are being considered in developing rules for reservoir operation in real-time. Inclusion of these aspects, will introduce uncertainty that needs to be handled. Fuzzy set theory is embraced in the present study to handle this issue in a mathematical programming framework.

In the past, various mathematical programming techniques have been used for solving the operation problem of multiple reservoir systems. To obtain optimal solutions using these techniques (which guarantee global optimal solutions), representation of the physical systems was simplified. Various assumptions were made to represent the system in a mathematical form that can be conveniently solved using the optimization tool. This approach ensures optimal solutions but at the cost of unrealistic formulations. On the other hand, complete physical representation with near-optimal solutions is acceptable for most of the real-life problems. Two models developed in the present study for solution of multi-period, multiple reservoir operation follow the latter approach that is conceptually far more superior to the former methodology. Spatial decomposition in a way different from earlier works is attempted in the present study. While the issues that plagued the multiple reservoir operation models are bound to surface, the near-optimal solution guaranteed by this approach is far superior than solution based on simplified and lumped representation of the physical systems

The gap that exists between theory and practice is a motivation to develop additional tools that can aid reservoir operators or managers when the models are implemented in the real-life situations. When the time frame is too short to run optimization models, simulation models are an appropriate choice for generation of scenarios based on actual conditions. Often the optimal operating rules have to be refined for application in real-time. Dynamics of real-time operation need to be captured in simple yet realistic models that are easy to develop, transparent and implementable. Object-Oriented simulation environment is ideal for rapid model development and policy analysis. One such environment conceived on the principles of *system dynamics* is used in the present study to develop real-time operation models.

Actual use of models in practice largely depends on support environment in which these models are interlaced. A Decision Support System (DSS) framework with traditional architecture (database, model-base and graphical user interface) is a perfect tool to provide such an environment. A framework based on this architecture is proposed and implemented in this study. An effort has been made to include a number of functionalities that support interactive and dynamic decision making environment as well as post-optimal analysis of operating polices generated by models.

1.4 Outline of the Thesis

The thesis starts with an introduction to the problem domain, real-time operation of reservoir systems. The three major issues, *information uncertainty*, *system representation* and *computational intractability* are discussed in Chapter 2, 3, 4, respectively in that order. The issues are addressed in the context of real-time operation of both single and multiple reservoirs systems. Application of these models in real-time and two approaches that aid this process are discussed in Chapter 5. Literature review relevant to these issues is included in the corresponding chapters.

The first chapter provides an introduction to the problem area and briefly describes the major issues that are addressed in the present research. Chapter 2 provides a detailed introduction to different uncertainty issues that are needed to be addressed in case of planning and management of water resource systems. Information uncertainty as an issue is addressed in case of a single reservoir operation. Fuzzy set theory is used to handle the uncertainty issue in an optimization framework. Fuzzy Linear and Non-linear Programming models are developed to address a variety of problems to model the uncertainty in the loss coefficients and imprecision in definition of penalty zones.

Chapter 3 discusses system representation in mathematical programming models. An example problem of hydraulically coupled hydropower reservoir is solved. A real-time operation model that uses MINLP (Mixed Integer Non-Linear Programming) formulation is proposed and reported in this chapter. The MINLP model also addresses the unit commitment problem. Idea of spatial decomposition of the models along with formulations are presented. The complexities of the approaches, optimization tools and the system representation are discussed in detail.

Chapter 4 introduces the idea of computational intractability and relevant issues associated with the implementation of the real-time operation models developed in the present study. This issue that surfaced out as a problem while implementing the MINLP formulations is discussed at length. A new optimization model based on a stochastic search technique, simulated annealing, is presented in this chapter as a last resort algorithm. The application of this approach is validated by applying it to a benchmark problem and to an existing multiple reservoir system.

Issues relevant to operation of reservoirs in real-time and the applicability of models are discussed in Chapter 5. The gap that exists between theory and practice, and tradeoffs between modeling and practical solutions in context of reservoir operation models are analyzed. Simulation models developed using the principles of system dynamics are presented. Details of a Decision Support System (DSS) developed in the present research are also discussed. The DSS is intended to assist reservoir operators in the actual implementation of operating rules in real-time.

Finally conclusions are presented in Chapter 6 along with suggestions for future research. The thesis ends with references, glossary and appendices, in that order.

Chapter 2

Information Uncertainty

Only one thing is certain

that is, nothing is certain.

If this statement is true, it is also false.

- Ancient Paradox

2.1 Introduction

Dealing with uncertainty in planning and management of water resource systems is a challenging task. Modelers of water resource systems are often confronted with uncertainty issues in handling the natural variability of a variety of hydrologic and physical processes, and systems with both stochastic and (not so) deterministic inputs in the modeling process. In general a major input to any water resource system is hydrologic in nature and its estimation for planning and management purposes is the main difficulty. This issue has been a topic of research for the past few decades that generated a variety of explicit and implicit stochastic approaches to handle such hydrologic uncertainty. Classical probability theory is often used in such approaches. A form of uncertainty that will be discussed later in this chapter is dealt using the principles of fuzzy set theory (Zadeh, 1965).

Uncertainty exists in water resource systems in a variety of ways. Attempts to classify it into different categories were made by many researchers in the past. Mays and Tung (1992) divide uncertainties in water resources engineering projects into four basic categories: (i) hydrologic (inherent, parameter and model); (ii) hydraulic (design, model, construction, material and operating conditions; (iii) structural (unusual failures) and economic (costs, revenue, operational and maintenance costs). A form of uncertainty that belongs to last category is addressed in the present research. An exhaustive description of these uncertain elements is provided by Ling (1997) and Simonovic (2000).

Simonovic (2000) describes an uncertainty paradigm that describes the sources of uncertainty in water resource systems. The paradigm extends the concepts proposed by Ling (1993). According to Ling, uncertainty is due to two major factors *variability* and *lack* *of knowledge.* In the first case, uncertainty is due to temporal and spatial variability of hydrologic variables that in a way also contribute to the heterogeneity. The variability is attributed to natural causes, whereas *lack of knowledge* or *information uncertainty* is believed to be existing to a larger extent in the modeling process or due to basic lack of our understanding of the physical processes.

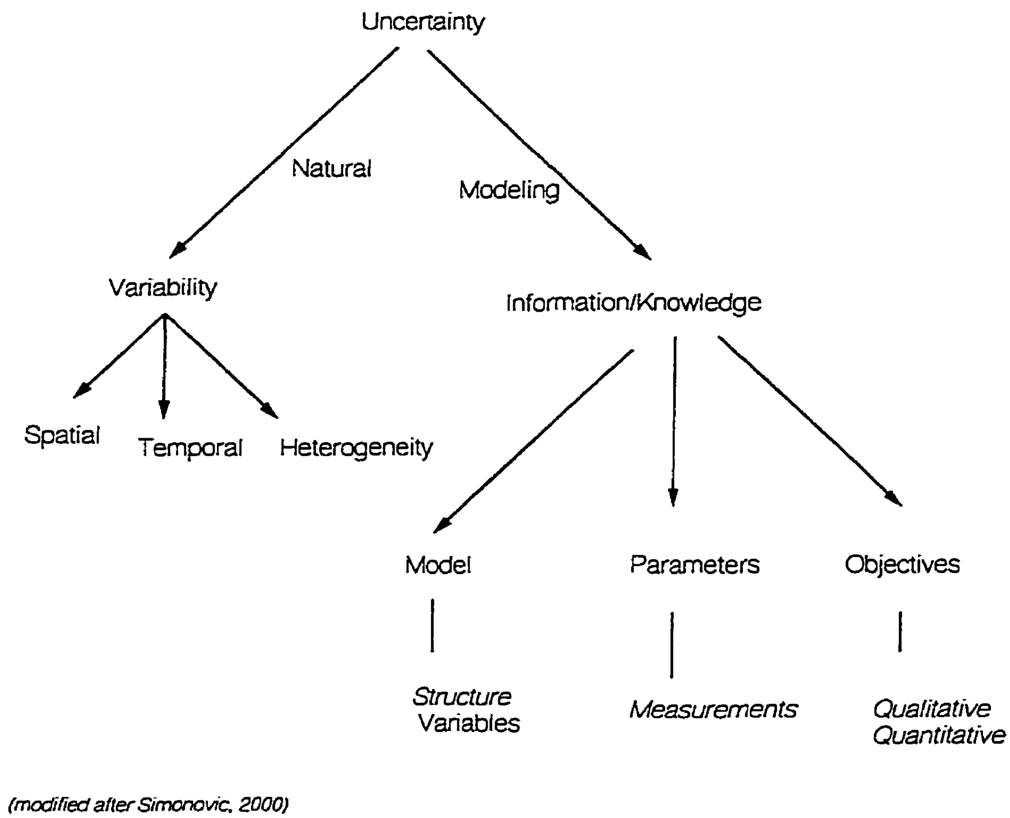


Figure 2.1: Sources of uncertainty

Figure 2.1 shows the sources of uncertainty in the field of water resources. Two major categories of uncertainty can be identified in water resources systems : (i) natural and

(ii) information or knowledge. Natural uncertainty is related to hydrologic inputs to the water resource systems that are not controlled by human beings and thus is very difficult to handle. Spatial and temporal variations of hydrologic variables are not deterministic in general and thus the uncertainty. The heterogeneity of hydrologic systems is mainly due to many factors that also include spatial and temporal variations. The next branch of uncertainty that is the main emphasis of the present research is the *lack of knowledge* or *information uncertainty*. Information uncertainty stems from the lack of understanding of various variables in the modeling process.

Uncertainty mainly due to lack of knowledge or information is an important aspect that needs to be considered in modeling process. Three different categories can be identified that are associated with model, parameters and objectives. Modeling a natural process can be wrong if the physical phenomenon is not captured properly in a mathematical framework. Then the structure itself is considered wrong thus leading to a specific form of uncertainty that will contribute to misrepresentation of the system.

Parameter uncertainty is generally related to lack of knowledge of both qualitative and quantitative nature of the parameters under consideration. Errors in measurement of parameter values are considered to be factors contributing to the uncertainty. In the present situation the parameters that define objective are considered to be unknown. This in a way qualifies for information uncertainty in defining the objectives. Qualitative objectives are much more difficult to handle than the quantitative ones. Sometimes the objectives cannot be defined not because of lack of understanding of the problem but due to the lack of complete information that will take into account the aspirations of the decision maker. Partial information about the goals to be achieved also contributes to this form of uncertainty.

Uncertainty exists in variety of forms and cannot be dealt always with the concepts of the traditional probability theory. Reservoir operation problems are no exception to this. The form of uncertainty that cannot be handled by probability theory can be addressed using the concepts of fuzzy set theory (Zadeh, 1965). Many ardent supporters of fuzzy set theory have defended the attacks of statisticians who claim that probability theory is applicable to any problem. One of the proponents of fuzzy logic concepts, Kosko (1992) explains:

> "Fuzziness describes event ambiguity. It measures the degree to which an event occurs, not whether an event occurs. Randomness describes the uncertainty of event occurrence. An event occurs or not and you can bet on it. The issue concerns the occurring event. To what degree it occurs is fuzzy".

Also, fuzziness is not another form of probability. Fuzzy set and probability theory are different conceptually. Each of them can handle a different type of uncertainty. The only difference is that probability concept is alive without information while fuzziness can coexist even with complete information. Do we need fuzzy set theory concepts to handle problems in the area of reservoir operation. The human element attached with the whole operation of reservoir systems brings about the need for a method to handle ambiguous events or information. This is true especially when the reservoir operation is governed by social and economic factors.

Uncertain and imprecise components that exist within any reservoir operation problem are shown in Figure 2.2. The identification and the classification of components into two categories can be as gray as a fuzzy set. However, the classification can be justified. It is fair to consider hydrologic inputs such as streamflows to reservoir as uncertain and also few problem specific model variables. The physical processes that govern the variability and availability of water belong to such category. The imprecise elements are the ones that cannot be estimated or pre-determined with 100% confidence. These include the objective of the operation model, targets and ranges of certain variables and the information about the forecasted variables (future demands). The list provided is not exhaustive whereas a variety of imprecise and uncertain components can be listed for a number of reservoir operation problems.

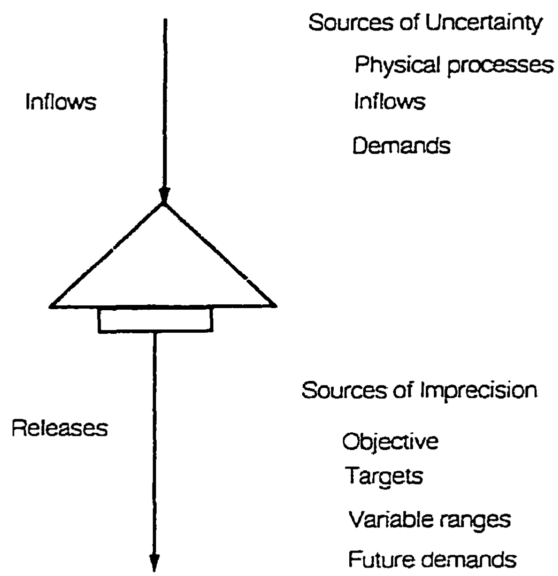


Figure 2.2: Uncertain and imprecision elements of reservoir operation

The type of uncertainty that is dealt in this chapter is different from randomness. To demonstrate a method of dealing with a specific form of information uncertainty in the planning and management of water resource systems, a real-time operation problem of a single reservoir is considered in the present study. The operation is governed by an economic objective that in a way is an appropriate problem to : (i) explain the nature of information uncertainty and (ii) provide a new method in dealing with it in an optimization framework. As the method uses principles of fuzzy set theory (Zadeh, 1965), a brief introduction to fuzzy set theory with an emphasis on the fuzzy mathematical programming is presented here. An array of already existing works that use the fuzzy set theory for water resources problems are also discussed. Short-term reservoir operation with economic objective is discussed first.

2.1.1 Reservoir Operation with Economic Objective

Reservoir operation problem in general is an optimization problem. Various problems in this area have been addressed by many researchers in the past using wide variety of optimization tools. These tools range from simple simulation approaches to complex optimization models. Yeh (1985) provides an excellent state-of-the-art-review of optimization models used for reservoir operation. Most recent studies (e.g. Simonovic, 1991; Hipel, 1992) have addressed the multi-objective nature of reservoir operation problems. The emphasis of the present study is on short-term reservoir operation considering the imprecision in the definition of conventional loss functions. Optimization of the short-term reservoir operation (*with an economic objective*) is usually achieved by formulating a model to minimize the economic loses incurred from deviating in operation from the release and storage volume values set as targets for the planning period. These losses are usually represented by loss functions (Datta and Burges, 1984) which in turn reflect the penalty incurred for a specific deviation from the target.

Reservoir operation problems concerned with the minimization of short-term economic losses, were addressed by many researchers in the past. Can and Houck (1984) addressed the operation problem using Goal Programming. They used reservoir loss functions to minimize the penalties associated with the deviations from the targets. In another work (Can and Houck, 1985) they discussed the problems involved in real-time operations. Simonovic and Burn (1989) presented an improved method for deriving short-term operating policies at the same time obtaining the optimal operating horizon. Following this work, Reznicek et al. (1991) worked on the same problem but used Goal Programming instead of Linear Programming. All the above works involved formulations that have employed piecewise linearized loss functions of storage and release.

One of the difficult aspects of the operation problem is quantification of loss functions. These functions are usually derived based on the experience of reservoir operators and economic information, and therefore are highly subjective. The values that make up the loss functions are penalty coefficients and their selection is ultimately the reservoir operator's prerogative. Despite the utility of loss functions in various reservoir operation problems, there still exist unresolved questions about their derivation, shapes and associated penalty coefficients.

In a recent study, Lund and Ferreira (1996) state that "the most difficult and expensive part of any practical reservoir operation model is usually the development of penalty functions". Use of loss functions for reservoir operation with irrigation as primary objective is discussed by ReVelle (1999). Dynamic nature of the irrigation infrastructure and selection of crops that influence the loss functions are also discussed. ReVelle states that " Loss functions are problematic to determine. Thus, functions determined a *priori* are unlikely to provide desired economic information". Loss functions can be derived for any timeframe. The variation of loss function values with respect to different season within a year can be captured by the use of two loss functions one for winter and another one for summer season (Datta and Burges, 1984).

The imprecise nature of loss functions associated with the difficulties in determining the shape and penalty coefficients makes the reservoir operation problem difficult to handle. Also, the operating policies entirely depend upon the exact definition of these functions. In practice the penalty coefficients are not *crisp* numbers but are certain aspiration levels which are not well defined. It can be observed that the loss function values are in turn the decision maker's degrees of importance attached to violation of various target values. Therefore, the decision making process involves dealing with the problem in an environment where the objectives and constraints imposed are vague. Fuzzy set theory concepts can be useful in this context as they can provide an alternative approach to deal with those problems in which the objectives and constraints are not well defined or information about them is not precise.

2.1.2 Fuzzy Set Theory

Fuzzy set theory concept was originated by L.A. Zadeh in 1965 as a mathematical theory of vagueness. Since then fuzzy set theory has been applied to a wide variety of problems in engineering and other allied fields. To provide a brief introduction, basic notation and terminology related to fuzzy sets is presented here. In the classical set theory, an element from some universal set X belongs or does not belong to the subset A defined on X. Mathematical symbolism describes this process as a characteristic function f_A from X to $\{0,1\}$.

$$f_A : X \rightarrow \quad \{0,1\} \text{ } and \text{ } f_A(x) = 1, \text{ } iff \text{ } x \in A \tag{2.1}$$

$$f_A(x) = 0, \quad iff \quad x \notin A \tag{2.2}$$

Thus if the value of $f_A(x)$ is known for every $x \in X$, then the subset A of X is completely determined and can be represented by

$$A = \{x \in X : x \in A\} \text{ } or \text{ } equivalently, \text{ } A = \{x \in X : f_A(x) = 1\}. \tag{2.3}$$

The theory of fuzzy sets on the other hand generalizes the above case in a way that allows the values of the characteristic function to be any real numbers in the interval [0,1]. A fuzzy set then can be defined using a set of ordered pairs:

$$\tilde{A} = \{(x, \mu_A(x)) : x \in X\} \tag{2.4}$$

where μ_A is a function: $X \rightarrow [0,1]$, and $\mu_A(x)$ is the grade of membership of x in A. It is the measure of how much an element x belongs to A. The higher the value of $\mu_A(x)$, the more x belongs to A . Operations on fuzzy sets are provided in many text books (e.g. Zimmermann, 1984). Some of the operations and relevant terminology is presented here.

Membership function : represents the grade of membership of x in A, and its values are allowed to be in the real interval $[0, 1]$.

Intersection of fuzzy sets : It is defined by the intersection of membership functions. The membership function of $A \cap B$ is defined as the minimum of the membership functions of A and B. This operation was extended from the classical set theory by the following relationship that has good use in decision making under fuzzy environment.

$$\mu_{A \cap B}(X) = min\{\mu_A(x), \mu_B(x)\} \qquad \forall x \in X \tag{2.5}$$

Details of operation on fuzzy sets and their properties can be found elsewhere (Mares, 1994; Pedrycz, 1999; Zimmermann, 1984). Computation over fuzzy sets and numbers is similar to operations over traditional sets. In summary, "There is nothing fuzzy about fuzzy set theory!" - Zimmermann (1984).

2.1.3 Applications in Water Resources

Wealth of literature related to concepts of fuzzy sets and their applications to problems within the area of operations research is available elsewhere (Zadeh, 1965; Zimmermann, 1984, 1987; Pedrycz and Gomide, 1999). Recent studies provide examples of application of fuzzy set theory to reservoir operation problems. Kindler (1992) used fuzzy set theory to develop a water allocation model where the water requirements are assumed to be fuzzy quantities. Linear programming formulations under fuzzy environment and simulation models are developed for single period water allocation problem as well as for different hydrological input situations. Rational allocation of water is achieved considering the imprecise objectives provided by the water managers. Sutardi et al. (1995) integrate Stochastic Dynamic Programming (SDP) and Fuzzy Integer Goal Programming (FIGP) to deal with the multi-objective water resource investment problems. They use FIGP approach to handle the uncertainties associated with budgetary and socio-technical aspects of water resources investment planning. SDP is used to obtain optimal investment planning policy.

Bardossy and Duckstien (1995) discuss a number of applications of fuzzy set theory in water resources including a model for sustainable reservoir operation. Russell and Campbell (1996) used fuzzy logic programming for deriving reservoir operating rules. They indicate that the fuzzy logic programming approach suffers from *curse of dimensionality* that might limit the application to problems with few control variables. Shrestha et al. (1996) developed a fuzzy-rule base for operation of a multipurpose reservoir. The rule-base is developed considering different operational decisions taken by the reservoir managers that have a simple *"if-then"* construct. The reservoir storage level, estimated (forecasted) inflows, and demands are used as the premises and release from the reservoir is taken as the consequence. Fuzzy rule based modeling has an advantage of capturing the reservoir operator's experience in a set of rules.

A recent study by Fontane et al. (1997) provides an useful application of fuzzy sets in planning reservoir operations with imprecise objectives and constraints. Membership functions are obtained based on the actual surveys which are used in a Dynamic Programming model. They emphasize the practical value of membership functions when included in optimization framework for reservoir operation problems. The development and use of fuzzy Dynamic Programming formulations has been discussed at length by Zimmermann (1984) and Kickert (1974). Srinivasan and Simonovic (1994) handled uncertain energy demands by treating them as fuzzy variables in a reliability model that is developed for operation of a hydropower reservoir.

Application of fuzzy decision making for a water quality management of a river system was reported by Sasikumar and Mujumdar (1998). They use fuzzy Linear Programming formulation to address the problem of water quality management of a river system with multiple-objectives. Their model incorporates the aspirations and conflicting objectives of the pollution control agency and the dischargers.

Most recent application of fuzzy set theory approaches can be found in the works of Despic and Simonovic (2000) and Bender and Simonovic (2000). Despic and Simonovic (2000) use fuzzy set theory for quantification of complex qualitative criteria for specific problems in water resources management. A multi-objective fuzzy compromise programming approach is used by Bender and Simonovic (2000) to select the most desirable water resource management alternative. They report the advantages of replacing the traditional MCDA (Multi Criteria Decision Analysis) technique with the fuzzy compromise approach to adopt fuzzy inputs.

The use of fuzzy set theory within an optimization framework provides a number of advantages in dealing with the uncertainty associated with economic objectives. The issues discussed in the literature survey and the difficulties associated with the derivation of loss functions had provided enough scope for formulation of models that consider these aspects in an optimization framework. Loss functions bear a close resemblance to the membership functions used in the fuzzy set theory. This similarity can be a motivation for replacing the former with the latter. However, achieving this objective through fuzzy mathematical programming is difficult and will be discussed at the end of this chapter.

This chapter concentrates on development of approaches to handle the uncertainty and imprecision in the definition of loss functions at the same time addressing the short-term reservoir operation problem. The terms *loss curve* and *penalty curve* are used interchangeably while they both mean a function representing the economic loss (quantified in some monetary units) associated with different reservoir operating zones. Formulations addressing the problems of imprecision in definition of penalty zones and uncertainty in estimation of coefficients are presented. Issues relating to imprecision in the definition of penalty zones are addressed first.

2.1.4 Imprecision and Uncertainty

The terms *imprecision* and *uncertainty* are appropriate for the problems addressed in this study. Imprecision can be loosely defined as lesser form of uncertainty. When defining unclear penalty zones, the word *imprecision* is used whereas penalty coefficients are considered uncertain as they are difficult to estimate. The difference in the meaning of these terms and their use will reflect the difference in the type of problems addressed.

2.2 Fuzzy Sets in Mathematical Programming

An optimization problem in general is expressed as a formulation maximizing or minimizing an objective under a set of constraints. If the objective or the constraints are vague, then the problem can be referred to as fuzzy optimization problem. Bellman and Zadeh (1970) first proposed the idea of decision making under fuzzy environment. They indicated that if goals (G_j) and the constraints (M_i) are fuzzy and characterized by their membership functions (μ_{G_j}, μ_{M_i}) then the decision space can be stated through their fuzzy intersection operation ($\mu_{G_j} \cap \mu_{M_i}$). "In short, a broad definition of the concept of decision may be stated as: Decision = Confluence of Goals and Constraints" (Bellman and Zadeh, 1970). The intersection is defined by *Min* operator and the decision is given as $\mu_d = Max\ [\ Min\ (\mu_{G_j},\ \mu_{M_i})\ ]$. More details about this criterion with applications can be found in Bojadziev and Bojadziev (1997) and Zimmermann (1987). The decision, in simple terms is the maximum membership value for the solution obtained by the intersection of constraints and objective function sets. Operators other than *Min* can be used that are discussed by Zimmermann (1987).

Fuzzy Linear Programming (FLP) applies the *Bellman-Zadeh criterion* for solution of many problems where the goals and constraints are fuzzy. Many applications of FLP to civil engineering problems and its variations can be found in literature (e.g., Kikuchi et.al 1991; Cui and Blockley, 1990). The present study uses both Linear as well as Non-Linear Programming under fuzzy environment to address non- symmetric and symmetric problems. In case of non-symmetric problems the objective function is *crisp* or well defined and the constraints are fuzzy or vague. A fuzzy mathematical programming problem is considered symmetric when both the objective function as well as the constraints are vague. A non-symmetric problem is handled first and then the symmetric formulation is addressed in this chapter.

To solve the problems that are non-symmetric, a procedure suggested by Zimmermann (1987) is used. The procedure includes the following steps : (a) the mathematical programming model is solved and the objective function value is obtained; (b) the model is again solved with modified constraints which are considered as vague or fuzzy; (c) the model is solved, with the objective function and constraints (which were earlier assumed as fuzzy) replaced by their fuzzy equivalents using membership functions. The objective function in the step (a) or (b) becomes a fuzzy constraint in step (c). The fuzzy constraints in the present study are related to the penalty zones and coefficients, whereas the objective function is the penalty value in monetary units. The procedure described in steps (a), (b) and (c) can be represented in a mathematical form. For a minimization problem the steps are given below :

Step I :

$$Minimize \quad CX \tag{2.6}$$

$$subject\ to \quad AX \leq b \tag{2.7}$$

where, CX is the objective function, $X = [x_1, x_2....]^T$ is the matrix of decision variables, and AX is the constraint matrix. If the sign $\leq$ is replaced by $\lesssim$ then the constraint(s) become fuzzy or have a linguistic interpretation - *essentially smaller than or equal.* The constraints in (2.7) are fuzzy and should be expressed as form $AX \lesssim b$ in standard fuzzy mathematical programming formulations. However, it is expressed here as any regular constraint matrix as a *crisp* formulation is solved in Step I. Let the objective function value obtained by solving the above problem be f_o.

Step II :

$$Minimize \quad CX \tag{2.8}$$

$$subject\ to \quad AX \leq b + t_o \tag{2.9}$$

Here, the tolerance value t_o value is added to the right hand side of the Equation (2.9). The tolerance is the value by which the b value changes. Let the objective function value obtained from the solution of Step II be f_1.

Step III :

$$Maximize \quad \lambda \tag{2.10}$$

$$subject\ to$$

$$AX - \lambda \ \ t_o \leq b \tag{2.11}$$

$$CX + \lambda\ (f_1 - f_o) \leq f_1 \tag{2.12}$$

Equations (2.11) and (2.12) represent the fuzzy constraints defined through a proper membership function that describe the preferences of the decision maker. The objective function from Step I becomes a constraint (2.12) in the present formulation. The objective function

(2.10) indicates that the objective as well as the fuzzy constraints are satisfied to maximum possible degree. This is similar to maximizing the membership function value ($\lambda \in [0, 1]$). The variable, λ, is referred to as *Level of satisfaction* and is represented as L in all the formulations hereafter. Complete description of the above procedure for different types of problems is available elsewhere (Zimmermann, 1987). The formulations, Step I, Step II, Step III are referred to as original, intermediate and final models respectively in the present study.

In the intermediate formulation an objective function value is obtained at the maximum level of satisfaction ($\lambda = 1$). The need for this formulation is based on the fact that the decision maker cannot provide a reasonable guess for the objective function value for the fuzzy decision space.

A better benchmark value for f_1 can be obtained when the degree of membership equals 1. Once this intermediate objective function value, f_1 is obtained, it can be used to construct the required membership function for the goal. Symmetry is now achieved and the objective function has been modified from *crisp* to fuzzy. Using similar fuzzy mathematical programming framework, problems under symmetric and non-symmetric environments can be addressed. Mathematical programming model in symmetric fuzzy environment is easy to handle and does not require the steps indicated above. Non-symmetric formulation used in the present study is discussed first and the symmetric problem that is relatively easy is addressed later.

Based on the utility of fuzzy set theory concepts in the present context of reservoir operation problem, two problems are addressed. The first problem deals with the imprecision in the definition of different penalty zones while the second one is for uncertain penalty coefficients.

Figure 2.3 shows one such problem where the location of the point "A" is not precise. This indicates that the penalty zone is not defined precisely. Similarly, point "B" indicates the uncertainty in penalty coefficients.

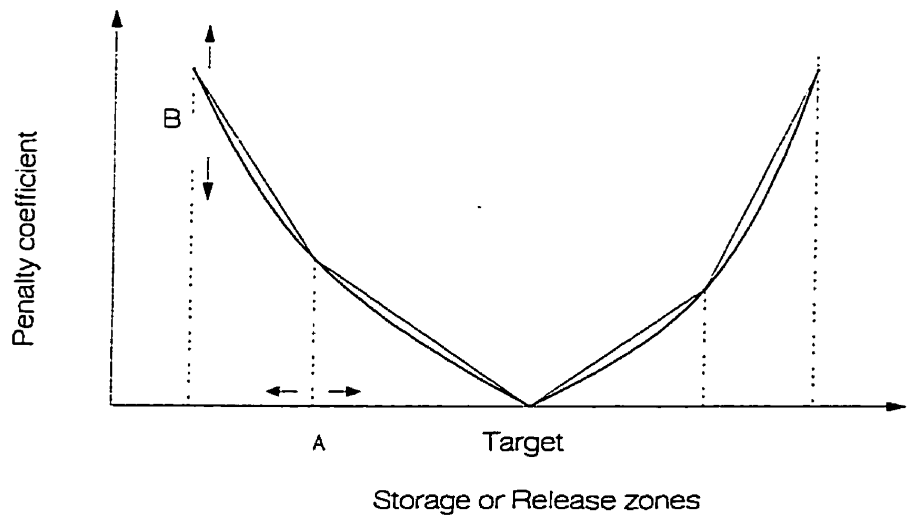


Figure 2.3: Loss function representing deviations in penalty zones and coefficients

Here the decision maker may be interested in decreasing or increasing the length of a particular zone or penalty coefficient values. The problem becomes difficult to handle if the decision maker has preferences attached to any movement in one particular direction. In this situation a fuzzy set approach would provide a meaningful solution when membership functions are used to capture the decision maker's preferences.

2.3 Formulation of Models

The operation problem is formulated as both Linear Programming (LP) as well as Non-Linear Programming (NLP) models under fuzzy environment to address the problems related to imprecision in definition of penalty zones and penalty coefficients. First the original formulations are presented and then their fuzzy equivalents. Both the models are adopted from the reservoir operation model discussed by Simonovic and Burn (1989) and are altered for the present study. This reservoir operation model was originally developed by Can and Houck (1984). A Non-Linear Programming formulation is developed based on this model that is used to address a specific problem in the present study. Formulation addressing the problem of imprecise penalty zones is presented first and the model for uncertain penalty coefficients is discussed later.

2.3.1 Imprecise Penalty Zones

A fuzzy Linear Programming model is used for solving reservoir operation problem at the same time to address the problem of imprecision in the definition of penalty zones. The formulation uses piecewise linearization of a non-linear loss function defined for storage and release. The inflow scheme for the periods for which optimal operation rules are required is assumed to be known. The objective is to minimize the sum of under-achievement or over-achievements in meeting the storage and release target requirements over a specific time horizon.

The piecewise linearization of loss function for release is shown in the Figure 2.4. Here, RD_1

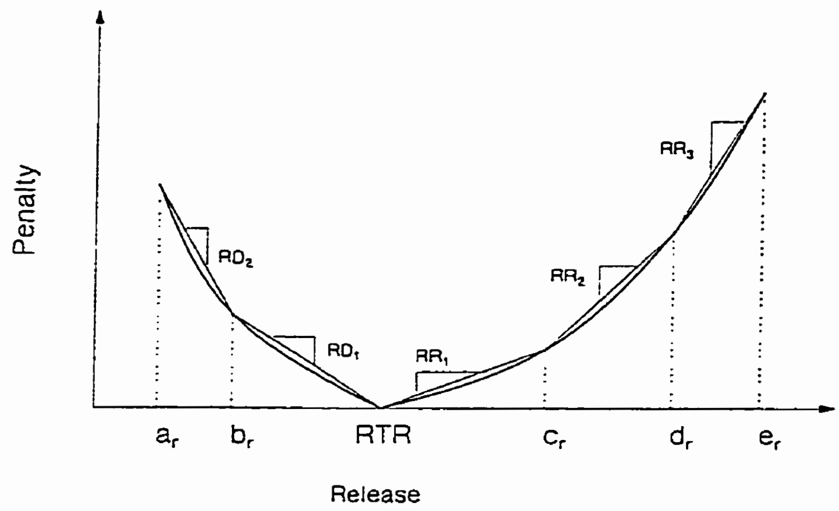


Figure 2.4: Piecewise linearized loss function for release

, RD_2 ... represent the unit penalties (refer to Table 2.1), and a_r, b_r ... represent various points on the X axis which define the deviation zones, i.e, $RD2$, $RD1$ .. etc. Similar loss function is chosen to be appropriate for storage. In case of storage, RD_1, RD_2 ... get replaced by SD_1 and SD_2 ... and a_r, b_r .... get replaced by a_s, b_s ..... and the deviation zones , $RD2$, $RD1$.. etc. get replaced by $SD2$, $SD1$ ... and RTR by STR respectively. The formulation of the operation model is given here.

MODEL I

Minimize

$$\sum_{t=1}^{T}(SD_2\ SD2_t + SD_1\ SD1_t + SS_1\ SS1_t + SS_2\ SS2_t + SS_3\ SS3_t$$

$$+RD_2\ RD2_t + RD_1\ RD1_t + RR_1\ RR1_t + RR_2\ RR2_t + RR_3\ RR3_t) \tag{2.13}$$

Table 2.1: Storage and release zones and corresponding penalties for winter season

Storage zone $10^6\ m^3$	Penalty points/$10^6\ m^3$	Release zone $10^6\ m^3$	Penalty points/$10^6\ m^3$
136.53 - 190.00	5000	0.367-1.50	10
190.00 - 200.99	1	1.50-2.50	0.1
200.99	Target	2.5	Target
200.99 - 220.00	50	2.50-7.00	150
220 - 893.58	800	7.00 - 9.79	900
893.58 -1507.09	15000	9.79 -14.67	2000

subject to :

$$S_t + SD2_t + SD1_t - SS1_t - SS2_t - SS3_t = STR \qquad \forall t \tag{2.14}$$

$$R_t + RD2_t + RD1_t - RR1_t - RR2_t - RR3_t = RTR \qquad \forall t \tag{2.15}$$

$$SD2_t \leq b_s - a_s \qquad \forall t \tag{2.16}$$

$$SD1_t \leq STR - b_s \qquad \forall t \tag{2.17}$$

$$SS1_t \leq c_s - STR \qquad \forall t \tag{2.18}$$

$$SS2_t \leq d_s - c_s \qquad \forall t \tag{2.19}$$

$$SS3_t \leq e_s - d_s \qquad \forall t \tag{2.20}$$

$$RD2_t \leq b_r - a_r \qquad \forall t \tag{2.21}$$

$$RD1_t \leq RTR - b_r \qquad \forall t \tag{2.22}$$

$$RR1_t \leq c_r - RTR \qquad \forall t \tag{2.23}$$

$$RR2_t \leq d_r - c_r \qquad \forall t \tag{2.24}$$

$$RR3_t \leq e_r - d_r \qquad \forall t \tag{2.25}$$

$$S_2 + R_1 = S_1 + I_1 \tag{2.26}$$

$$S_{t+1} - S_t + R_t = I_t \qquad t = 2, 3......T \tag{2.27}$$

$$R_t \leq R_{max} \qquad \forall t \tag{2.28}$$

$$R_t \geq R_{min} \qquad \forall t \tag{2.29}$$

$$S_t \leq S_{max} \qquad \forall t \tag{2.30}$$

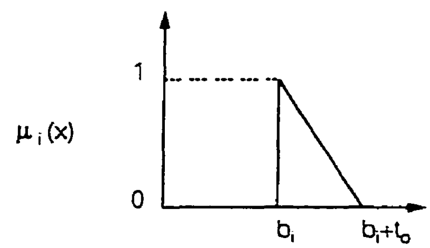
$$S_t \geq S_{min} \qquad \forall t \tag{2.31}$$

The objective is to minimize the penalties, which are incorporated into deterministic Linear Programming formulation. STR and RTR represent the storage and release targets respectively. I_t represents the inflow in the time period, t. The constraints (2.14 and 2.15) relate to reservoir target storages and releases, the next ten constraints (2.16 - 2.25) relate to penalty zones, next two relate to reservoir mass balance (2.26 - 2.27) and the final four constraints (2.28 - 2.31) represent the upper and lower bounds on release and storage.

Membership functions which represent the decision maker's preferences are assumed to be known in the present study. These functions are used to derive the appropriate fuzzy constraints. Membership functions are required for Step II and III formulations. A brief description of membership functions and their derivation is provided next.

2.3.2 Membership Functions

The decision maker's preferences for reducing or increasing the length of the penalty zones can be used to derive two different membership functions (Zimmermann, 1984). A membership function can be derived by providing the aspiration levels for the tolerance. A typical membership function in a graphical form and its derivation for a constraint is shown in the Figure 2.5. The membership value (μ_i) takes on values 1 or 0 or any value in between depending on the conditions. The range, $[b_i, b_i + t_o]$ refers to tolerance interval. Similar membership functions are derived based on the preferences for the constraints and objective that are assumed to be fuzzy. The variable, μ_i is denoted by L in all the formulations.



$$\mu_i(x) = \left| \begin{array}{ll} 1 & a_i x_i \leqslant b_i \\ 1 - \dfrac{(a_i x_i - b_i)}{t_o} & b_i \leqslant a_i x_i \leqslant b_i + t_o \\ 0 & a_i x_i > b_i + t_o \end{array} \right.$$

Figure 2.5: Derivation of a membership function

The membership functions in graphical form are shown in the Figure 2.6(a), 2.6(b) and 2.6(c). These functions indicate the preferences on $0-1$ scale on the Y-axis for the length of penalty zone indicated on X-axis. To keep the scope of study to linear formulations, the membership functions are chosen to be linear, while there is no conceptual difficulty in handling non-linear membership functions if appropriate formulations are developed. Also, membership functions can be derived from actual surveys (Fontane et al., 1997).

