140

SUSTAINABLE PLANNING OF THE OPERATION OF RESERVOIRS FOR HYDROPOWER GENERATION

by

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ABSTRACT

Consideration of the uncertainties in future reservoir inflows and energy demands is essential for planning the operation of predominantly hydroelectric generation systems. In addition, hydropower generation and flood control are often the conflicting objectives in planning and managing the predominantly hydro systems. A quantification of the impact of the uncertainty in inputs and the tradeoffs involved in the reservoir system allows a planner to compare the economic losses due to this impact with the benefits accrued from the system, thus, leading to planning the sustainable operation of the system.

A reliability programming model is developed which considers the uncertainty in inflows and energy demands in planning the operation of a single as well as a system of multipurpose reservoirs, and also evaluates the hydrologic risk as a measure of the system not being able to satisfy the storage requirements for hydropower generation and flood control. The model determines the optimal levels of risk, by trading off the total benefits accrued from the operation of reservoirs with the economic losses which may be incurred as a consequence of these risk levels. The economic losses are explicitly specified in the model through risk-loss functions which quantify the costs of deviations from the goal, and a new four-step algorithm is proposed in this research to derive the risk-loss function for the purpose of hydropower generation. The nonlinear energy production function is linearized, and a three-level algorithm which combines the Complex Box search procedure with a Linear Programming routine is developed to evaluate the optimal risk levels.

The direct implementation of the reliability model in its basic form is limited by the assumption of independence between monthly reservoir inflows, which leads to conservative planning of the operation of reservoirs. Three new approaches are proposed in this research to alleviate the problem of conservative planning, thus, making the reliability model a robust tool for the complex task of planning.

The application and the practical implementation of the reliability model are demonstrated for the case study of Manitoba Hydro, a predominantly hydro based electrical utility company for the Province of Manitoba, Canada.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

GLOSSARY OF SYMBOLS

BF_t	Benefit per unit flood control storage provided in the reservoir
B_T	Benefit per unit storage left at the end of planning period for energy generation in future
C^{ls}	Conversion factor in the energy equation ($C^{ls} * R^{ls} * h^{ls}$ = Energy produced)
CALFA1	Coefficient for the assumed risk-loss function for flood control
CALFA2	Coefficient for the assumed risk-loss function for energy generation
CCP	Chance-constrained programming
CDF	Cumulative distribution function
CE	Energy potential from controlled inflow
CUSUM	Cumulative Sum
$cimp^{ls}$	Cost of importing unit energy from other utility companies
DN_t	Number of days in time period t
DOM	Domain
DP	Dynamic programming
E_t^{ls}	Energy exported from the utility company
$EMAX_t^{ls}$	Maximum bound on the exportable energy
$ENMIN_t^{ls}$	Energy demand (domestic + firm export - firm import)
EP_{res}	Energy potential from the reservoir storage
EENS	Expected energy not supplied by the generation system
e	Efficiency of the turbines in the generation system
$F_{\Sigma t}^{-1}(.)$	Inverse of the CDF of the sum of inflows up to and including t
$F_E\ (.)$	Inverse of the CDF of energy demand
f	Value of the objective function
HMAX	Maximum head on the turbine (upper bound of operating range minus the tail water level)
HMIN	Please refer to h^{min}
h_t	Average hydraulic head on the turbine in the time period $(t-1, t)$

h^{min}	Head corresponding to lower bound of the operating range minus the tail water level (also equal to *HMIN*)
I_t	Stochastic inflow in the time interval *(t-1,t)*
I_t^c	Controlled inflow in the time interval *(t-1,t)*
I_t^{lim}	Limit on the total inflow used for energy generation in the interval *(t-1,t)*
IM_t^{ls}	Energy imported from other utilities
j	Index for reservoir j in a multiunit system
kcfs	kilo cubic feet per second (unit for storage used in Manitoba Hydro)
ls	Load strip
$L_1(\alpha)$	Risk-loss function for flood control in the planning period
$L_2(\beta)$	Risk-loss function for hydropower production in the planning period
LC_t	Loss coefficient per unit of storage spilled from the reservoir
LO_t	Loss of water from the reservoir
LP	Linear programming
M Cdn.	Million Canadian (used for benefits and costs throughout this report)
MH	Manitoba Hydro Integrated system
MSF	Membership function
m	Total number of reservoirs in a multiunit system
n	Total number of time periods (months) in the simulation period
n_f	Frequency of violations from the minimum storage requirement
nsl	Number of load strips in a unit time period
P	Probability value selected from the CDF of inflows
PDF	Probability density function
PG&E	Pacific Gas and Electric Company
PU	Pumped water from one reservoir to another
p^{ls}	Lower bound of energy demand in the fuzzy set with MSF=0
pe	Probability of exceedance in the PDF of energy demands
q^{ls}	Upper bound of energy demand in the fuzzy set with MSF=0
R_t^{ls}	Release from the reservoir(s) for hydropower production

$RMAX$	Maximum allowable release from the reservoir
$RMIN$	Minimum required release from the reservoir
r^{ls}	Revenue per unit energy supplied for domestic use
$rexp^{ls}$	Revenue per unit energy exported to other utility companies
RP	Reliability programming
S_{max}	Maximum storage in the reservoir
S_{min}	Lower bound of the operating range of the reservoir storage
S_0	Storage in the reservoir in the beginning of the planning period
S^s_t	Simulated storage in the reservoir at the end of time period t
S_t	Storage in the reservoir at the end of time period t
SDP	Stochastic dynamic programming
SP_t	Spill from the reservoir not used for hydropower generation
t	Time period
T	Total number of time periods in the planning period
UE	Energy potential from uncontrolled inflow
UI_t	Uncontrolled inflow (also termed as local inflow) in the time interval $(t-1,t)$
X_t	A new variable defined in terms of R_t and h_t
Y_t	A new variable defined in terms of R_t and h_t
v_t	Minimum volume to be maintained for hydropower production
z	Function which converts storage depletion into equivalent reservoir release
α	Reliability of the reservoir for the purpose of flood control (lower bound of which is α')
β	Reliability of the reservoir for the purpose of hydropower generation (lower bound is specified by β')
ψ	Slope of the linearized stage-storage relationship
θ_t	Flood control storage requirement
λ	MSF of the decision space (also denoted by μ_D)
μ	Membership function
ρ	Correlation coefficient between monthly inflows

γ^j	Reliability of flood control for each reservoir j
$\Gamma(a,b)$	Gamma distributed variable with parameters a and b

1. INTRODUCTION

Planning the operation of a system of reservoirs is a complex task since the reservoirs are usually multipurpose units wherein the available water has to be distributed to several competitive users. So planning the operation of a reservoir is essential before actually operating it. This task, however, demands the use of systems techniques. Systems methodology can help define and evaluate, in a rather detailed manner, numerous alternatives that represent various possible compromises among conflicting groups, values, and management objectives. The objective of a planning model is to generate policies (using the systems techniques approach) which are optimal in some sense and which will aid the decision maker in the real-time operation of the reservoir.

Planning the reservoir operation for hydropower generation involves several complexities such as the uncertainty in reservoir inflows, the uncertainty in energy demands, multiple time periods, multiple reservoirs, nonseparable benefits etc. Many of the planning models developed to date, are deterministic. However, planning the operation is essentially a stochastic problem since the inputs such as reservoir inflows and energy demands are very difficult to find *a priori* for the whole planning period and hence, are uncertain.

The variability in the inputs can be incorporated in the planning model using two approaches. The first approach is to incorporate the variability in inputs implicitly through sensitivity analysis. The second approach is to consider the variability in inputs explicitly in the formulation of the planning model.

One of the explicit approaches used for modelling the reservoirs with hydropower generation is stochastic dynamic programming. Although the nonlinearity in the objective function can easily be handled by dynamic programming, which has resulted in its use by many researchers, the drawbacks of the approach such as the approximations involved, the computer memory, and the computational time required, limit its application. Another explicit approach is chance-constrained programming in which the uncertainty in inputs is modelled by considering them as stochastic variables. The stochastic nature of inputs is incorporated in the model through 'chance constraints' which are written with a finite probability of being violated (tolerance measure). A modification of the chance-constrained approach, in which an optimal allocation of tolerance measures can be determined along with an optimal operation policy, is termed as 'system reliability programming'. Through appropriate formulation, these tolerance measures could represent the hydrologic reliabilities of the reservoir system performance which will be useful in managing the risk. Should a failure event occur, the utility planners could take preventive measures to reduce the consequences of the failure. These measures may involve, for example, making commitments for importing energy from other utilities or buying additional fuel for the thermal generating stations. None of the stochastic dynamic programming formulations evaluate the value of the reliability explicitly.

Almost all of the explicit stochastic models consider the uncertainty in reservoir inflows through the transition probability matrices or the probability distributions. None of these formulations considers the uncertainty in energy demand explicitly. It appears that the task of incorporating the uncertainty in energy demand in formulations such as stochastic dynamic programming is quite complex.

As a first contribution in this research, a reliability model for planning the optimal operation of a single multipurpose reservoir with uncertain inputs is developed. Hydropower generation is the major purpose served by the reservoir, and flood control is the secondary purpose. The model considers the reliabilities of system performance as decision variables in the optimization scheme by introducing the 'risk-loss functions' in the objective function. The objective of this model is to maximize the net benefits represented as a tradeoff between the maximum benefit accrued from hydropower generation and the losses incurred due to not meeting the reliability requirements. The variability in reservoir inflows is incorporated through their probability distribution functions. The variability in energy demands is incorporated in the model by considering the demands as stochastic or vaguely defined.