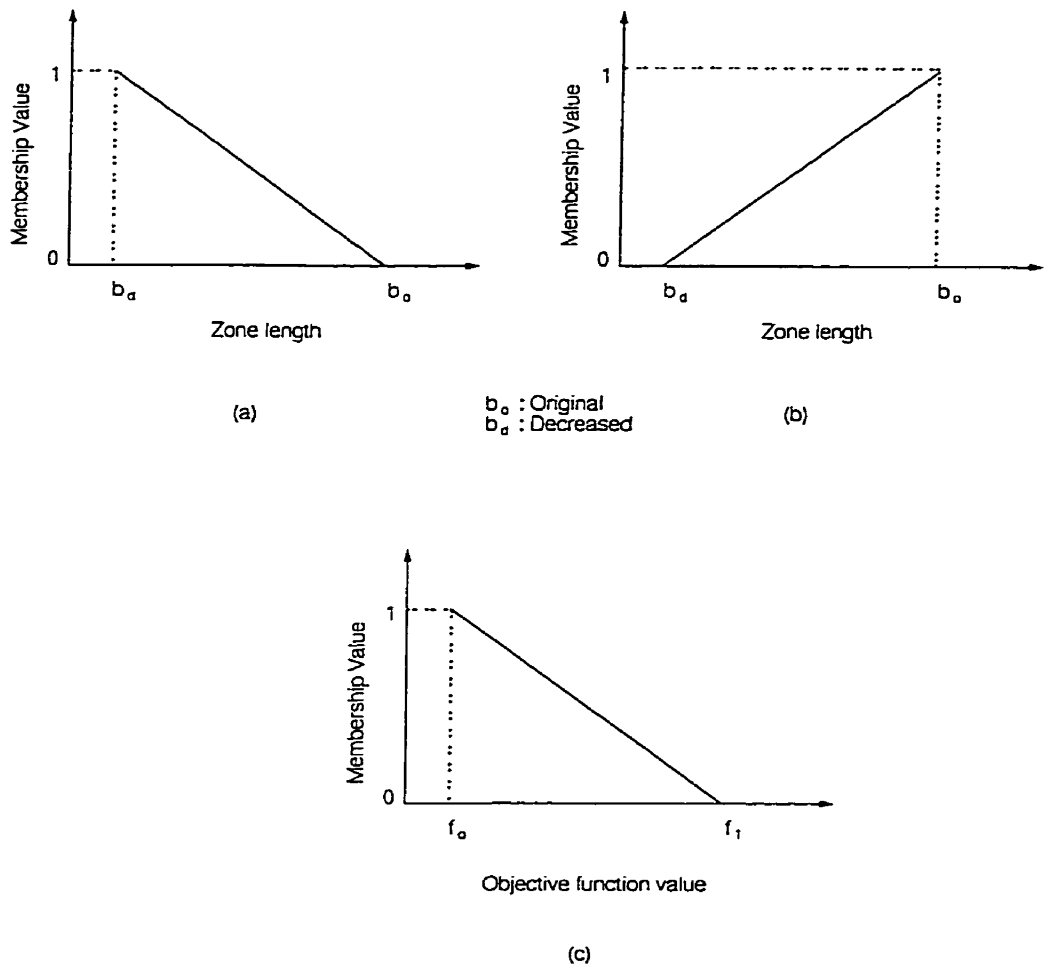


Figure 2.6: Membership functions for deviations and objective function

Fuzzy Formulations

The formulation (2.13 - 2.31) is first solved to obtain the objective function value, $'f_o'$, mentioned in the Step I. The formulation can be referred to as *crisp* as neither the objective function nor the constraints are fuzzy. Tolerances are then added or subtracted to the constraints which are considered fuzzy. This formulation refers to Step II. Finally, Step III formulation is solved using the membership functions.

Membership functions for the constraint (2.22) can be developed, assuming that the decision maker wants to reduce the first penalty zone of the release on the left side of the target release and storage. It is assumed that the unit slopes which determine the penalty values for these zones will remain unaltered even after the length of the zone is changed. Using the membership function given in the Figure 2.6a, the constraint (2.22) can be modified as follows.

$$RD1_t + (H)\ L\ \leq RTR - b_r \quad \forall t \tag{2.32}$$

Where H indicates the amount of reduction in the first penalty zone, $(RTR - b_r)$, that is equal to $b_o - b_d$ as given in the Figure 2.6(a) and L represents the level of satisfaction for the constraint. For the membership function given in the Figure 2.6(b), constraint (2.22) will be modified as,

$$RD1_t + (H)\ (1 - L)\ \leq RTR - b_r \quad \forall t \tag{2.33}$$

Similar modifications have to be made to constraint (2.17) to represent imprecision in the storage penalty zones for different membership functions. An additional constraint has to be modified to account for the possible reduction in the first penalty zone, which in turn might increase the second zone, adjacent to the first one, on the left side of the target. The constraint relating to second zone is modified as,

$$RD2_t - (H)\ L \leq b_r - a_r \quad \forall t \tag{2.34}$$

The formulations in Step I and Step II when solved provide two different objective function values, (f_o, f_1), which are used to develop membership function for objective, which is shown in Figure 2.6(c). The objective function (2.13) is modified and is now used as a constraint in the final formulation (Step III). **Model IA** and **Model IB** given below refer to final formulations based on the membership functions derived from Figure 2.6(a) and Figure 2.6(b) respectively. The objective now is to maximize the level of satisfaction, L. All the models are solved with complete set of constraints (2.14 - 2.31) from the original formulation, **Model I**, except the constraints which are now modified to their fuzzy equivalents.

MODEL IA

$$Maximize\ \ L \tag{2.35}$$

subject to

$$\sum_{t=1}^{T}[SD_2\ SD2_t + SD_1\ SD1_t + SS_1\ SS1_t + SS_2\ SS2_t + SS_3\ SS3_t$$

$$+RD_2\ RD2_t + RD_1\ RD1_t + RR_1\ RR1_t + RR_2\ RR2_t + RR_3\ RR3_t] + (f_1 - f_o)\ L \leq f_1 \quad (2.36)$$

$$RD2_t - (H)\ L \leq b_r - a_r \qquad \forall t \qquad (2.37)$$

$$RD1_t + (H)\ L \leq RTR - b_r \qquad \forall t \qquad (2.38)$$

Where H indicates the amount by which the first zone, $(RTR - b_r)$ is reduced, thereby moving the point, b_r, closer to RTR and L having the same notation as that in the earlier fuzzy formulation.

MODEL IB

$$Maximize \quad L \qquad (2.39)$$

subject to

$$\sum_{t=1}^{T}[SD_2\ SD2_t + SD_1\ SD1_t + SS_1\ SS1_t + SS_2\ SS2_t + SS_3\ SS3_t$$

$$+RD_2\ RD2_t + RD_1\ RD1_t + RR_1\ RR1_t + RR_2\ RR2_t + RR_3\ RR3_t] + (f_1 - f_o)\ L \leq f_1 \quad (2.40)$$

$$RD2_t - H \quad L \leq b_r - a_r \qquad \forall t \qquad (2.41)$$

$$RD1_t + H(1 - L) \leq RTR - b_r \qquad \forall t \qquad (2.42)$$

This formulation is same as the previous one (**Model IA**) except that a different type of membership function (Figure 2.6(b)) is used for the constraint (2.22). For formulations to reflect the imprecision in the storage zones, the equations (2.41) and (2.42) have to be replaced by appropriate constraints which reflect the change in storage zones. Problems addressing the imprecision in both release and storage zones can be handled at the same time.

2.3.3 Uncertain Penalty Coefficients

Penalty coefficients are the points on the loss functions which define the penalty in monetary units corresponding to the penalty zones. These values are usually derived from economic information considering the impacts of reservoir operation. In the present study these coefficients are considered fuzzy in a sense that they are not well defined. Only points where the slopes of the loss function change are considered as vague since any change in location of these points (eg. "B" in Figure 2.3) would cause a change in the slope of the loss function in the zone and there by affecting the reservoir operations schedule. A Non-Linear Programming formulation is used to address this problem. The membership function defined in the Figure 2.6(a) is used for the constraints and the one defined in Figure 2.6(c) is used for objective function. As unit slopes are no longer constant, they become unknown variables in the objective function. This transforms the Linear Programming formulation

(**Model I**) into a Non-Linear optimization model. The problem formulation is essentially the same (with respect to constraints) as that of Linear Programming formulation, with a non-linear objective function and some additional constraints. The complete formulation is presented next.

MODEL II

Minimize

$$\sum_{t=1}^{T}(\alpha\ SD2_t + \beta\ SD1_t + SS_1\ SS1_t + SS_2\ SS2_t + SS_3\ SS3_t$$
$$+RD_2\ RD2_t + RD_1\ RD1_t + RR_1\ RR1_t + RR_2\ RR2_t + RR_3\ RR3_t) \tag{2.43}$$

subject to

$$\beta\ SD1 = a_1 \tag{2.44}$$

$$\alpha\ SD2 = a_2 \tag{2.45}$$

and all the constraints (2.14 - 2.31). Here, a_1 and a_2 indicate the lengths shown in Figure 2.7. The above formulation is used for representing the uncertainties in the penalty coefficients of loss curve used for storage. Also, the constraints (2.44) and (2.45) correspond to

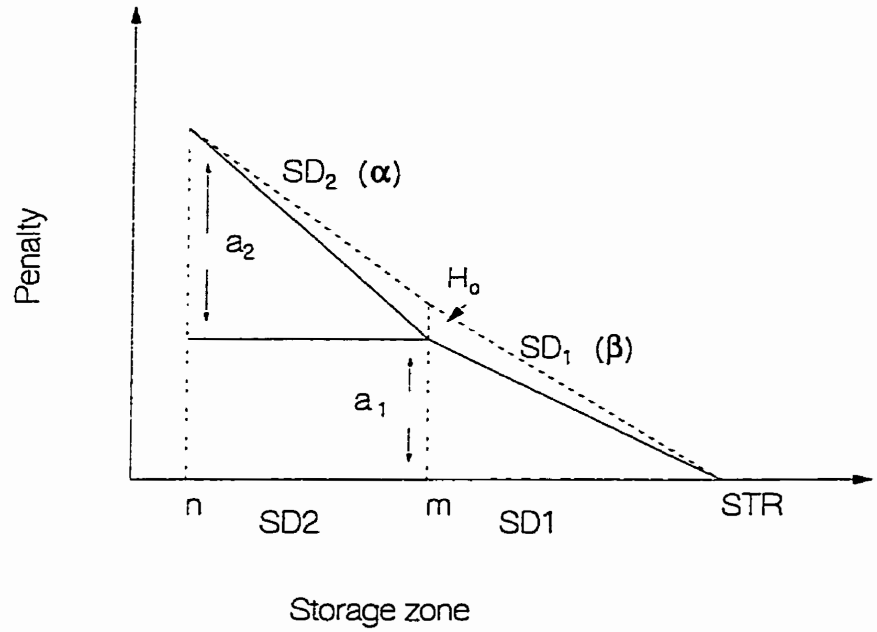


Figure 2.7: Schematic representation of deviations in penalty coefficients for storage loss function

the loss function to the left side of the target storage. Based on the actual values of unit slopes, SD_1 and SD_2, and the lengths (a_1, a_2) the following equations can be written,

$$a_1 = SD_1\, SD1 \tag{2.46}$$

$$a_2 = SD_2\, SD2 \tag{2.47}$$

Using the above constraints, formulations for all the three steps (Step I, Step II and Step III) can be derived. The fuzzy equivalents of these constraints are based on the membership function defined in Figure 2.6(a) and are given below.

$$\beta\, SD1 - H_o\, L \;=\; SD1\, SD_1 \tag{2.48}$$

$$\alpha\, SD2 + H_o\, L \;=\; SD2\, SD_2 \tag{2.49}$$

Where H_o indicates the amount by which the penalty coefficient value is increased. The final formulation (Step III) for this problem is similar to one written for **Model IA**. The formulation is given below,

Model IIA

$$Maximize \;\; L \tag{2.50}$$

subject to

$$\sum_{t=1}^{T}[\alpha\, SD2_t + \beta\, SD1_t + SS_1\, SS1_t + SS_2\, SS2_t + SS_3\, SS3_t$$
$$+RD_2\, RD2_t + RD_1\, RD1_t + RR_1\, RR1_t + RR_2\, RR2_t + RR_3\, RR3_t] + (f_1 - f_o)\, L \leq f_1 \tag{2.51}$$

The formulation is complete with all other constraints (2.14 - 2.31) along with constraints (2.48) and (2.49). To address the problem of uncertainty in release loss function coefficients, appropriate changes have to be made in constraints (2.48), (2.49) and (2.51). The formulation presented here is based on the membership function shown in the Figure 2.6(a). It is fairly straightforward to modify this formulation to consider other types of membership functions. It should be noted here, that formulation based on Step II should be solved before this one, as the value of objective function, f_1 is required for the constraint (2.51).

2.4 Application of Models

A case study of an existing reservoir is chosen for the application of proposed models to evaluate the sensitivity of reservoir operating policies to the change in the shapes of loss functions. Green Reservoir in Kentucky, USA is chosen for this purpose. The primary objective of the reservoir is flood control in the Green River Basin as well as in the downstream areas of the Ohio River. Secondary objectives include recreation, low flow augmentation and water quality. The reservoir is the most upstream reservoir in the Green River system located 489 km above the mouth of the stream with a maximum storage capacity in excess of 1500 10^6 m^3. The reservoir storage up to the top of spillway is 892.02 10^6 m^3, while the minimum reservoir storage is 136.53 10^6 m^3.

The maximum daily release is based on the downstream flood protection and is 14.67 10^6 m^3, whereas, the minimum daily requirement of 0.367 10^6 m^3 is based on water quality requirements. The original LP formulation (**Model I**) uses linearized penalty function values given in the Table 2.1. These values are based on the intended use of the reservoir. It is evident from the Table 2.1 that the primary purpose of the reservoir is for flood protection indicated by the penalty values (values being high for storage and less for release deviations). Details of the case study and loss functions can be obtained from earlier work by Can and Houck (1984).

2.4.1 Results and Discussion

The fuzzy mathematical programming framework in a symmetric environment is used to address two modeling issues: (i) the imprecision in the definition of storage and release zones (ii) the uncertainty in the available penalty coefficient values. Symmetric fuzzy formulations applicable in some situations are discussed later. These two problems are solved using mathematical formulations, especially, Fuzzy Linear and Non-Linear optimization models respectively. The models are developed using **GAMS**(**G**eneral **A**lgebraic **M**odeling **S**ystem) (Brooke et al., 1996) optimization software. The non-linear formulations developed in the present study are solved using *CONOPT* solver available within the GAMS environment. All the three formulations involving Step I, Step II, and Step III are solved for each of the cases mentioned above.

Depending upon the type of membership function chosen (Figure 2.6(a) or Figure 2.6(b)), the formulations would differ. The membership function used in the Figure 2.6(c) is used for converting the original objective function (2.13) into a fuzzy constraint in all Step III formulations. The original, intermediate and final formulations refer to Step I, II and III respectively. The **Model I** refers to the original formulation, while **Models IA** and **IB** refer to final formulations based on the membership function used for addressing the imprecision in the release or storage zones. **Model II**, again refers to original formulation, while **Model IIA** to final formulation used to handle uncertainty in the penalty coefficients using the membership function given in Figure 2.6(a). The intermediate formulation refers to Step II procedure, where **Model I** or **Model II** is solved with the appropriate constraints modified. It is apparent from the Figure 2.6(c) that the decision maker has higher preference for a lower value of penalty, which is realistic. The following sections give details of the cases modeled along with the results and interpretations.

The storage and release deviations from the target storage are represented by dividing the entire range of operational storage and release values into different zones. These are generally fixed by decision makers or reservoir operators. Different simulations are performed to evaluate the sensitivity of reservoir operations to the fuzzy penalty zones. Simulations are performed for a period of 18 days using a known historical inflow scheme and adopting the penalty function values given in the Table 2.1. The reservoir storage at the beginning of first period is taken as 199 10^6 m^3. **Model I** and **Model IA** are solved for a case in which the first release zone, on the left side of the target release is reduced by 0.3 10^6 m^3.

The Membership function shown in Figure 2.6(a) is used for this case to represent the decision maker's preference in reducing the zone. This indicates that the higher penalties are now attached to certain deviations from the target, which had lower values earlier. The storage loss function is unaltered. Figures 2.8 and 2.9 show the results from all the three formulations. The final solution indicated is the optimal release rule for the fuzzy stipulation imposed. To reduce the penalties associated with reduced zone, the model opts for increased releases close to the target. Figure 2.9 shows the resulting storage variations.

The membership functions used in deriving the constraint (2.38) and objective function

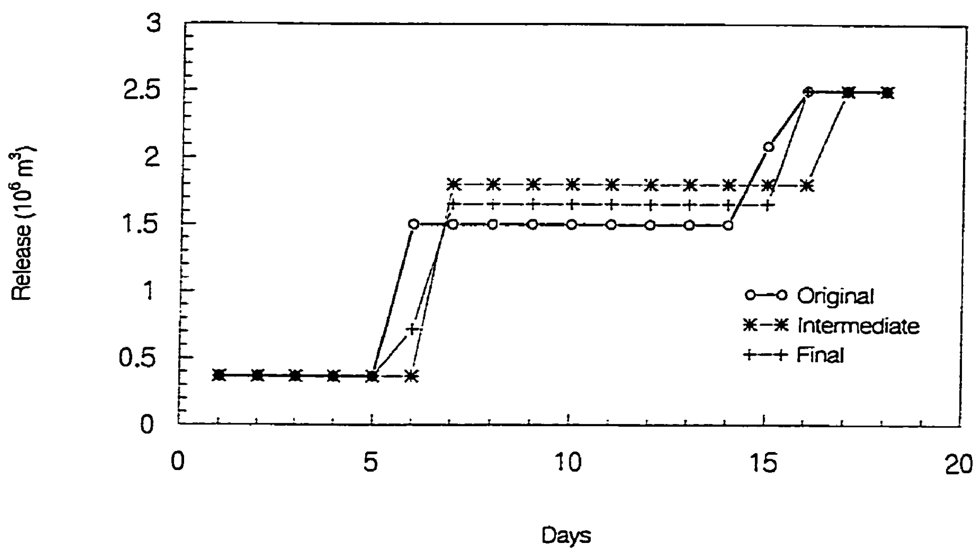


Figure 2.8: Release variations due to reduction in the release zone

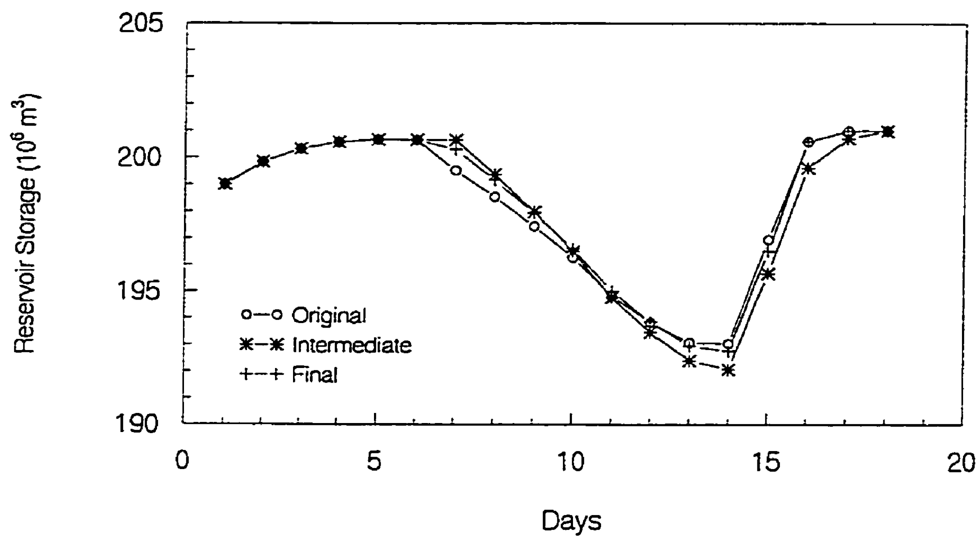


Figure 2.9: Storage variations due to reduction in the release zone

(2.36) incorporate the preferences that are conflicting, thus producing a satisfying solution to the degree of L. Any value of L between 0 and 1 does not necessarily indicate that the final results relevant to storage and releases will lie between the results due to intermediate and original formulations. This is apparent from the Figures 2.8 and 2.9, where the L value obtained is 0.51. This is due to the fact that L value is a satisfying value based on membership function for the constraints in all the time periods. On the other hand, the final objective function value will always lie between the values f_o and f_1, obtained from original and intermediate formulations respectively. In the present case, the final objective function value in monetary units is 124.07, whereas f_o and f_1 are 108.86 and 139.73 respectively. This can be attributed to the property of membership function given in the Figure 2.6(c).

In an another experiment, reductions in penalty zones of release as well as storage are introduced simultaneously. The first storage zone on the left side of the target is reduced by 5 10^6 m^3 and the reduction for release is same as that of previous case. The membership function used in this case are again from the Figure 2.6(a).

Figure 2.10 gives the details of the release decisions for all the three formulations. The release decisions are different from the one shown in Figure 2.8. Reservoir storage variations for this case are shown in Figure 2.11. The L value, or the degree of satisfaction achieved in this case is 0.63. It can be noted from the Figure 2.10, that the release decisions are higher than the original decisions. Similar trend can be seen in the Figure 2.11 for storage variations.

The release values and the storage values are higher than those in the previous formulation. The final objective function value in this case is 131.09, which is higher than the previous

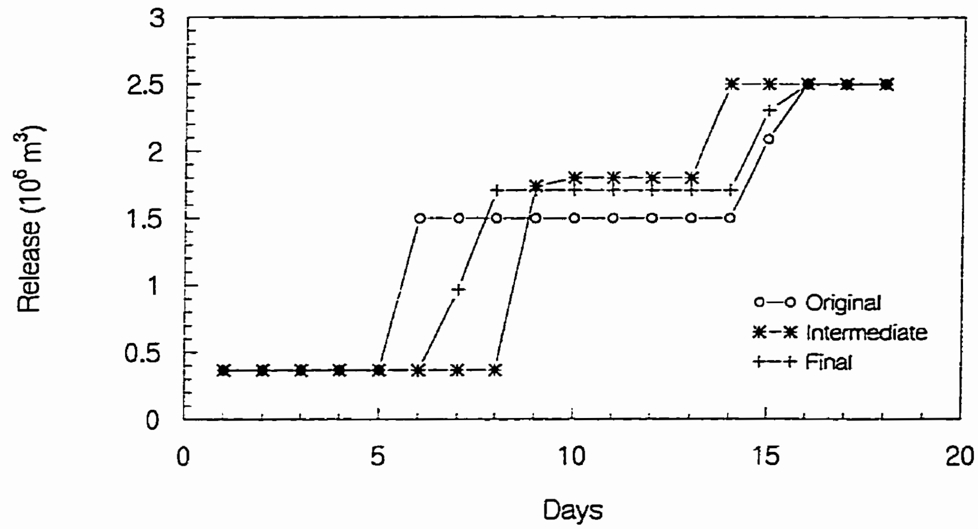


Figure 2.10: Release variations based on reduction in the release and storage zones

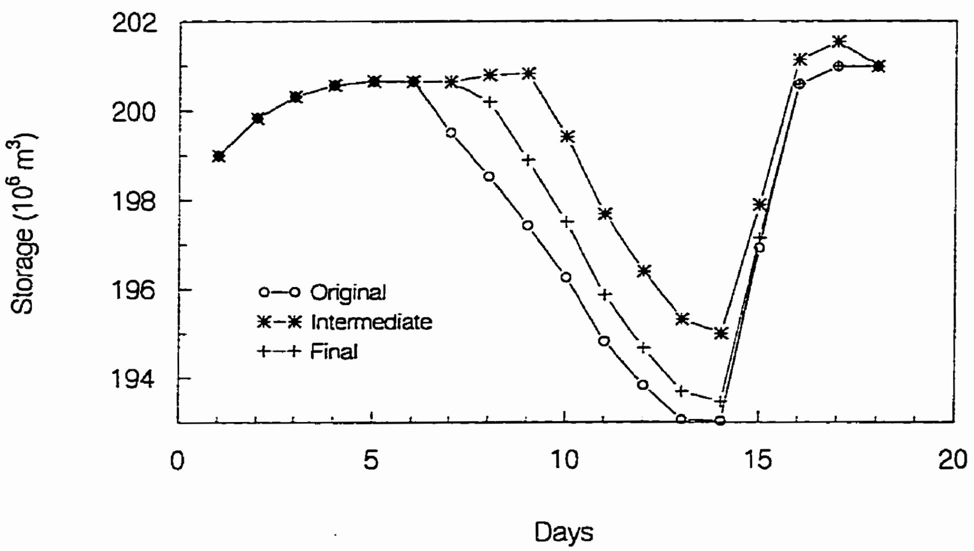


Figure 2.11: Storage variations based on reduction in the release and storage zones

value (124.07). This is due to the fact that the penalty values of both release and storage contribute to the overall penalty value. To evaluate the effect of L value and the type of membership function on the operation schedule, the following simulation is performed. In this case the membership corresponding to Figure 2.6(b) is used. Only the reduction in the first zone of the release is considered. It is evident from Figure 2.6(b), a decreased preference is attached to the reduced zone than the original zone. As the objective of the **Model IB** is to minimize the penalty (reflected indirectly in the constraint (2.40)), the formulation will force the result to match with the original formulation results (**Model I**). In these type of cases, the L value or the degree of level of satisfaction can be limited to a predetermined constant (Munro, 1984). This constant value can be interpreted as a minimum level of support in terms of satisfaction. Figure 2.12 shows the storage variations for such an experiment where the L value is limited to 0.75.

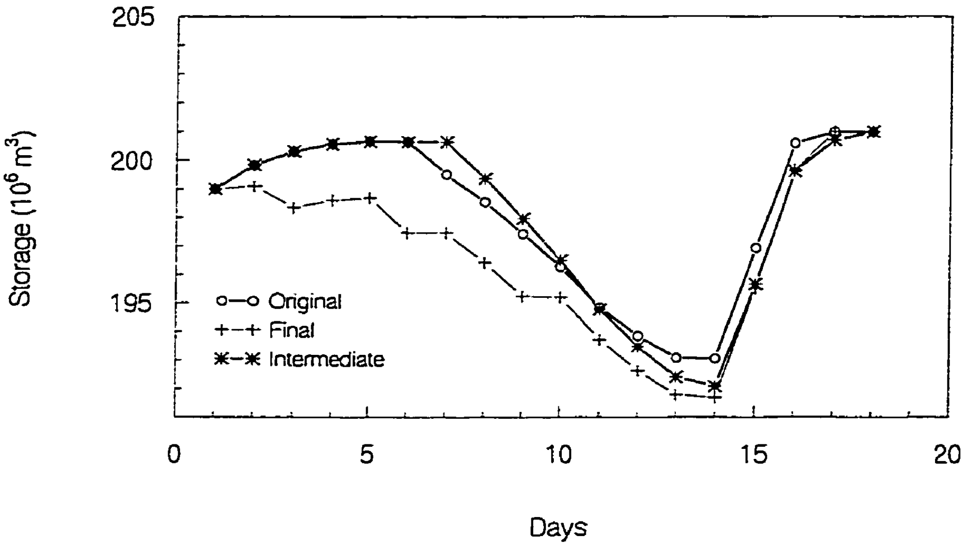


Figure 2.12: Storage variations based on the reduction in the release zone

The variations due to the final formulation are lower than those obtained from all the previous cases. This is attributed to the fact that the restriction on the value of L results in higher release decisions and lower storage values. The uncertainty in the definition of penalty coefficients is addressed through **Model II** and **Model IIA** formulations. The membership function used in this case is similar to one shown in the Figure 2.6(a). For the present case, the value, b_d, refers to the original penalty coefficient while b_o represents the increased coefficient value. The difference, $b_o - b_d$, is represented by H_o. Simulations are carried to evaluate the sensitivity of reservoir operation for a change in the penalty coefficient values. Figure 2.7 represents a schematic diagram of loss function where the value of penalty coefficient at the point "m" is increased by an amount H_o. Simulation is performed using 90 (monetary units) as a value for H_o. The results are shown in the Figures 2.13 and 2.14.

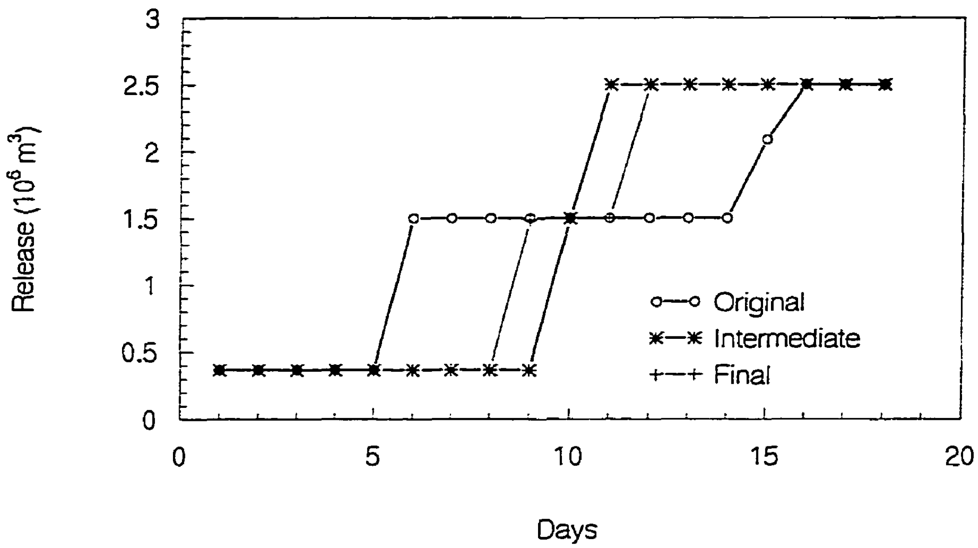


Figure 2.13: Release variations due to increase in penalty coefficient of storage

Release decisions are different from the results due to original formulation shown in the same figure. It is interesting to note that the storage variations are close to that of the intermediate formulation. This is attributed to the nature of membership function used.

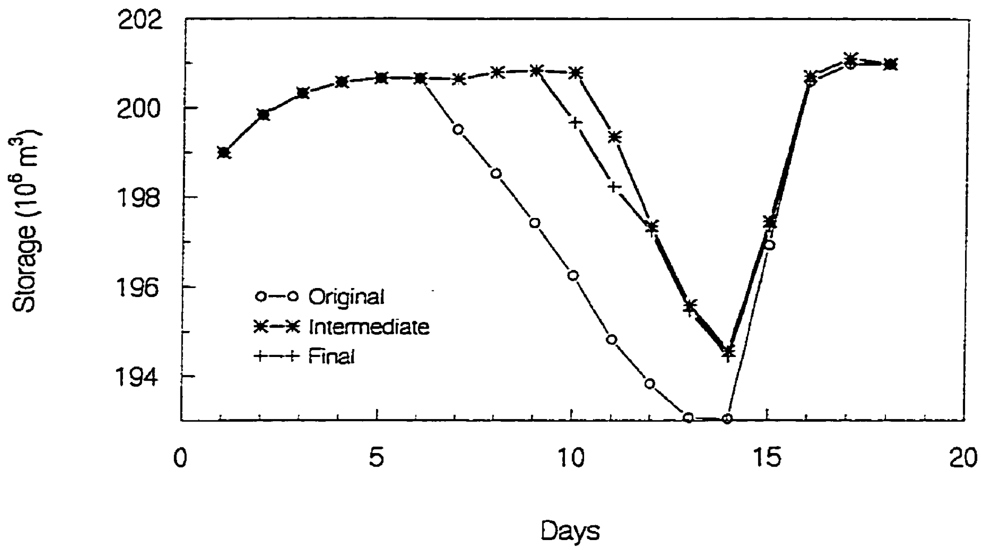


Figure 2.14: Storage variations due to increase in penalty coefficient of storage

Release decisions are lower than the original formulation as there is no change in the release loss function, whereas the storage values in the first zone now have increased penalty values. This results in higher storage values. In another simulation, the penalty coefficients related to release and storage are increased. The values of H_o in this case are 90 and 6 monetary units, for storage and release respectively. The membership function used to indicate the preference is same as the one used in the previous simulation. Figures 2.15 and 2.16 show the release decisions and the storage variations respectively for the case considered.

It is interesting to note that the final formulation results are close to the intermediate formulations in case of both release as well as storage. This can be attributed to the increased penalty coefficient values for both storage and release.

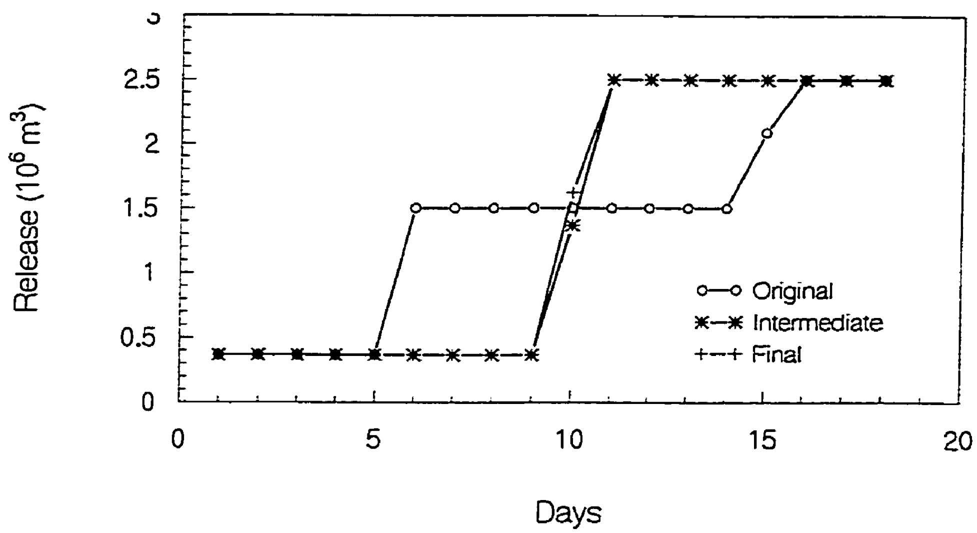


Figure 2.15: Release variations due to change in penalty coefficients

2.5 Symmetric Problem

The Linear and Non-Linear optimization models developed earlier under fuzzy environment were initially non-symmetric and were later modified to a form that is symmetric. Formulations at three steps are solved to obtain the final solutions. These formulations are required for problems where the solution space is fuzzy and objective function is *crisp* (Teegavarapu and Simonovic, 1999). In case of symmetric fuzzy mathematical programming problems, the objective function as well as the constraint space are considered fuzzy and therefore there is no need for the Step II formulation. A non-symmetrical model can be transformed into a symmetrical one if an equivalent model can be derived so that the objective function can be fuzzified. In the present context it is assumed that the decision maker can provide a specific interval within which the objective function value can lie along with preference

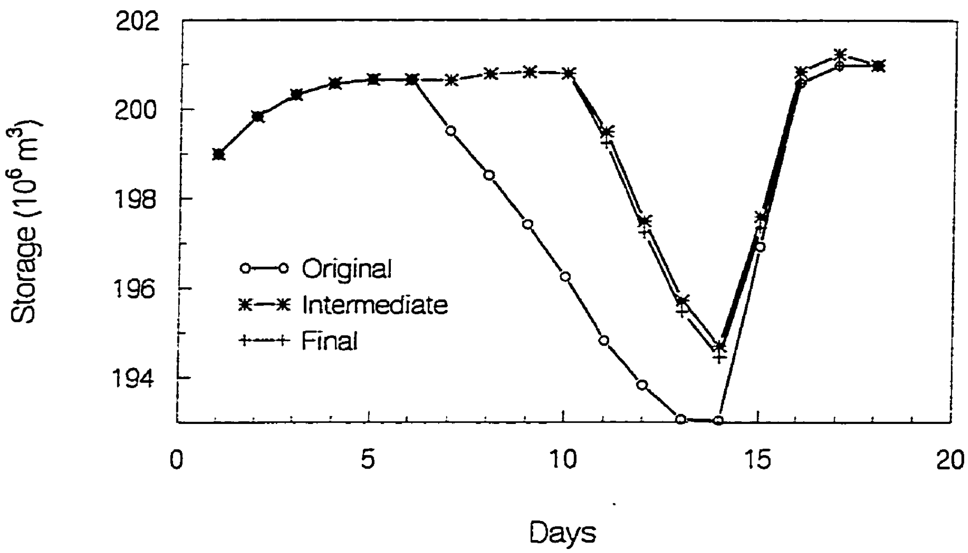


Figure 2.16: Storage variations due to change in penalty coefficients

through membership functions. Tolerances can be used to obtain the intervals if the initial values of the objective function and the lower bounds on the constraints are known. A symmetric fuzzy Linear Programming model can be described as follows:

$$Minimize \quad CX \underset{\sim}{\leq} f_z \tag{2.47}$$

$$subject\ to \quad AX \underset{\sim}{\leq} b \tag{2.48}$$

CX and AX are the objective and constraint matrices have similar definitions that are already provided, whereas f_z is the upper bound on the objective function. This is equivalent to sum of f_o and any tolerance value t_z provided by the decision maker. The value of f_o can be obtained by using the original formulation. The final formulation can be directly solved if this appropriate interval, $([f_o, f_o + t_z])$, is available.

MODEL III

$$Maximize \;\; L \tag{2.49}$$

subject to

$$\sum_{t=1}^{T}[SD_2\ SD2_t + SD_1\ SD1_t + SS_1\ SS1_t + SS_2\ SS2_t + SS_3\ SS3_t$$
$$+RD_2\ RD2_t + RD_1\ RD1_t + RR_1\ RR1_t + RR_2\ RR2_t + RR_3\ RR3_t] + (t_z)\ L \leq f_z \tag{2.50}$$

Experiments are conducted using few cases of symmetric problem. **Model III** is solved for a case in which the first release zone, on the left side of the target release zone is reduced by 0.2 10^6 m^3. The Membership function shown in Figure 2.6(a) is used for this case to represent the decision maker's preference in reducing the zone.

The membership functions used in deriving the constraint (2.38) and objective function (2.36) in **Model IA** incorporate the preferences that are conflicting, thus producing a satisfying solution to the degree of L. The L value obtained is 0.51. On the other hand, the final objective function value obtained is different than the one obtained using the **Model IA** formulation. In the present case, the final objective function value in monetary units is 120.92, whereas in the previous case is 124.07. This can be attributed to the property of membership function given in the Figure 2.6(c). If the tolerance value is equal to the value 30.88 ($f_1 - f_o$) and the initial objective function value is 108.86 (f_o) then final objective function value (124.07) will be the same as obtained by the **Model IA** formulation. Another requirement is that change made to release zones and the preference attached through membership functions for its reduction must be the same.

Table 2.2: Results of symmetric fuzzy model application

Tolerance (t_z) 10^6 m^3	Reduction in release zone points/10^6 m^3	L	Objective
50	0.3	0.62	127.68
20	0.3	0.40	120.81
10	0.3	0.26	116.29
30.88	0.3	0.51	124.07
30.88	0.2	0.61	120.92
30.88	0.1	0.76	116.21

It can be observed from the Table 2.2 that using the base value of objective function f_o, in the first three experiments, the final objective function value decreases as the tolerance is decreases. The L value also decreases to satisfy the fuzzy constraint and the objective function with decreased tolerance interval. In the next set of experiments (reported in the table), it can be noted that the reductions in the penalty zones for a constant tolerance value for the objective function will reduce the final objective function values. This is obvious as the magnitude of reduction in the first release zone influences the penalty value and the L value. A comparison of final storage variations due to use of **Model III** with tolerance of 20 above the base value and due to **Model IA** formulation is shown in the Figure 2.17. It is evident from the figure that storage values are almost identical excepting in few time intervals.