Risk-loss functions are the important components of the reliability model, which quantify the cost of goal deviations. Such functions have been developed for purposes such as flood control and water supply in the literature. A new four-step simulation algorithm is developed as a second major contribution of this research to derive the risk-loss function for the purpose of hydropower generation. A hydrologic risk level is defined for the purpose of hydropower generation as the probability of the storage in the reservoir violating a preferred storage level such as the rule curve volume. The parameters which influence the storage in the reservoir are the expected values of future reservoir inflows, future energy demands and the available storage in the beginning of the planning period. In this four-step algorithm, the risk levels are defined for different storage levels in the reservoir and the corresponding expected values of the energy deficit from the generation system are evaluated. The cost of an energy deficit is computed based on the strategies adopted by the electrical utility company to manage the deficit.

The reliability model in its basic form ignores the temporal dependence between the reservoir inflows, which results in an underestimation of future inflows. This leads to conservative planning of the operation of reservoirs, which is considered as a major limitation for the direct implementation of the reliability model. Three new approaches, namely, the 'Windows Approach', the 'CUSUM Approach' and the 'RISKSUM Approach' are proposed, as the third major contribution of this research, to alleviate the problem of 'conservative planning'.

In all the three contributions, the planning criteria used by the utilities or the models are improved over the existing criteria and the models. Also the failures in the system are explicitly evaluated which allows the decision makers to look for system operation procedures with an 'acceptable risk at a reasonable cost' instead of the traditional 'no risk at some huge cost' approaches. All of these contributions, thus, lead to the planning of the sustainable operation of the reservoir system for energy generation.

Data required for the case study is provided by Manitoba Hydro, a predominantly hydro based electrical utility for the Province of Manitoba, Canada. The planning horizon is taken as one year with 12 monthly time periods. Manitoba Hydro's goal is to satisfy the domestic energy demand in each time period. To achieve this goal, the utility has to import energy from other utilities in the periods of energy deficiency. While trying to attain the maximum net benefits from the reservoir system, to avoid a plan which would empty the reservoir, there is an assigned value of water at the end of the planning horizon which would reflect the benefits expected in future from the stored water.

This thesis contains seven chapters, including the introduction. The second chapter details the literature of different techniques used for mid-term operation planning of hydropower reservoirs, and also presents the literature pertinent to the reliability model. In Chapter 3, the reliability model for planning the operation of a single multipurpose reservoir is formulated, and the incorporation of uncertainty in inputs is detailed. The methodology for developing the risk-loss function for hydropower generation is presented in Chapter 4. Implementation of the reliability model to planning the operation of a single as well as a system of reservoirs is detailed in Chapter 5. The proposed reliability model is applied, and the results are discussed in Chapter 6 for the case study of Manitoba Hydro. The last chapter contains the conclusions and recommendations of this research, and highlights a few directions for future research.

2. REVIEW OF LITERATURE

Hydropower optimization is closely associated with the problem of reservoir operation and management. Reservoir analysis comprises three types of problems: sizing, or design, planning the operation, and real-time operations or optimal control. A reservoir is usually a multipurpose system wherein the available water has to be distributed to several competitive users and hence, planning the operation of the reservoir is essential before actually operating it. For this purpose, the analysis of reservoirs demands the use of systems analysis techniques. Systems methodology can help define and evaluate, in a rather detailed manner, numerous alternatives that represent various possible compromises among conflicting groups, values, and management objectives. These techniques can represent in a fairly structured and ordered manner the important interdependencies and interactions between the various control structures and users of a water resources system [Sabet and Coe, 1986; and Rogers and Fiering, 1986]. Friedman et al. [1984] emphasized the use of systems analytic approaches to water resources management.

Rosenthal [1980] identified the four important characteristics of a reservoir system that should be incorporated in the model as: (1) multiple reservoirs; (2) multiple time periods; (3) stochastic inflows; and (4) nonseparable benefit functions. He surveyed more than 100 different scheduling models and found that none of them deals simultaneously with all the complexities of the problem. Yeh [1985] summarized the different kinds of techniques used for reservoir management and operations, and also used for hydropower system operation as: (1) linear programming; (2) dynamic programming; (3) nonlinear programming; and (4) simulation. Combinations of the above techniques have also been reported in the literature.

Planning the operation of reservoirs can be classified into three types, namely, short-, medium- and long-term planning depending on the duration of the planning period. This duration can range from a year to a few years in long-term planning, from a month to a few months (up to one year) in medium-term planning (also termed as mid-term planning), and from a few hours to a week in short-term planning. Since the research presented in this thesis focuses on mid-term planning, a comprehensive review of the optimization techniques used for the mid-term planning and management of single/ multiple multireservoirs is given in the next section, followed by the need for the development of a new technique for the complex task of planning. The literature relevant to the reliability model is discussed throughout this thesis, and hence a brief review of literature for the reliability model is presented in the final section of this chapter.

2.1. OPTIMIZATION TECHNIQUES FOR PLANNING THE MID-TERM OPERATION OF RESERVOIRS FOR HYDROPOWER GENERATION

2.1.1. Linear Programming

Linear programming (referred to as LP) has been one of the most widely used mathematical programming techniques for optimization of water resources systems. The technique encompasses a special class of problems where the objective function and the constraints are both linear or can be approximated by a linear relation. The major advantage of this technique over the others is that the solution algorithm efficiently identifies the global optimum, and there is a mathematical proof for the existence of such a solution. LP software packages are widely available which allows the planner to focus only on the problem formulation. The fact that LP problems can be solved very efficiently has inspired planners to structure nonlinear problems as linear ones. Any nonlinearities may be addressed either by approximation (e.g., piecewise linearization of the concave function to be maximized), or by approximation and iteration (e.g., linearization of a nonseparable function). The optimization of complex objective functions can be solved by piecewise linearization applying a variant of simplex method called separable programming [Daellenbach and Read, 1976].

It should, however, be noted that with any applied linearization approximation, the identified solution is not necessarily the global optimum as in the case of linear problems. The LP models could be classified into two major groups, namely, the deterministic and the stochastic. A brief description of the recently developed models is given here.

2.1.1.1. Deterministic Models

Daellenbach and Read [1976] described a deterministic LP model used by the Pacific Gas and Electric (PG & E) Company of San Francisco. The program utilizes the increasing marginal thermal costs and decreasing marginal efficiency of hydro generation due to loss of hydraulic head on the turbines by piecewise linear approximations. The objective is to minimize the total cost over the planning period. Every power source is constrained by a number of technical and behavioral limitations, but most of the constraints are related to the modelling of reservoir and hydro plant operation. They include constraints on storage levels, flow continuity, release limits, and for reservoir head variation due to its nonlinear effect on the result. There is a minimum target level for each reservoir to be met at the end of the planning period. The model has been used to aid the decision process of long term allocation of power sources in PG & E.

Takeuchi and Moreau [1974] have developed a method for finding optimal operating policies for a multireservoir system that extends more than two river basins and serves multiple demands. The problem of determining optimal values for control variables within a monthly interval (for a set of initial state variables) is formulated as a convex piecewise LP problem. The objective is to minimize the monthly value of the loss function (which represents the losses in the current month) and to minimize the expected value of the economic efficiency losses over all future months. The economic efficiency losses are the unknown function of the end-of-month state variables. That function can be estimated from the stochastic dynamic programming problem solution within which the LP problem is nested. Special techniques are applied to obtain a large number of solutions to similar LP problems which are needed as input for the stochastic dynamic programming problem to find an approximate overall solution.

Draper and Adamowski [1976] applied LP as a screening or allocation model to provide information on system operation and response. This information is later used in the preliminary design of hydropower generation facilities. The objective is to maximize the ability to generate continuous system power. The constraints include the storage limits and the power requirements. Synthetically generated inflows are given as an input. The nonlinear power response is approximated by a linear power-discharge relationship for three different storage volumes.

Dagli and Miles [1980] formulated a model with an objective of maximizing the sum of average monthly hydrostatic heads of four power plants on the same river over a yearly time horizon. Requirements are set to supply water for irrigation, as well as maintaining river flows downstream of the reservoirs. The authors applied a deterministic LP modelling procedure with updating, called *adaptive planning*. The idea of adaptive planning is to optimize the operations of the system on the basis of deterministic streamflow forecast. The obtained result is applied only for the first time step. To determine the operation of the system in the next time step, the program is run again with the updated streamflow forecast. In this way new additional information is added to the optimization. The obtained solution is not necessarily optimal but it is very close to the optimum. The model is used for long-term planning to determine the operating policies for a set of four dams each of which is associated with a hydropower plant.

Bechard et al. [1981] developed a deterministic linear-separable programming model to optimize the operation of the reservoirs located in the Ottawa River basin. The model has the objective of reducing flood damages and maximizing energy production benefits. The basic approach is the multiple-objective optimization by weighting coefficients to trade off the two objectives. The energy objective requires a one year period because the load and reservoir elevation have a yearly repetitive cycle. The flooding objective requires a time horizon of only three or four months to capture the flooding season. The problem is solved by applying a hierarchical approach. The hierarchical structuring is achieved by using the long-term optimal storages as targets to be met by the mid-term model. The continuity between the mid-term and the short-term model of about ten daily steps is provided in a similar way. The hydropower production is modelled by piecewise linearization and an iterative solution procedure to handle its nonseparable nature. It can be applied as a tool to determine the effect of future development in the basin or the impact of modifying one or more operating constraints.

The major obstacle for applying LP to a hydropower optimization problem is the nonseparable nature of the hydro production function. Can et al. [1982] described three methods to overcome the nonlinearity. The first method assumes a constant head during the time step and iteratively improves this assumption using the LP solution. The second method calculates the upper and lower bounds based on the forecasted inflows. The head is assumed to be constant for specified intervals in the calculation of the hydro production function. The third method utilizes separable programming to find the approximate optimal solution. The stage-storage curve is piecewise linearized and two new variables are introduced to transform the hydro production function into a separable form.