The advantage of symmetric formulation is that tolerances for both constraints and objective function can be changed as long as the feasible solutions can be obtained. The decision maker can provide vague upper and lower bounds on the penalty value (i.e. objective function) that is acceptable while providing the tolerances for the constraints. The L value obtained as a solution will change based on tolerances and the membership functions used for including the preferences.

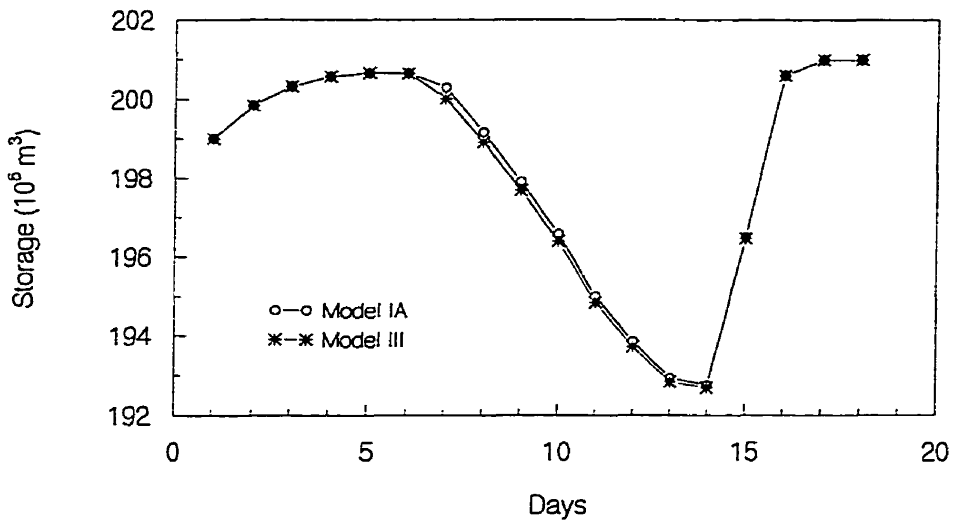


Figure 2.17: Storage variations based on reduction in the tolerance value

A variety of cases can be modeled using the symmetric approach provided the decision maker is able to provide required information for allowances on objective function. Symmetric problems are easy to solve and also provide an option to explore the possibility of considering more flexible operational decisions. Infeasibility can be avoided by judicious selection of tolerance intervals.

2.6 Modeling the Shape of Loss Functions

In the introduction part of this chapter, an idea was tossed that modeling the shape of loss function or replacing them with fuzzy membership function may be possible. This idea is tested and the concerns regarding modeling issues are discussed here. Figure 2.18 shows a comparison between loss curve and an appropriate membership function. It is interesting to note the similarity between these two curves.

The loss function in one way indicates the increasing penalty as the deviations from the target point increase. This type of relationship is also reflected in the membership function that shows a similar property. The value of membership decreases as the deviations increase on both the sides of the target, indicating a decreasing preference to increasing deviations.

The problem can be posed as fuzzy Linear Programming formulation. The tolerances can be used to modify the constraints to include under and over achievements and corresponding aspiration levels in the form of membership functions. The idea is to solve a non-symmetric fuzzy model with deviations as fuzzy constraints.

The concept is different from the one proposed by Fontane et al. (1997) where the membership functions are derived from actual surveys and are used as a part of objective function in a fuzzy dynamic programming formulation. In the present case, the membership function is modeled by defining the problem of deviations as tolerances for the constraints. An experiment is conducted with a formulation (not reported here) considering a two-sided membership function as shown in the Figure 2.18. A feasible solution is obtained. However, the physics of the problem is not captured in the model as over and under achievements

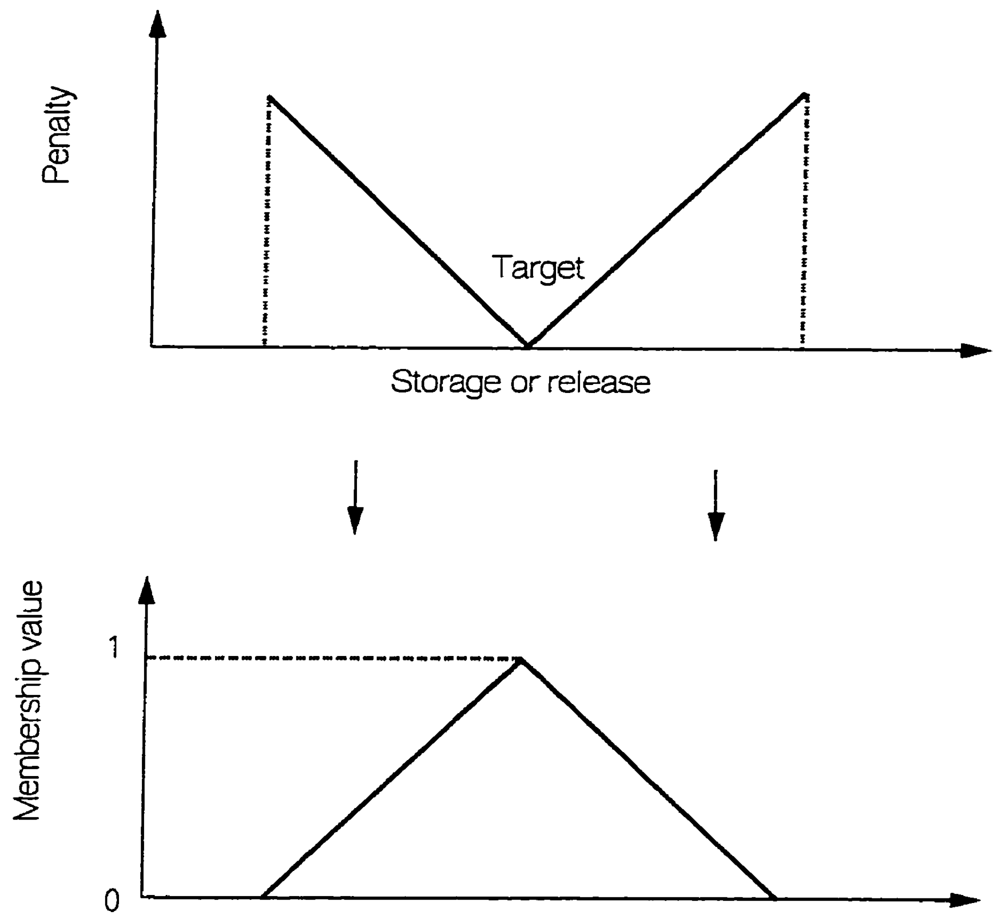


Figure 2.18: Resemblance between loss curve and a membership function

are not feasible at the same time once an appropriate value for L is obtained as a solution.

One way of handling this problem might be to use two separate variables that represent different satisfaction levels for both under and over achievements. An appropriate condition that both cannot be positive in any given time interval can be included in the formulation. It should be noted that modeling of loss functions using fuzzy mathematical programming provides an alternative method of including the loss functions and the feasibility of such an approach needs to be tested using the formulations with specific restrictions suggested here. This idea is not without advantages. Fuzzy set theory provides many procedures (Kickert, 1978) to aggregate membership functions (if derived from more than one decision maker) that may not be not possible using traditional approaches.

2.7 Modeling Issues

In the fuzzy mathematical programming framework presented in this study, intersection operator, *"Min"* was used to define the *crisp* equivalent that can be solved using any Linear Programming code or solver. While, *"Min"* is considered appropriate there are several other operators (Zimmermann, 1987) that can be used. The simulations carried out in the present study are limited to the use of a portion of release and storage loss functions. This is due to a fact that low inflows associated with winter, would force the models to generate storage levels or release decisions that lie on the under-achievement side of the storage and release targets respectively. Hence any changes made in the loss functions on the other side (right side) might not affect the reservoir operating rules. The changes made in the penalty zones and coefficients for all the simulations are in such way that they increase the overall penalty value in monetary units. This is more realistic as the reservoir managers tend to impose higher penalties for achieving the preset targets.

To test the operation models in critical situations, low inflows associated with winter are used in the present study. However, there is no conceptual difficulty using any type of loss functions associated with any season. The results due to final formulations will depend on the inflows, changes made to loss curves and the membership functions used for preferences.

Many variations of the cases mentioned above can be used to generate results for evaluation of operation rules and their sensitivity to decision maker's preferences.

From the experiments conducted, it can be concluded that the reservoir operating rules are sensitive to decision maker's preferences attached with the definition of loss functions. This is evident from the results due to final formulations, that can be called as *compromise operating policies.* Sensitivity analysis of operation rules for a variety conditions is not equivalent to what is achieved by the fuzzy optimization models proposed in the present study. A major limitation of traditional sensitivity analysis is the inability to handle the preferences. Conflicting nature of the fuzzy constraints dealing with the penalty zones and coefficients, and the objective, which is the value in monetary units, is captured in the optimization framework. Finally, an important aspect that should be noted is that one cannot expect improved solutions (objective function values) by using fuzzy formulations. The solutions obtained are appropriate for the stipulations imposed. Therefore the results can only be more realistic, meaningful and sensitive to decision maker's preferences.

The membership functions for the preferences are assumed to be linear and are known. Functions based on actual surveys, if available, can be used with appropriate modifications to the formulations presented in the study. The approach presented can be summarized in three steps: (i) development of loss functions to include in mathematical programming formulations (ii) obtain decision maker's preferences to develop fuzzy formulations (iii) generate *compromise operating rules.* While the first issue was addressed in the past by many researchers (e.g. Datta and Burges, 1984; Lund and Ferreira, 1996), the latter two are handled by the procedures developed in the present study.

Uncertainty associated with inflows and operation of multiple reservoir systems are the major aspects that need attention when extension to the present methodology is planned. Extensions along these lines are possible. However, the complexity of formulation can be commented on, only after preliminary experiments are conducted considering these issues using the approaches presented in this study. These aspects when included in the present framework will increase the scope of the problem. In the past uncertainty associated with inflows into the reservoir systems are considered using either explicit and implicit stochastic approaches. In a recent study Russell and Campbell (1996) discuss the development of a fuzzy rule base (FRB) for a reservoir operation problem while considering the stochastic nature of inflows and energy prices implicitly. They indicate the difficulties involved in explicit representation in this context. To address the problem of stochastic nature of inflows, the concepts of probability and fuzzy set theory can be combined to derive a *fuzzy-risk approach.*

2.8 Summary

The frameworks both in symmetric and non-symmetric fuzzy mathematical programming environment presented in this chapter can be extended to a system of interconnected reservoirs where the formulations would depend on the number of reservoirs and decision makers managing the system independently or collectively. In case of multiple decision makers, application of fuzzy multi- person decision making approach (Kickert, 1978) is applicable. On the other hand, formulations are relatively simple if no conflicting preferences exist among the decision makers.

A new approach in dealing with the problem of uncertainty associated with the definition of conventional loss functions used in reservoir operation models is discussed in this chapter. The methodologies are well suited for applications where the information or the method by which the loss functions are derived is debatable. As the penalty zones and coefficients are considered fuzzy, the decision maker is no longer compelled to provide precise definitions (shapes) of loss functions. The optimal operating rules generated are a *compromise* between the original decisions and the rules when no preferences are attached to the changes made to the loss functions.

The problem of handling both uncertain penalty coefficients and imprecise zones at the same time is not attempted here, while there is no conceptual difficulty in extending the present approach to consider this case. Modeling the shapes of the loss curves to replace them with fuzzy membership functions using the concepts of fuzzy mathematical programming approach is difficult, if not impossible, even though a mathematical solution is possible. The models developed are easy to implement in real-life situations if appropriate methods are used to generate the preferences in the form of membership functions.

The concept of *compromise operating policies* can be extended to cases where rules from long- and short-term operation models are available. In the former case the rules can be derived from stochastic optimization approaches (e.g. Stochastic Dynamic Programming) with an objective of maximizing or minimizing an expected value of a performance measure. In case of real-time operation, any model based on deterministic inputs (through forecasted values) can be used. The *compromise operating polices* derived in this case are in fact sustainable operating rules. The sustainable operating rules derived by Shrestha et al. (1996) using a Fuzzy Rule Based (FRB) model are conceptually different from the *compromise operating policies* suggested here.

2.8.1 Postscript

Issues relevant to information uncertainty are discussed in this chapter. The method presented is not exhaustive in dealing with a variety of problems within the area of reservoir operation relevant to imprecise information. However, this research work can be regarded as a starting point in dealing with a form of information uncertainty for specific reservoir operation problems that make use of economic information. Probability theory can be used to complement fuzzy sets to process the uncertainty while modeling real world systems. Pedrycz and Gomide (1999) state:

> " .. no single universal vehicle exists to cope with uncertainty. Some other formal frameworks may well be developed (and likely will be developed) to address specific issues of uncertainty. In this sense, fuzzy sets and probability seem to be complementary rather than antagonistic ideas"

The *fuzzy-risk approach* discussed earlier projects a similar idea. A topic of significance in regard to short-term and real-time operation of reservoir systems is *"system representation"* within the optimization models. Next in the line of issues addressed in the present study is this area. Representation of physical system in mathematical programming formulations and other relevant issues are addressed in the next chapter.

Chapter 3

System Representation

The mere formulation of a problem is far more often essential than its solution, which may be merely a matter of mathematical or experimental skill.

- Albert Einstein

3.1 Introduction

In the previous chapter, approaches that can handle uncertain and imprecise elements of reservoir operation are presented. The present chapter extends the scope of the research to real-time operation of multiple reservoir systems to address the issue of system representation. System representation in the present study is defined as the *"mathematical representation of the physical system within a model formulation developed for optimizing an objective"*. System representation or formulation is an important issue that needs attention while developing optimization models.

Edgar and Himmelblau (1988) provide a set of the six general steps that can be used to formulate and solve optimization problems. One of the steps relevant to the topic of *system representation* is appropriate here:

> Develop via mathematical expressions of a valid process or equipment that relates the input-output variables of the process and associated coefficients. Include both equality and inequality constraints. Use well-known physical principles, empirical relations, implicit concepts, and external restrictions. Identify the independent and dependent variables to get the number of degrees of freedom.

In general, the extent and nature of representation of the physical system in a optimization or simulation model depends on : (i) basic understanding of the system; (ii) transferability of knowledge of the system into a mathematical form; (iii) approach and the tool selection, and their availability and (iv) limitations of the tool to accept variables or mathematical forms in order to incorporate specific conditions. These issues in the context of optimization models are discussed briefly here. System representation issues relevant to simulation models are discussed in Chapter 5.

Knowledge of the System

The formulation or representation issue begins with the understanding of the underlying physical processes that govern the system behavior. Identification of system boundaries, selection of state variables that influence the system the most, recognition of non-linear processes and nature of inputs (stochastic or deterministic) is the next essential step. Also, a basic idea about the nature of expected solution and limits (ranges) of some variables is important. The strength of the formulation and its use depends on this issue.

Mathematical Representation

Translation of system processes or capturing the physics of the problem into a mathematical form is the next step. This involves identification as well as definition of objective function (performance measure). Functional description of the system in a form acceptable by the optimization approach follows. For example, in case of Dynamic Programming (DP) model, the development of recursive relationship is crucial. Development of constraints based on system boundaries, binding and relaxed, upper and lower limits that are generally represented by equalities or inequalities, is the next essential step.

In mathematical programming formulations, a measure of system performance is often used as an objective function that is maximized or minimized. The physical processes are represented as constraints (equalities and inequalities). System representation can be exhaustive in case of simulation models as they are developed using high level programming languages. Also, any degree of complexity associated with the natural system can be incorporated into a serial computer code. If a simulation model is developed using high level programming language (e.g. FORTRAN or C) then the physical processes are captured and coded in a specific order. This is due to the fact that computer code is executed in a serial order. Parallel implementations of serial code is an exception to this. If the models are developed using other approaches (e.g. Objected-Oriented simulation), the representation can be limited in some cases.

Approaches and Tools

Selection of optimization approach, more appropriately, the right tool to solve the model is the main issue that would influence the extent of representation. Depending on the nature of the formulation either linear or non-linear optimization approaches can be selected. A Dynamic Programming (DP) is ideal for highly non-linear as well as discontinuous objective function and constraint relationships within multi-stage decision making problems. A variety of conditions (decision alternatives, discrete variables, special conditions) can be represented in DP models. Linear programming (LP) is appropriate for large scale formulations that are linear in nature and for efficient solutions with negligible computational times.

Representation of constraints and functional relationships in an easy algebraic form rather than using matrix notations is an aspect that should be given due consideration. Tools that provide this feature should be selected. For e.g. GAMS and NUMERICA[1] optimization software provide modeling languages to represent the formulations in algebraic forms that can be linked to a variety of solvers. Non-traditional optimization approaches such as

[1] Global optimization software, ILOG corporation

Genetic Algorithms (Michalewicz, 1998) and Simulated Annealing can be used for problems that cannot be solved by available state-of-the-art tools. Since, non-traditional approaches use simulation models, there are no constraints on the system representation in such cases.

Tool Specific Limitations

Use of special variables (discrete, integer or binary) is made whenever a specific condition has to be specified or as the physics of the problem demands. Decision alternatives in formulations can be represented by the use of binary variables. On the similar lines, binary variables can be used to activate or de-activate some variables that take on values on continuous domain. The presence of these variables in formulations limits the tool selection process. In order to handle integer, binary or discrete variables in a non-linear environment, a mixed integer non-linear programming solver should be used. A number of constraints associated with computer implementation of approaches and development of tools limit the exhaustive system representation. These include: (i) number of constraints with special variables; (ii) dimensionality problems in case of DP; (iii) requirement of initial guess (for variables) for most of the standard non-linear programming solvers and (iv) conditional statements and iterative solution procedures.

3.2 Representation of Water Resources Systems

In general, Linear, Non-Linear and Dynamic Programming techniques have been used in the past for solution of the most of the routinely encountered problems in the field of reservoir operation (Yeh, 1985). Dynamic Programming (DP) has played a major role in sequential decision-making process inherent in many water resources management problems (Yakowitz, 1982). Wealth of references concerning the applications of these optimization techniques to reservoir operation problems can be found in the literature (Loucks et al., 1991; Wurbs, 1993). The advantages and difficulties associated with the use of these optimization techniques in a variety of reservoir operation models are discussed by researchers (e.g. Yeh, 1985; Mays and Tung, 1992). The classical optimization techniques are ideal tools for solving many of the reservoir operation problems, however the computational requirements are intractable in many instances.

The computational burden and representation of the problem itself have been consistent hurdles in solving many complex multiple reservoir operation problems characterized by large number of decision variables. In attempting to solve a problem of multi-period and multiple reservoir operation, it is important to consider the nature of the formulation (e.g., number of variables, non- linearities, constraints) and the computational power required to solve the problem in real-time. Traditional optimization algorithms still suffer from at least one of these limitations : (i) computational intractability; (ii) requirement of calculation of derivatives of complex functions; and (iii) need for too many assumptions for the problem to be transformed into a standard form required by the optimization technique. These modifications may range from linearization of the objective function and constraints to incorporating problem specific assumptions into the formulation.

To use the techniques that can guarantee global optimal solutions or at least optimal solutions, representation of the physical systems is often simplified in mathematical programming models. Various problem-specific assumptions are used to represent the system in a mathematical form that can be conveniently handled by the optimization tool. This approach ensures global optimal solutions if at all, however at the cost of unrealistic formulations. On the other hand, an exhaustive representation of the physical system along with a technique that provides near-optimal solutions can be accepted for most real-life problems.

In this chapter, issues relevant to system representation are addressed with the help of a real-time operation model developed for a multiple reservoir system. The model description, formulation, application to an existing reservoir system and discussion on representation issues are provided next, in that order.

3.3 Test Problem

The reservoir operation problem selected in the present research has all the complexities that provides an opportunity to address a number of issues relevant to system representation. These complexities include a non-linear objective function, a variety of constraints (equality and inequalities) and special variables (in this case, binary). Above all this, there is a need for this formulation structure to develop a realistic representation of the system. System representation issues can be addressed in a better way if an alternate formulation or a simplified formulation can be developed and implemented. The reservoir system selected in this research is a set of four hydropower plants in series. An important feature of the system is that the generating plants are hydraulically coupled. Literature review relevant to this problem area is provided here and then the model formulation and results follow.

3.4 Real-Time Operation of Hydropower Systems

A comprehensive survey of existing optimization models for general real-time operation of reservoirs would be quite an undertaking. Wealth of literature is available in the areas of long term, mid-term and short-term operation of single and multiple reservoirs systems. A comprehensive review of these models is not attempted here. Detailed reviews of reservoir operation models and the optimization techniques used are provided by many researchers. Reviews by Yeh (1985), Yakowitcz (1982) and Wurbs (1993) provide an exhaustive compilation of research works. Considering this, works closely related to proposed research study are reported. The operation of multiple reservoir systems with an emphasis on hydropower reservoirs is discussed next. It should be noted that the specific areas on which the present research work concentrates (hydropower reservoir operation) limits the literature survey to a certain extent.

Optimal operation of hydropower reservoirs in real-time is a complex and challenging task addressed by many researchers in the past few decades. Comprehensive models (e.g. Yeh et al., 1992, Tejada-Guibert et al., 1990, Turgeon., 1981) that deal with variety of problems related to short-term operation of hydropower reservoirs are now available in literature. These models address various problems relevant to hydro and thermal power systems. Grygier and Stedinger (1985) report a set of algorithms for hydropower optimization that include Successive Linear Programming (SLP), optimal control and LP - DP. An improved algorithm based on SLP was developed by Reznicek and Simonovic (1990) for optimal operation of a single hydropower system. Recent review by Wurbs (1993) provides description of models developed for hydropower scheduling considering both hourly and daily time intervals. Lund (2000) in a recent study provides a set of theoretical rules for hydropower reservoirs in series and parallel derived based on economic incentives of operation. The present study deals with the development of a short-term operation model for a system of cascading hydropower plants. The work addresses the problem of hydraulic coupling between reservoirs which influences the operation schedules.

The following discussion on the recent studies relevant to hydropower reservoir operations provides a representative sample of a number of works reported in literature in the past decade. The words *reservoir* and *plant* are used interchangeably in the text, while they mean a hydropower generating reservoir. Yeh et al. (1992) developed an optimization model for real-time operation of hydro-thermal system. Three models were developed for obtaining optimal operating schedules on a daily basis. Even though they did not consider a hydraulically linked system, they indicate the importance of hydraulic coupling in the operation of cascading hydropower plants.

Tejada-Guibert et al. (1990) developed a non-linear optimization model for multi-month operation of a hydropower system. They generate alternate operating schedules using different objective functions in the optimization model. The issue of hydraulic coupling was not addressed in their study. Martin (1995) developed a method based on optimization as well as simulation to develop hourly generation schedules. Linear Programming was used as an optimization tool. Turgeon (1981) used progressive optimality technique to arrive at optimal operating rules for a system of hydropower plants located in series on the same river. Time of water travel between the plants was considered while deriving the operating rules.

For plants located on a single river, two aspects are of importance: (a) hydrologic linking; and (b) hydraulic coupling. Hydrologic linking indicates that all the flows from the upstream reservoir and the local inflows join the immediate downstream reservoir. Hydraulic coupling is assumed to exist when the forebay elevation of a plant influences the tailwater elevation of an immediate upstream plant. Since the head required for power generation is calculated based on the forebay elevation and the tailwater elevation, hydraulic coupling becomes an important aspect that needs to be considered while developing operating rules. Generating plants with Pelton turbines are an exception. One of the important issues addressed in the present study is the hydraulic coupling between the plants. In many cases, the effect of hydraulic coupling can be neglected if the distance between reservoirs is too large that the tailwater elevation is not influenced by the downstream reservoir's forebay elevation.

Hawary and Christensen (1979) have presented an elaborate discussion on different types of approaches used for scheduling of coupled hydropower reservoirs. The approaches consider hydraulic coupling between the plants. In all the cases they considered, the plant discharges were assumed to be pre-specified over the optimization time interval. This assumption might be helpful in solving the optimization problem but is not realistic. Also, the forebay elevation at one plant is assumed to be equal to the tailwater elevation of the next upstream plant. The variation of tailwater elevation with respect to plant discharge and conditions at the immediate downstream plant are not considered. This issue is addressed in the present study to handle the hydraulic coupling within an optimization framework.

Recent works (Soares and Carneiro, 1991; Lyra and Ferreira, 1995) have provided useful real-time operation models for generation scheduling for a series of plants on the same river (stream). Wood and Wollenberg (1984) report application of Discrete Differential Dynamic Programming (DDDP) to two hydropower reservoirs that are not hydraulically coupled. Lund and Guzman (1999) discuss operating rules for hydropower reservoirs in series and parallel. PRSYM (Power and Reservoir System Model) (Shane et al., 1995) of United States Tennessee Valley Authority (US TVA) and Hydro-Quebec model (Robitaille et al., 1995) developed by Hydro Quebec are the two comprehensive operation models now available for solving the real-time operation problem of complex network of hydropower systems. These models are capable of handling dynamic tail water effects in case of cascading reservoir systems. The PRSYM (Magee et al., 1995) uses a look up table of tailwater elevation curves, while Hydro-Quebec model (Robitaille and Lafond, 1995) uses an iterative technique to address the issue of hydraulic coupling in the optimization framework. In the latter work Successive Linear Programming (SLP) is used as an optimization approach. The methodology proposed in the present study is different from that of these two models.

Soares and Carneiro (1991) have developed an operation model where the hydraulic coupling between the plants is assumed to be negligible. They provide a systematic study of cascading reservoirs and comment about the operating schedules based on the position of the reservoir in the complete system.

Lyra and Ferreira (1995) developed a multi-objective approach for short term scheduling of a highly coupled system of hydropower reservoirs. DDDP was used to solve the optimization problem. In their study, the variation of forebay level within the time interval was not considered. Even though the present study addresses a similar kind of problem, the methodology of handling the hydraulic coupling is different. The variation of forebay level while arriving at the gross head is considered in the present work. Also, discretization of variables is not required in the model developed in the present study, which is required in case of DDDP formulation. This can be considered as an advantage, as discretization may lead to approximations.

The model developed in the present study is a deterministic scheduling model similar to the earlier models developed by Soares and Carneiro (1991) and Lyra and Ferreira (1995). The model can be adopted in an adaptive manner whenever information about the inflows or other variables (e.g. energy demands) becomes available. This type of approach is widely accepted in literature (e.g. Yeh, 1985; Soares and Carneiro, 1991) relevant to reservoir operation and is referred to as adaptive real-time operation.

The problem addressed here is concerned with short-term operation of a series of hydropower reservoirs. One main characteristic of the system of reservoirs considered is the high hydraulic coupling between the cascading plants. Therefore emphasis is placed on this issue in the present study. An exhaustive review of existing models (limited in number) that consider hydraulic coupling in case of a network of hydropower reservoir systems, leads to the following observations: (i) only few models consider the hydraulic coupling aspects through a number of assumptions; (ii) physical representation of the system within an optimization framework is often simplified; (iii) approximations are made in some instances due to discretization of variables using certain approaches and (iv) models are confined to short-term operation as opposed to real-time operation. Based on these observations, the present study attempts to address the issue of hydraulic coupling in the context of real-time operation of multiple hydropower systems. An optimization model developed for this purpose is discussed next.

3.5 Model Features

The main objective of the operation model is to provide optimal real-time generation scheduling rules for a set of hydropower generating plants on a single river. The optimization model to be formulated should address two important issues: a) non-linear objective function (energy generation) and non-linear constraints; and b) hydraulic coupling. While the first aspect can be handled by using a non-linear optimization model, the latter needs a set of constraints to model the physical linking between the plants. These constraints can be incorporated using binary variables that help address the aspect of hydraulic linking.

The type of formulation discussed above falls into the category of Mixed-Integer Non-Linear Programming (MINLP) models. MINLP formulations are used in many applications especially in transshipment and process synthesis problems related to the fields of operations research and chemical engineering respectively. Floudas (1995) provides a comprehensive review of the development of algorithms for solving the MINLP formulations along with their computer implementations. The author uses a special structure, referred to as superstructure to represent various problems in a general form. A superstructure provides a representation of the problem indicating the type of constraints involved and the objective function along with the description of the nature of the variables (for e.g. binary, integer, discrete or continuous). The superstructure of a typical minimization problem using MINLP formulation can be written as,

$$Minimize \;\; f_m(x) \tag{3.1}$$

$$subject \;\; to$$

$$h(x, y) = 0 \tag{3.2}$$

$$g(x, y) \leq 0 \tag{3.3}$$

$$x \in X \subseteq \Re^{n_c} \tag{3.4}$$

$$y \in Y = \{0, 1\}^{l_b} \tag{3.5}$$

Here, $f_m(x)$ represents the objective function which can be minimization of the cost of energy production and other costs in the present context of real-time reservoir operation. x is a vector of n_c continuous variables that can represent plant discharge, storage, spill and all other variables which can take continuous values. The variable, y, represents a vector of l_b $0-1$ variables which can be used for modeling the physical link between the plants using tailwater elevation curves.

The formulation (equations 3.1 - 3.5) is referred to as a Mixed-Integer Non- Linear Programming (MINLP) problem with binary variables. Formulation of MINLP problems should be developed with complete knowledge of the problem at hand. Nemhauser and Wolsey (1988) emphasized that in the case of integer programming formulating a good model is of crucial importance than solving it. Many applications of MINLP with binary variables are available, especially in the field of chemical engineering (Floudas, 1995). Applications in the specific areas of power industry can be found in the works of Bertsekas (1983) and Bloom (1983).

Binary variables are generally used in formulations where the existence or non-existence of processes are represented with these variables taking only discrete values (0 or 1). Unit commitment problem is an example where decision has to be taken regarding turning the unit on or off. In the present context, binary variables are required to select the appropriate tailwater elevation curve to address the issue of hydraulic coupling. The non- linear nature of the objective function (power generation) and constraints along with the binary variables make MINLP an appropriate choice for formulating the real-time operation problem. The model formulation based on the above superstructure and details of the constraints are given in the following section.

3.6 Model Formulation

A non-linear programming model with binary variables is formulated for optimum daily operation of the power generation plants on a single river. The model provides optimal power production schedules at each of the generating stations considering the strong hydraulic coupling between the plants. The problem considers within the week scheduling with the weekly power target demand assumed to be known. Flow transport delay between plants is also considered in the formulation.

The objective is to minimize the total cost of energy production and the surrogate cost associated with the spill at each of hydropower plants. For the present study the maximum power that is required to be generated, the initial and final conditions (storage states) and forecasted values of local inflows are assumed to be known. These values are obtained from the EMMA (Energy Management and Maintenance Analysis) model (Barritt-Flatt and Cormie, 1988), presently used by the local power utility, Manitoba Hydro, in the case study region for obtaining the weekly operating rules. Based on the weekly target demand, local inflow values and the initial and final forebay elevations, the present model is formulated to obtain optimum daily scheduling rules.

The objective function used in the present study is case study specific, an explanation to this regard is provided here. The function is similar to the one used by Reznicek and Simonovic (1990). It is generally agreed that the objective in case of operation of a hydrothermal system would be to minimize the cost associated with the fuel. On the other hand, for systems without thermal generation, techniques developed for scheduling of hydrothermal systems can be used by assigning a pseudo-fuel cost to the hydroelectric plants (Wood and Wollenberg, 1984). The hydropower plants considered in the present study are a part of a larger network and the objective is to obtain the scheduling rules for the plants with minimum cost of energy production while meeting the target demand. This implies optimal distribution of load between the plants within the time horizon considered.

An objective function different from the traditional objective of maximizing energy is chosen to facilitate the comparison of the performance of the present model to that of an already existing model (EMMA) used by the local power utility. It should be noted that the operational cost of hydropower production used here is provided by the power utility that uses the similar cost structure in the EMMA model. The cost structure for energy production, import of energy and spill (Reznicek and Simonovic, 1990) are available from the power utility. The objective function therefore is application specific and may not be appropriate for situations where the set of plants considered are not part of a larger network of plants and stipulated conditions do not exist.

Details of the EMMA model are given under the section 3.7. The non-linear model formulation developed for the present study is discussed next.

Objective function :

$$Minimize \sum_{t=1}^{T} \sum_{j=1}^{n} (NO_t \ \gamma_o \ (h_{j,t} - T_{j,t}) \ Q_{j,t} \ \beta_{j,t}) + (MO_j \ \ SP_{j,t}) \qquad (3.6)$$

Where : γ_o is a constant; $\beta_{j,t}$ is the overall efficiency of the generating station j for time interval, t; NO_t is the cost of generating a unit of power; and MO_j is the surrogate cost associated with spill; $Q_{j,t}$ is the plant discharge and $SP_{j,t}$ is the spill for the generating station j. The surrogate cost associated with spill for each of the reservoirs in given in the Appendix 1. The head for power generation is given as the difference between forebay elevation $(h_{j,t})$ and tailwater elevation $(T_{j,t})$. Here, n is the total number of generating plants and t is the time interval index, while T is the last time interval under consideration.

A conceptual diagram of the cascading reservoirs is given in the Figure 3.1 to explain the notation used for different variables in the formulation. The objective function confirms with the traditional objective of economic operation of hydropower systems while meeting the system demand. The cost associated with the spill (MO_j) is appropriate for the case study region, where the local power utility decides the priority of the location of the spill. The aim is to develop a real-time operation model for a series of plants that are a part of a network of hydropower reservoirs.

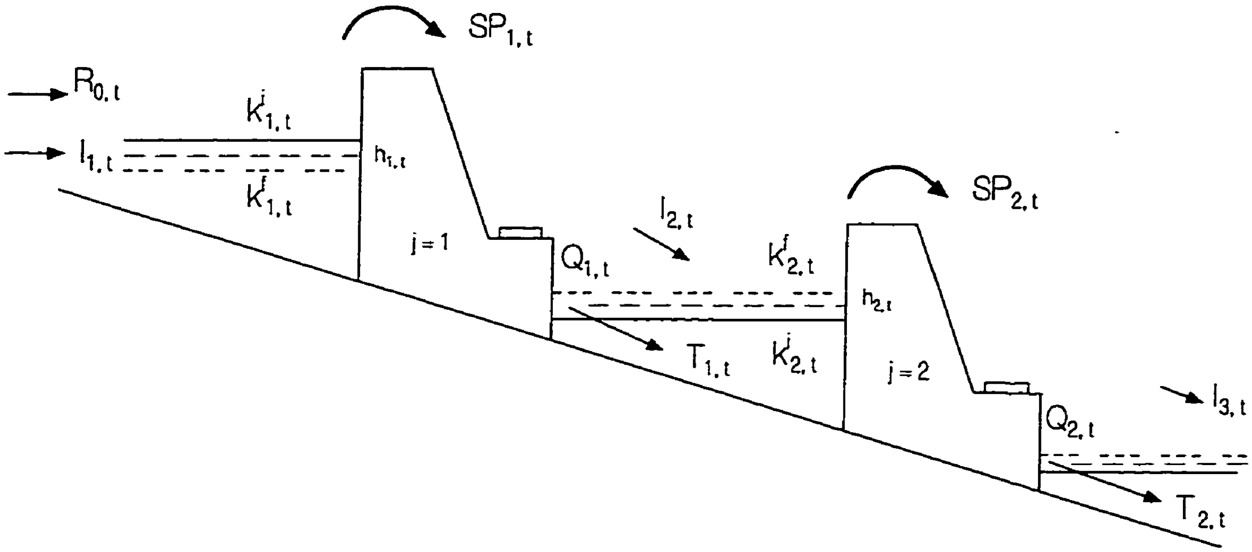


Figure 3.1: Conceptual diagram of cascading reservoirs

Constraints :

1. *Average elevation*

$$h_{j,t} = (k^i_{j,t} + k^f_{j,t})\ 0.5 \qquad\qquad j = 1, n \ \ \&\ t = 1, T \qquad\qquad (3.7)$$

The above constraint is used for obtaining the average forebay elevation at each of the generating stations. An average value is used as the forebay elevation fluctuates within the time period considered. Here $k^i_{j,t}$ and $k^f_{j,t}$ are the initial and final forebay elevations for the time interval, t, associated with the station j respectively.

$$h_{j+1,t} = (k^i_{j+1,t} + k^f_{j+1,t})\ 0.5 \qquad\qquad j = 1, n\ \ \&\ t = 1, T \qquad (3.8)$$

The value of $h_{j+1,t}$ refers to average forebay elevation of reservoir, $j+1$. The subscript, j, t, is used instead of $j+1, t$, as $h_{j+1,t}$ is used for calculation of head at the generating station j.

2. *Selection of tailwater elevation curves*

For any generating station, tailwater elevation curves represent discharge- elevation curves for different downstream forebay elevations. A general form of these curves is given by the equation,

$$T_{j,t} = k^o_{l,j+1} + C_{l,j+1}\ G_{j,t} \qquad\qquad \forall j,\ \forall l,\quad \&\ t = 1, T \qquad (3.9)$$

Where, $T_{j,t}$ is the tailwater elevation, $k^o_{l,j+1}$ is a discrete downstream reservoir's forebay elevation, which is taken as downstream condition for deriving the curves. The complete range of forebay elevation is divided into $m_{j+1} - 1$ equal intervals. For example, $k^o_{l,j+1}$ and $k^o_{l+1,j+1}$ represent the upper and lower values of one such interval respectively. The variable $G_{j,t}$ represents the sum of plant discharge and spill from plant j, while the variable $C_{l,j+1}$ is a constant in the linear equation (3.9). If the local inflow influences the tail water elevation, it has to be included in calculating the total discharge (or project discharge), $G_{j,t}$. A set of typical tailwater elevation curves used in the present study is shown in the Figure 3.2.

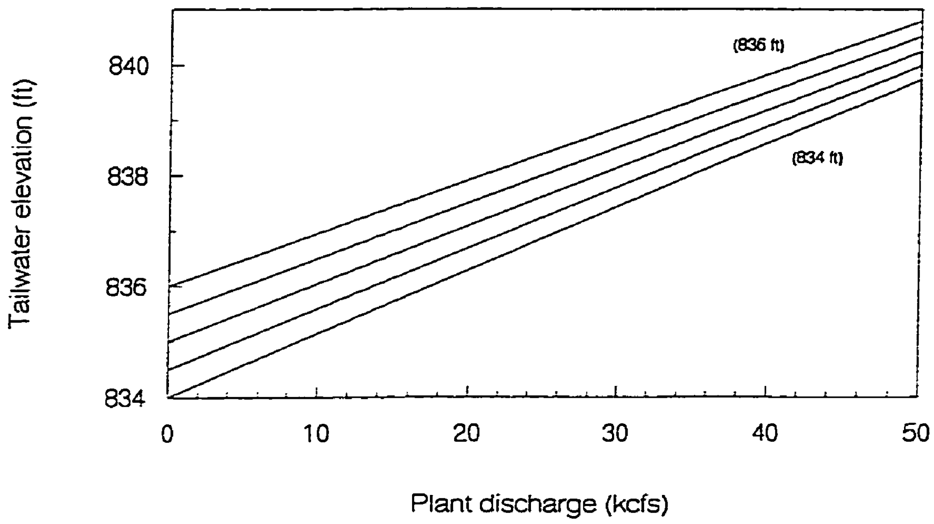


Figure 3.2: Typical tailwater elevation curves

$$h_{j+1,t} - k^o_{l,j+1} \leq \mathbf{M}\ (1 - Y_{l,j+1,t}) \qquad j = 1, n, \quad \forall l \ \ \&\ t = 1, T \tag{3.10}$$

$$h_{j+1,t} - k^o_{l,j+1}\ \ Y_{l+1,j+1,t} \ \ \geq 0 \qquad l = 1, m_{j+1} - 1, \ \ \forall j \ \ \&\ t = 1, T \tag{3.11}$$

$$T_{j,t} = \sum_{l=1}^{m_{j+1}} (k^o_{l,j+1} + C_{l,j+1}\ G_{j,t})\ \ Y_{l,j+1,t} \qquad j = 1, n \ \ \&\ t = 1, T \tag{3.12}$$

The above constraint is for the selection of appropriate tailwater elevation curve. Based on the value of $Y_{l,j+1,t}$ (either 0 or 1), the tailwater elevation curve is selected. The curves have a form $k^o_{l,j+1} + C_{l,j+1}\ G_{j,t}$. Also, the index m_{j+1} indicates the number of tailwater elevation curves available at each of the stations. The intervals and binary variables for a specific case are shown in the Figure 3.3.