Pereira and Pinto [1983] described a methodology to coordinate the mid- and short-term scheduling of hydro-thermal systems. The technique is able to incorporate the electrical problems encountered in the short-term planning into a constraint which is added to the mid-term scheduling problem. This constraint refers to the weekly target variable in the mid-term problem. In this way, a feedback is achieved between the short- and mid-term planning with only a few modifications required in the specialized algorithms used at each level. The performance of the model is tested on a case study of the Brazilian Northeast Network.

From the principles of Successive LP found in the literature, Grygier and Stedinger [1985] developed a deterministic successive LP model for hydropower optimization. The objective of their study is to maximize the value of energy generated by a hydropower system over the planning period, and the expected future returns from water left in storage at the end of that period. The basic successive LP method consists of solving a large LP using a first-order approximation to the nonlinear objective function and minimum energy constraints. After finding the optimal solution to the linearized problem, a new approximation to the objective function is developed at the best solution, and the LP is resolved. The authors have emphasized that the successive LP algorithm performs as good as the nonlinear algorithms, such as, MINOS [Murtagh and Sanders, 1980] and Generalized Reduced Gradient code GRG2 [Palicios-Gomez et al., 1982] for nearly linear problems. Among the three algorithms which the authors have discussed, namely: (1) Successive LP; (2) Optimal Control; and (3) LP-DP; they have concluded that only the Successive LP and the Optimal Control algorithms consistently found a local optimum. The Successive LP algorithm is easier to implement and seems to converge to a global optimum.

Reznicek and Simonovic [1990] extended the Successive LP approach to an energy management problem and have developed an iterative algorithm named Energy Management using Successive LP to solve the optimization problem. This algorithm has two iteration levels: at the first level a stable solution is sought, and at the second the interior of the feasible region is searched to improve the objective function whenever its value decreases. The objective in their study is to maximize the energy export benefits, while minimizing the costs of satisfying the domestic energy demand over the planning period.

Ellis and ReVelle [1988] used the principles of Successive LP in a different way than Grygier and Stedinger [1985], and developed a deterministic, separable, linear algorithm. The objective is to maximize the hydropower production. But the proposed approach differs substantially from Successive LP in that it avoids the explicit linearization-expansion step. The authors have further explored the alternate optima by constructing an explicit multiobjective extension of the model. A second objective designed to minimize the spill is formulated. For comparison purposes, the basic hydropower maximization model is also solved using MINOS [Murtagh and Sanders, 1980], a large-scale nonlinear, nonseparable routine. The authors' observations led to the conclusion that the solution obtained from this linear algorithm forms a good starting point for subsequent solution by MINOS to attain a quicker convergence.

2.1.1.2. Stochastic models

Stochastic LP models are developed to incorporate the nondeterministic character of the input data (e.g., streamflows, energy demands, cost coefficients, etc.). The need for modelling uncertainty is well described by Daellenbach and Read [1976]. It is emphasized that the planning based on the expected values (e.g., streamflows) essentially assumes that the costs of the positive and negative deviations from these averages as well as the probability of such deviations are perfectly symmetrical, and independent from one period to another. None of these assumptions correspond to reality. The uncertainty of the input data can be taken into account in deterministic modelling through sensitivity analysis. However, the procedure does not consider explicitly the stochastic character of the input data and may not lead to satisfactory results.

There are several methodologies to be used for characterization of the nondeterministic parameters in LP models. A brief review follows:

Two-stage or stochastic programming with recourse is described by a practical example presented in Loucks et al. [1981]. This method is able to deal with constraints which include random variables. In the work by Yeh [1985], the importance of distinguishing the decision stages is emphasized to understand the method. At the first stage the activity levels are determined. At the second stage, after the occurrence of the random event, a correction follows minimizing the negative effects of the activity at the first stage. In a water resources system, the decisions taken in the first stage can be described as the target levels. At the second stage the minimization of the losses of not meeting the set targets is performed. The objective function has two parts: one where the effect of the target values is evaluated and the other which gives the expected value of losses not meeting the targets from the first part. In order to solve this problem by LP, the probability distribution of the random event(s) has to be discretized. This results in the addition of multiple constraints pertaining to the second part of the objective function, to the set of constraints corresponding to the first part of the objective. The discretized problem can be solved simultaneously although there are two decision stages. In cases where the discretization is not possible, a nonlinear deterministic problem can be formulated. The major shortcoming of the method is that it requires the evaluation of the recourse action by an adequate estimation of losses from the effect of random variations. There are also dimensionality problems due to the additional constraints and variables introduced by the discretization of the distribution function of the random event.

Marino and Loaiciga [1985 a] developed a sequential dynamic decomposition algorithm which maximizes the system annual energy generation while satisfying constraints imposed on the operation of the reservoir network. The stochasticity in inflows is incorporated using a multivariate autoregressive streamflow forecasting technique that takes into account the cross correlations between different streamflow stations and permits the use of multiple lags in the autoregressive process. The solution algorithm (based on a progressive optimality algorithm proposed by Turgeon [1980]) consists of the sequential solution of two-stage problems which maximize the revenues accruing from power sales only while operating the system so as to provide adequate fulfilment of other functions by satisfying contractual agreements or specified storages and releases ranges. Losses including spills are usually ignored and several formulations are shown depending on how these loss components are considered in the models.

An alternative method to represent uncertainty in an LP model is chance-constrained programming (CCP). The method refers to problems with one or more random coefficients in the constraint set (either on the right or left-hand side of the constraints). In these situations, instead of applying the expected value of the random variable as the right-hand side expression, chance constraints can be written to define the probability of failure of that constraint. Chance-constraints can be converted into deterministic equivalents if the probability distribution of the random variable is known. The reliability model developed in this study is based on CCP. A detailed description about CCP is given in Section 2.2.

In conclusion, it should be emphasized that the major task of decision making under uncertainty is to try to derive a deterministic equivalent of the stochastic problem. In cases where this is not possible, an alternative is to apply a Monte Carlo simulation to assess the impact of random effects on the operation.

2.1.2. Dynamic Programming

Dynamic programming (DP) is a technique for optimization of multistage decision processes and is used extensively to optimize water resources systems. The advantages of the DP formulations, quoted by Yeh [1985] are: (1) nonlinear features which characterize a large number of water resources systems can be translated into its formulation, (2) highly complex problems with a large number of variables can be effectively decomposed into a series of subproblems which are solved recursively. Formulations based on the DP techniques fall under two categories namely the deterministic and the stochastic.

A deterministic model for a power generation system with pumpback developed by Hall and Roefs [1966] shows the applicability of the method to mid-term planning.

Young [1967] proposes a method to deal with the stochastic characteristics of the inflows while optimizing with deterministic DP. Reservoir operating rules are obtained using a combination of streamflow generation and DP optimization of releases. The stochastic character of the inflows is taken into account by generating a long inflow sequence using a Monte Carlo technique. The release policy for this sequence is optimized by a deterministic forward DP. The reservoir operating rule is a regression function of the release to the storage, inflow, and forecast of the next inflow. The generated/ forecasted inflows and the optimal storages are used as a sample to estimate the coefficients of the regression function by the least squares method. This operating rule may then be tested in simulation or used in operation. Using the derived operating rules, the economic loss as a function of the release is minimized for annual usage of a single reservoir. However, the regression rule has been shown to perform poorly compared to the DP results on which it is based.

Yeh [1985] has stated that the major drawback of DP in its original form is the inability to handle big multiple reservoir systems. The memory and computing time requirements are the major limiting factors. Each reservoir requires at least one state variable (e.g., storage) which can have several values (in the discrete case) at every stage (e.g., time step). The possible number of combinations (state vectors) to be explored grows exponentially with the number of state variables at each stage. The computational burden is unbearable for a system of more than a few reservoirs. This problem is called the 'curse of dimensionality.' Toebes et al. [1981] have stated that the models using a DP approach cannot be used for large reservoir systems because of dimension considerations.

They also have shown that the objective function is inseparable due to cross product terms for realistic river flow modelling and penalty functions.

Pereira and Pinto [1985] have given an example to illustrate the infeasibility to explicitly resolve the recursive equations of a DP algorithm even for very small reservoir systems: Supposing the number of storage intervals is 20, then

1 reservoir	=>	20^2	=	400 states
2 reservoirs	=>	20^4	=	160,000 states
3 reservoirs	=>	20^6	=	64 million states
4 reservoirs	=>	20^8	=	25 billion states
5 reservoirs	=>	20^{10}	=	10 trillion states

Several DP-based models are presented in this section based on the nature of the applied methodology rather than the chronological order of appearance.

The remedial measure to alleviate the 'curse of dimensionality' is to decompose the complex multiple state variable problem into a series of subproblems which can be solved recursively. The methods of dimension reduction besides the decomposition of the original problem also follow an iterative solution procedure. One of the methods is Incremental DP used by Larson and Keckler [1969], systematized and referred to by Heidari et al. [1971] as Discrete Differential DP. The method starts with a trial state trajectory satisfying a specific set of initial and final conditions and applies the DP recursive equation to the neighbourhood of this trajectory. At the end of each iteration step a locally improved trajectory is obtained and used as the initial trajectory for the next step. The procedure stops when no further improvement is identified, and it is assumed that a local optimum is found.

Allen and Bridgeman [1986] have developed a deterministic DP algorithm for three case studies involving three different time perspectives: the optimal instantaneous scheduling of hydropower units with different generating characteristics to maximize overall plant efficiency, the optimal hourly scheduling of hydropower generation between two hydrologically linked power plants to maximize overall daily/ weekly system efficiency, and the optimal monthly scheduling of hydropower generation to minimize the purchase cost of imported power supply subject to a time-of-day rate structure. Though the first two studies involve short-term scheduling, the third one is for mid-term planning in which a two-dimensional discrete differential DP algorithm has been developed to minimize the cost of purchased capacity and energy from Ontario Hydro on an annual basis. One advantage of this algorithm is that it can impose different objectives based on seasonal needs.