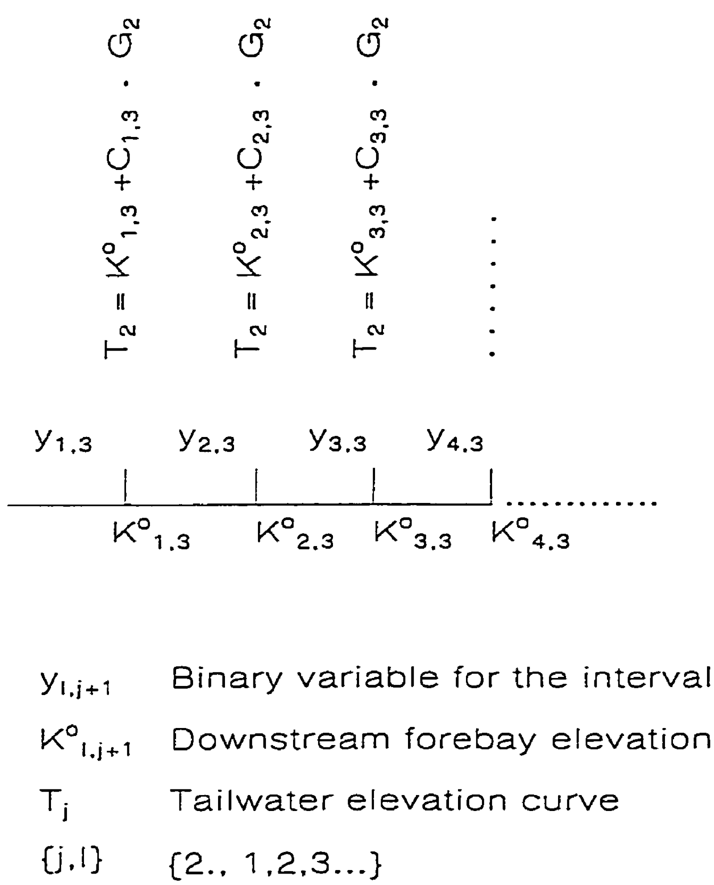


Figure 3.3: Representation of the storage intervals and tailwater elevation curves

Selection procedure

The selection procedure involves two steps : i) determination of the interval to which the average forebay elevation belongs; and ii) selection of appropriate tailwater elevation curve. As the tailwater elevation curves are available for specific forebay elevations, the average forebay elevation, $h_{j+1,t}$ of reservoir $j+1$ is used to determine the interval. This is achieved by using a large integer constant M, and the binary variable $Y_{l,j+1,t}$. $k^o_{l,j+1}$ is the level of the forebay for the plant, $j+1$ for which the tailwater elevation curve is defined. Equation (3.10) is used to determine the upper limit of the interval to which the average value belongs, while equation (3.11) will provide the lower limit.

The number of curves, m_{j+1} is equal to the number of binary variables. Once the interval is decided, either of the two curves (curve associated with the lower or upper value of interval) can be used to obtain the tailwater elevation. In the present formulation, the curve associated with lower limit of the interval is selected. This is achieved by using the constraints (3.12) and (3.25), which ensure that only one curve is selected out of all the curves at any generating station and is used for calculations. An interpolated curve, corresponding to the average value, $h_{j+1,t}$, that lies within the interval is possible. However, the formulation has to be modified to incorporate the interpolation constraints. The error induced in the formulation due to this selection method can be reduced if the number of tailwater elevation curves are increased, thereby increasing the number of intervals.

3. *Mass Conservation equations*

$$S_j^{t+1} = S_j^t + I_{j,t} + R_{j-1,t} - R_{j,t} \qquad \forall j \ \ \& \ t = 1, T \qquad (3.13)$$

$$R_{j,t} = SP_{j,t} + Q_{j,t} \qquad \forall j \;\; \& \; t = 1, T \tag{3.14}$$

$$S_j^{t+1} = S_j^t + I_{j,t} + R_{j-1,t} - O_{j,t} \qquad j = n+1 \;\; \& \;\; t = 1, T \tag{3.15}$$

Here, S_j^t and S_j^{t+1} represent reservoir storages at the beginning of time intervals t and $t+1$ in volume units respectively. The variables $R_{j,t}$ and $SP_{j,t}$ are the release and the spill values from reservoir j respectively, while $I_{j,t}$ forecasted value of local inflow. The equation (3.15) represents the continuity equation for the lake into which the last plant is discharging. The variable, $O_{j,t}$ represents the controlled flow out of the lake.

4. *Functional relationships*

$$\beta_{j,t} = f(Q_{j,t}) \qquad \forall j \;\; \& \; t = 1, T \tag{3.16}$$

This constraint specifies the functional relationship between the plant discharge, $Q_{j,t}$ and overall plant efficiency, $\beta_{j,t}$ for generating station j for time interval t. Efficiency, in general is also a function of head. Since a non-linear optimization formulation is used, the inclusion of a constraint which relates efficiency with both discharge and head poses no conceptual difficulty. However, the relationship (equation 3.16) is used to facilitate the comparison of the present model with the already existing weekly scheduling model, EMMA, that uses similar relationship.

$$S_j^t = f(k_{j,t}^i) \qquad j = 1, n+1 \;\; \& \; t = 1, T \tag{3.17}$$

$$S_j^{t+1} = f(k_{j,t}^f) \qquad j = 1, n+1 \;\; \& \; t = 1, T \tag{3.18}$$

The storage-state relationship for initial ($k_{j,t}^i$) and final ($k_{j,t}^f$) values of forebay elevations are obtained for each of the generating stations. For convenience, two relationships are used. When, $j = n + 1$, the equations (3.17 - 3.18) provide the storage-state relationships for the lake or the reservoir into which the last hydropower plant (j=n) is discharging.

5. *Spill and other constraints*

$$SP_{j,t} \quad \leq P_j \qquad \forall j \;\; \& \; t = 1, T \tag{3.19}$$

The above constraint is added to limit the spill to the discharge capacity of the spillway. Here, P_j is the maximum value of allowable spillway discharge.

$$Q_{j,t} \quad \leq \; Q_j^{max} \qquad \forall j, t \tag{3.20}$$

Q_j^{max} is the maximum allowable plant discharge at plant j.

$$\gamma_1 \ (h_{j,t} - T_{j,t}) \ Q_{j,t} \ \beta_{j,t} \leq Pcap_j \quad \forall j \ \ \& \ t = 1, T \tag{3.21}$$

This constraint provides a upper limit on the power production at each of the plants. Here, $Pcap_j$ is the maximum power production capability of the plant j. The variable γ_1 is a constant.

$$\sum_{t=1}^{T} \ \sum_{j=1}^{n} \gamma_o \ (h_{j,t} - T_{j,t}) \ Q_{j,t} \ \beta_{j,t} \geq E_{target} \tag{3.22}$$

The constraint indicates that the total power produced from all the plants summed over all time intervals should equal or exceed the total weekly target E_{target}. The value of γ_o is constant.

$$\sum_{j=1}^{n} \gamma_o \ (h_{j,t} - T_{j,t}) \ Q_{j,t} \ \beta_{j,t} \geq Emin_t \qquad\qquad t = 1, T \tag{3.23}$$

The above constraint specifies that a minimum amount of power, $Emin_t$ to be generated within a time interval, t from all the generating stations.

$$k^i_{j,1} = Ist_{j,1} \qquad\qquad j = 1, n+1 \tag{3.24}$$

$$k^f_{j,T} = Fst_{j,T} \qquad\qquad j = 1, n+1 \tag{3.25}$$

Constraints for initial and final forebay elevations at each of the generating stations and the elevation values (when $j = n + 1$) for the lake or the reservoir downstream of the last reservoir under consideration.

6. *Binary variables*

$$\sum_{l=1}^{m_{j+1}} Y_{l,j+1,t} = 1 \qquad j = 1, n \;\; \& \; t = 1, T \tag{3.26}$$

As only one out of the total m_{j+1} tailwater elevation curves at each plant for every time interval will be used, the sum of the binary variables is equated to unity.

The optimization solver used in the present study requires that the binary variables which appear in the non-linear constraints (e.g, equation 3.12) should be included in such a form that the constraint becomes bilinear. This is achieved by adding the following constraints to the formulation.

$$Z_{l,j+1,t} - Y_{l,j+1,t} = \;\; 0 \quad \forall j, l, t \tag{3.27}$$

$$Z_{l,j+1,t} \leq 1 \quad \forall j, l, t \tag{3.28}$$

The variable, $Z_{l,j+1,t}$ is continuous and the equations (3.26 - 3.27) will force the value to limit to either 0 or 1. The binary variable, $Y_{l,j+1,t}$, will be replaced by $Z_{l,j+1,t}$ while solving using the optimization solver. The binary variables do not appear in the non-linear terms or equations.

The formulation does not account for head losses in the penstock and reservoir evaporation losses. Their inclusion is quite straight forward. The constants, γ_o, γ_1, are numerical constants which include the specific weight of water and an appropriate numerical value to maintain unit consistency. The values of numeric constants are given in Appendix 1.

3.6.1 Time Delay

Time delay or the time of travel for the water between two plants is an important aspect to be considered in scheduling the plants especially when the delay is equal to or more than the time interval considered for optimization. Yeh et al. (1992) indicate that in short-term operation models, hydropower plants may introduce additional complications of hydraulic time delays for cascaded plants. Approximate flow transport delay in terms of a fixed time, without a physical model for flow was used by Turgeon (1981). This approach is justified when data relevant to the river characteristics between the plants are not available. Considerable insight can be gained into the change in operational schedules even by using fixed flow transport time as delay.

The formulation presented earlier does not consider the river flow delay between the cascading plants. The hydraulic characteristics of the river sections between plants are important issues that are needed to be considered. Based on the location of the plants on the same stream there is need for inclusion of river flow dynamics in the modeling effort. Two approaches are discussed by Hawary and Christensen (1979): (1) state space model; and (2) transport delay approach. The state space model considers the river characteristics at regular intervals and principles of hydraulic routing are used. For the transport delay approach, travel time is accounted by the attenuation or lengthening of time base of the discharge wave which moves towards the immediate downstream reservoir. This lengthening of time base is represented by an attenuation factor (Hawary and Christensen, 1979). If this attenuation factor is neglected, then the effect of time delay can be modeled using the equation below.

$$S_j^{t+1} = S_j^t + I_{j,t} + R_{j-1,t-\tau} - R_{j,t} \qquad \forall j \ \ \& \ t = 1, T \qquad (3.29)$$

The river transport time is represented by τ and the variable $R_{j-1,t-\tau}$ is the delayed flow from the upstream of reservoir j. Constraint (3.13) can be replaced with equation (3.28) to incorporate transport delay into the main formulation. It is obvious that if the delay is less than the time interval considered for optimization, then no effect on the scheduling will be observed. On the other hand if the delay equals or exceeds the time interval, the scheduling will be affected. Due to lack of data relevant to the river characteristics, only a simplified transport delay approach model is used in the present study.

The objective function used in the earlier formulation (3.6 - 3.29) is case study specific. A traditional objective function for general hydropower optimization problems is given by the following expression.

$$Maximize \sum_{t=1}^{T} \sum_{j=1}^{n} \gamma_o \, (h_{j,t} - T_{j,t}) \, Q_{j,t} \, \beta_{j,t} \tag{3.30}$$

3.6.2 Unit Commitment

Unit commitment is a process of scheduling the available turbine or thermal units for optimal power generation. The turning on (commitment) and off (decommitment) is based on the efficiency characteristics of the individual units. In case of hydropower generating reservoirs, the water allocation among turbines is optimized based on the turbine efficiency curves. The problem is handled by Dynamic Programming (DP) and Priority List Schemes (Wood and Wollenberg, 1984). DP has many advantages compared to other methods, as any specific conditions can be incorporated at any stage within the formulation with ease, which is not the case with other traditional methods.

Binary variables are used for selection of appropriate tail water curves in the MINLP formulation. On similar lines these variables can be used to address the unit commitment problems. The following constraints can be added to the main formulation. The advantage is that an exhaustive power generation scheduling problem can be addressed that includes unit commitment also. For any given time interval, t, the total plant discharge is given by

$$Q_j = \sum_{tb=1}^{Tn} \quad qt_j^{tb} \, yb_{tb} \qquad \forall j \tag{3.31}$$

Q_j represents the total plant discharge from turbines, qt_j^{tb} is individual turbine discharge and yb_{tb} is a binary variable associated with the particular turbine.

$$\beta_j = \sum_{tb=1}^{Tn} \frac{\eta_{tb} \quad qt_j^{tb}}{Q_j} \qquad \forall j \tag{3.32}$$

The overall plant efficiency is given by the above relationship. Individual turbine efficiency (η_{tb}) relationships are given by

$$\eta_{tb} \;=\; f(qt_j^{tb}) \qquad \forall j, tb \tag{3.33}$$

$$qt_j^{tb} \leq qtm_j^{tb} \quad yb_{tb} \qquad \forall j, tb \tag{3.34}$$

qtm_j^{tb} is the maximum allowable discharge for the particular turbine. The time index, t, is omitted for clarity. The binary variable can be used to decide the non-zero discharge value. Conditions as to how many number of units to be started, or commit a specific unit and a variety of stipulations can be specified using binary variables in the formulation. For example, conditions can be specified using binary variables that look like: $\sum_{tb=1}^{Tn} \; yb_{tb} \; \leq 5$, that indicates that at any time a maximum of five units can be started or $yb_1 + yb_5 \;=\; 0$ suggests that specific turbines (numbered one and five) are turned off. When the constraint (3.32) is used, the constraint that relates the total plant efficiency to discharge (3.16) can be eliminated from the main formulation. On the other hand if the total plant efficiency is available, it should be included in the constraint 3.32 on the left hand side. The problem of unit commitment if addressed increases the number of binary variables in the MINLP formulation. The product of number of turbines and the time intervals gives the number of binary variables in the case of unit commitment problem.

DP and MINLP formulations suffer from problems relevant to discretization and binary variables respectively if unit commitment problem is addressed.

3.7 Model Application - Winnipeg Reservoir System

The real-time operation model is applied to a series of four reservoirs on the Winnipeg River, Manitoba, Canada. These four reservoirs in cascade form a part of a much more complex network of hydropower reservoirs maintained by the local hydropwer corporation, Manitoba Hydro. Only the plants on the Winnipeg River maintained by Manitoba Hydro are used as test bed for the developed model. A schematic representation of the plants in the case study region is given in the Figure 3.4. The first plant, Seven Sisters receives the controlled flow from the Slave Falls reservoir located upstream, while the last plant under consideration, Pine Falls reservoir drains into the Lake Winnipeg.

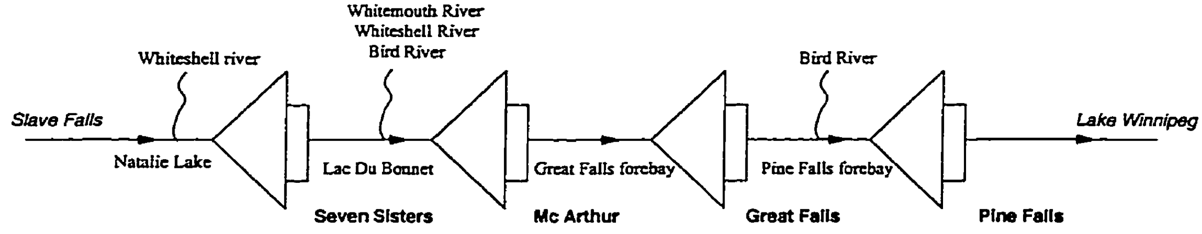


Figure 3.4: Schematic representation of hydropower reservoirs in the case study region.

The McArthur reservoir has the largest storage of all the plants. Strong hydraulic coupling between the hydro-generating plants on the Winnipeg river is one of the important features of the present system. More details of the case study region can be obtained from earlier work by Barritt-Flatt and Cormie (1988). The weekly target power production for all the power plants, initial and final forebay levels and the forecasted values of inflows are provided in the present study by EMMA model. The reservoir system in the case study area will be henceforth referred to as Winnipeg Reservoir System. This system will be used later in chapters 4 and 5 as a test bed for approaches developed in the present research.

Energy Management and Maintenance Analysis (EMMA) Model

The EMMA model (Barritt-Flatt and Cormie, 1988) is presently used by the local power utility, Manitoba Hydro, to obtain generation and maintenance schedule for all the hydropower plants in the system. The model is used to maximize the net revenues considering the operation of hydro-electric and thermal generation, maintenance, hydraulic characteristics of reservoir and river system, domestic loads and external market sales. The model is a deterministic model which is run repeatedly with different combinations of loads and inflows. The operations problem addressed by EMMA has planning horizons ranging from a week to one year. The present study focuses on development of a short-term operation model for daily scheduling using the targets specified by the EMMA model. The formulated short-term operation model is applied to the plants on the Winnipeg River where strong hydraulic coupling exists between the plants.

The EMMA model provides the weekly target demand, E_{target} and the initial and final forebay conditions to the short-term operation model developed in the present study. The short-term operation model considers the hydraulic coupling and provides the daily scheduling rules for the plants.

3.7.1 Results and Discussion

The short-term optimization model formulated in the present study is solved using an optimization software, GAMS (General Algebraic Modeling System). GAMS (Brooke et al., 1996) is a modeling tool in which problems can be specified in algebraic form and automatically interfaced with the linear or nonlinear and mixed integer programming solvers. For solving the MINLP formulation, a solver, DICOPT (DIscrete Continuous OPTimizer) under GAMS environment, is used with specific restrictions to the representation of some constraints. Forecasted values of the local streamflows, total energy demand (load), plant discharge from Slave Falls to first reservoir and the conditions downstream of the last plant are specified by the EMMA model which provides the weekly scheduling rules for all the plants in the system. The purpose of the short-term operation model is to provide daily scheduling rules for the four plants on the Winnipeg River taking into consideration the strong hydraulic coupling between these cascading plants. The cost of hydropower generation and spill are specified in Canadian dollars. Time delay effects are considered using simplified transport delay formulation (Hawary and Christensen, 1979). A delay of one day is used between two plants to evaluate the effect of time delays on the scheduling.

The main contribution of the present research work is the MINLP formulation (Teegavarapu and Simonovic, 2000a) along with a procedure for selection of tailwater elevation curves to address the short-term operation problem as well as the issue of hydraulic coupling. In the main formulation, j refers to reservoir index in the case study region where n is equal to 4. The four reservoir system in the case study region is shown in the Figure 3.4. For $j = 1$, the reservoir is Seven Sisters; and for $j = 2$, the reservoir is McArthur; and so on. Tail water elevation curves are developed at regular intervals of the forebay elevations of each of the plants taking into account the upstream plant discharge. Regular intervals of half foot along the entire forebay elevation range are used to develop the curves for varying discharge values. A total of 5, 11, 11, 15 tailwater curves are developed at each of the reservoirs in the order of $j = 1, 4$ respectively.

The total number of binary variables in the formulation is given by the product of total number of curves and time intervals under consideration. A set of tailwater elevation curves for McArthur reservoir are given in the Figure 3.2. The forecasted inflows and total power to be produced for the week, E_{target}, are provided by the EMMA model. To obtain the optimal daily generation schedules, the week starting from September 15-21, 1997 for which the weekly power generation figures are available, is used. The initial and final forebay elevations (at the start and the end of the week) are provided by the EMMA model.

Table 3.1: Forebay levels and Inflows

Location	Initial Forebay level (ft.)	Final forebay level (ft.)	Local Inflow (Kcfs)
Seven Sisters	899.30	899.30	20.76
Mc Arthur	835.68	835.68	0.5
Great Falls	811.74	811.74	0.0
Pine Falls	751.66	751.66	0.36
Winnipeg Lake	714.32	714.12	93.09

The values of initial and final forebay levels for all the plants as well as the local inflows are given in the Table 3.1. The large values of inflows for both Seven Sisters and Winnipeg Lake are due to regulated flows from Slave falls and flows from many small rivers respectively. Using these values, the MINLP model is first solved without considering the flow transport delays.

Table 3.2: Daily power generation at different plants

	Power (GWhrs)			
Day	Seven Sisters	Mc Arthur	Great Falls	Pine Falls
1	2.22	1.16	2.93	1.87
2	2.23	1.13	2.04	1.46
3	2.23	0.95	2.39	1.68
4	2.24	1.09	2.03	1.36
5	2.24	0.65	1.80	1.26
6	2.24	0.53	1.01	0.78
7	2.18	0.67	1.13	0.79

The daily power production values at each of the plants are given in the Table 3.2. Also, the total power production at each plant compared to that of EMMA model are shown in the Figure 3.5. It is apparent that the values of power production are different from the EMMA suggested values. The power production values for EMMA models are weekly figures while those for the present model are the cumulative seven day production values. The generation value is different at each of the generating plants due to the reason that EMMA model does not consider the hydraulic coupling between the plants in an exhaustive way the present MINLP formulation considers.

It should be noted that the total power production is equal to the weekly demand, E_{target}. Therefore the total power production will be equal for both MINLP and EMMA models while distribution among plants is different. In case of first two reservoirs, the energy production using MINLP formulation is 4.24% and 6.71% higher than the respective values due to EMMA model. For the last two reservoirs, the energy production values based on the EMMA model are 4.01% and 5.67% higher than those of MINLP model. This difference in scheduling can be attributed to the way in which the MINLP and EMMA models consider the aspect of hydraulic coupling.

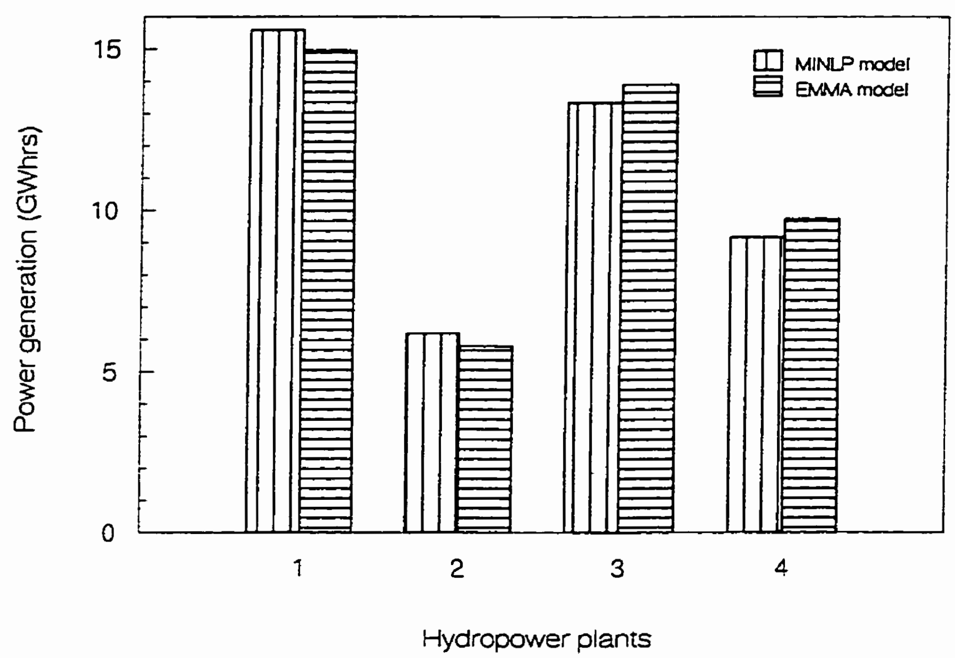


Figure 3.5: Power Generation values from MINLP and EMMA models

Due to approximations involved in modeling of hydraulic system and the limitations of the optimization tool used (Barritt-Flatt and Cormie, 1988), an exhaustive representation of the dynamic tailwater effects was not possible in the EMMA model. The percentage variations, even though small are considerable, as the power production values are expressed in $GWhrs$. Also, the generation schedules confirm that consideration of hydraulic coupling might result in unusual rules (Lyra and Ferreira, 1995). A better comparison of the MINLP model would be with a model that does not consider the dynamic tailwater effects. It can be easily accomplished by modifying the original MINLP formulation.

Table 3.3: Forebay level variations at different locations

	Forebay level (ft)				
Day	Seven Sisters	Mc Arthur	Great Falls	Pine Falls	Lake Winnipeg
1	899.30	835.20	807.26	751.66	714.23
2	899.30	834.79	810.74	751.66	714.21
3	899.30	834.68	807.17	750.34	714.19
4	899.30	834.29	810.83	750.66	714.18
5	899.30	834.68	807.17	751.66	714.16
6	899.26	835.32	808.26	751.34	714.14
7	899.30	835.68	811.74	751.66	714.12

It can be observed from the Table 3.3 that the forebay level variations for Seven Sister and Pine Falls are very small when compared to the other plants. These two plants are functioning like run-of-the river plants, while the two plants in middle are playing a regulatory role. This can be attributed to low storage in case of Pine Falls and high flows to the Seven Sisters plant from the Slave Falls plant that result in low storage variations. The spill values are zero for all the days for all the plants indicating that the water is completely utilized for power production. The total power production is specified by the target demand, E_{target}

which can be modified. Another variable which controls the optimum distribution of load among the plants is E_{min_t}.

Increasing the value of this variable above a certain value has resulted in infeasible solution. This is due to fact that the daily generation is limited to the total amount of water available for power generation. The constraint related to minimum power generation can be eliminated if such a requirement is not imposed by the power utility. This will eliminate few constraints in the formulation and would lead to an increased feasible region. The accuracy of the calculation of the head in the MINLP model can be increased if more storage intervals are considered for deriving the tailwater curves, provided data are available or can be interpolated based on the existing data.

To understand the effect of river transport delay on the power generation scheduling, time delay is introduced into the main formulation. A time delay of one day is considered, as the time step for the scheduling model is one day. Any delay less than one day will not affect power generation at each of the plants. Again, all the initial conditions used in the previous run are used. Table 3.4 provides the values of power production at each of the plants. It is evident that there is lag in the production until some time before the water becomes available for the power production.

Total power generated from all the plants is 40.16 $GW\ hrs$. This value is less than the total power generated, 44.3 $GW\ hrs$, in the earlier case when transport delay was not considered. The reason for this can be attributed to the non-availability of water for power production within the seven day period because of the transport delay. The transport delay model can be replaced by the state space model if the river dynamics can be appropriately modeled. It should be noted here, that considering fixed time delay is not an innovative

Table 3.4: Daily power generation considering flow transport delays

Power (GWhrs)				
Day	Seven Sisters	Mc Arthur	Great Falls	Pine Falls
1	2.20	0.36	0.19	0.05
2	2.78	0.71	0.74	0.17
3	2.83	1.29	1.98	0.56
4	1.76	1.35	2.92	1.46
5	1.22	1.23	2.77	1.82
6	2.63	0.39	3.02	1.82
7	1.23	0.39	0.47	1.82

approach, while modeling effort is primarily meant to emphasize the need for its inclusion in an optimization framework.

The unit commitment problem is solved for a single generating station (Great Falls) along with the MINLP formulation to demonstrate the applicability of the extended model. Discharge-efficiency curves of the 6 turbines at Great Falls generating station are used. A condition that units 1 and 5 are turned off is used for this sample experiment and results are shown in the Table 3.5 for 4 daily time intervals.

Table 3.5: Turbine discharges for unit commitment problem

Day	Turbine Discharge (Kcfs)					
	1	2	3	4	5	6
1	0.0	4.03	7.56	7.56	0.0	7.56
2	0.0	4.00	6.60	6.60	0.0	6.60
3	0.0	4.00	6.64	6.68	0.0	6.68
4	0.0	4.00	6.69	6.69	0.0	6.69

3.8 Modeling Issues

The approximation of using the average forebay elevation in calculation of head is justified, as it is difficult to model the variation of forebay level within the time frame of optimization. As the forebay elevation changes within the time interval, the average value used implies a fixed head assumption which is valid only for large reservoirs. The error induced due to this approximation will be negligible if the time interval is decreased. This would in turn increase the number of binary variables required in the formulation. Also, an increase in the number of binary variables is inevitable if the number of tailwater elevation curves at each reservoir/plant is increased. This might increase the computational time required to solve and produce problems in obtaining the optimum solution using the DICOPT solver under the GAMS environment.

A sample experiment was conducted where the number of tailwater elevation curves is increased. Variations in the results are observed as expected and confirm that better estimation of head is possible if number of storage intervals is increased. Thus model is more realistic compared to original formulation with number of intervals lower than the modified one. The computational time required to solve the problem has not increased considerably when compared to the time required to solve the original problem. The case study to which the present model is applied is limited to four reservoirs. The solution time is expected to increase once the number of reservoirs is increased. Further studies are needed to be conducted to corroborate this point, otherwise any conclusion made about the computational time and nature of solution can only be speculative.

The modeling and solution of MINLP optimization problems has not yet reached the stage of maturity and reliability as of Linear Programming and Non-Linear programming (Floudas, 1995). Therefore a global optimum solution is not guaranteed. A satisfying solution obtained in case of real-time operation model will depend on the specified target power demand. The cost of energy production obtained from the solution can be used to make a decision about the actual implementation of the operation schedules. The scope of the present study is limited to operation of four cascading reservoirs on a single river. However, the methodology can be extended to any configuration of system of reservoirs and to any time frame. The only concern would be the increase in the computational burden especially due to the increase in binary variables in the formulation. The configuration of the reservoir system will affect the computational time and depends on the number of hydraulically coupled reservoirs in the system.

The time interval used for optimization is equal to a day in the present formulation. A reduced time step (e.g. hour) can be used to obtain real-time operational decisions. As time horizon for optimization decreases, there is a need for consideration of plant level decisions (e.g., unit commitment, turbine allocations) to obtain practical real-time operations schedules. In the formulation present earlier, a gross representation of the plants is achieved by using the total plant efficiency-discharge curves. While, this representation is adequate for the short-term scheduling problem, a detailed plant level optimization model to work in conjunction with present model is required for real-time operation.

3.9 Further Extensions

The MINLP formulation model developed can be extended for application to handle any time frame for obtaining real-time operation decisions. There are two areas where the model can be still improved: (1) inclusion of a routing model to consider the flow transport delay effects and (2) optimization model at the generating plant. The routing model can be included in the form of constraints provided the routing parameters are available for the river section between the reservoirs. Incorporating plant level optimization model is straightforward if the efficiency-discharge relationships are available for all the turbines at each of the plants. This is already attempted by using the unit commitment formulation discussed in the section 3.6.2.

Exhaustive representation of the system might be required in some instances. As the number of time intervals increase there would be a combinatorial increase in the number of binary variables in MINLP formulations. Problems while solving a multi-period optimization problem surfaced when MINLP formulation is extended to a time frame of 8 hours with a maximum optimization time horizon of one week. Realistic representation of physical system is possible by the use of spatial and temporal decomposition methodologies. This is possible by formulating models at different levels considering the physical representation of the system. The next section will discuss such an approach in dealing with the real-time operation problem.

3.10 Short-Term Operation Model

Considerable amount of work has been reported in the past few decades involving scheduling of hydro-power, thermal systems or both. Hydro scheduling models in the past, in general have followed temporal decomposition approaches (Becker and Yeh, 1974; Becker et al., 1976, Yeh et al., 1979, Yeh et al., 1992) where in different models were developed at various levels under different time frames. This procedure has helped in alleviating the dimensionality problem in terms of handling many variables at a time. Also, the models developed were coupled in such a way that a periodic updating (or re-running) of higher level models is possible. In this approach the models at the higher level force decisions (targets) on the lower models. A possibly different approach is the one presented by Georgakakos et al. (1997b) that uses a spatial decomposition approach, where three models were developed for operation of the hydropower reservoirs. Dynamic Programming (DP) and Extended Linear Quadratic Gaussian (ELQG) techniques are used for optimization. The approach used in the present study relies on a similar kind of methodology.

The proposed approach uses the spatial decomposition where in different models are used at various levels and are linked. The present study differs from the previous study by Georgakakos et al. (1997a, 1997b) in two important aspects : (1) hydraulic coupling and (2) linking of models formulated at different levels. The former aspect is not addressed in the earlier study (Georgakakos et al. 1997b), while the later aspect is handled in a way described here. The optimization models in the earlier study interact in such a way, that relationships are developed for different possible combinations of variables at each level and are passed on to the other models. Therefore the linking is made possible through pre-defined relationships between the variables.

In the present approach, the models interact with each other by passing information about the variables and obtain the value of the performance measure. The performance measure can be indicated by the total energy production that is representative of the objective function of the optimization. The status of the system is used every time to obtain the value of the performance measure. The short-term operation model proposed in the present study consists of three models formulated at different levels. These models are: (1) operation model; (2) river system model and (3) plant level optimization model. All these models are linked in such a way that the required spatial decomposition is achieved.

The operation model provides the optimal operating schedules for all the hydropower generating plants on the river. This model is formulated using a backward moving DP algorithm to optimize a measure of performance of the system. In the present context, the measure could be the total energy production within the specified number of time intervals.

The state space for the DP formulation is a vector of initial storage states of all the hydropower reservoirs. These are considered appropriate as they represent the state of the entire system. The formulation is deterministic in a sense that the stochastic components of the system, the inflows and the energy demands are taken as single valued forecasts. Based on the status of the system (represented through storage states), forecasted values of inflows and the energy demand values and other constraints, the performance measure value is sought which is obtained by solving the river system and plant level models. The river system model is formulated to achieve the objective of optimum load distribution among the plants. Finally, the plant level optimization model is used to obtain the optimal turbine load allocations and the optimum value of performance measure required by the operation model. In every time interval all these three models are solved. The formulations of these models are presented next.

3.10.1 The Operation Model

The operation model is formulated using DP with backward recursion. The state space is composed of the storage state of each reservoir. Forecasted values of local inflows and energy demand constraints, initial storage states for the first time interval and the final storage values for the last interval under consideration are assumed to be available. Following backward recursion in DP and the objective of maximizing the energy production, the recursive relationship for any period t' and corresponding stage r between the last period T and first period t_p is written as

$$f_{t'}^{r}(K_1, K_2, K_3, K_4) = \underset{feasible\ \ L_1}{Max} \ \ [\ \Phi(K_1, K_2, K_3, K_4, L_1, t') + f_{t'+1}^{r-1}(L_1, L_2, L_3, L_4)] \qquad (3.35)$$

Here, $[K_1, K_2, K_3, K_4]$ and $[L_1, L_2, L_3, L_4]$ refer to initial and final storage states at each of the reservoirs respectively. Φ is a function of storage values that provides the performance measure at any stage. For the last period, since the final storage values are known from the **EMMA** model, the end of the period storage values are restricted to these values.

For the first time interval, since the initial storage values $(K_1^o, K_2^o, K_3^o, K_4^o)$ are known, the recursive relationship is given by

$$f_{t^p}^{\tau}(K_1^o, K_2^o, K_3^o, K_4^o) = \underset{feasible\ \ L_1}{Max} \ [\ \Phi(K_1^o, K_2^o, K_3^o, K_4^o, L_1, t^p) + f_{t_p+1}^{\tau-1}(L_1, L_2, L_3, L_4)] \quad (3.36)$$

3.10.2 River System Model

The river system model is the MINLP formulation reported earlier in this chapter, except that the model is solved only for a single time interval. Formulation details are avoided as they are already presented. The initial and final storages values are provided as input obtained from the operation model. The river system model uses total plant efficiency-discharge relationships in arriving at the optimal decisions for the time interval under consideration. The plant level optimization model is then solved in an iterative way to obtain the actual performance measure. The formulation of the plant level optimization model is presented next.

3.10.3 Plant Level Optimization Model

The model is formulated as a Dynamic Programming optimization problem similar to one developed by Allen and Bridgeman (1985), Wunderlich and Giles (1988) and Georgakakos

(1997a). Iterative procedure for calculation of head is not required in the present case as the value of head and total plant discharge for each of the plants are provided by the river system model. A DP (with backward recursion) is used again with the state variable as the amount of water to be allocated to any turbine. The recursive relationship for any stage s, is given by

$$f_u^s(X) = \underset{feasible\ \ w,\ h}{Max}\ \ [\beta(w, h, e, u) + f_{u+1}^{s-1}(X - w)] \tag{3.37}$$

Here, h indicates the head available for the plant, e is the efficiency of the turbine for the particular head, h, and the discharge w for allocation to a turbine. The head and the total plant discharge are obtained from the solution of the river system model for the time interval considered. Plant efficiency-discharge curves are used in the river system model as opposed to individual turbine efficiencies in deriving the operation rules. To match the total plant efficiency with the cumulative efficiency resulting from the allocation of water to different units, the DP model can be run in an iterative mode.

The model formulation (DP) is not an innovative approach considering the relevant works reported in literature. On the other hand, iterative execution of the DP within the complete model can be considered as a novel approach. The limitations associated with state variables can be overcome by using a search technique. The idea is to search the discretized interval to which the optimal solution belongs. A stochastic search method that will be discussed in the chapter 5 can be used for this purpose.

3.11 Model Execution Issues

Considering, the three models at different levels the execution can result in computational intractability. The *curse of dimensionality* problem associated with DP would surface if the number of state variables or the state variable discretization are increased. On the other hand the computational time required to run the river system model will reduce as the MINLP formulation is solved for one time interval for every execution of operation model. The binary variables in the MINLP formulation will be reduced by the order of T for each execution of river system model, where T is the total number of time intervals considered for optimization. Considering the problems associated with the execution, it can be concluded that model is better suited for short-term operation. However, model can be solved for real-time operation if appropriate computational resources are available.

The spatial decomposition approach is not tested due to reasons of non-availability of data at a scale required by the approach. However, the conceptual background provided here indicates the validity of the approach. The only downside of such an approach is the discretized state variables that would lead to approximations. Exhaustive representation of the system using this spatial decomposition approach has many advantages compared to the extended MINLP formulation. DP formulation at plant level is superior compared to a unit commitment module included within the MINLP formulation. Unit commitment problem is much easier to handle using DP as any problem specific conditions can be incorporated without any restrictions. Handling unit commitment in MINLP needs binary variables. The use of these variables increases the complexity of the formulation and can be hindrance in obtaining a solution. DP formulation at the river system level has the similar advantages over MINLP formulation.