Another method to alleviate the curse of dimensionality is called Incremental DP with Successive Approximations. The concept is to decompose the multiple-state variable DP problem to a number of subproblems of one state variable and to optimize one at a time while the others have assumed state trajectories. In the following step, another subproblem is optimized after the state vectors are updated with the previous solution. The procedure is repeated until the solution of the original problem converges. The method is first applied by Larson and Keckler [1969] for a multiple reservoir system.

Nopmongcol and Askew [1976] combined the incremental DP and the DP with Successive Approximations. Their algorithm uses DP with Successive Approximations to obtain the input state trajectory combination for the two-at-a-time Incremental DP execution. The results of both of these approaches can be influenced by the choice of the initial state trajectory, but this is a common problem for many other iterative procedures.

Stochastic DP (SDP) can take into account the uncertainty in the input data. One datum which is inherently random is the reservoir inflow, and its impact on the operational policy has to be considered. SDP models can directly incorporate this aspect of the analysis into the solution procedure. Yakowitz [1982] pointed out that for an optimization problem with a separable benefit function, it is theoretically possible to obtain a solution with the methods of SDP, though his comment on these methods is:

> *"The largest numerical SDP solutions within and outside the water resources literature to come to our attention are for problems having at most two or three state variables. Even then, the authors reporting their findings often remark on the ferocity of the computational burden."*

McLaughlin and Velasco [1990] indicate that these methods usually are computationally infeasible if the problem is posed in its most general form. They also indicate that this problem has given rise to a number of approximate solution techniques based on the concepts of DP but which make compromises in the generality of the problem formulation, the optimality of the solution, or both. The techniques used to solve these problems are generally either limited to single reservoir applications or are based on iterative methods which may not converge to a global optimum.

In the work of Daellenbach and Read [1976] an SDP model of the Swedish State Power Board [Gustafsson, 1968] is described. All reservoirs and streamflows are aggregated and presented by a single reservoir and a single hydro station. The program derives water value curves as a function of reservoir level for the planning period of 52 weeks. The reservoir levels are optimized to have a minimal thermal energy production cost of the power system. The model is used in conjunction with a simulation model, which helps to aggregate the streamflows and storage contents of the various river systems.

Representation of stochastic characteristics of some variables in DP models imposes severe constraints on the modelling technique, due to the considerable increase in memory requirements and processing times. Therefore, according to Neto et al. [1985], most of the real systems are represented by aggregate models in order to make SDP algorithms applicable, specially when two-dimensional state variables are used. Pereira and Pinto [1985] identified the two basic approaches to find the approximate solutions to the operating problem using DP with a reasonable computational cost, which are: (1) to reduce the number of state variables, retaining the stochastic nature (aggregation-disaggregation methods); and (2) to ignore the stochastic nature of inflows retaining a detailed representation of the generating system (deterministic equivalent methods).

In Aggregation-Disaggregation methods, the problem can be decomposed in two steps: (1) aggregate the hydroplants into one equivalent energy reservoir and use an optimization technique to calculate the optimal operation of the system; and (2) disaggregate the total hydroelectric generation calculated in Step 1 into generation targets for each hydroplant in the system. In order to build an aggregate reservoir, it is necessary to assume simplified depletion rules [Arvaniditis and Rosing, 1970 a; b]. Pereira and Pinto [1985] and Lalonde [1993] have shown that this approximation is reasonable when the system has a very large regulation capacity and the basins are hydrologically homogeneous (i.e., having large cross-correlation between annual streamflows of different sites). As pointed out by Pereira and Pinto [1985], the main difficulty in the Aggregation-Disaggregation methods appear in the disaggregation step, because the system performance in terms of spillage in the plants or loss of peak power due to reservoir depletion is sensitive to the allocation of generation targets. Besides this, Li et al. [1990] have listed the following inherent problems of Aggregation-Decomposition procedures: (1) equivalent hydro plant model which assumes the constant net head over the operation period; and (2) the existence of hydrologic homogeneity between the river basins may affect the solution obtained by these methods. So, the main advantage of these methods is to focus on the most important aspect in economical terms, which is the decision about the acceptable losses of the system. The main drawback is on the definition of the disaggregation criteria, i.e., on the 'fine tuning' of the performance of the hydroelectric system.

The deterministic equivalent approach assumes that the inflows are known for the whole planning period. With this hypothesis of deterministic inflows, the dimensionality problem disappears. In theoretical terms, the hypothesis of deterministic inputs is not well suited to the operation planning problem, as discussed in the work of Gjelsvik [1982]. In his study, the objective is to minimize the thermal generation exports. Because the operation with deterministic inflow is 'better' (more flexible) than could be expected from the SDP solution approach, the deterministic equivalent methods will tend to use less thermal generation than the amount recommended by any stochastic solution. However, a qualitative evaluation of this effect has been carried out only for the system of Turkey [Dagli and Miles, 1980] and New Zealand [Boshier and Read, 1981] with favourable results. The main advantage of these methods is to allow a correct representation of the hydroelectric system and the disadvantage is to produce an 'optimistic' operation which, in case of severe droughts, can lead to high losses.