3.12 System Representation Issues

An important feature of the problem that had a major impact on selection of optimization approach used and the formulation developed in the present study is the hydraulic coupling. The hydraulic link (coupling) between the plants is modeled using tailwater elevation curves. The curves provide the tailwater elevation values for different plant discharge values at pre-determined downstream reservoir's forebay levels. Selection of appropriate curve was possible by using binary variables in the formulation. A non-linear programming formulation with binary variables was used to address the present problem.

One way of handling the hydraulic linking without using binary variables is to develop a single curve (through regression) based on a set of curves that relate tailwater elevation, plant discharge and downstream reservoir forebay elevations. However, it is unrealistic even though it is mathematically possible. The only approach viable is either to select the appropriate curve by using a look-up table or use an iterative procedure. These procedures have been used in the past with varying success. To address this issue within an optimization framework, binary variables are required.

If the hydraulic coupling is assumed to be negligible, then a Dynamic Programming (DP) formulation can be used. However, DP suffers from the *"curse of dimensionality"* problem that surfaces if the number of state variables or discretisation intervals is increased. Techniques such as spline interpolation can be used to reduce the severity of this problem. On similar lines if hydraulic coupling is ignored, then a linear formulation can be used if the non-linear functions can be linearised following a standard rule - *"When faced with non-linear problem, linearise"*. However, this is not realistic as the function relationships that define the hydropower production function and others are highly non-linear in reality. Linearization of these functions would lead to approximations in representing the physics of the problem in a mathematical form.

On the other hand, if coupling is strong, DP algorithm can be a hindrance in formulating the present problem as a multi-stage optimization problem and to consider the reservoirs as stages. This is based on the inherent underlying assumption of *"separability"* on which the DP approach is based. The functions that are used to calculate the performance measure at any stage should only have variables of that stage and not of any other stage. In case of hydropower system handled in the present study, the tailwater elevation, which constitutes a variable of a particular stage is dependent on the conditions (e.g. elevation) at downstream reservoir forebay (a variable at another stage).

Since a MINLP formulation is used to address the problem of hydropower optimization, extending it to consider the unit commitment problem is fairly straightforward. Binary variables are again used to activate or de-activate some units (or continuous variables in case of discharge values). A variety of conditions can be specified to provide different scenarios. It is already indicated that the optimization solver used in the present study does not allow inclusion of binary variables in non-linear constraints. To by-pass this problem, continuous variables are introduced with an upper limit of 1. Similar modifications have to be made for unit commitment problem.

The hydropower production is non-separable in nature that becomes an obstacle in applying LP technique. The hydropower optimization problem similar to the one handled in the present study can be solved by Successive Linear Programming (SLP) formulation where the non-linearities can be reduced by using first order *Taylor* series expansion (Reznicek and Simonovic, 1990).

3.12.1 Simplifications

To reduce the complexity of the model in cases where the hydraulic coupling is negligible, the MINLP model can be simplified to Non-Linear Programming (NLP) model. For a NLP model, the head required for energy generation is calculated based on the difference between tailwater elevation and forebay elevation. Since the tailwater elevation is no longer influenced by the project discharge from the plant, the tailwater curves are not required so are the binary variables. It is obvious that the model that does not include the dynamic tail water effects would over estimate the head.

$$Maximize \quad \sum_{t=1}^{T} \sum_{j=1}^{n} \gamma_o \, (h_{j,t} - h_{j+1,t}) \, Q_{j,t} \, \beta_{j,t} \tag{3.38}$$

here, $h_{j+1,t}$ represents the average downstream elevation. The objective function value obtained in this case will be an upper bound for the objective value that can be obtained when hydraulic coupling is considered.

Results obtained from the NLP model can be used to reduce the number of binary variables in MINLP model. The forebay elevations at each of the plants provided by the NLP model can be used to reduce the number of binary variables when the MINLP formulation is finally solved. The reduction is possible, as an appropriate range for the forebay elevation can now be fixed. To use this approach, NLP model is first solved for the results and then the MINLP formulation is solved.

In some cases where the plants are hydraulically isolated, the tailrace geometry will influence the tailwater elevation. The tailwater elevation that is required for calculation of head for energy generation will then depend on the tail-race geometry. This issue can be handled by modeling the tailrace dimensions and deriving a relationship. Another form of simplification is to reduce the number of tailwater curves thus reducing the number of binary variables in the formulations.

Flow transport delays can be considered by including the time lag in the formulation whereas a routing model can be used if available. Depending on the time interval for which decision is required details of the river reaches have to be included. Inclusion of flow routing process (through a simulation model) in the optimization framework is a challenging task handled by one of the emerging techniques, *optimal control method* (Nicklow, 2000).

3.12.2 Solution Issues

To check the accuracy of the MINLP formulation, the problem can be solved as Relaxed Mixed Integer Non-Linear Programming (RMINLP) model to obtain an initial solution. In case of RMINLP formulation, the binary variables are relaxed to take on any values between 0 and 1, thus providing a solution. If no solution exists, the formulation needs to be checked for any conceptual errors.

In some cases the convergence criteria for the solver (e.g. GAMS) need to be adjusted to obtain a solution, as MINLP problems in general are difficult to solve. It is found from the experiments conducted in the present study improved computational solution times can be achieved by replacing constraints containing three or more variables (that are non-linear in form) by a number of constraints.

3.12.3 Computational Issues

One of the hard constraints (as opposed to soft constraints in mathematical programming jargon) in the formulation (minimization of the cost of energy production) is related to the total energy ($Emin_t$) from all the plants in a single time interval. The constraint should be handled with care as this may introduce infeasibility due to reduction in the feasible space. However, this constraint is required if a specific amount of energy is required to be produced in a particular time interval from all the generating stations.

Solution time

The time taken by the optimization solver is important especially for real-time operating rules. In case of hydropower scheduling problems, decisions are made hourly and the solver should be able to provide the results within that time frame.

Few formulation aspects of the MINLP model dictate the computational time and the resources required for solution. The number of binary variables is one such aspect. Increase in the number of binary variables will result in what is referred to as *combinatorial explosion problem* (Floudas, 1995). This issue is discussed in detail in the next chapter. An attempt was made to solve the formulation for daily, half-day, 8 hour and hourly intervals. The first three formulations with respective time intervals were successfully solved, whereas the final formulation with a total of 168 time intervals is intractable.

This will lead to computational intractability which is the topic of the next chapter.

3.12.4 Postscript

System representation within mathematical programming formulation is an important issue that will determine the nature of the solution. The extent to which the physics of the problem is represented in a mathematical programming formulation dictates the availability of the solution using a particular optimization approach. Floudas (1995) stresses the need for realistic system representation in a process synthesis optimization problem (similar to the reservoir operation problem dealt in this chapter):

> "The *representation problem is crucial on the grounds of determining* a superstructure which on the one hand should be rich enough to allow all alternatives to be included and on the other hand should also be clever to eliminate undesirable structures"

Computational issues surface if the problem has to be solved within a time frame required for actual implementation of the operating rules. The computational time can be reduced by simplification that might lead to unrealistic formulations. Considering the limitations of the traditional optimization tools and difficulties associated with modeling, emerging non-

Chapter 4

Computational Intractability

"Can you do addition ?" the White Queen asked.
"What's one and one and one and one and one and one and one and one and one and one ?"
"I don't know," said Alice. "I lost count."

- Lewis Carroll

Through the Looking Glass.

4.1 Introduction

Problems associated with the use of a traditional optimization approach (MINLP) in solving the real-time operation problem of multi-period, multiple reservoir systems are discussed in the previous chapter. In the wake of this discussion and also the experimentation already carried, it can be concluded that the issue of computational intractability needs to be addressed. The intractability issue is analyzed and details of an approach that is developed to handle the same are provided in this chapter. Application of the approach is demonstrated by using the case study problem (Winnipeg Reservoir System) used in the previous chapter.

It is well known that solution of non - linear programming problem depends on the number of constraints and the variables, and nature of objective function that constitute the complete formulation. Hentenryck et al. (1997) state that

> "From a computational standpoint, nonlinear programming in general, and many of its subclasses in particular are intractable".

Quadratic programming with linear constraints is now regarded as a difficult problem to solve. The dimensionality problem surfaces and in a form that is different for the formulations. The formulations that were attempted in the previous chapter do suffer from computational intractability when the size of the problem is increased. In plain words, the problem is so difficult that an exponential amount of time (related to size of the problem) is needed to obtain a solution. Computational intractability suggests that using an optimization approach or tool it is impossible to obtain a solution due to difficulties in the computer implementation of the algorithm on which the approach is based. The solution capabilities of the solver are sometimes limited due to available computational memory requirements and resources.

The motivation to address the issue of computational intractability in this research is based on need to obtain optimal (global optimal if at all) solutions to problem that have the similar features of MINLP formulation. The MINLP formulation reported in the earlier chapter uses binary variables in the formulation to address the issue of hydraulic coupling. The traditional optimization technique already experimented has not provided the required results (e.g. release decisions) that can be implemented in real-time. It was observed that the computation time required to solve the model often exceeded the actual time within which a decision is required. Solution of an hourly scheduling problem with a total of 168 time hourly time intervals (considering a total optimization horizon of a week) was attempted using the MINLP formulation with the help of GAMS (General Algebraic Modeling System) optimization solver (Brooke et. al, 1996). The model execution was aborted as the solver failed to produce the results even after four hours of computation time. This can be attributed to the capabilities of DICOPT (DIscrete COntinuous OPTimizer), a state-of-the-art solver used for solution within GAMS environment and the complexity associated with the problem formulation.

A more concise and clear definition of computational intractability is that *"an algorithm or approach exists for solution of a particular instance of the problem and not for all the instances of the problem"*. In the previous chapter it was mentioned that a MINLP formulation for day and eight hour scheduling problem can be solved. However, an hourly scheduling problem cannot be solved using the existing computational resources and time. The former is the instance of the latter with higher dimensions. The size of the problem has increased as the number of time intervals is increased. The computational time is specific to application.

A general definition of *computational intractability* does not clearly imply any time limit within which a solution has to be obtained. However, it suggests that if a large amount of time is required to be invested for the solution of the problem then the problem can be marked as intractable. In the present case, it is fair to consider MINLP as intractable for specific instances, whenever the solution is not obtained within some specified time limit. This limit is dictated by the actual time frame within which a decision is required. Experiments are conducted in the present study using the MINLP formulation by extending the limit beyond the actual time frame to mark it as intractable beyond any doubt.

A detailed description of problems (some of them relevant to Operations Research), their complexity and the computational intractability is provided by Garey and Johnson (1979). Computational intractability is due to several reasons some of them relevant to the mathematical programming are discussed here.

4.1.1 Complexity

Complexity of the formulation relates to the number of variables and the time required to obtain a solution. Theoretical computer scientists provide a number of definitions to discuss complexity. One of those definitions is given here. Complexity is defined as measure of computer time to solve a problem by an algorithm as a function of the problem's dimensions. For example, if $TI(n)$ is the time it takes to solve an instance of the problem with dimension

n. Then, the algorithm has time complexity of $K(n)$ if the greatest time it could take to solve an instance of the problem is $O(K(n))$ of order O. When $K(n)$ is a polynomial then the algorithm is said to have polynomial time complexity. The average time complexity is the average (rather than worst) time taken by an algorithm over some class of problems.

4.1.2 Curse of Dimensionality

Curse of Dimensionality (a phrase coined by Richard Bellman) refers to a problem associated with solving multi-stage optimization problems using Dynamic Programming with large number of state variables. As the name suggests that complexity of problems scales up as the number of variables are increased. Curse of dimensionality is a general problem associated with any complex system with large number of variables. Kosko (1999) refers to this as *rule explosion* when dealing with problems that involve development of fuzzy rule bases. Kosko continues to state

> "It means that most math schemes do not "scale up". The math scheme becomes more than twice as complex when you double the number of inputs. The complexity tends to grow in an exponential way while the inputs grow in a linear way".

Approaches are available to address the *curse of dimensionality* problem in DP. One such approach is Discrete Differential Dynamic Programming (DDDP) proposed by Chow et al. (1971). Recent efforts (e.g. Hentenryck et al., 1997) have concentrated on development of *global optimization approaches*, that do not assume convexity of the problem. Apart from traditional approaches, optimization techniques based on evolution process in nature and annealing process used in metallurgical processes are emerging. The former approach is a well known as Genetic Algorithms and the latter is referred to as Simulated Annealing.

4.1.3 NP-Complete Problems

NP stands for *Non-deterministic Polynomial time* - a classification used by theoretical computer science and operations research communities. Problems that can be solved by a computer are divided into two categories: those for which there exists an algorithm to solve (it with polynomial time complexity), and those for which there is no such algorithm. The former class of problems are denoted by **P**. There are also problems for which no known algorithm exists that solves (it in polynomial time), but there is also no proof that no such algorithm exists. Among these problems that are not known to be in P, there is a subclass of problems known as NP-complete: those for which either all are solvable in polynomial time, or none are. In general, all NP-Complete problems have exponential time complexity. Problems that are unsolvable and at least as hard as NP-complete are referred to as NP-hard.

The definition of **NP** has some relevance to the MINLP formulation discussed in the earlier chapter. An increase in the number of binary variables in the MINLP formulation results in a large combinatorial problem and the complexity analysis results characterize the problem as NP-complete (Nemhauser and Wolsey, 1988). The determination of global optimum for MINLP non-convex problems is also NP-hard (Murty and Kabadi, 1987).

4.1.4 Combinatorial Explosion

In case of combinatorial problems (MINLP formulations), especially the one that is solved in the previous chapter, suffer from *"combinatorial explosion problem"* due to presence of binary variables. These formulations belong to a class of problems that are referred to as **NP-complete** problems. The solution of combinatorial problems is difficult as the computational time required increases polynomially with the problem size. A direct consequence of **NP-completeness** is that optimal solutions are not guaranteed in reasonable amount of computational time (Aarts and Korst, 1989). Some of the NP-hard problems include, Traveling Salesman Problem (TSP), vehicle routing and cutting stock problems. Algorithms that are developed for solution of MINLP problems that do not assume convexity of objective function or constraints are referred to as global optimization approaches.

4.2 Solution of Intractable Problems

The nature of mathematical programming formulation and the representation of the system have enormous impact on the solution. These issues decide whether a formulation is computationally tractable or not. In some cases remedial measures can be taken or available feasible solution is accepted if the existing formulation cannot be altered. These issues are discussed here.

4.2.1 Constraint Satisfaction

In case of complex non-linear programming and combinatorial optimization problems it is often difficult to obtain optimal solutions, let alone feasible solutions. There are many reasons for the difficulty that include complexity of the formulation and optimization approach or the specific tools used. In those cases any optimal solution is accepted and the solution is referred to as *constraint satisfying solution.* This indicates that all the constraints in the formulation are satisfied to obtain a feasible solution.

4.2.2 Problem Abstraction

One of the easy solutions to intractable problems is dealing with the *problem abstraction* aspects. The intractability may be due to some details that have been ignored or included in the formulation that cause the same. For example in the present case, the problem of coupled hydropower reservoir operation : selection process of tailwater elevation curves using binary variables. The inclusion or deduction of some details will determine whether the problem is solvable or not. The question is: What is the effect of considering reservoirs as hydraulically isolated when they are not?. If hydraulic coupling is ignored, the problem becomes computationally tractable at any time frame.

4.3 MINLP Formulation and Intractability

The MINLP formulation suffers from combinatorial explosion problem due to the presence of binary variables, whereas Dynamic Programming algorithm if implemented, has limitations due to the *curse of dimensionality*. From the experiments conducted using the MINLP formulation, it can be concluded that an hourly scheduling problem for a time horizon of a week cannot be solved within the time limit of one hour in real-time. The optimization techniques or algorithms developed for solution of Mixed-Integer Non-Linear optimization problems have not reached the maturity and reliability of the standard Linear Programming technique (Floudas, 1995). The experiments conducted using the MINLP formulation in the previous chapter confirm the validity of this statement.

The number of binary variables required in formulations for a variety of situations are given in the Table 4.1 assuming a constant number (e.g. 5) of tailwater curves available for each of the hydro generating reservoirs for a total time horizon of one week.

Table 4.1: Characteristics of different formulations

Scheduling	Time intervals	Formulation	Binary variables	Solution
Daily	7	MINLP	140	Tractable
8 Hour	21	MINLP	420	Tractable
Hourly	168	MINLP	3360	Intractable
Hourly	168	RMINLP	3360	Intractable

Here RMINLP refers to Relaxed MINLP formulation where the binary variables can take on continuous values. It is evident from the table, that RMINLP is also intractable. It should be noted that the transformation of MINLP into RMINLP model does not reduce the total number of variables. If unit commitment problem is also included considering tb number of turbines at each plant and n being the number of reservoirs, then an additional, $(tb \ . \ T \ . \ n)$, number of binary variables will become part of the formulation.

4.3.1 Alternative Approaches

To solve problems that are computationally intractable, alternative formulations (sometimes simplified) or sophisticated algorithms can be developed to at least obtain sub - optimal solutions when it is computationally feasible. Some alternative approaches include: (i) Mixed Integer Linear Programming (MILP) and (ii) DP-MINLP formulation. MILP formulation is a linearized version of MINLP model where the non-linear relationships are linearized using different techniques (piece-wise linearization, Taylor series approximations, etc.). Binary variables are still required to address the issue of hydraulic coupling in the formulation. One major disadvantage of this formulation is that it is unrealistic and approximations due to linearization process are unavoidable. DP-MINLP is a relatively superior formulation compared to MINLP model considering the issue of computational intractability. This is discussed as a part of spatial decomposition approach in the earlier chapter. However, the *curse of dimensionality* problem may surface and the model cannot be solved in time frame within which decisions are required.

Another way is to search for sophisticated algorithms to solve intractable problems. Search for such algorithms has led to a new breed of approaches that have emerged in the past decade referred to as *natural algorithms* (Haupt and Haupt, 1998) to solve intractable optimization problems. These algorithms are based on the idea that processes occurring in nature can be used as analogies to solve complex function optimization problems. Two emerging approaches that fall under this category are Genetic Algorithms (GA) (Holland, 1992) and Simulated Annealing (SA) (Kirkpatrik et al. 1983). Genetic algorithms belong to the class of evolutionary algorithms whereas simulated annealing algorithm belongs to the category of stochastic search techniques. Some researchers regard SA as an evolutionary algorithm as the solutions are generated in SA based on the existing ones. Whatever may be the classification both GA and SA are based on imitating the processes occurring in nature.

SA is referred to as a single trial search approach, where as GA (Michalewicz, 1998) are known to be multiple trial search approaches. Application of GA to reservoir operation problems are most recent. Olivera and Loucks (1997) and Wardlaw and Sharif (1999) used GA to derive operating rules for multiple reservoir systems. It is evident from these studies that GA can be effectively implemented for operation problems with multiple reservoirs. However, they are difficult to implement when compared to simulated annealing technique. Certain aspects of GA such as parameter coding, precision and various operators are difficult to formulate for complex reservoir optimization problems. It has been proved that simulated annealing can be a competent alternative to GA for many optimization problems (Ingber, 1993).

Eglese (1989) provides a detailed survey of applications of the simulated annealing in operations research. Considering simulated annealing as a heuristic algorithm for obtaining good, though not necessarily global optimal solutions to complex optimization problems in some situations, Eglese (1989) indicates its several attractive features. Advantages of simulated annealing include: (1) efficient search technique that can surpass local minima in case of a general minimization problem; (2) global optimum solutions are possible if the parameters of the algorithm are chosen appropriately; (3) suitable for highly combinatorial optimization problems; and (4) ease of implementation.

Gen and Cheng (1997) report that simulated annealing has performed better than genetic algorithms in few cases of job shop scheduling problems in the field of industrial engineering. In case of function optimization problems, both SA and GA need the estimation of performance measure. The measure is associated with a particular state of the system that is defined by pre-defined values of the variables. A simulation model is essential to model a complex physical system and to obtain the performance measure. In this context, SA is much easier to implement compared to GA if a simulation model can be developed.

Simulated Annealing is selected as an approach to deal with the computationally intractable problem in the present study due to a number of reasons: (i) SA is easy to implement and is robust compared to GA; (ii) SA has been found to perform better than GA in some specific optimization problems (Ingber, 1993) and (iii) SA has not been applied in the past to reservoir operation problems. The last reason provides an opportunity to evaluate its capabilities.

Considering the models based on MINLP, DP and simulated annealing to be three possible candidate models to solve the multiple reservoir operation problem an approximate assessment of the computation time required for solution can be made. The DP formulation is feasible only if the hydraulic coupling between two hydropower reservoirs is neglected. The computation time requirements can be linked to the different aspects of the respective formulations. The requirement is proportional to the number of state variables and discretized class intervals in case of a DP formulation, whereas in MINLP formulation it is a function of the number of binary variables, l, and is given by 2^l. The model based on simulated annealing requires the majority of the computational time and effort in obtaining the performance measure, which is proportional to the number of times the simulation model is executed.

4.3.2 Stochastic Search Techniques

Simulation models have been used in the past in many instances for developing models for operation of complex water resource systems (Yeh, 1985; Wurbs, 1993). One of the major advantages of simulation models is the ease with which a real- world problem can be represented in a mathematical form. The power of combining simulation with any method of selecting the best among the alternatives has been advocated by many researchers. An example of such approach is presented by Burn (1989) where Monte-Carlo simulation model is used along with a mathematical programming technique. Also, an execution of one single run of a simulation model is much faster than that of any conventional/traditional optimization algorithm.

Search methods can be easily combined with a simulation model to obtain near-optimal solutions for many complex problems. Simulated annealing is one such stochastic search method that is proved to be useful in obtaining solutions for complex combinatorial optimization problems. The model proposed in the present study is based on this technique. Recent applications of simulated annealing technique in the area of water resources can be found in the works of Dougherty and Maryott (1990), Wang and Cheng (1998), Cunha

(1999) and Cunha and Sousa (1999). While the first three works were applications to groundwater management problems, the last one is concerned with the operation of water distribution networks.

An exhaustive search on applications of simulated annealing in water resources suggests that application of this technique to reservoir operation problems has not been reported earlier. The present study concentrates on the development of optimization models for multi-period operation of a multiple reservoir systems. While, the proposed models are developed for operation of a specific network of reservoirs, any configuration of network of reservoirs meant for any purpose can be handled provided appropriate simulation models are developed. The algorithm can be implemented using any simulation model developed using a high level programming language.

Heuristics search methods are used especially in case of combinatorial problems where they are referred to as *randomized* or *local search* or *approximation* algorithms. The algorithms based on heuristics are broadly classified as *tailored algorithms* as they use problem specific information in obtaining the solution. The model that will presented later in this chapter for solution of multi-period, multiple reservoir operations problem falls into one of the categories. The annealing technique used in the present study is improved by the use of problem specific heuristic rules. Recent applications of evolutionary algorithms with heuristic improvements are discussed by Ilich and Simonovic (1998, 2000).

4.4 Simulated Annealing

Search techniques belong to the class of the algorithms that use the concept of searching the entire solution space in order to obtain feasible and optimal solutions for an optimization problem. These techniques range from simple hill climbing heuristics to complex *tabu* search methods. A vast literature is available on these techniques (e.g., Openshaw and Openshaw, 1997). Simulation becomes a perfect tool in many of the search methods to obtain the performance measure associated with a particular solution obtained through perturbation of system variables. In general, traditional search techniques are brute force methods and do not use any problem specific information or gradients for guidance in obtaining optimal solution. Almost all the available standard non-linear optimization solvers (e.g., GAMS, MINOS) do suffer from the problem of escaping local minima and are generally based on hill-climbing approaches. A recent message posted on a news group (Sarle, 1993) provides an insightful yet funny look at these algorithms using a situation where kangaroos climb up a hill.

> Notice that in all [hill-climbing] methods discussed so far, a kangaroo can hope at best to find the top of a mountain close to where he starts. There's no guarantee that this mountain will be Everest, or even a very high mountain. Various methods are used to try to find the actual global optimum.
>
> In simulated annealing, the kangaroo is drunk and hops around randomly for a long time. However, he gradually sobers up and tends to hop up hill.

Stochastic search techniques are an improvement over the traditional search techniques. The direction of search in this context is guided by a stochastic criterion that will help to surpass the local minima in case of a general minimization problem. One of the stochastic search techniques that adopt this concept is simulated annealing. The technique derives its name from the physical annealing process in metals. The following section provides a brief description of the simulated annealing technique, which is used in the present study to develop optimization models for operation of multiple reservoir systems.

Simulated annealing (SA) as a stochastic search technique is used for solving complex combinatorial problems (e.g., Traveling Salesman Problem (TSP); circuit layout). The algorithm is based on the work by Kirkpatrick et al. (1983). The technique derives its name from the *annealing* process generally used in glass industry and metallurgical processes. It uses an imperfect analogy between the process of cooling in metals to a low energy state and optimization of complex functions. This analogy is shown in the Figure 4.1. In annealing, a metal or alloy is slowly cooled at each intermediate temperature until some kind of equilibrium is achieved. Higher temperatures correspond to greater kinetic energy. The best structures are stably obtained at lower temperatures, but rapid cooling a metal can result in a brittle structure. Annealing process involves slow and controlled cooling thus resulting in better structural properties. Annealing can be viewed as solving an optimization problem, maximizing the strength, minimizing the brittleness, by generating a structure with least *energy* (Mehrotra, 1997).

Simulated annealing is a probabilistic algorithm that uses a similar analogy to solve difficult combinatorial optimization problems for which traditional gradient descent methods may not provide the required solutions. Application of simulated annealing to global optimization of statistical functions was discussed by Goffe et al. (1994). An energy (or cost) function is defined, which is to be minimized by the algorithm. A candidate move is generated from the current state, and the system must decide whether to accept that move

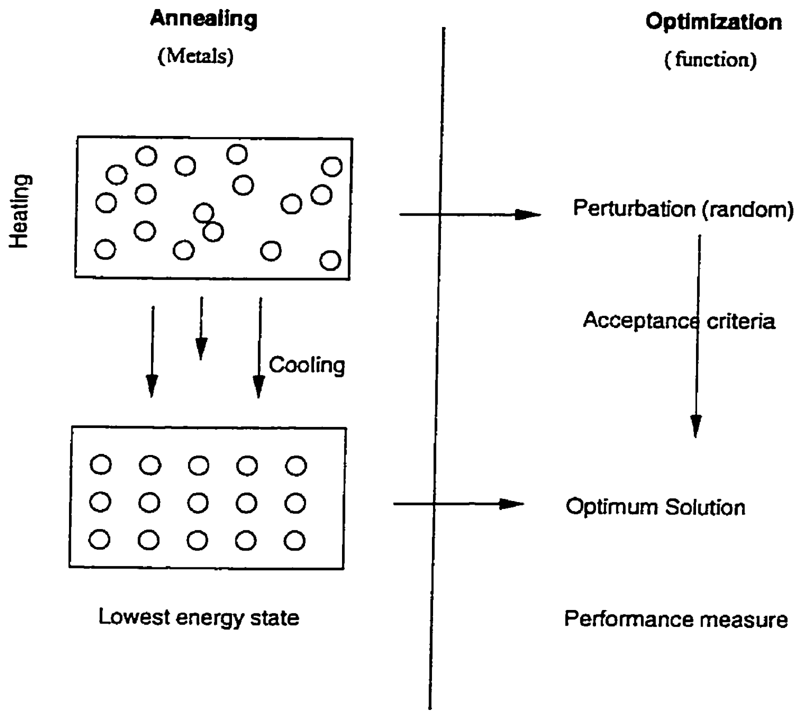


Figure 4.1: Imperfect analogy between annealing and optimization

based on the temperature parameter and resulting energy change. A general description of the algorithm is given below.

The following steps are carried out while implementing a general simulated annealing algorithm for a minimization problem:

1. Selection of variables that influence the system
2. Initialize the parameters (T_o^e, L_c, α) of the algorithm
3. Introduce random perturbations to generate a solution
4. Obtain the performance measure (e) associated with the solution using a simulation model

5. IF ($e_n < e_o$), THEN *accept the move*

   ELSE *accept/reject based on a stochastic criterion*

6. Repeat steps 3 - 5 for L_c

7. Lower the temperature (T^e)

8. Store the best solution obtained so far.

9. Repeat steps 2 - 8 till: stopping criterion is met

The steps 1-4 are problem specific, whereas changes can be made in steps 5-9 to improve the efficiency of the algorithm in terms of quality of solution and reduction of computational time. The state of the system can be changed using a generation mechanism that implements a random perturbation of current state. The move from one state to another is referred to as one transition. The total number of transitions between initial and final states constitutes a homogenous *Markov chain* of length given by the variable L_c. Laarhoven and Arts (1989) have shown that there must be a number of transitions at each temperature level that is exponential with the problem size to achieve stationary distribution. The variables e_o and e_n refer to energy (performance measure) in two consecutive iterations. Each transition is defined as a *metropolis step* (Kirkpatrik, et al., 1983).

If sufficient number of transitions is guaranteed at a given temperature and the temperature is lowered in a specific number of steps, global optimum solution is guaranteed in theory with a probability of 1 using the SA algorithm (Geman and Geman, 1984). This amounts to saying that every energy state has a non-zero chance of occurrence if the annealing procedure is run for a long enough time and the global optimum is likely to be found. The variable, T_o^e, is the initial temperature and its value is problem specific. The stochastic criterion indicated in the step 5 is explained here. The energy difference between two states is obtained by the expression,

$$\psi = exp\ (e_o - e_n/k_b\ T^e) \tag{4.1}$$

$$\psi > ran(0,1) \tag{4.2}$$

In the equation, k_b represents Boltzmann constant[1]. A move from one state to another is accepted if the equation (4.2) is satisfied, else it is rejected. The probability of accepting a move which results in a deterioration of the objective function is calculated by comparing the ψ value with a random number generated from an uniform distribution. The number of minor iterations (or transitions) at each temperature level is given by L_c, and the decrement parameter (temperature factor), α is used to decrease the temperature at the end of every major iteration given by the expression,

$$T_{i+1}^e = T_i^e\ \ \alpha \tag{4.3}$$

where T_i^e and T_{i+1}^e represent the temperature values at the start of two consecutive major iterations. A high temperature value in the initial stages would allow a larger number of moves to be accepted compared to that at a low value at the end of the cooling process.

[1]Taken as 1 in this study

The acceptance criterion is satisfied most of the time in the initial stages as the ψ value is high due to high temperature. As the cooling progresses, the low value of temperature reduces the value of ψ.

The number of minor iterations, L_c constitute a major iteration. The value of α ranges between 0.8 and 0.99, which is suggested by Kirkpatrik et al. (1983). The cooling schedule is referred to as geometric cooling schedule. A stopping criterion is generally used to end the annealing process. Two criteria are suggested in the literature that are: (1) when the temperature reaches below a specified level; and (2) the change in the performance measure is insignificant over a number of major iterations. In the present study, the second criterion is adopted to stop the algorithm implementation or the annealing process.

Modifications to annealing algorithm are proposed by Ingber (1993) to handle several types of non-linear optimization problems. More detailed description of the algorithm and the proof of global optimality can be found in the works of Kirkpatrik et al. (1983) and Laarhoven and Aarts (1989). Simulated annealing is ideal for application to combinatorial optimization problems where the solution space can be generated by a combination of finite number of configurations or transitions.

In the present context, the solution space is continuous within the range of the different decision variables. This imposes a difficulty in devising a mechanism to generate the changes in the system and to define the range of the variables. However, this is not a concern in applications where the problem is of combinatorial optimization nature (e.g., selection of pipes of different diameters in case of a water distribution network, number of cities in Traveling Salesman Problem (TSP)). Pardo-Iguzquiza (1998) reports application of simulated annealing for the combinatorial problem of optimal selection of number and location of rainfall gauges for areal rainfall estimation. The annealing technique is applied for two different optimisation problems, the optimal selection of a subset from a set of stations that already exist and the optimal augmentation of a previously existing network.

4.4.1 Problem Representation

Problem representation becomes an important aspect of the models developed using simulated annealing algorithm. This involves selection of variables and identification of a performance measure or cost function. The performance measure is often the objective function used in the mathematical programming model if the problem is formulated as an optimization model. A cost function is generally a performance measure for minimization problem. The control variables that affect the system the most are generally selected. Considering a general reservoir operation model, release (or discharge) and storage are regarded as the state (control) variables that influence the system. These variables have been identified as decision variables as well as state variables in many optimization models used in the past (Yeh, 1985).

Problem specific information is generally helpful in selection process of the control variables. Appropriate selection of the state variables is important as it may influence the nature of solution or the computational time required to solve the problem. A general description of the problem representation and the most probable control variables for reservoir operation problems is given in the Table 4.2. The list provided in the table is not exhaustive, whereas some of the control variables suggested are appropriate for reservoir operation problems while implementing the SA algorithm. It can be seen from the table that storage is not suggested as a control variable in case of multiple reservoir systems. The reason for this will be evident from the discussion provided later in the section 4.6.

Table 4.2: Problem representation

Configuration	Control Variable(s)	Problem specific information
Single reservoir		
hydropower	Storage, Discharge	Discharge– Efficiency curves
Irrigation	Storage, Release, Soil moisture	Soil moisture – Yield curves
Multiple Reservoirs		
hydropower	Discharge	Discharge –Efficiency curves
Irrigation	Release, Soil moisture	Soil moisture – Yield curves

4.4.2 Generation Mechanism for Transitions

Simulated annealing is a variant of an iterative improvement technique where a solution is obtained by perturbing the variable values associated with the previous solution. This process is achieved by using a generation mechanism. A generation to a particular state is referred to as a configuration of the system. The annealing technique is applied in the present study to problems where the variables take on continuous values. The generation mechanism is different and difficult compared to that is generally used for a combinatorial optimization problem using the annealing algorithm, where the transitions occur between discrete sample spaces.

Considering $\mathbf{V_i}$ as a vector of values for a variable, v, the vector $\mathbf{V_{i+1}}$ after each perturbation, i, is given by

$$\mathbf{V}_{i+1} = \mathbf{V}_i + \mathbf{\Delta} \qquad \forall i \tag{4.4}$$

$$\mathbf{\Delta} = \mathbf{V}_{range}((ran(0,1)\ 2) - 1) \tag{4.5}$$

$ran(0,1)$ is a random number that is uniformly distributed between 0 and 1. Equation (5) can be used to derive increments or decrements within a range, $(-1,1)$ $\mathbf{V}_{range}$. The value of the $\mathbf{\Delta}$ can be scaled to reflect the amount of changes to be incorporated. If the value of any specific variable, v' is not within the allowable range of that variable, then the following expression can be used to obtain a value that lies in the feasible range of that variable.

$$v' = v'_{range}\ \ ran(0,1) \tag{4.6}$$

To reduce the time required to obtain optimal solutions, problem specific heuristics are used in the present study. These are aimed at reducing the search space of the continuous variables.

4.5 Improvements

Modifications are made to the general annealing technique in the present study to improve the nature of solution and the computational time required to obtain it. These include: (1) repair strategy to generate feasible solutions which otherwise are infeasible; and (2) heuristic rules to reduce the range of the values the state variables assume. The modifications are explained below.

4.5.1 Repair Strategy

This refers to a process of producing a feasible solution from an otherwise infeasible solution mainly generated due to the pre-defined values of the state variables. The strategy is to eliminate the infeasibilities by adjusting some of the variable values that influence the physical system. This idea of repair is borrowed from the field of evolutionary algorithms (Michalewicz, 1998) and is implemented within the annealing algorithm. Since considerable amount of computational time is wasted on obtaining the performance measure for infeasible solutions, it is prudent to reduce the number of those solutions. The strategy is applied within the simulation model and therefore is problem specific and demands knowledge of the basic structure of the problem. The strategy is applied based on the number of infeasibilities that are counted based on the violation of constraints.

If the count is non-zero, then procedure is applied. Use of this strategy specific to reservoir operation problems addressed in the present study is discussed later. The main disadvantage of using this method is that it is problem dependent. Sometimes, the repair procedure becomes so complex that it is better to solve the problem without any repair. The repaired individual variable values can be replaced back for searching or rejected if the number infeasibilities exist even after repair strategy is implemented. These approaches are referred to as replacing and non-replacing procedures. In the present research, all the repaired solutions are replaced. If the solution is found to be infeasible based on the count of constraint violations, a penalty is added to the performance measure. Recent studies (Michalewicz, 1998) have suggested the use of a percentage of repaired solutions for replacing. Details of the repair strategy are presented later.

4.5.2 Heuristic Rules

An important aspect that needs attention while using the annealing algorithm is the determination of the possible ranges of the variables that assume continuous values. This will help in reducing the computational time required for the algorithm to converge to an optimum solution. Heuristics can take one of these forms: (1) approximate estimation of ranges for the variables; and (2) modification of generation mechanism. As the mechanism to generate transitions is random, there is possibility that the solution obtained may be a local optimum if ranges are defined too narrowly. However, narrowing the range of values can drastically reduce the computational time required. The heuristic rules are problem specific. The idea here is to introduce a bias towards a particular set of transitions based on the problem specific information. Heuristics are used to modify the generation mechanism within the annealing module to accomplish this. More details of the use of these rules are explained in the following sections.

4.6 Proposed Models

It is prudent to test a new approach on few benchmark problems before applying it to large-scale problems. This study investigates and evaluates simulated annealing approach for application to multi-reservoir optimization problems. The technique is applied to: (1) four-reservoir operation problem (Heidari et al., 1971); and (2) operation of a system of hydropower reservoirs - Winnipeg Reservoir System. The four-reservoir operation problem is already solved using a Linear Programming formulation with the global optimum reported in the earlier study.

The hypothetical four-reservoir problem has been used by many researchers (e.g. Chow et al., 1975; Kitanidis and Andricevic, 1989; Johnson et al., 1993) in several applications. The problem has become a benchmark for testing a variety of approaches ranging from DDDP to optimal control methods. In many cases, the model was used with little or no modifications. The latter is specific to a series of hydropower plants on a single river with strong hydraulic coupling and is computationally intractable. This is due to large number of decision variables in the formulation that is proportional to the number of time intervals considered for optimization.

The solution for the second problem is attempted to investigate the suitability of the algorithm for a reservoir operation problem with many decision variables, nature of optimum solution, computational time requirements and a comparison of its performance to that of a traditional optimization technique. The motivation to use the annealing technique in the present study is largely due to the need for obtaining optimal solutions for problems that reflect the characteristics of the second problem.

The models developed using the annealing algorithm are for: (1) four reservoir problem (Heidari, et al., 1971); and (2) operation of a system of hydropower reservoirs. The models are referred to as the benchmark and Winnipeg Reservoir System models respectively. The proposed models have two modules: (1) annealing algorithm; and (2) simulation. The module that incorporates the annealing algorithm uses the steps 1-3 and 5-9, whereas step 4 is executed using the simulation model. These steps are described in the Simulated Annealing section. Convergence criteria and values for different parameters of the annealing algorithm are set a priori.

The solution of the simulated annealing algorithm is based on the evaluation of the performance measure after every perturbation that is obtained using a simulation model. The simulation models that form the backbone of the complete models are developed using the programming language, C. The models cannot be strictly referred to as simulation models in a general sense, since they also check for infeasibilities resulting from violation of imposed constraints. The performance measures required by the algorithm are obtained from the simulation models. The simulation model developed for the benchmark problem is discussed first and the model developed for the Winnipeg Reservoir System is explained next.

For the reservoir operation problems considered in the present study, plant discharge or release at each of the reservoirs is selected as a control variable. This is based on the experiments conducted in the present study using storage state and discharge as main control variables. It was observed from experiments conducted in the present study that the use of storage as a state variable has resulted in higher number of infeasible solutions compared to the similar usage of discharge variable. This is attributed to the fact that random values of discharge within a specified range would most likely result in feasible storage states as opposed to feasible discharge values produced by transitions in storage states. Since, release is the main decision variable with which performance measure is usually associated in most of the reservoir operation problems, a positive value for release is essential and its use is appropriate as a control variable. If storage is chosen as a state variable, care should be taken to ensure that the transitions are generated such that a feasible value of release is always realized. This procedure requires a condition that in a set of two consecutive storage values generated, the final value should be at least equal to or lower than previous value.

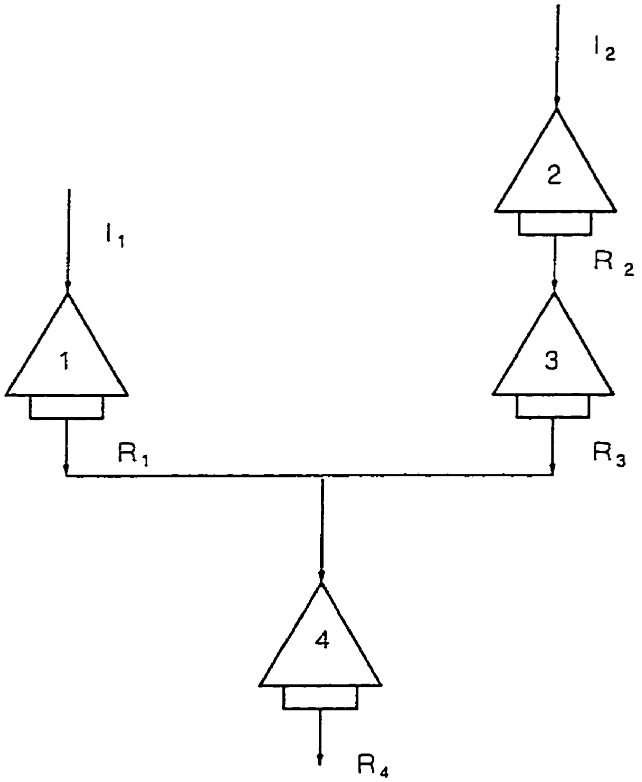


Figure 4.2: Schematic diagram of four reservoirs (Heidari et al., 1971)

4.6.1 Benchmark Model

The annealing technique is applied to a four reservoir problem where benefit functions are available to calculate the benefit from the release made from each of the reservoirs for every time interval. A schematic diagram of the four reservoir system is shown in the Figure 4.2. The objective function used for the optimization problem is given by the following expression.

$$Maximize \quad \sum_{t=1}^{T} \sum_{j=1}^{n} R_{j,t}\, b_{j,t} \tag{4.7}$$

The index j refers to the reservoir and T is the total number of time intervals for which the operation is considered. The variables $R_{j,t}$ and $b_{j,t}$ represent the release and the benefit values respectively. In case of the $j = 4$, the benefits are from the release made for hydropower and irrigation. Constraints for storage include, $S_1, S_2, S_3 \leq 10$ and $S_4 \leq 15$ and for release are: (i) $R_1 \leq 3$; (ii) $R_2, R_3 \leq 4$ and (iii) $R_4 \leq 7$. The inflows for the reservoirs for first and second reservoirs are 2 and 3 units respectively and the initial storage for all the reservoirs is taken as 5 units. Details of the benefit functions for the release are avoided, as they are available elsewhere (Heidari et al., 1971). A negative sign attached to objective function can be used as a cost function (performance measure) in order to apply the annealing algorithm in its standard form. To reduce the range of the variables (release values), problem specific information is used. The approximate range of the variables are obtained using normalized benefit values within the generation mechanism. The benefit values associated with the release values in each time interval are normalized using the highest possible benefit value of all the time intervals for a particular reservoir using the expression,

$$b'_{j,t} = b_{j,t} \;/\; b_{j,max} \quad \forall j, t \tag{4.8}$$

These normalized values are calculated for all the reservoirs and the time intervals.

$$\epsilon_{j,t} = {b'_{j,t}}^{\theta} \quad \forall j, t \tag{4.9}$$

The variable, θ can take any value above 1. In the case of θ assuming a value of unity, the curve would be linear. Higher values of θ would reinforce the effect of benefit values associated with the release. The values of $\epsilon_{j,t}$ can be used in introducing the bias towards specific transitions in the generation mechanism as given by

$$\mathbf{R_{i+1}} = \mathbf{R_i} + (\epsilon_{j,t}\ \mathbf{R}_{range}\ ((ran(0,1)\ \phi) - \phi_1)) \qquad \forall i, j, t \tag{4.10}$$

Here, $\mathbf{R}$ refers to a vector of release values at a particular reservoir. The nature of perturbation (increment or decrement) to generate a transition is influenced by the values of ϕ and ϕ_1. Appropriately selected values for these parameters can introduce a skew or uniformity in the distribution of $\mathbf{R_{i+1}}$. A skewed distribution would introduce a bias towards a particular set of values.

The benchmark model is a closed-end problem wherein the target values of some variables are fixed for the final time interval. Infeasibilities are bound to occur in such problems where the predefined state variable values are not appropriate to satisfy the constraints that relate to the target values. Repair strategy is used to obtain feasible solutions whenever the infeasibilities are associated with such constraints. In the present operation problem, the final storage values are fixed. The strategy would be to re-calculate the release values from the continuity equations with the available target storage values. For example, for reservoir (1), the release value is calculated if the final storage is not equal to the target storage, $S_{1,target}$, that is required to be met at the end of final time interval.

$$R_{1,T} = S_{1,T} - S_{1,target} + I_{1,T} \tag{4.11}$$

Re-adjusting the values can eliminate the infeasibilities related to the variables. One such modification for storage values is provided here.

$$S_{j,t} = S_{j,t}^{max}\,(1 - b'_{j,t}) \qquad \forall j, t \tag{4.12}$$

This modification is appropriate whenever the constraints related to the upper and lower bounds of the storage are violated. Incorporation of normalized benefit function value into the constraint serves as a heuristic to limit the storage to low value if benefit is high and vice versa. This will lead to corresponding release decisions. Based on the modifications made to the storage, the discharge values are re-calculated using mass balance equations for all the reservoirs. Similar modifications may be needed for the variables at the end of the last time interval, where the target storage values are known or set a priori.

(1) Generate random values of the releases for all the time intervals and for each reservoir. Heuristic rules used to generate appropriate values are discussed later.

(2) Calculation of storage states: based on the release values the storage states are determined for all time intervals. The storage values are estimated starting from the first reservoir ($j = 1$) to the last reservoir ($j = n$). As the reservoirs are in series, this order has to be maintained to account for the appropriate mass balance between the reservoirs.

(3) Average storage: using the initial and final values of the storage in any time period the average value of the storage is calculated.

$$h_{j,t} = (k^i_{j,t} + k^f_{j,t})\ 0.5 \qquad j = 1, n \ \ \&\ t = 1, T \tag{4.13}$$

where $h_{j,t}$ represents the average storage value with $k^i_{j,t}$ and $k^f_{j,t}$ indicate the initial and final storages for the time interval, t.

(4) Calculation of average forebay elevations: the head required for hydropower generation is calculated using the average of initial and final forebay elevations, $k^i_{j+1,t}$, $k^f_{j+1,t}$ respectively.

$$h_{j+1,t} = (k^i_{j+1,t} + k^f_{j+1,t})\ 0.5 \qquad j = 1, n \ \ \&\ t = 1, T \tag{4.14}$$

(5) Selection of tailwater curve: to account for hydraulic coupling, the tailwater elevation

that is a function of the total plant discharge and the elevation at the immediate downstream reservoir is used. Based on the discharge $G_{j,t}$ which includes plant release and spill, and the average downstream elevation, $h_{j+1,t}$, a specific tailwater curve is selected. This curve will be used to estimate the tailwater level elevation.

$$T_{j,t} = k^{o}_{l,j+1} + C_{l,j+1}\ G_{j,t} \qquad j = 1, n \ \ \& \ t = 1, T \tag{4.15}$$

here, $T_{j,t}$ is the tail water elevation based on the downstream storage elevation, $k^{o}_{l,j+1}$ for which the tailwater elevation curve is defined. $C_{l,j+1}$ is a constant. The selection is possible since the initial and final values of the storage at each of the reservoirs is already known.

(6) Validation of constraints: the constraints related to power production at each plant, maximum and minimum allowable storage levels, target storages and allowable discharge values are checked. Major constraints that are checked are given below.

$$\sum_{t=1}^{T} \sum_{j=1}^{n} \gamma_o\ (h_{j,t} - T_{j,t})\ Q_{j,t}\ \beta_{j,t} \geq E_{tar} \tag{4.16}$$

$$k_{j,t} \geq k_j^{min} \qquad \forall j, t \tag{4.17}$$

$$k_{j,t} \leq k_j^{max} \qquad \forall j, t \tag{4.18}$$

Here, k_j^{min} and k_j^{max} represent the minimum and maximum storage values allowed at the reservoirs. E_{tar} refers to the target demand that has to be met.

(7) Real-time constraints: the storage states are updated in real-time using the following constraints.

$$k_{j,1}^{i} = Ist_{j,1} \qquad j = 1, n+1 \tag{4.19}$$

$$k_{j,T}^{f} = Fst_{j,T} \qquad j = 1, n+1 \tag{4.20}$$

Where, $k_{j,1}^{i}$ and $k_{j,T}^{f}$ represent the initial and final storage values for all the reservoirs. The variables, $Ist_{j,1}$ and $Fst_{j,T}$ are the initial and final storage states whereas $n+1$ refers to the lake, river or reservoir into which the last reservoir is discharging.

(8) Evaluation of infeasibilities: the number of infeasibilities is counted based on the constraint violations obtained from the step 6. If the count is zero, the next step is executed; otherwise a repair strategy is implemented. If infeasibilities remain after implementing the repair strategy, the solution is either rejected or modified to incorporate a penalty associated with the violation of each of the constraints. The severity of the penalty depends on the importance of the constraint.

(9) Performance measure: once the evaluation of infeasibilities is complete, the performance measure is obtained by the following expression.

$$M_s = \sum_{t=1}^{T} \sum_{j=1}^{n} (DO_t \ \gamma_o \ (h_{j,t} - T_{j,t}) \ Q_{j,t} \ \beta_{j,t}) \tag{4.21}$$

The expression (4.21) is same as the objective function that is used to minimize the cost of energy production in the MINLP formulation. In general, for hydropower plants that are not operated in conjunction with thermal plants the power production cost is zero. However, a psuedo-cost is associated with the power production to reflect the variations in power production with respect to different time intervals and to primarily assess the capabilities of the algorithm. The variation of the cost in different time intervals is shown in the Figure 4.3.

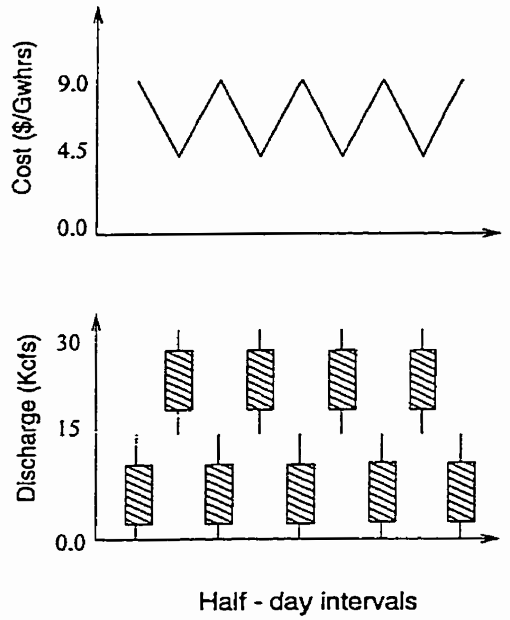


Figure 4.3: Cost structure in different time intervals

If the energy production cost is zero, as it is in most of the real-life situations, the energy generation would depend on the plant discharge-efficiency curves. The discharge-efficiency curves can be used for the range selection. A typical discharge-efficiency curve and the identification of approximate range value are shown in the Figure 4.4. The range for the discharge variable can be selected considering the portion of the curve where highest efficiency is possible. Steps 1 - 9 described for the simulation model are specific to the type of network of reservoirs considered. The steps are to be carried in the order specified to allow the calculation of the variable values and expressions. The annealing module is implemented and is stopped when the convergence criterion is met.

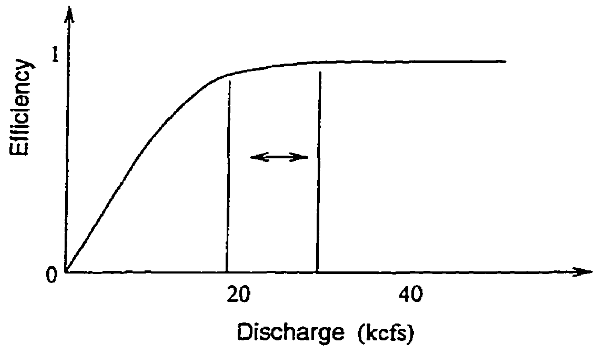


Figure 4.4: Identification of approximate range

An important parameter associated with the annealing module is the initial temperature. The value for this parameter is problem specific. In the present context, the initial temperature, T_o^e, can be obtained by one of the following expressions :

$$T_o^e = c_{max}\; E_{tar} \tag{4.22}$$

$$T_o^e = 0.5\; E_{tar}\; (c_{max} + c_{min}) \tag{4.23}$$

where, E_{tar} represents the target energy demand for a specific total time horizon, and

c_{max} and c_{min} are the maximum and minimum cost of energy production in any given time interval. The cost obtained from the expression in the equation (4.22) can used as it provides higher value for temperature. Higher value of initial temperature is generally adopted as this would allow for higher number of configurations to be accepted to avoid local minima. In the absence of any problem specific information a very large value of initial temperature in the annealing algorithm can be used.

4.7 Model Applications

The benchmark and Winnipeg Reservoir System models developed using simulated annealing algorithm are applied to hypothetical and real-life hydropower reservoir systems respectively. Details of the Winnipeg hydropower reservoir system can be obtained from the previous study (Barritt-Flatt and Cormie, 1989) and from chapter 3. The fact that both models deal with a four reservoir system is a coincidence. Release is considered as state variable for both operation problems while using the annealing algorithm. The benchmark model is applied for solution of the four-reservoir operation (Heidari et al.,1971) for 12 time intervals. The initial and final storage states, inflows to the reservoirs and the benefit functions for the release are taken from the previous study. The model is applied to an existing system of hydropower reservoirs in Winnipeg, Canada.

Hourly scheduling is considered based on the weekly targets available from the EMMA (Energy Management and Maintenance Analysis) model (Barritt-Flatt and Cormie, 1988). The objective is to minimize power generation cost for all time intervals while meeting system demand. Forecasted inflows for all time intervals, the initial and final storage targets and tailwater elevation curves are provided by the local power utility, Manitoba Hydro. A weekly time interval between September 15-21st, 1997 is used for application of the model.

The Winnipeg Reservoir System model is solved for two different problems of constant overall time horizon considering different number of time intervals. An hourly scheduling problem is considered with 168 time intervals. In another experiment a total of 14 time intervals are considered thus reducing the problem to a half-day scheduling problem. The latter has provided an opportunity to compare the results from the real-time operation model with those of a MINLP model. The solution obtained for the first problem is not necessarily a global optimal solution. The nature of the solution (global or local optimum) could not be determined, as a feasible solution was not obtained using the solver used for the MINLP model. This can be attributed to the number of time intervals, binary variables and the decision variables that increase the complexity of the formulation and make the model computationally intractable.

To assess the nature of solution obtained by SA an alternate comparison was attempted. Two cost structures that reflect the variation of cost of energy production are used. These are: (1) constant cost of power production per hour through out the day; and (2) varying cost of power production for specific time intervals of the day. The model is run for a time horizon of one week with 168 hourly intervals using the two cost structures. Using a varying cost structure will aid in the visual inspection of the nature of the solution.

4.8 Results and Discussion

The annealing algorithm is applied to two different multiple reservoir operation problems. Results from the application to four-reservoir problem are presented first, followed by results from the hydraulically coupled hydropower Winnipeg reservoir system.

4.8.1 Benchmark Model

The objective of this experiment is to evaluate the ability of the simulated annealing to obtain the global optimum solution for a multiple reservoir operation problem with linear benefit functions. Release is selected as the variable that is perturbed using the generation mechanism. The range for the variable is based on the lower and upper limits of the release at each of the reservoirs. The selection of the initial temperature, T_o is straight forward as the value is reflective of the objective function. As the global optimum value is already available the task is to replicate that using the simulated annealing technique.

The α value is taken as 0.99. It was observed that the number of feasible solutions were directly related to the number of the minor iterations, L_c carried out. The value of L_c varied anywhere between 10000 to 40000. Experiments are conducted with changing values of ϕ and ϕ_1. Using higher values for ϕ (e.g. a value above 2) and values lower than 1 for ϕ_1 has resulted in more number of near optimal solutions in the first few major iterations. This is suggestive of the mechanism that higher values of the control variables would result in higher benefit values.

Since the objective function depends on the release-benefit curves, higher values of releases would always increase objective function values. The value of ϕ used in the experiments ranged from 1 to 5. A value of 5 was found to be ideal in generating more feasible solutions compared to other values. A higher value for ϕ and a lower value for ϕ_1 is appropriate for the present problem as this would introduce a heavy bias towards one set of transitions. Since these transitions produced better objective function values, these are preferred. It is advisable to experiment with different values of ϕ and ϕ_1 for few iterations before using them for the complete annealing process.

Repair strategies are applied at two instances within the simulation model. As no benefit value is attached to spill at any reservoir, the continuity equations are modified through repair strategy to modify the release to include the spill wherever and whenever possible. Release values are recalculated in the last time interval based on the target storages for all reservoirs whenever the target storage states are not met based on the pre-defined release values. If constraints related to upper and lower bounds are violated, a corrective mechanism (in Equation 4.12) is applied. The results were compared with those of Heidari et. al (1971). A global optimum value of 401.3 is achieved by the simulated annealing algorithm as compared to the one obtained using Linear Programming. The number of minor and major iterations needed for the solution are 36000 and 132 respectively. In the present case, global optimum value is achieved when the release values are restricted to integer values. The use of integer values is also justified based on a specific property relevant to solution of a special category of Linear Programming problems.

The benchmark problem belongs to a special case of Linear Programming problem (expressed in standard form) where the entries in the constraint matrix are either of the form [-1, 0, +1] and the constants on the right hand side are integers. Kolman and Beck (1990) refer to Hoffman and Kruskal (1956) who showed that the solution to these problems would always yield an integer solution for the variables.

Near optimal solutions (e.g. 400.8) close to the reported global optimum were obtained if this restriction was not applied. It should be noted that the improvements to generation mechanism are in general useful for any problem with variables taking continuous values. However, in this case, restriction of variables to integer values has resulted in global optimum solution. A trial run with this restriction on variable values is worth undertaking to explore the nature of solution for any reservoir operation problem. The computational time taken to obtain global and near-optimal solutions is reasonable considering the nature of the annealing algorithm and not considered as an advantage when compared to traditional LP technique. The storage trajectories were similar to those obtained by Heidari et al. (1971) except in two time intervals. Minor variations in a few time intervals were observed when the values ϕ and ϕ_1 are changed. The storage trajectories for reservoirs 2 and 3 from the LP, GA (Wardlaw and Sharif, 1999) and SA approach from the present study are shown in the Figures 4.5 and 4.6.

In case of reservoir 2, the storage trajectory from SA and LP are almost the same. The storage values are different from LP formulation in two intervals in case of SA and four in case of GA. Similar trends can be seen in the case of the reservoir 3 using all the three approaches. However, the global optimum, 401.3, is obtained using GA approach (Wardlaw and Sharif, 1999). The difference in the storage trajectories generated by SA and GA does not necessarily indicate that one approach is better than the other.

Implementing the annealing algorithm with two different generation mechanisms can show the value of using heuristic rules for reduction of the range of variables. It was observed that

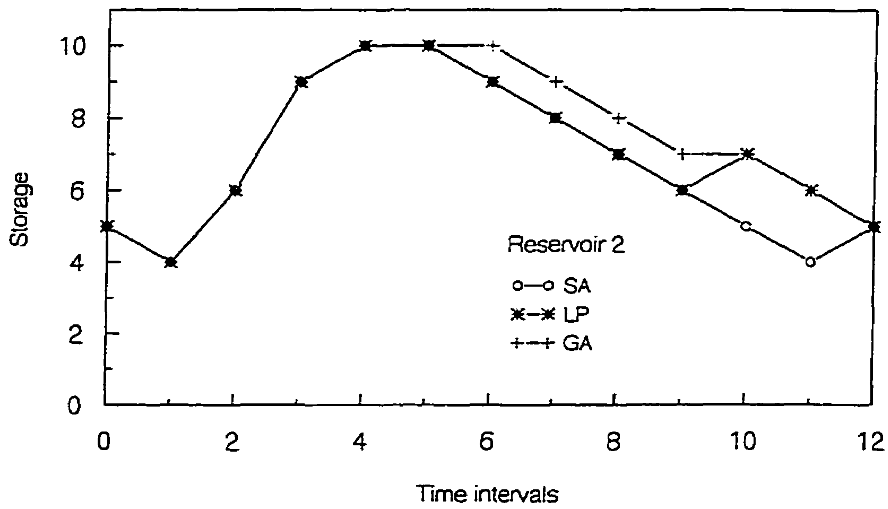


Figure 4.5: Storage trajectories for reservoir 2

a relatively many feasible and near-optimal solutions were obtained using the generation mechanism in equation (4.10) compared to the standard mechanism provided by equation (4.4). An experiment is conducted using the standard and improved generation mechanisms and the number of feasible solutions are compared. In the former case, only 3 feasible solutions were obtained while the latter produced more than 1000. In this experiment, a solution is regarded as feasible only when the objective function value is more than 380. It should be noted that the generation mechanism is heavily biased by problem specific information.

The number of transitions at each temperature has an effect on the number of solutions obtained. Figure 4.7 shows the cumulative number of solutions obtained for different number of transitions at each temperature level. The number of transitions chosen for each case is indicated in the figure. For this experiment, solutions are regarded feasible and are accepted only when the objective function is greater than 400. It is evident from the graph

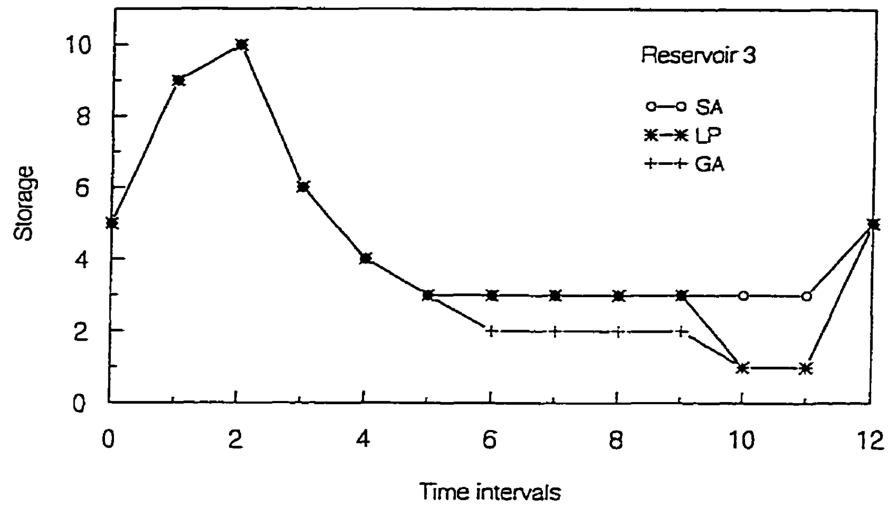


Figure 4.6: Storage trajectories for reservoir 3

the number of feasible solutions depends on the number of transitions allowed at a given temperature.

The global optimum solution was obtained using the mechanism where the transitions are guided by heuristic rules. The exercise of solving the benchmark model is intended to show the advantages of using heuristics within the simulated annealing algorithm for reservoir operation problems. Application of SA to the four-reservoir problem is not based on the need for global optimal solution and is not recommended for problems that can be solved using traditional optimization techniques. However, the application provides insight into the generation mechanism used for continuous variables, incorporation of problem specific information and repair strategy for closed-end problems.

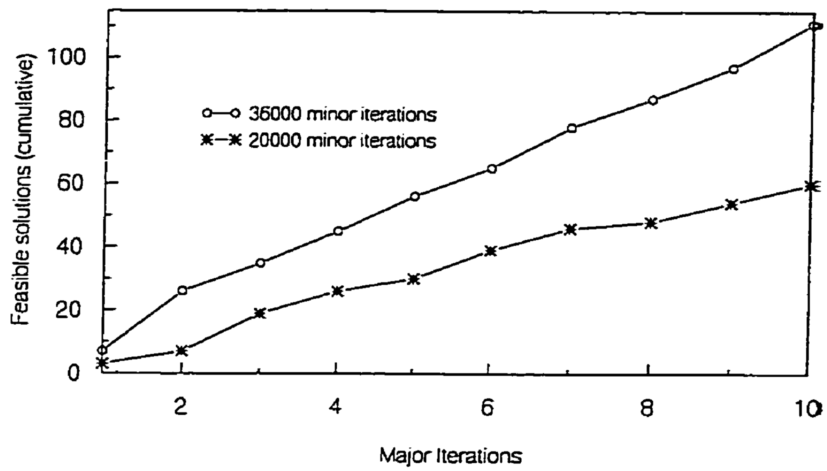


Figure 4.7: Effect of number of transitions on the number of solutions

4.8.2 Winnipeg Reservoir System Model

The model is developed to test the capability of SA algorithm in two cases: (1) obtain an optimal or near-optimal solution for a reservoir operation problem with many decision variables; and (2) comparison of the performance of the annealing algorithm to a traditional optimization technique. The real- time operation model is applied to a system of four hydropower reservoirs in series on a single river. The state variable selected in both the cases is release. The ranges of the variables are provided using heuristics. An initial guess of the range of the variables is obtained from the EMMA model that provides a weekly optimal release values. Problem specific information was proved to be useful in the present case and allowed better results. The range and cost of production values for different time intervals are shown in the Figure 4.3.

The results relevant to these conditions are shown in the Figures 4.8 and 4.9 respectively. The power production figures shown in the graphs indicate the total amount of power produced at all the power plants for half-day intervals. The values shown in the Figures 4.8 and 4.9 are for constant and varying cost structures respectively. It can be noticed from the graphs the variation of power production in the first case is erratic while an oscillatory trend is observed in the case of the varying cost structure. This provides a clear sign of optimization that is achieved using the present algorithm. As it is impossible to solve the problem using any other state-of-the-art optimization technique available, the solution obtained cannot be guaranteed as global optimum. The average computation time taken to obtain a solution using a PC (under Windows NT environment with Pentium III processor) is 20 minutes.

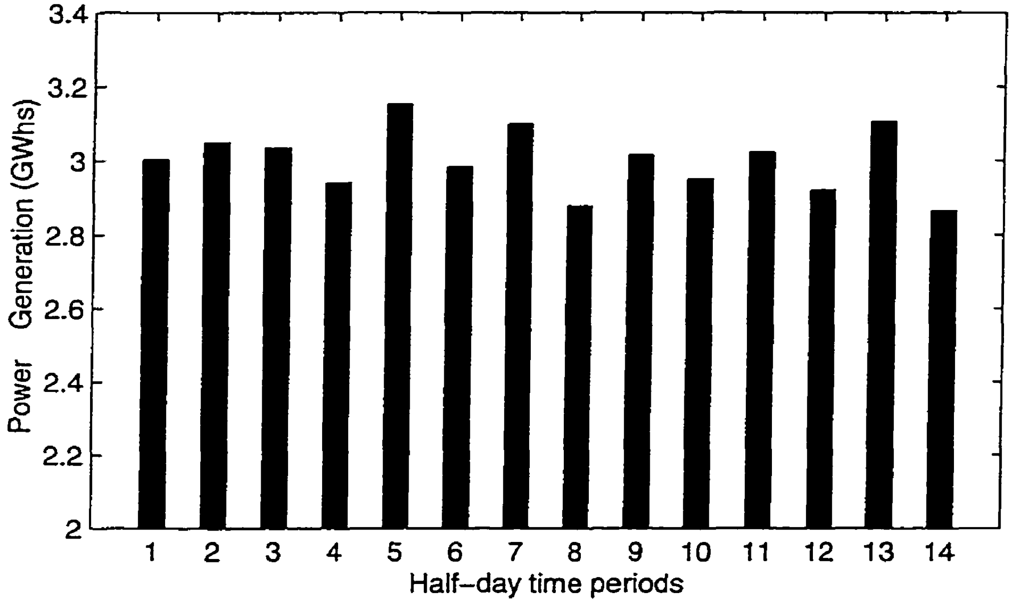


Figure 4.8: Power production values with constant cost structure

The model also is applied to operation of a coupled hydropower reservoir system considering a time horizon of one week comprising of half-day time intervals with total of 14 decision intervals. Plant discharge (release) is again selected as the control variable and the generation mechanism given by equation (4.4) is used to obtain the values of the variable.

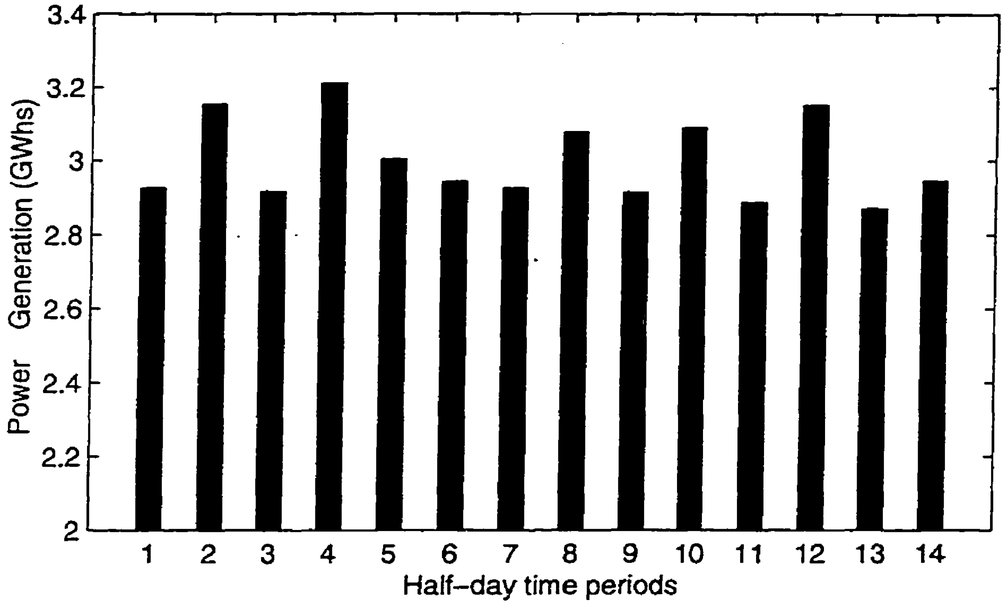


Figure 4.9: Power production values with varying cost structure

A trial and error procedure was used to arrive at the feasible ranges of the discharge variables. The variation of cost of energy production with respect to time was used to approximate the range of the discharge variables. After few trials using the annealing algorithm, the ranges are fixed. For each trial, the number of feasible solutions is counted for a specific number of major iterations. The range values that resulted in larger number of feasible solutions are selected and the annealing algorithm is applied. The generation mechanism needs to be modified if the ranges of the discharge variables are not fixed using this trial and error procedure.

Since the cost structure varies in a periodic fashion, the determination of the ranges after few trials is easy. However, if the cost structure is complex, then normalized cost values (similar to normalized benefit values) can be used to introduce the bias into the generation mechanism. The α value used in the annealing algorithm is 0.98 which ensures a slow cooling schedule for the annealing process.

There are two ways of applying the generation mechanism for the discharge variable :

(i) Use an appropriate range for the discharge variable different for every time interval and reservoir.

(ii) Use an appropriate range that is constant for all the time intervals and different for the reservoirs.

In the present study a constant range for the discharge for each reservoir is used. The standard generation mechanism given in equation (4.4) is used as appropriate range values for the discharge variable are already defined. The increments or decrements (Equation 4.5) are scaled using a factor of 0.1.

The problem is also solved using the traditional MINLP formulation using a state-of-the-art solver, GAMS (Brooke et. al, 1996). The MINLP and SA models are run for the similar conditions to obtain the optimal power generation values at each of the hydropower plants. The total power demand to be met is fixed in both the formulations and is equal to 43.1 $GWhrs$. The objective function (cost) values obtained are 264.17 and 260.15 by MINLP and SA models respectively. These figures represent the cost of energy production in monetary units. The SA model provided a better value of objective function than the MINLP model. Also, the computation time for solving the operation problem is much less compared to that of the MINLP model. The objective function value indicated was obtained within few major iterations. An average computation time of 10 minutes was required to obtain the solution on a PC (under Windows NT environment with Pentium III processor). The power generation values obtained from the models at two reservoirs for 7 time intervals are given in the Table 4.3.

Table 4.3: Power generation at McArthur and Great Falls

	Power (GWhrs)			
Time interval	Mc Arthur		Great Falls	
	(MINLP)	(SA)	(MINLP)	(SA)
1	0.54	0.28	0.17	0.73
2	1.63	0.59	0.68	1.43
3	0.52	0.26	0.17	0.60
4	1.63	0.55	0.68	1.45
5	0.52	0.31	0.17	0.74
6	1.63	0.64	0.68	1.34
7	0.53	0.31	0.17	0.60

4.9 Modeling Issues

The results obtained in the present study provide considerable insight into the working of the annealing algorithm and its application to reservoir operation problems. The cooling schedule within the annealing can be incorporated at a faster rate (referred to as *quenching*) to assess the capability of the simulated annealing technique in solving a multi-period and multiple reservoir operation problems and obtaining near-optimal solutions. However, global optimal solutions are not guaranteed by this procedure.

The problem specific heuristic rules and the repair strategies used in the present study for two different reservoir operation problems are useful in generating larger number of feasible solutions. The repair strategy is useful for operation problems where some of the variables take on target values at the end of the time horizon. This can be referred to be a closed-end problem, where larger number of infeasibilities is bound to occur. The repair strategy may not be required in cases where the problems are cast as open-end problems without end-of-period target constraints. However these types of problems are quite rare in the field of reservoir operation.

The results presented corroborate that near optimal solutions can be obtained within a reasonable amount of computational time for complex multiple reservoir problems involving many decision variables. Even though, global optimum solutions are guaranteed in theory using the annealing algorithm, the decision maker can decide to use the available near optimal solutions for application in real-time. The improvements incorporated into simulated annealing can be used to address any configuration of reservoirs. Problem specific information is essential in improving the search for optimal solutions and reducing the computation times. In the present study, the use of heuristics to define the range of discharge variables proved to be useful. A functional relationship between the cost of production and plant discharge has helped narrow the ranges of discharge variables used as control variable in the annealing model.

4.9.1 Complexities

The complexity issue surrounding the MINLP formulation is related to computational intractability resulting from combinatorial increase in the number of binary variables. The increase is proportional to the number of time intervals and tailwater curves considered. In the case of annealing, simulation model is an integral part of the algorithm that provides an easy mechanism to incorporate any detail while considering the representation of the physical system that is not possible using traditional optimization techniques. Improvements in the reduction of search space are possible, while conceptually better algorithms such as very fast simulated re-annealing (Ingber, 1993) can be experimented. The annealing algorithm is simple and easy to implement for many reservoir operation problems. The annealing parameters (number of major and minor iterations, temperature and the stopping criterion) play a major role in obtaining global or near optimal solutions.

The experiments conducted in the present study suggest that the speed and convergence of the annealing algorithm to a near- or global optimal solution depends more on the range of the state variables appropriately defined than on the parameters used for the annealing algorithm. The random perturbation part of the annealing algorithm needs attention. The spectral properties of the random number generator used within the annealing algorithm to a certain extent influence the performance of the algorithm. In the present study two functions (*rand and rand48*) available on the Unix (Solaris) platform are experimented. The *rand48* function has better spectral properties, a fact confirmed by the literature relevant to the random generator functions and the number of feasible solutions obtained in the present study. A generator with good spectral properties is always preferred to obtain a wide range of solutions.

4.9.2 Implementation of Simulated Annealing

A major difficulty with the use of simulated annealing is the definition of the range of the continuous variables. Since reservoir operation problems are bound to have continuous variables, heuristic rules can be used to reduce the range of these variables. General guidelines while applying annealing to reservoir operation problems:

- define the relationships between the state variables and the performance measure to develop heuristic rules.
- experiment with the appropriate range values for the variables based on the problem specific information.
- use screening models that provide sub-optimal solutions for simplified models to obtain variable ranges.
- identify any problem specific conditions to devise heuristic rules.

The performance measure or objective function often provides clues for developing heuristic rules. Linear Programming formulations can serve as screening models. Discrete Dynamic Programming can also be useful for obtaining the optimal range of the variables through the discretized class intervals. However, these screening approaches apply only when they are computationally feasible and insightful.

4.10 Summary

A stochastic search technique, simulated annealing, is used to develop operation models for multiple reservoir systems. Considering the number of decision variables and the constraints, the near-optimal solutions obtained are considered adequate for practical applications, especially in the absence of tools to precise globally obtain optimal solutions. The annealing technique can be regarded as a *last resort algorithm* for solving reservoir operation problems marked as computationally intractable (Teegavarapu and Simonovic, 2000d). The model based on the annealing technique is proved competitive with a traditional optimization technique used in the present study. The problem specific heuristics used make the annealing technique a tailored algorithm applicable only to specific reservoir operation problems. However, this should not be regarded as a disadvantage as the problem specific information can be used in improving the solution and reduce the computation time required. The annealing technique in general is easier to apply for reservoir operation problems compared to a genetic algorithm.

For problems where continuous variables space pose a problem, suggestions are provided in this research. The algorithm used here is a sequential implementation of standard annealing technique. Recent studies (Azencott, 1992) have dealt with the development of approaches useful for parallel implementation of the algorithm. Further research is aimed at developing parallel implementations of the annealing algorithm and general heuristic rules for the various problems relevant to operating of multiple-reservoir systems. The simulated annealing algorithm was applied to two problems here, one a standard test problem. At this point it is tempting to make global claims about the general nature of algorithm and its applicability for a variety of reservoir operation problems. With cautious optimism it can be stated that the algorithm has potential for application to a number of computationally intractable problems in reservoir operations.

4.10.1 Extensions

A real-time multiple reservoir operation problem was solved using the proposed simulated annealing model. The near optimal solutions obtained are adequate for practical applications. However, some issues relevant to the algorithm's performance still need to be addressed. Belonging to a similar class of search techniques, genetic algorithms (Michalewicz, 1996; Haupt and Haupt, 1998) are becoming increasingly popular for solving complex optimization problems. These algorithms simulate nature's evolution process in solving complex optimization problems. Genetic Algorithms can be used to solve the real-time operation problem to assess their performance compared to that of SA.

An ideal extension to the present study would be to compare the performance of GA and SA for several multiple reservoir operation problems or at least using the reservoir operation problem already addressed. The simulation model and the problem representation experiments conducted in the present study will be of great use in developing the optimization models using genetic algorithms. The simulation model developed for simulated annealing algorithm can be used to calculate the fitness values of the population in case of Genetic Algorithms.

4.10.2 Postscript

Computational intractability must be considered in developing real-time optimization models. The use of heuristics within the stochastic search techniques is inevitable for solving complex problems. The essence of this statement is well summarized by H. Bremermann in "Optimization Through Evolution and Recombination" reported by Kosko (1999):

> "Problems involving vast number of possibilities will not be solved by sheer data processing quantity. We must look for quality, for refinements, for tricks, for every ingenuity that we can think of. Computers faster than those of today will be of great help. We need them."

Use of problem specific heuristics in any algorithm marks it as a *tailored* approach or technique. In instances where the problems cannot be solved using existing classical and non - traditional optimization approaches, *tailored* algorithms will become the last resort.

The next chapter addresses the tail-end issue handled in the present research relevant to the actual implementation of the reservoir operating rules. The chapter also discusses a few tools developed in the present study to aid such an implementation process.

Chapter 5

Implementation Issues and Practical Solutions

Results ! Why man, I have gotten a lot of results.
I know several thousand things that won't work.
- Thomas A. Edison

5.1 Introduction

Three major issues relevant to the real-time operation of reservoir systems are discussed in the earlier chapters. The models developed considering these issues are validated by a few test cases of real-time operation of existing reservoir systems. However, application of these models in real-time and their practical utility in a variety of situations needs to be assessed. A fair evaluation can only be possible when the models are applied in real life situations by reservoir operators or managers, decisions are implemented and the system performance is estimated. As actual implementation will reflect on these aspects, this chapter will discuss some additional approaches and tools that are developed in the present research to aid this process. It is imperative that reservoir operators and model developers should be involved in such a process.

The perspectives of modelers and the reservoir operators on reservoir operation models and their application in real-time are completely different. Many of the models developed in theory are not finding their way into practice. Some of the issues the modelers generally concentrate on are: (1) development of models to capture the dynamics and exhaustive representation of the system; (2) adopt state-of-the-art optimization tools that provide globally optimal solutions; and (3) model execution time within an operational time frame. However, reservoir operators/managers are interested in: (1) comprehensive, yet easy to use operation models; (2) transparency of the modeling environment to adopt, modify and run for a variety of situations in real-time; (3) interactive user interface and add-on tools to obtain real-time operational scenarios; (4) reasonable computational resources and time within which operational decisions can be obtained; and (5) acceptable quality of solutions as long as the performance of the system is better than the one obtainable using existing standard operational decisions. While these are some of the views on which modelers and operators differ, a variety of issues that stem out of these might hold the key to the better acceptance of models developed in theory for application.

5.2 Theory and Practice

The gap that still exists between theory and practice in the field of reservoir operations and a variety of reasons for the same have been already discussed by many researchers (e.g. Yeh, 1985, Simonovic, 1992; Labadie, 1997; Nicklow, 2000). Efforts are still being made by many researchers to reduce the gap by involving reservoirs operators in model development to a larger extent and embracing the emerging optimization tools (Simonovic, 2000). These new tools are referred to as non- traditional approaches in this research. A major issue related to the existence of the gap is the practical application of the models in real-time.

The model execution or run time that has an enormous influence on the actual usage of models in real-time is not explicitly spelled out as an issue in the earlier works (Yeh, 1985; Simonovic, 1992; Labadie, 1997). Execution time (computational) of the model assumes importance in case of short-term or real-time operation of reservoir systems, where operational decisions are required within a short time. Examples of such applications include hydropower and flood control reservoir operations. The execution time and the nature of the solution are affected by the system representation in the formulations. As discussed in previous chapters an exhaustive representation of the system at a finer time scale increases the number of variables and non-linear functional relationships in the formulations. A direct consequence would be an increase in the computational time required for solution or in some cases the existence of feasible solutions.

Where it is difficult to run the optimization models, simulation models can aid the reservoir operators in implementing the operation rules in real-time. Also, improving the practical utility of optimization models revolves around better packaging of associated software (Goulter, 1992). Decision makers will more readily accept models that support their thinking process, provide graphical interfaces and enhance the understanding of the results. A decision support framework to aid the implementation process should have the capabilities of scenario generation and policy analysis. Simulation models are useful for policy analysis and scenario generation based on the dynamic inputs.

A framework that combines these elements in the form of Decision Support System (DSS) is developed in the present study. The framework encompasses all the optimization models developed in the present research. Simulation models developed based on a relatively new approach, Object-Oriented System Dynamics and Simulated Annealing are also included in the system. The development of the simulation model is discussed first and then details of the Decision Support System (DSS) are presented.

5.3 Object-Oriented Simulation

Modeling reservoir systems is generally achieved by developing mathematical programming formulations for optimizing the operations or by using a simulation model to understand or capture the dynamics of reservoir operation. In recent studies, operation models are developed using relatively new non-traditional optimization approaches such as Genetic

Algorithms (Oliviera and Loucks, 1999), optimal control methods (Nicklow, 2000) and Simulated Annealing. The use of simulation models is not uncommon in the field of reservoir operation. A detailed review of traditional simulation models used for reservoir operation is given by Wurbs (1993) whereas models based on principles of System Dynamics (Forrester, 1961) are discussed by Simonovic et al. (1996) and Simonovic and Fahmy (1999).

Simulation models have been used for almost 50 years for planning and analysis of water resources systems. Excellent state-of-the-art reviews are provided by Yeh (1985) and Wurbs (1993). A variety of simulation models are developed by agencies such as U.S. Army Corps of Engineers and the Colorado Water Resources Institute (ReVelle, 1999). However, many of the simulation models developed in the past use high level programming languages with many disadvantages. These disadvantages include: (i) problem specific codes; (ii) rigid model structure; (iii) non-transparent structure that is difficult to decipher or change; (iv) lack of generic structure and (v) often huge time investments are required in model development.

Recent developments in computer science have lead to design of software approaches that eliminate many of the disadvantages associated with traditional models. One such approach that has gained attention is Object-Oriented simulation. The advantages of such an approach are discussed by Wurbs (1993) and Simonovic et. al (1997). An Object-Oriented simulation environment is ideal for carrying out the simulations, since the elements within in any system can be represented as a set of interrelated objects. One of the advantages of such an environment is that the objects can have generic properties that can be used to model specific elements. Objected-Oriented Analysis (OOA) (Tisdale, 1996) and Objected Modeling Technique (OMT) (Rambaugh et al., 1991) are different from Object-Oriented simulation conceptually.

The Object-Oriented simulation environments (e.g. STELLA, POWERSIM[1]) developed more recently are conceived on the principles of System Dynamics (SD) Forrester (1961). The concept of SD is relatively old compared to the environments that are based on its principles. The advantage of these environments is that they provide objects with generic structures and embrace the basic principles of SD. SD concepts explain the behavior of any system over time, whereas OOA and OMT help in understanding a real-world system using objects with specific properties. Object-Oriented simulation environments provide a number of advantages in developing simulation models. The benefits include: (i) flexible model structure; (ii) transparency; (iii) generic objects; (iv) negligible time investment in the development of models and (v) ease of use. One of the major features of the OO simulation environments is the ease with which qualitative information can be included in the model. This feature is useful while modeling water resource systems influenced by social and economic factors.

The simulation model developed in the present research use a specific Object- Oriented simulation environment that is conceived on the principles of System Dynamics. Hereafter, the models will be referred to as Object-Oriented System Dynamics or System Dynamics simulation models. The following sections provide the background to SD approach and details of the models.

[1]Developed by High Performance Systems Inc and Palisade Corporation respectively

5.3.1 System Dynamics Simulation

The field of water resources is replete with problems where traditional methods require complex mathematical representation of the physical systems and at the same time being excessively abstract. The non-linearities inherent in hydrological processes and socio-economic aspects associated with water resources systems sometimes make them less amenable to traditional models. The complexity of these models is a driving force for the research community to abstain from reductionist approaches and work towards holistic approaches to understand the dynamic behavior of these systems.

The weaknesses of traditional models are overcome by the paradigm of systems dynamics put forth by Forrester (1961) and Object-Oriented modeling tools. The paradigm relies on understanding of complex inter-relationships between the elements in any system and constructing a mental (conceptual) model. The mental model is then transformed into computer simulation to understand the behavior of the system over time. Coyle (1993) and Wolstenholme (1990) and Ford (1999) discuss the concepts and applications of system dynamics approach to a variety of problems. The concept of system dynamics approach is explained next.

System dynamics simulation (Forrester, 1961) approach relies on understanding complex inter-relationships existing between different elements within a system. This is achieved by developing a model that can simulate and quantify the behavior of the system. Simulation of the system over time is considered essential to understand the dynamics of the system. Understanding the system and its boundaries, identifying the key variables, representation of the physical processes or variables through mathematical relationships, mapping the structure of the model and simulating the model for understanding its behavior are some of the major steps that are carried out in the development of a system dynamics simulation model. The central building blocks of system dynamics approach are well suited for modeling any physical system.

Central to the theme of systems dynamics (Forrester, 1961) are two important building blocks, stocks and flows that can be used to model the elements that govern the water resource systems. Two important assumptions also are used while constructing these system dynamics models: (a) processes modeled form a closed loop and (b) system boundaries influence the dynamics. Causal loop diagrams or influence diagrams representing the interrelationships between various elements of the system are first developed. Flow diagrams are then extracted to develop simulation models. Computer simulations are performed using difference equations to integrate stocks and flows.

In general, the models developed using the system dynamics principles are validated by several tests that include: (1) replication; (2) sensitivity; and (3) prediction. These tests confirm the structure of the model with the physical system. Various other tests that validate the dimensional consistency of the equations used and robustness of the model in handling extreme conditions are carried out before the model is adopted for implementation. The model developed in the present study is validated using all these tests.

Recent applications of OOP methodology to water resource planning and policy analysis were provided by Lund and Ferreira (1996), Simonovic et al.(1997) and Fletcher (1998), Simonovic and Fahmy (1999). Keyes and Palmer (1993) indicate the advantages of such an approach to problems in water resources by demonstrating its utility in drought planning policy scenario generation. The principles of system dynamics are well suited for modeling and application to water resources problems, a fact that is confirmed by the previous works. Simonovic and Fahmy provide a general approach for policy analysis that uses the principles of system dynamics. Simonovic et al. (1997) apply system dynamics simulation to operation of High Aswan Dam in Egypt. The advantages of Object-Oriented simulation over traditional simulation models are discussed in detail by them. Lund and Ferreira (1996) use STELLA (Systems Thinking Educational Learning Laboratory with Animation), a tool based on System Dynamics approach to develop a rule based reservoir operation model. They compare the performance of this model with that of an optimization model, HEC-PRM. Ahmad and Simonovic (2000) in a recent study used similar approach to simulate reservoir operating polices for different flood control options.

In the present research work a SD simulation model for operation of a hydropower reservoir system is developed. However, the model can be modified to handle operation of any multi-purpose reservoir. The model is developed using an Object-Oriented simulation environment, STELLA, conceived on the principles of systems dynamics approach. The modeling environment is developed by High Performance Systems (1994). While describing simulation models, Wurbs (1993) refers to the tool, STELLA, as an Object-Oriented simulation environment.

The model developed in the present research is differs with the earlier work (Simonovic et. al, 1997, Simonovic and Fahmy, 1999) : (i) in addressing the issue of real-time operation of multiple reservoir system; (ii) exhaustive modeling of the system and the use of two indices (Hashimoto, 1982) to quantify the system performance and (iii) few problem specific objects and functions used in the simulation environment. Since the model is built around a simulation environment using pre-defined objects with specific properties, several special structures are developed to achieve this objective.

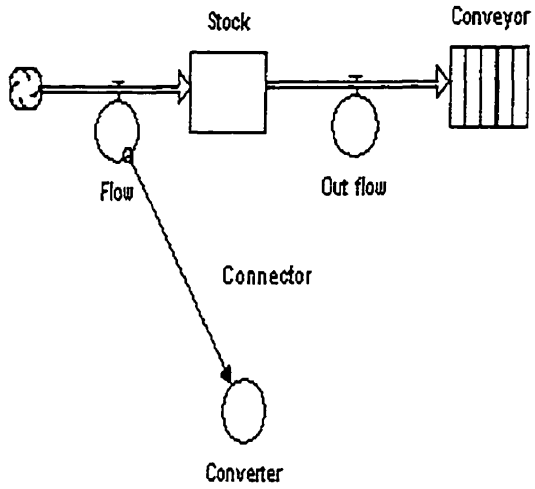
5.3.2 Governing Equations

The governing equations used for modeling different elements in a system are represented by finite difference expressions that are solved using a standard numerical scheme. The simulation environment (STELLA) used in the present study uses three different schemes with varying levels of accuracy. The equations are transparent to the user and can help understand various mathematical relationships. The governing equations are generic in nature and are associated with the objects. For example in case of Stock (object), a continuity equation for mass balance will be developed considering the inflows and outflows, while a Converter carries a functional relationship between different variables that can be represented in a mathematical or a graphical form. The time interval for simulation is also an important aspect that will determine the accuracy of the numerical scheme used for solving the finite difference equations.

5.3.3 Modeling Environment

The Object-Oriented simulation environment, STELLA, used to model the operation of a multiple reservoir system is conceived on the principles of system dynamics and uses objects that have specific properties. The basic building blocks, "Objects", are shown in the Figure 5.1. The environment provides three layers (mapping, model building and equation) that are used to develop a complete model. These are linked and any modification made in any one of the layers is reflected in all other layers.

The mapping layer provides the user interface, while the modeling layer is used for the



Objects:

Stock: to model storage (e.g. Reservoir)
Flow : to model any time series (e.g. Inflow)
Connector: to carry information about variables
Converter: to model functional relationships
Conveyor: to introduce delay in the system.

Functions:	Graphical Interface:
RANDOM	Graphs, Tables, Sliders
IF-THEN-ELSE	Sectors.
DELAY.	

Figure 5.1: Basic building blocks of the model

construction of the model. Different objects are used in the modeling layer to develop the model. For example, the object, Stock is used to model a reservoir while a Flow is used to represent inflow, spill and release from a reservoir. In order to incorporate a flow transport delay between two reservoirs, a Conveyor object is used.

Functional relationships and dependencies are defined using converters and connectors respectively. The simulation environment also provides a number of built-in mathematical, logical and statistical functions that can be used in any of the objects. The governing equations based on the model structure are automatically created in the equation layer by the STELLA environment and can reviewed for accuracy of the structure of the model. In the present study, functions such as RANDOM, IF -THEN-ELSE and DELAY are used. The environment also provides features such as sensitivity analysis, provision for graphical inputs and a simulation mode in which the inputs can be changed dynamically.

5.3.4 Model Architecture

The first step in the development of a System Dynamics simulation model is the creation of causal loop diagram. The diagram is used to identify the elements of the system and their relationship with each other. A causal loop diagram for a two-reservoir system (relevant to the Winnipeg River System) is shown in the Figure 5.2.

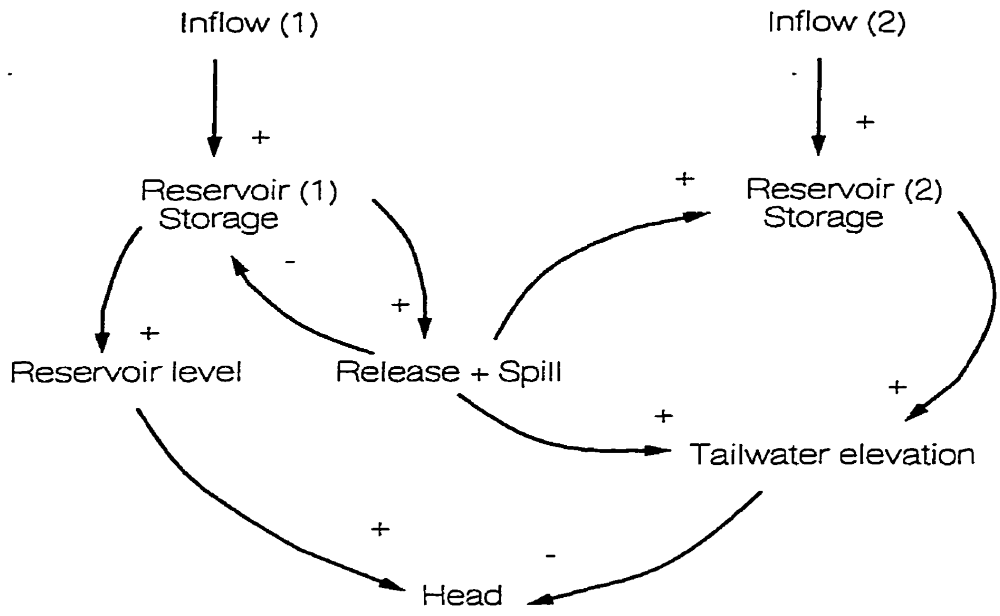


Figure 5.2: Causal loop diagram for a two reservoir system

The arrows indicate the relationships between different elements and the sign attached at the front of the arrow suggests the type of effect one element has on the other. For example, an increase in inflow would lead to an increase in storage. Similarly an increase in taliwater elevation would lead to a decrease in the *head* required for power generation. The spill, release, reservoir level and head shown in the Figure 5.2 are associated with reservoir (1). More details of the development of causal loop diagrams are available elsewhere (Roberts et al., 1983). The utility of the diagram will be evident when it is developed for a system with large number of interdependent elements. Development of SD models for large systems is difficult if causal loop diagrams are not created. However, this diagram provides a basic understanding of the system and its components. The structure of the model can be developed using the basic building blocks of any Object-Oriented simulation environment.

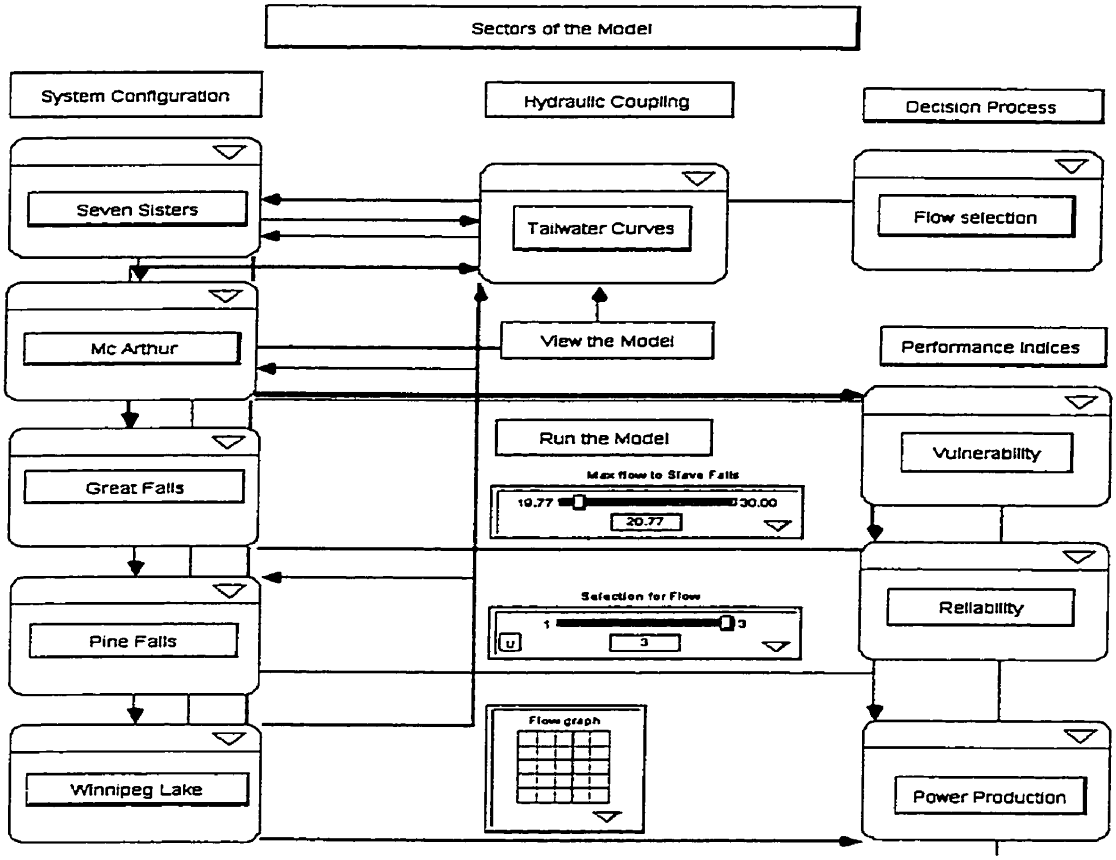


Figure 5.3: Main interactive layer of the simulation model

To facilitate the development, the model is divided into three major sectors. The major sectors and the initial interactive layer of the STELLA model are shown in the Figure 5.3. One of the advantages of dividing the model into sectors is that each sector can be run individually or in a group. The sectors also help incorporate the required modularity in the model structure.

The object structure of one of the main sectors (reservoir) is given in the Figure 5.4. The structure represented in the figure is for the Seven Sisters reservoir from the Winnipeg Reservoir System. The model structure is aimed at reflecting the operation of a system of reservoirs in series, with the final reservoir discharging into a lake with a strong hydraulic coupling existing between the plants. A brief description of the sectors is given here.

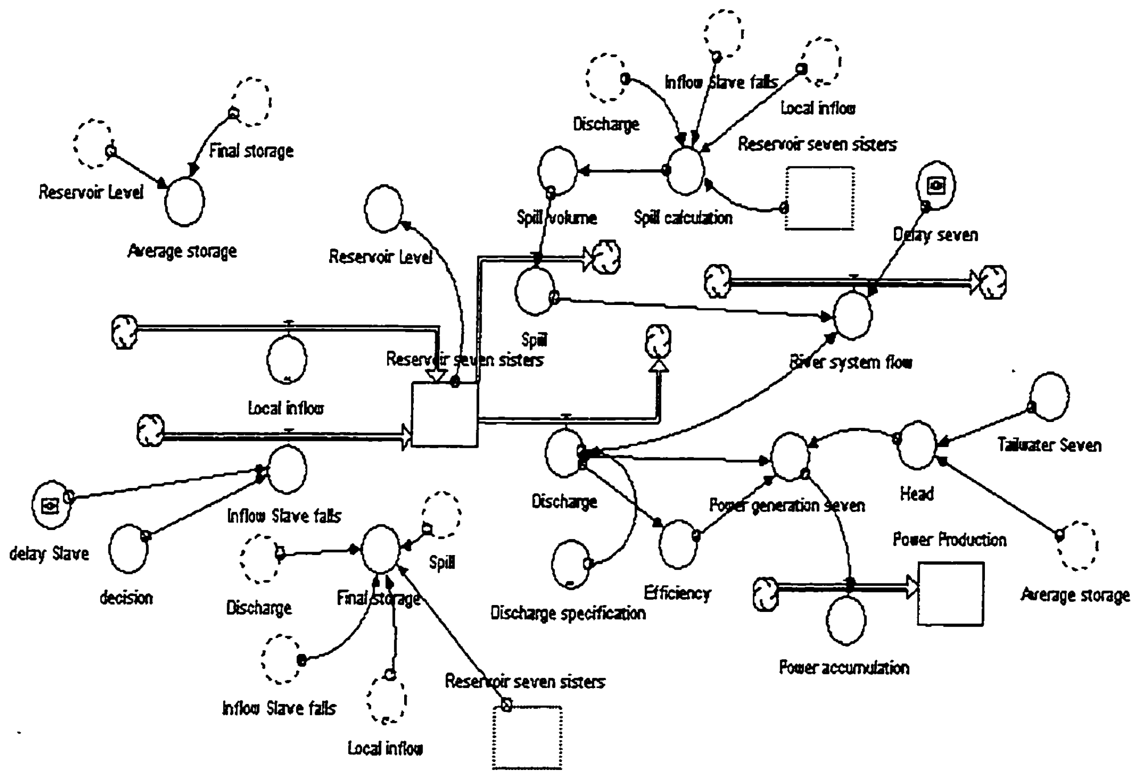


Figure 5.4: Object structure of one of the sectors (reservoir)

5.3.5 Reservoirs

Each reservoir is represented as a sector that has reservoir specific properties. The object structure shown in the Figure 5.4. refers to the first reservoir, Seven Sisters, in the complete system. Similar structures are required for all the other reservoirs and a lake that add up to a total of five sectors. The reservoir specific characteristics for a particular sector include, stage-storage relationships, local inflow, controlled flows from any other reservoirs, discharge-efficiency curves, spill calculations, plant release, average storage level, flow transport delay and calculation of head required for power generation. The description of all the sectors all developed for the Winnipeg River System is provided here.

5.3.6 Tailwater Elevations

The model developed considers the strong hydraulic coupling that exists between the hydropower reservoirs. This feature is taken into consideration while calculating the head required for energy generation at each of the hydropower plants.

This sector uses objects with logical functions (e.g. IF-THEN-ELSE) to determine the appropriate tailwater elevation curve for use in the calculation of the head. These objects are shown in the Figure 5.5. A sample set of rules using IF-THEN-ELSE construct (for McArthur generating station) are given next.

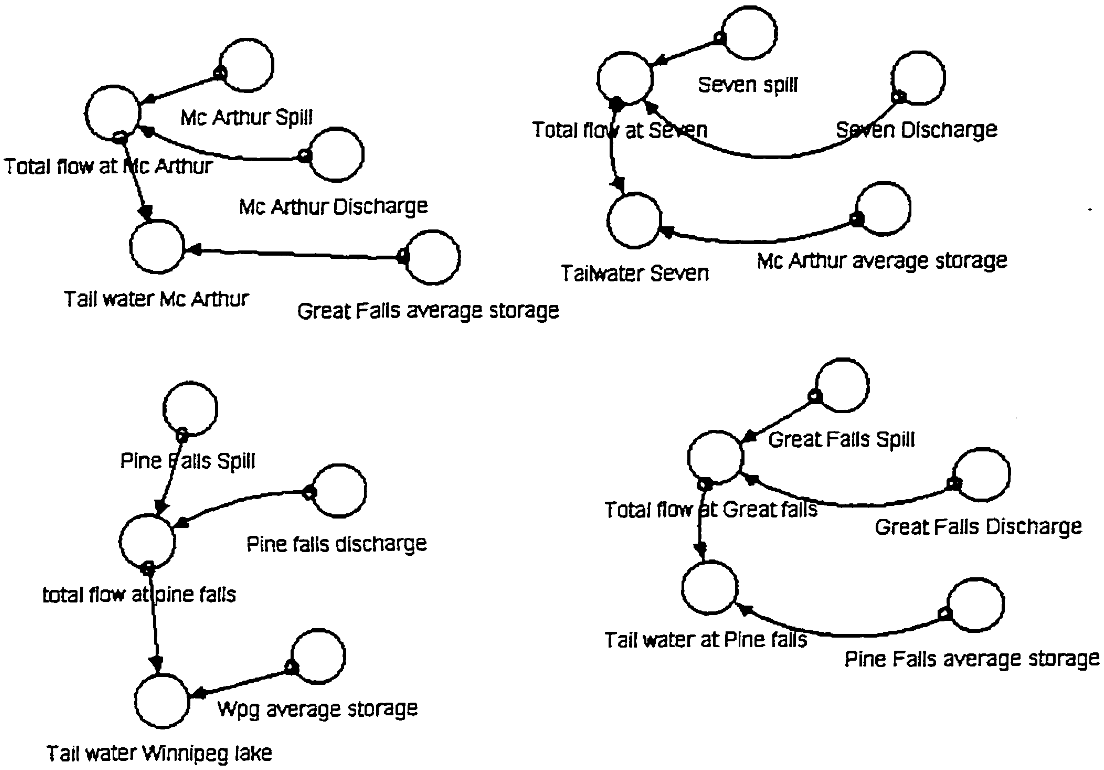


Figure 5.5: Object structure for tailwater elevation calculations

```
IF(average_storage_3 >= 809) AND(average_storage_3 < 809.5)THEN
(809 + (Total_flow_at_Mc_Arthur*0.06774)) ELSE

IF(average_storage_3 >= 809.5) AND (average_storage_3 < 810)THEN
(809.5 + (Total_flow_at_Mc_Arthur*0.06404)) ELSE
Endif
```

In optimization and simulation models developed in the past for hydraulically coupled reservoirs, similar rules were used and they are referred to as *look-up tables*. Similar rules exist for all the reservoirs that are considered in the present study. If hydraulic coupling is neglected the average storage value can be used for head calculation. This eliminates all the converters that house the IF-THEN-ELSE rules.

5.3.7 Lake

The object structure of a lake (Winnipeg Lake) is shown in the Figure 5.6. The structure includes a *stock* as a water body into which the final reservoir (Pine Falls reservoir) is discharging and also a controlled outflow from the lake. Converters are used to calculate the average volume of the lake and for determination of tailwater elevations curves.

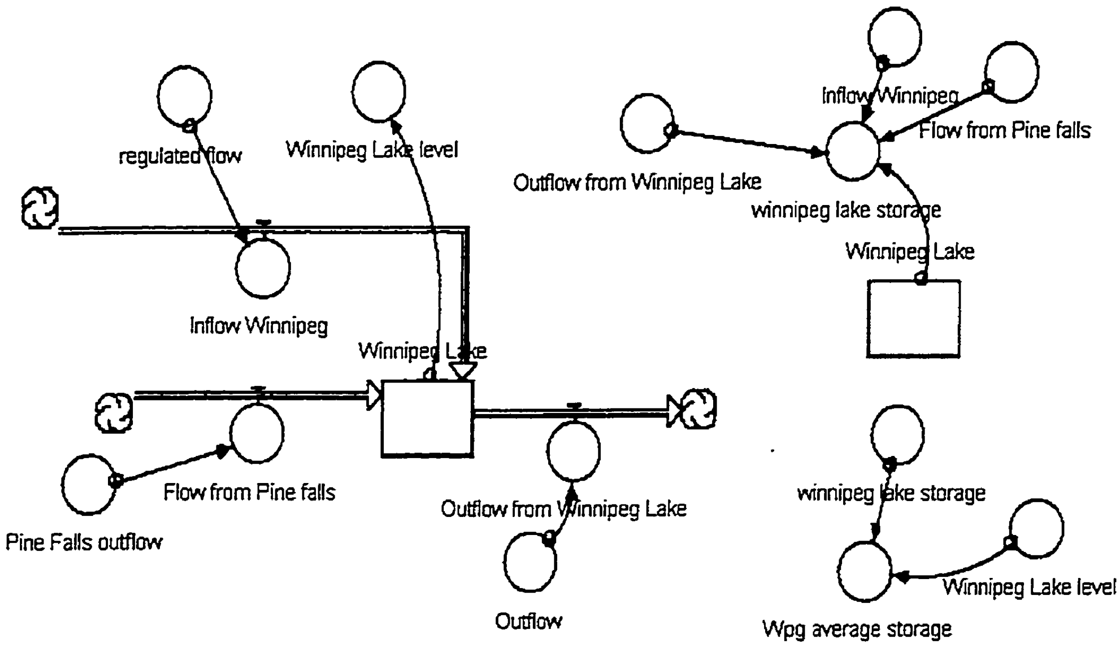


Figure 5.6: Object structure of the Lake Winnipeg

5.3.8 Performance Indices

Two indices that are used as a performance measure of the system are incorporated in this sector. The sector uses objects with graphical relationships for penalty/loss functions to determine the vulnerability index and logical and mathematical functions to obtain the reliability of the system. Individual indices for each reservoir and the whole system are defined in this sector.

Apart from these major sectors few others are used to incorporate different features in the model. These include, selection process for variable values, graphical relationships and all other calculations that are not included in the major sectors. Link exists between different sectors if and only if the variables in the sectors are interdependent. This can be seen in the main mapping layer of the STELLA. The user can modify any graphical relationship or provide any input required by the model. Any parameter permitted by modeling environment can be used for sensitivity analysis.

5.4 Model Application - Winnipeg Reservoir System

The system dynamics model is applied to a case study problem discussed in chapters 3 and 4. Few details are provided here to refresh the memory of the case study area. The Winnipeg Reservoir System consists of series of reservoirs, i.e., Seven Sisters, McArthur, Great Falls and Pine Falls respectively in that order. The last reservoir drains into the Lake Winnipeg. The reservoirs are hydraulically coupled, an aspect that is considered in the model in arriving at release decisions. The initial storage states, the plant discharge-efficiency curves, discharge values are obtained from a seasonal model used by the power utility presently operating the plants on the Winnipeg River.

The local flows to the plants are considered negligible compared to that of controlled flow contributed by the reservoir upstream of the first reservoir. The simulation model developed in the present study is used to obtain the daily scheduling rules based on the available weekly operation rules.

5.4.1 Results and Discussion

The modeling environment used in the present study provides an easy mechanism to generate a large number of scenarios based on variety of conditions. Different initial storage conditions and the value of controlled flow into the system are considered for performing the sensitivity analysis. More scenarios can also be obtained by changing the flow transport delay between the plants. Two different performance indices, reliability in meeting the target demand and vulnerability of the system to any failure are analyzed. The system dynamics model also allows sensitivity analysis of different parameters used in the model. The model is particularly useful for reservoir/plant managers to generate operating rules for various uncertain conditions and also in instances where the time interval within which decisions are required is too small to run an optimization model. The model can be run to obtain the operation rules using different values of initial storage states while retaining a constant inflow scheme to the reservoir system.

The plant discharge at each reservoir can be varied either graphically or based on operating policy provided by any optimization model. This will result in different power generation values. In the present study, the plant discharge values are obtained from the optimization model. Sensitivity analysis can be easily performed using simulation environment. One such experiment is carried out where the plant discharge for the first reservoir (Seven Sisters) is varied starting with the initial value and five constant increments within the interval $[17.8, 20.8]$. The variation of the reservoir level is given in the Table 5.1. Each scenario is based on a particular value of plant discharge. Three scenarios are provided in the Table 5.1.

Table 5.1: Forebay elevation of Seven Sisters reservoir

Day	Forebay elevation (ft.)		
	Scenario 1	Scenario 2	Scenario 3
1	899.30	899.30	899.30
2	898.32	898.03	897.74
3	897.34	896.76	896.18
4	896.36	895.49	894.62
5	895.38	894.22	893.06
6	894.40	892.95	891.50
7	893.42	891.68	890.00

The controlled inflow into the reservoir is restricted to $15Kcfs$. The variation of tailwater elevation for three scenarios corresponding to different release patterns is given in the table 5.2. The variation in the tailwater elevation will not be observed if the inflow is high enough to cause spill when release is restricted. For inflow level of $20.7 Kcfs$ (actual controlled inflow), no variation in the tailwater elevation is observed.

Table 5.2: Tailwater elevation at Seven Sisters reservoir

Day	Tailwater elevation (ft.)		
	Scenario 1	Scenario 2	Scenario 3
1	836.46	836.54	836.62
2	836.04	836.13	836.21
3	837.79	836.13	836.21
4	837.79	837.86	837.94
5	837.79	837.86	837.94
6	837.79	837.86	837.92
7	837.79	837.86	837.53

The flow transport time between the plants can be used to evaluate the effect of the delay time on the total amount of power produced at each of the plants. The model developed in the present study uses a fixed delay approach. The delay time can be changed using the graphical interface in the interactive layer of the modeling environment as shown in Figure 5.3. A built-in function, DELAY or an object, Conveyor, can be used to introduce the flow transport delay. Conveyor as Stock object has special properties that allow it to convey material (in this case flow) at a pre-defined time intervals. The modeling environment can also be used to incorporate a routing model. A number of stocks can be used in between the two reservoirs to model the storage effect of the stream.

Details of the power production at each of the hydropower plants with and without flow transport delay are given in the Table 5.3. A flow transport delay time of one day between the plants is considered for this simulation.

Table 5.3: Power generation (GWhrs) at four reservoirs

Hydropower Station	Power generation (GWhrs)	
	No delay	Delay
Seven Sisters	15.32	13.85
Mc Arthur	5.85	6.03
Great Falls	13.81	11.62
Pine Falls	9.85	7.23

5.4.2 System Performance Measure

Two indices, namely reliability and vulnerability (Hashimoto, 1982) are used to measure the system performance. In the present study, loss functions are developed to obtain a monetary or a penalty value associated with a particular failure (e.g. failure to meet the target demand). These curves can be modified by user with the help of Graphical User Interface (GUI) provided by the simulation environment. One such interface is shown in the Figure 5.3. Vulnerability is defined in terms of a monetary value attached to a particular failure decided by a penalty function provided by the user. The values of the indices for an arbitrarily selected inflow scheme, associated with a specific reservoir (Mc Arthur) are given in the Table 5.4. It should be noted that there is no conceptual difficulty in developing these criteria for the whole system.

Table 5.4: Performance indices for different inflow schemes

Inflow Scheme	Reliability	Vulnerability
1	1.0	15.18
2	1.0	14.32
3	1.0	15.60

The Object-Oriented simulation model developed in the present study will have enormous utility in variety of real-time operational conditions. Advantages of the model include: (1) generation of different operating rules based on a variety of conditions; (2) evaluation of system performance through different indices; (3) online usage for real-time operational decisions. The modeling tool is ideal for application to reservoir operation problems. It can be concluded that the simulation runs can be useful for reservoir operators for analyzing and understanding various real-time conditions.

One of major advantages of the simulation environment is that qualitative information can be handled. For example, if two operating polices are available, then operator's willingness to use any one of the policies can be incorporated through graphical functions. The functions would look similar to membership functions from the fuzzy set theory. The model can be extended to include the simulation of individual turbine operations at each of the reservoirs. In order to achieve a complete representation of the physical system (e.g. incorporation of hydraulic coupling and calculation of average storage elevations), additional objects are defined in the model. This is due to the limited number of objects provided by the modeling environment.

Reliability and vulnerability are used as indicators to quantify the system performance in response to different inflow conditions. The model uses objects that provide a good representation of the physical system under consideration. The simulation environment provides an easy mechanism to include certain aspects of the modeling which otherwise are difficult to incorporate into traditional simulation models. The scenarios generated will be useful for real-time implementation of the operating rules. Even though the model is specific to reservoir operation related to hydropower generation (Teegavarapu and Simonovic, 2000b), the modeling concepts can be extended to any type of reservoir system. The objects used in the simulation environment can easily represent the basic governing processes of many hydrological and water resources systems.

Simulation model that is developed using Object-Oriented environment discussed in this chapter is useful for real-time operation of reservoirs. However, optimization models also play a major role in providing the decisions for implementation. A framework that combines these two categories of models while capturing the experience of reservoir operators is an ideal tool that can assist on-line implementation of decisions. A decision support system conceived on these ideas is discussed next.

5.5 Decision Support System

Decision support systems that aid human decision-making process are existent for a long time in field of water resources. Extensive literature on development of decision support systems is available elsewhere (Mallach, 1994; Guariso and Werthner, 1989). Simonovic (1996a, 1996b) discusses the general principles of DSS and their application to few case studies in the field of water resources. The idea of Intelligent Decision Support System (IDSS) for operation of reservoir systems was initially proposed by Savic and Simonovic (1991). The support system draws engineering expertise and includes a *database* and a *modelbase*. The *database* is a repository of data while a *modelbase* is storehouse of a set of models developed for a specific problem. An interactive graphical user-interface is developed to link all the components of the Decision Support System. These three elements form the general architecture of any DSS.

A decision support system is developed based on the above basic architecture in the present study. The system is designed to aid the decision maker in the implementation of models developed for operation of reservoirs in real-time. The system is referred to as Decision Support System for Operation of Reservoirs (DSSOR). The system encompasses all the models developed in the present study under one interactive environment. Figure 5.7 shows the architecture of the DSS developed in the present study. In general, *Knowledge base* is also an important component of any traditional DSS architecture. The *knowledge base* component is not included in DSSOR architecture, as the amount of experience and knowledge captured in the form of rules is not large enough to be identified as a separate identity.

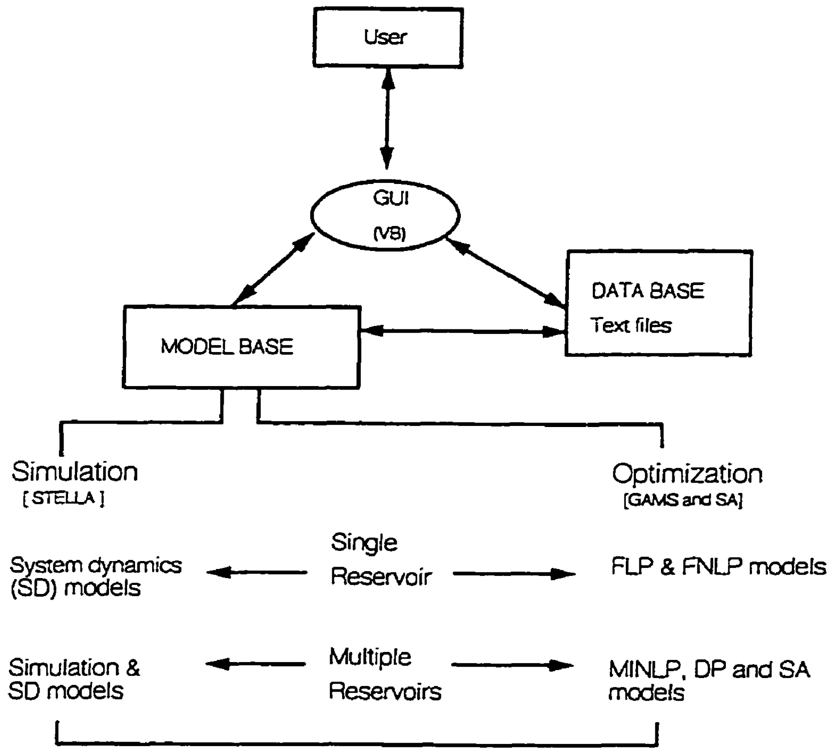


Figure 5.7: Architecture of the Decision Support System

The DSSOR encompasses all the simulation and optimization models developed in the present study. Therefore, the DSS is specific to the nature of operation problems and reservoir systems dealt in the present research. General applicability of DSS is debatable at this point of time, however practical utility is beyond any doubt. The DSS skeleton can be used to add other models. Different components of DSSOR and their features are discussed next.

5.5.1 Graphical User Interface

The Graphical User Interface (GUI) is developed using Visual Basic (VB) programming language. The interface is developed using a variety of programming procedures. It provides an interactive link between the user and the system. A set of model descriptions and data preparation menus are provided for the user to select and provide data at various levels. The interface generates warnings in case if non-numerical inputs are provided by the user at any instance.

The GUI provides help at any point in the consultation session. The DSSOR, presently does not possess capability to view the data files in a graphical form. Scripts (command *m* files) are developed for execution within in a **Matlab**[2] environment and one such script is included in the Appendix 2. The **Matlab** scripts can be used for viewing graphs.

5.5.2 Database

The database consists of a set of data files (in *ascii* format) required by the models. Data provided by the user through the interface are stored in model specific text files. The files are updated when the models are run and can be viewed or altered in an interactive mode. The database primarily contains files that provide: (1) storage-elevation curves; (2) maximum and minimum allowable range values for the variables (e.g., discharge, power plant capacity, etc.) and (3) coefficients for the regression equations of the tail-water elevation curves at each of the hydropower plants.

[2]A numeric computing and visualization software from Mathworks, Inc.

Much of the data that is relatively constant for the optimization and simulation models are provided within the models (e.g., GAMS). In case of simulation models that are developed under STELLA, the data can be provided and can be changed in an interactive mode within that environment. Database is modified whenever user provides data through GUI.

5.5.3 Modelbase

The *modelbase* consists of models that are developed for both optimization and simulation of the single and multiple reservoir systems. The single reservoir operation is aimed at predominantly flood control with economic objective, whereas the multiple reservoir system operation is for optimal power generation. A variety of models are available that consider different problems that include coupled and non-coupled systems, different time horizons, single time interval simulation and optimization.

Optimization Models

The optimization models for reservoir operation are developed using both GAMS and Simulated Annealing approach. The *modelbase* has models that deal with different conditions: (1) coupled reservoirs and (2) non-coupled reservoirs for different time frames and with different objective functions. The model based on simulated annealing approach is used for solution of hourly scheduling problem with 168 decision intervals. In case of single reservoir operation, fuzzy optimization models with Linear and Non-Linear formulations are used. These are indicated as FLP and FNLP in the Figure 5.7 respectively.

Simulation Models

The simulation models are developed using high level programming language (C language) and an Object-Oriented simulation environment (STELLA). The simulation model developed using high-level language also serves as backbone for the Simulated Annealing approach that is used as a part of optimization models. Separate models are available for hydraulically coupled and isolated hydropower reservoirs.

5.5.4 Consultation Sessions

The initial consultation session provides a background to the problem and set of questions for the user to answer about the problem domain. An initial consultation session is shown in the Figure 5.8. Based on the answers (selected from a set of multiple-choice questions) provided by the user, the DSS will launch appropriate data preparation sessions.

These sessions depend on the nature of the approach selected. Different menus are provided and user can input appropriate values for the variables required by the optimization and simulation models. The user is warned at times when data is not provided in a required format. Help is provided at every stage and user can end the session at any time.

Using data preparation session, the user can select specific options such as *coupled* or *non-coupled* hydropower reservoirs, objective functions and time frames for optimization. An example of such a session is shown in the Figure 5.9. If data are already available and exist in text files, the option, *"continue"* can be used to proceed to the next session.

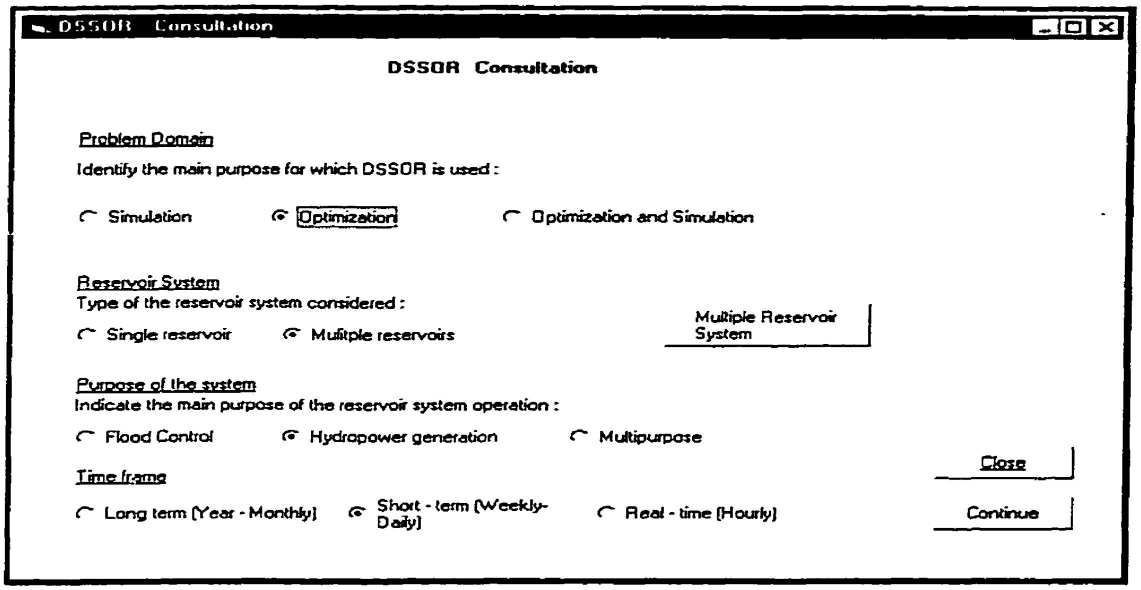


Figure 5.8: Initial consultation session of DSSOR

A detailed data entry interface is provided by the consultation session for specific cases. Figure 5.10 shows a detailed data entry interface for the hydropower system used as a case study in the Chapters 3 and 4. In case of simulation models developed using STELLA, the user can change the data interactively in the modeling environment.

Model Execution and Solution Status

Once the data preparation is complete, appropriate models are run and status of the solution is reported. The whole procedure involves invoking GAMS solver and providing the appropriate data files for execution and writing the output files. The output files (results) are written in *ascii* format in text files when the execution is completed. This is achieved by modeling statements within the GAMS environment. The system automatically provides help in case if the obtained solution is feasible or infeasible or no-integer solution is available (in case of MINLP formulation). The optimization solver used in the present study reports

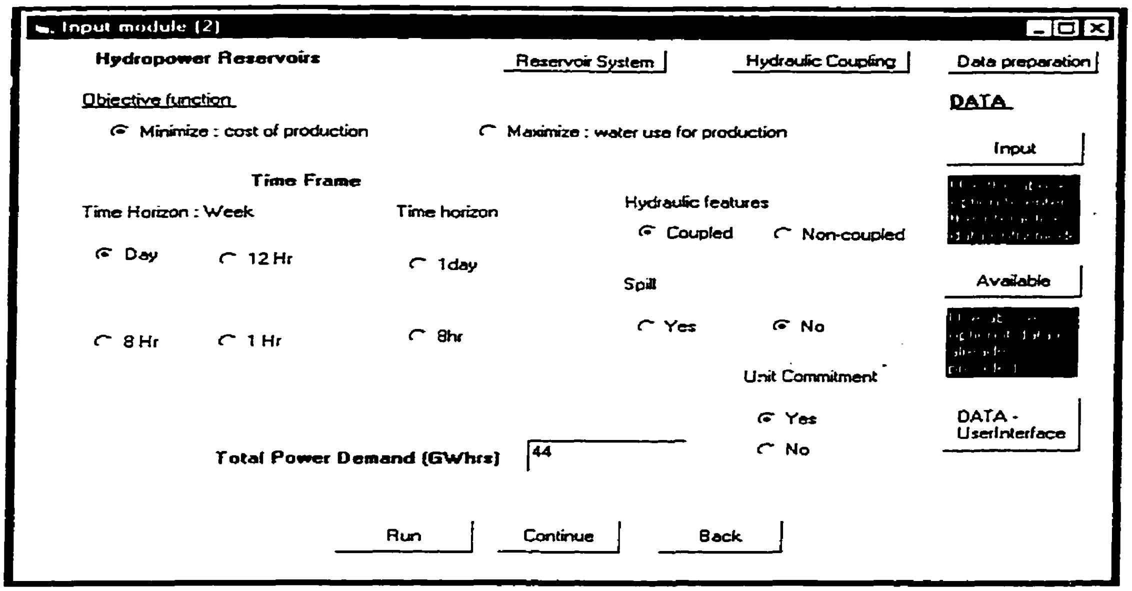


Figure 5.9: Data entry session of DSSOR

a number of solutions. In order to identify the nature of solution, a search is conducted in the result files generated by the optimization model (run by GAMS solver) and the nature of the solution is identified. This is one of the difficult aspects of the DSS development. Remedial measures are provided to the user in case of infeasible solution or if Relaxed Mixed Integer Non-Linear Programming (RMINLP) solution is reported. Guidelines are provided for selecting meaningful values for the constants associated with constraints that are binding and may cause models to produce infeasible solutions.

If an infeasible solution is obtained, the user can get back to data preparation menu for data re-entry. The new data is now used to rerun the models and establish feasible and optimal solutions. Once the execution is completed, the results-display menu is launched by the system. A sample results display menu is shown in the Figure 5.11. The user will be able to view any file with complete description about the results. These range from storage states to power generation figures.

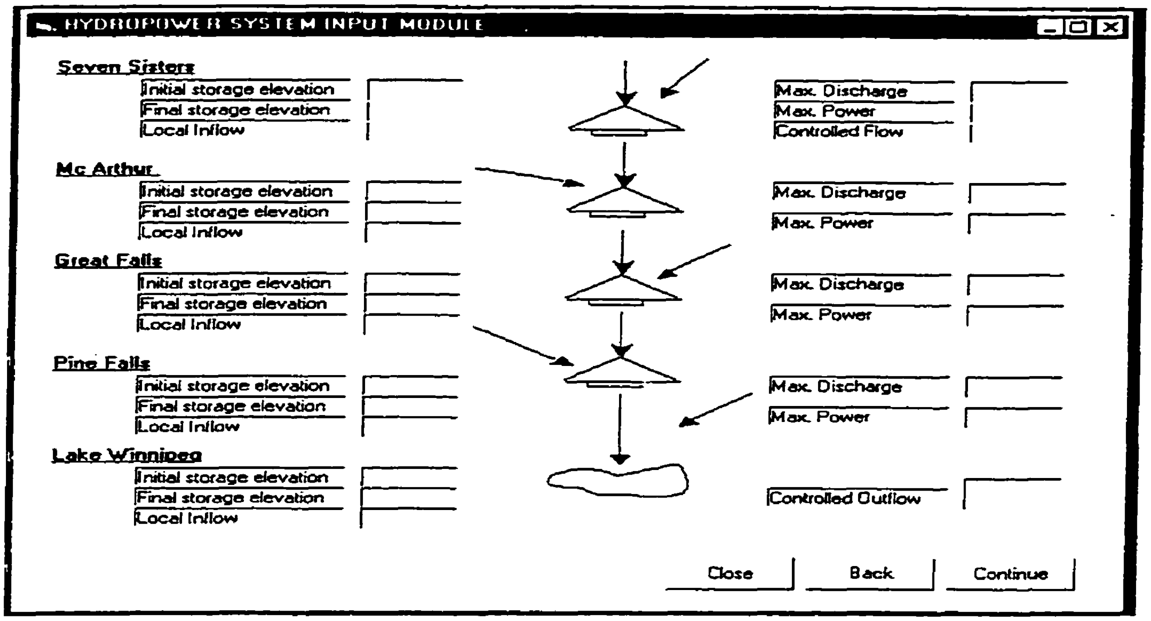


Figure 5.10: Detailed data entry session for a system of Reservoirs

Data files can be viewed one at a time and the results can be used for policy analysis using simulation models developed using STELLA. At this point of time, the user could chose from three options: (i) end the session; (ii) rerun the models with different data files and (iii) start a new consultation. The DSS also provides an option to continue to use simulation models after the optimal operating rules are obtained. This is of help to reservoir operators as they can use simulation models to generate scenarios with use of optimal operating rules already available.

The DSS developed in the present research will aid the reservoir operators in implementing the operating rules in real-time. Online use of this system is possible and needs to be tested in *live* conditions. Considering the existing literature on DSS applications in the field of reservoir operation, the system developed in the present study may not be considered completely innovative. However the framework and specific features of the system can be considered novel.

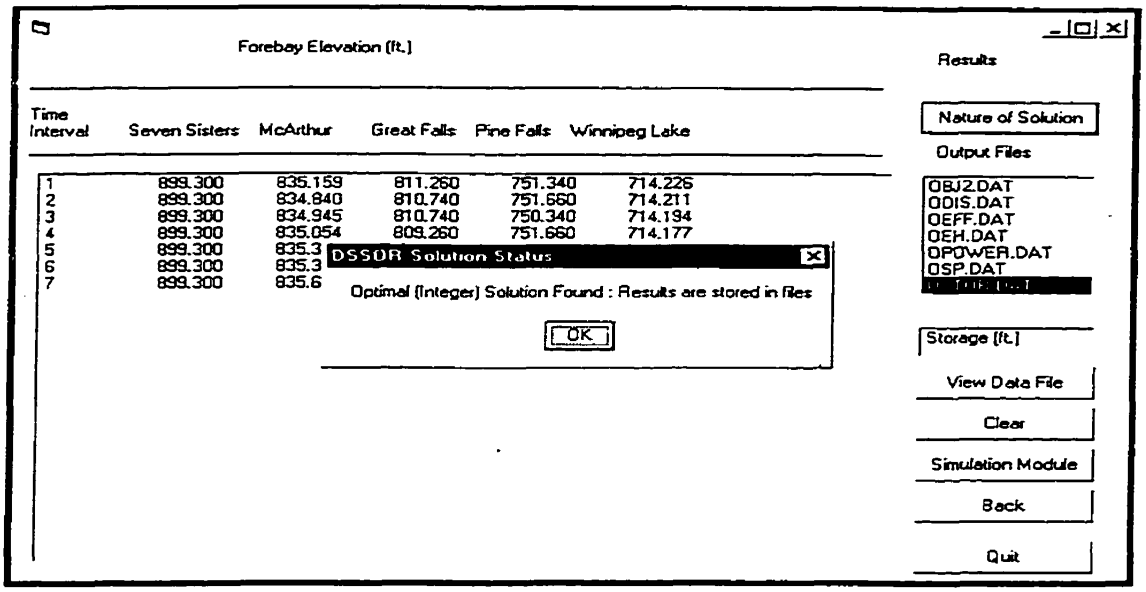


Figure 5.11: Results display session of DSSOR

5.6 Practical Solutions

General observations relevant to computational time requirements, feasibility and the quality of solutions, implementation of operational decisions in real- time and their acceptance by the operators are discussed here. These are based on the optimization and simulation models developed in the present research. The conclusions in few cases are problem specific and depend on the optimization tool used. However, a more general analysis of tradeoffs between the modeling and solutions relevant to operation of multiple reservoir systems is discussed. The next few sections summarize the observations in the form of schematic diagrams.

5.6.1 Complexity

A measure of the complexity of any mathematical programming formulation can be related to difficulties associated with use of an optimization solver to obtain an optimal solution. One such measure defined in the present study relates to the number of decision variables in the mathematical formulation, non- linearities in the objective function, constraints and existence of special variables that take on integer or discrete (including binary) values. This measure is appropriate, as the nature of the solution, computational tractability and time required to obtain a solution depend on the solution algorithm used by the solver and its ability to handle the special variables. A typical relationship between the nature of optimal solutions and complexity of formulations is shown in the Figure 5.12. The nature of solutions obtained from two different optimization approaches starting with the same-level of problem complexity are indicated. Figure 5.12 also suggests that the search techniques that are regarded as non-traditional approaches are more efficient in providing better quality solutions than the traditional optimization techniques.

5.6.2 Solutions and Computation Time

Based on the experiments conducted using both MINLP and SA approaches for multiple reservoir operation problems in chapters 3 and 4, few general observations can be made. A general indication of complexity associated with the nature of mathematical programming formulations is shown in the Figure 5.13. Few standard optimization tools are identified for use at different levels of complexity while a variety of others can be used to solve problems that fall within the range of any two different formulations. Acceptability of the tools by

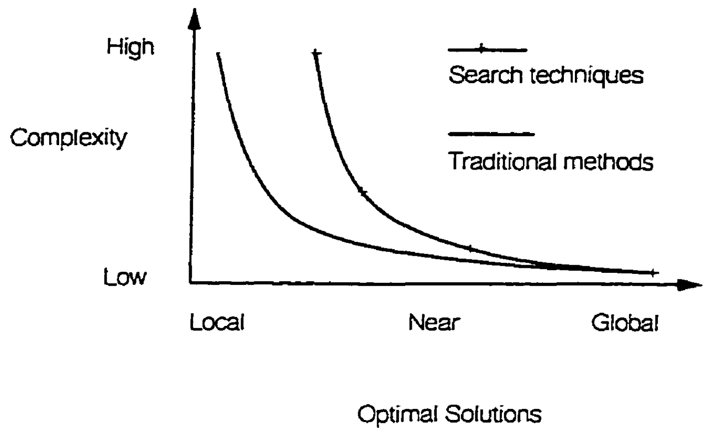


Figure 5.12: Complexity and nature of solutions using non- and traditional optimization techniques

reservoirs managers or operators is shown by a different curve suggesting that it is relatively high for tools that are easy to use and low for non-standard approaches. The curves are projected based on the experience from the use of different tools and also from experiments conducted in the present study. While the observations are case study specific these are valid for most of reservoir operation problems.

5.7 Tradeoffs

The computational time and modeling of the physical system are the two important aspects that are to be considered while developing and implementing the models for real-time operation of reservoir systems (Teegavarapu and Simonovic, 2000c). The complexity of the formulation increases with the increase in the number of time intervals and thus making

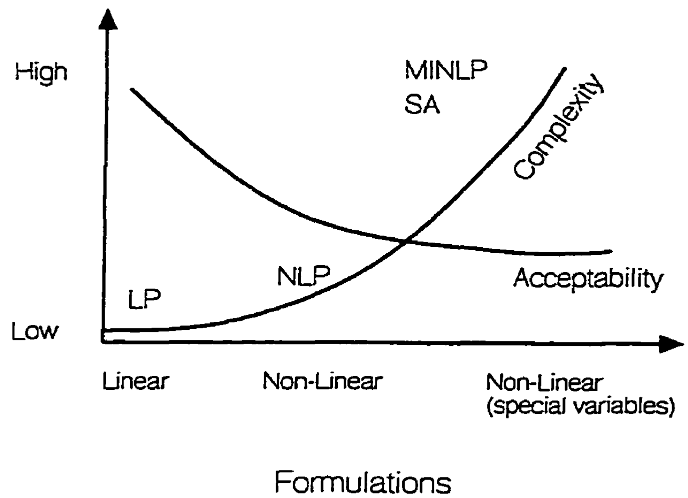


Figure 5.13: Complexity of formulations, tools and their acceptability

the problem computationally intractable. In the absence of the tools to obtain optimal solutions, the tools/techniques that can provide at least near-optimal solutions are always favored. The stochastic search method used in the present study has overcome the limitations of a traditional model (MINLP) besides giving the advantage of an exhaustive representation of the physical system. Considering these observations, it can be concluded that tradeoffs exist between: (a) nature of solution and time within which it is required; (b) exhaustive representation of the system and computational tractability; (c) computational time and the nature of the solution; and (d) type of approach chosen, acceptability and ease of implementation of the model in real-time.

Optimization models are not always the solution for many instances of operation of reservoirs in real-time. System performance evaluation and rapid scenario generation based on available operating policies is possible using appropriate simulation tools that can incorporate the dynamics of the operation in real- time. In a recent study, Simonovic and Fahmy

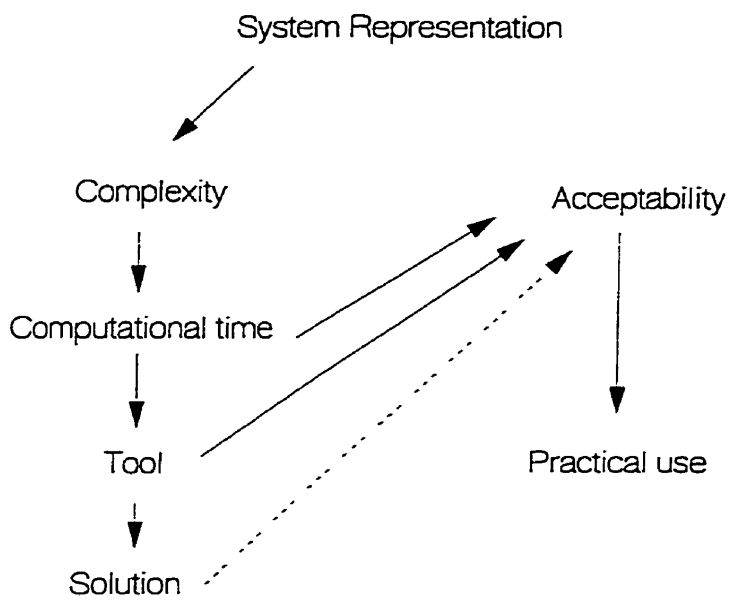


Figure 5.14: Factors affecting the acceptability and use of models

(1999) emphasize the advantage of developing simulation models based on the principles of system dynamics and Object-Oriented programming. They also suggest that these models are applicable in situations where it is difficult to run optimization models, especially for real-time operations. The acceptability of the models by the operators and influencing factors are shown in the Figure 5.14. The arrows show how different aspects are linked and dependent. The acceptability as it can be seen is dependent more on the tool and computational time than on the nature of solution.

In summary, the following observations can be made : (a) emerging optimization methodologies and techniques such as optimal control methods, simulated annealing and genetic algorithms offer solutions to operation problems that otherwise are not possible using traditional techniques; (b) even though reservoir operators prefer models that are easy to use and implement, exhaustive representation of the physical system within the models is increasingly accepted; (c) simulation models used as stand alone or embedded within optimization techniques are essential as they can incorporate any system detail, judgment and experience of operators; (d) operators are generally interested in rules that are easy to implement rather than solutions and their quality (near - or global optimum); and (e) tradeoff between exhaustive modeling of reservoir operation and practical solutions exist and it directly influences the selection of optimization tools.

5.8 Summary

Issues such as computational solution time, tractability and the utility of the approach for application are to be considered in arriving at or selecting the models for real-time operation of multiple reservoir systems. The reservoir operators are generally interested in models that are relatively easy to modify, adopt and run within the specified time to implement the decisions. Evaluation and modification of already existing standard operating policies using a simulation model is required in cases where the time is too small to run an optimization model. Computer intractability is a direct consequence of exhaustive representation of the physical systems in the mathematical programming formulations. Exhaustive system representation is possible in simulation models whereas it is limited in mathematical programming models in some situations.

Distinction between near and global optimum solutions is not an important issue for the reservoir operation managers as long as the pre-specified targets are met and the performance of the system using the operating policies is better than the available standard operating polices if implemented. Finally, involvement of reservoir operators in the model development process, appropriate selection of optimization tools, generation of practical operating rules and recognizing the tradeoffs can help reduce the gap between theory and practice in the field of reservoir operation.

5.8.1 Postscript

Closing the gap between theory and practice in the field of reservoir operation is perhaps more difficult compared to solving the existing complex problems plagued by dimensionality and optimality issues. Many of the models developed in theory are not finding their way into practice for a variety of reasons. One reason indicated by Yeh (1985) is appropriate here.

> "Most of the reservoir operators have not been directly involved in the development of the computer models and are not entirely comfortable in using the model, particularly under the situation where modifications have to be made in the model to respond to changes encountered in the day to day operation."

The Object-Oriented simulation model and the Decision Support System described in this chapter indicate an attempt made towards bridging the existing gap, at least in the case of the specific hydropower reservoir system handled in this research. The simulation environment used in the present research allows rapid modifications in the model structure at a rate required by reservoir operators in case of real-time implementation of operating rules. The simulation model is easy to modify, transparent and ease to use. Considering these features, reservoir operators can be easily involved in the model development.

Use of emerging non-traditional optimization approaches (Simonovic, 2000) and development of decision support systems can help narrow the gap. Simulation models will play a major role in future in the planning and management of water resource systems as a backbone for non-traditional optimization approaches (e.g. Simulated Annealing, Genetic Algorithms and optimal control concepts).

The next chapter provides the conclusions based on the research work conducted on the three major issues that are relevant to real-time operation of reservoir systems.

Chapter 6

Conclusions

Referee's report: This paper contains much that is new and much that is true. Unfortunately, that which is true is not new and that which is new is not true.

- Anonymous

In H. Eves Return to Mathematical Circles, Boston: Prindle, Weber, and Schmidt, 1988.

6.1 Thesis Summary

The dissertation covers a wide spectrum of topics in the area of real-time operation of reservoir systems. However, three issues (*information uncertainty, system representation and computational intractability*) that are relevant to real-time operation of single and multiple reservoir systems received more emphasis in this thesis. The issues fall within the stages of planning and operation of reservoir systems. The first issue is addressed in the context of a single reservoir operation, primarily meant for flood control whereas for the last two the emphasis is on development of real-time operation models for predominantly hydropower generating reservoirs.

Modeling reservoir operations with economic objectives is as difficult as understanding available information that is vague. The challenge is to deal with information uncertainty in a mathematical programming framework. The present research work uses fuzzy set theory to address some forms of uncertainty. Fuzzy mathematical programming has been effectively implemented in this research work to handle vagueness. The idea of *compromise operating rules* is appropriate for real-time reservoir operation where the preferences of decision maker are given due consideration. The models developed in Chapter 2 address these issues.

The extent of system representation in mathematical programming models reflects on the physics of the problem that is actually captured. The hydropower optimization problem solved using MINLP formulation in Chapter 3 clearly demonstrates the difficulties associated with system representation, optimization approaches and solutions. An approach using spatial decomposition is also presented. Exhaustive system representation is possible using this approach. However, computational time and resources would limit the use of such an approach.

Solution of mathematical programming models is the stage where the issue of computational intractability surfaces. The issue can be handled in variety of ways ranging from problem abstraction to constraint satisfaction. Non - traditional optimization approaches (Simulated Annealing, Genetic Algorithms, etc.) are one way out to resolve this issue. One such approach that uses the idea of combining simulation with a stochastic search method (to find solutions to computationally intractable problems) is presented in this thesis. Simulation of the system behavior that is realistic is far more essential than obtaining optimal solutions for unrealistic formulations. The models that provide near-optimal solutions based on exhaustive representation are considered superior to models that use simplified representation. These ideas discussed in Chapter 4 are tested in this thesis and are shown to be feasible and applicable.

Practical on-line use of models is a meaningful end for modeling and optimization. Better acceptance of the models developed in theory is only possible if appropriate support systems are developed. This dissertation advocates the use of modeling environments (e.g. object-oriented simulation) that are easy to use, transparent and valuable in scenario generation. Use of Decision Support Systems (DSS) cannot be underestimated in the process of actual implementation of rules. The models and DSS framework discussed in Chapter 5 embrace these ideas.

6.2 Contributions

Approaches for addressing the issues of *information uncertainty*, *system representation* and *computational intractability* are developed in this thesis. In most cases, these approaches are tested using case study applications. However, the practical significance of the models developed in the present research can only be known when they are put to rigorous tests and actual use in real-time. Meanwhile, some of the approaches developed in the present research can at least now qualify as "beneficial additions" to the field of real-time reservoir system operation.

6.2.1 Approaches for Handling Information Uncertainty

Uncertainty issues dominant in reservoir operation models that make use of economic loss functions are dealt in an exhaustive manner in this dissertation. Fuzzy mathematical programming in symmetric and non-symmetric environments is used to address the issues of imprecision and uncertainty in the definition of loss functions. The models provide a new methodology to capture the decision maker's preferences and aid in the development of *compromise operating polices.*

6.2.2 Innovative Method to Operate Coupled Hydropower Reservoirs

Optimization of hydraulically coupled hydropower systems is handled using a MINLP formulation. The concept of using binary variables for selection of curves to address the hydraulic coupling is considered to be a novel approach. The approach eliminates the need for discretization of state variables which is required in DP and DDDP formulations. Unit commitment problem is addressed within the same framework. Transport delays are considered using a simplified approach to emphasize the need for a detailed modeling of the flow transport processes. A spatial decomposition approach different from earlier work is presented. The exhaustive system representation is a merit, however the computational burden in solving the problem needs to be evaluated.

6.2.3 Last Resort Algorithm for Computationally Intractable Problems

A Simulated Annealing technique is used to develop models for real-time operation of multiple reservoir systems. The approach is beneficial when solutions are required considering the constraints of computational time and resources. Few conceptual and algorithmic improvements are proposed and implemented borrowing ideas from the field of evolutionary algorithms. General guidelines are provided to implement this approach for operation of multiple reservoir systems. The proposed approach has been shown to be viable for a benchmark problem as well as for a real-time reservoir operation problem with a large number of decision variables.

6.2.4 Object-Oriented System Dynamics Simulation Model for Real-Time Operation

Dynamics of the real-time operation process is simulated using an object- oriented simulation environment. Principles of *system dynamics* are used to develop the models of varying complexity. The main feature of hydraulic coupling dominant in the hydropower optimization problem is incorporated into the model. The study demonstrates the advantage of building complex models using basic building blocks (objects) with pre-defined properties. Few simulation environment specific objects and the performance indices used to quantify the system performance mark the study as different one from the earlier works in the literature. The transparency and ease of use of these models in real-time are beyond any doubt.

6.2.5 Decision Support Framework

A decision support framework is proposed and developed in the present study to combine the optimization and simulation models in an interactive environment. The system is not without some merits and these include: (i) interactive environment for analyzing the operating rules; (ii) scenario generation with the help of simulation models; (iii) post-optimal analysis of results, and (iv) post-mortem analysis and advice on infeasible solutions.

Few conceptual enhancements are possible in future. However, the present status of the system qualifies for a title of "practical decision support system" that can aid reservoir operators in implementing the rules provided by the models. A framework of this kind would have enormous practical utility.

6.3 Opportunities for Future Research

Improvements in methodologies and developed models are possible at various levels. Some possible research directions for future work are outlined here.

6.3.1 Information Uncertainty

Issues relevant to imprecise penalty zones and uncertain coefficients are addressed independently within the optimization models in this research. Conceptually it is possible to address these issues together in one framework. Multiple reservoir operators and systems can also be dealt under fuzzy decision making environment. Future work can explore these ideas. Replacing loss functions with membership functions from fuzzy set theory is difficult but not impossible. Some ideas are already suggested in Chapter 2 to handle this issue. The issue of *compromise operating polices* can be addressed with the help of long- and short-term operation models. This approach will have wide range of applications and would be appropriate to develop sustainable operating polices.

6.3.2 Hybrid Otpimization Models

Combining simulated annealing with classical optimization approaches will yield a new breed of optimization models. The traditional optimization approaches can be used as screening models to obtain the feasible variable ranges and insights into the structure of the model. Using this information, the annealing algorithm can be tailored to obtain better computational efficiency and near-optimal solutions. Examples of such combinations include LP-SA (Linear Programming - Simulated Annealing) and DP - SA. The DP application provides the optimal discretized intervals for the variables, where the solution obtained from LP can used to devise the ranges for decision variables.

6.3.3 Parallel Simulated Annealing

A number of conceptual enhancements are possible in Simulated Annealing algorithms. These include ways to reduce: (i) computation time and resources required for solution; (ii) number of infeasible solutions and (iii) time required to obtain the performance measure. The repair and reject strategies already employed in the present research can be improved. Development of a general method to handle any configuration or network of reservoirs is possible and should be explored.

Simulated annealing in its original form can only be applied using a serialized computer code. Parallel implementation of the annealing algorithm on a number of computers can be explored in future research. This might extend the capability and application of the algorithm to a large network of reservoirs.

6.3.4 Decision Support and Modeling Systems (DSMS)

The Decision Support System (DSS) framework presented in this thesis can be improved by adding the capability of automatic model generation to the existing system. The mathematical programming formulations can be developed interactively and translated into algebraic modeling language for solution by an appropriate solver. The original DSS can now be transformed into a DSMS. DSMS can provide many advantages compared to DSS in terms of eliminating the need for development of a number of replicates of the model for variety of situations and flexibility in the model development process. Inclusion of knowledge and experience of the reservoir operators is next step in enhancing the use of the system for real- time operations.

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Glossary

Annealing	Cooling of metal after having been heated [Metallurgy].
Algebraic modeling system	A modeling framework in which the mathematical formulation is represented in algebraic form.
Boltzmann Distribution	A probability distribution function.
Crisp value	A value that is defined exactly.
Combinatorial problem	A problem with countably finite number of solutions.
Combinatorial explosion	Problem associated with solution of combinatorial problem with too many solutions.
Compromise polices	Polices derived from traditional and fuzzy optimization models.
DSS	Decision Support System.
DSSOR	Decision Support System for Operation of Reservoirs.
Extremum	A minimum or maximum.
Fuzzy Mathematical Programming	Mathematical programming formulation where objective function or constraints are fuzzy.
Function optimization	Process of finding the extremum of a function.
Generation mechanism	A process used to generate feasible states (solutions).

Genetic Algorithm (GA)	An algorithm based on the evolution process.
Global optimum	Extremum of a function better than any of the optimal solutions (see also Local optimum).
Global optimization	Mathematical programming without convexity assumptions.
GUI	Graphical User Interface.
Local optimum	Extremum in a subspace of the search space that is not better than a global optimum.
Loss curves	Functions representing penalty in monetary units
MINLP	Mixed Integer Non-Linear Programming.
Membership function	A graded function generally that ranges between [0,1].
Natural algorithms	Algorithms which are based on processes occurring in nature.
NP-complete	A combinatorial problem for which the solution time varies in a polynomial way with respect to increase in variables.
OOE	Object-Oriented Environment.
OOSE	Object-Oriented Simulation Environment.

Optimal control theory	An approach where the optimization model is combined with a simulation model.
Reject strategy	A process of rejecting infeasible solutions (evolutionary algorithms).
Repair strategy	A process used to transform a infeasible solution to feasible one.
RMINLP	Relaxed - MINLP, A programming problem where the variables are relaxed from binary to real values.
Simulated Annealing (SA)	An algorithm that uses an analogy between annealing. and function optimization.
System Dynamics	A concept based on feedback processes to describe behavior of dynamic systems.
Superstructure	Formulation structure for a MINLP problem.
VB	Visual Basic.

Appendix 1

Conversion Units and Constants

Conversion to SI units

To convert	To	Multiply by
ft	m	0.305
cu ft/sec X 10^3	m^3/s	28.37
cu ft/sec X day X 10^3	m^3	2451394.8

Values of constants

$\gamma_o \quad = 0.203\ 10^{-2}$

$\gamma_1 \quad = 0.085$

Cost coefficients (spill) (\$/(cu ft/sec X 10^3))

$MO_1 \quad = 0.714$

$MO_2 \quad = 1.875$

$MO_3 \quad = 0.789$

$MO_4 \quad = 1.154$

Appendix 2

Matlab Scripts *"m" files* for generation of graphs

General script for any data file

```
load data.dat
in=input(' GIVE # of columns')
in1=input('GIVE the curve ')
a(2)='r'
a(3)='b'
a(4)='m'
a(5)='r'
a(6)='y'
bt(2)='o'
bt(3)='x'
bt(4)='+'
bt(5)='x'
bt(6)='O'
for i=in1:in1
plot(data(:,1), data(:,i),a(i), data(:,1),data(:,i),bt(i))
end
```

Script for *"bar chart"* to graph Power Generation values

```
load power.dat
echo off
a(2)='r'
a(3)='b'
a(4)='m'
a(5)='c'
subplot(4,1,1)
bar(power(:,2),0.5,a(2))
axis([0,8,0,4.5])
title('Seven Sisters GS')
subplot(4,1,2)
bar(power(:,3),0.5,a(3))
axis([0,8,0,4.5])
title('McArthur GS')
ylabel(' POWER GENERATION (GWhs)')
subplot(4,1,3)
bar(power(:,4),0.5,a(4))
axis([0,8,0,4.5])
title('Great Falls GS')
```

```
subplot(4,1,4)
bar(power(:,5),0.5,a(5))
axis([0,8,0,4.5])
xlabel('Day')
```