The algorithm proposed by Pereira and Pinto [1985] retains the detailed representation of the hydroelectric system while representing at least partially the stochastic characteristics of streamflow. This algorithm solves the problems with multiple inflow sequences which can be seen as an extension of the deterministic equivalent methods in which the stochasticity of inflow is represented by the different alternatives of inflow vectors at each stage. This algorithm is based on the results of stochastic programming and on the extension of Benders' Decomposition Method to the stochastic case. The advantage is that this algorithm supplies at each iteration an upper and lower bound to the optimal solution, allowing an efficient tradeoff between computational effort and accuracy.

The flaws in the traditional SDP approach in the representation of stochastic nature of inflows have been pointed out by Kelman et al. [1990] who have developed a sampling SDP which is mostly free from these flaws. This approach introduces a hydrologic state variable and the associated conditional distributions for the various streamflow scenarios and values of future hydrologic state variables. This employs an empirical multivariate temporal and spatial streamflow distribution for a basin, allowing a detailed simulation within the optimization of the hydroelectric system. Because this approach employs selected historical or synthetic streamflow traces, the actual multimonth persistence of streamflows can be captured in the calculation of the expected benefits. Except for the better representation of temporal and spatial streamflow distributions, it appears that the sampling SDP also suffers from the other problems of SDP, such as large computational requirements.

Turgeon [1980] compared two DP techniques applied to the problem of optimal operation of a multireservoir power system with stochastic inflows. One is the one-at-a-time method (also referred to as DP with Successive Approximations). The other is the Aggregation-Decomposition method. The first technique exclusively gives an optimal feedback operating policy for each reservoir. An assumption that the release is related to the storage in the other reservoirs, that is, the open-loop solution, requires execution of DP with Successive Approximation for every time step, which is expensive in computer time. The Aggregation-Decomposition technique breaks up the original complex system of parallel reservoirs and power plants into two components. One component is the actual reservoir/ power plant of the original complex system, while the other is an aggregate of all the remaining elements of the system. In this way, a two-state variable SDP problem is formulated, which can be solved without dimensionality problems.

Saad and Turgeon [1988] proposed a principal component analysis to determine the optimal long-term operating policy of a multireservoir system that borrows from both the implicit and explicit approaches. This method uses only the major principal components of the reservoir system's operation to represent the state of the entire system. The particular feature of this approach is the search for linear dependencies among the variables which derives the required transformation to find a reduced model, which is then solved by the explicit SDP. The major drawback is that the state variables must be interdependent in order to apply this method, that is, the reduction is possible only if the correlation or linear dependency is very high. Nonlinear relations among the state variables may exist.

Saad et al. [1994] developed a neural network based algorithm to disaggregate when nonlinear relations among state variables are considered. Aggregation is done by adding the potential energy as in the work of Turgeon [1980]. The neural network generates by 'learning' the nonlinear functions to minimize the quadratic error between the deterministic optimization and the outputs (disaggregate storage levels) of the network. The training is achieved by back propagation method, and the minimization of the quadratic error is computed by a variable step gradient method. A comparison of the disaggregated policies obtained using this method with those from the principal component approach [Saad and Turgeon, 1988] shows that the learning disaggregation technique is more efficient, especially during summer periods, when the variations in the reservoir are quite big and consequently the correlation (the linear association among the reservoirs) is not very high. During winter, the correlation is usually important, and the principal component and the neural network techniques give similar results.

Valdes et al. [1992] proposed an Aggregation-Disaggregation procedure to obtain the optimal daily releases at each reservoir of the system. The aggregation model has the objective of minimizing the total operating costs of a national hydrothermal system and the optimization is done in energy units (rather than water units) by an SDP approach with Successive Approximation. The monthly steady state operating policies obtained using this aggregation model are then disaggregated using procedures that allow the user to obtain, in real time, the optimal release at each reservoir on a monthly basis if only spatial disaggregation is carried out, or the optimal daily releases at each reservoir if both disaggregation in time and space are carried out. Both of these disaggregation schemes are developed based on an iterative LP algorithm which maximizes seasonal (monthly or daily) energy generation subject to local constraints.

For the problems where the objective function is separable and convex (in the case of minimization) and the system can be described solely by dynamic equations (for example, linear-quadratic problems), an analytical solution can be obtained. The methodology can be generalized for multiple state variable problems without running into the dimensionality problem like in the classical discrete DP. For the problems where the above conditions do not hold, the objective function or the system dynamics equation can be expanded into a Taylor Series. In this way, around the initial estimate the requirements for the analytical solution are satisfied. The solution procedure for these nonlinear quadratic programming problems is iterative. This method, referred to as the Differential DP, is introduced by Jacobson and Mayne [1970].

Turgeon [1981] presented an algorithm based on the DP approach. The task is to optimize releases from a system of hydropower plants located in series on the same river. The solution procedure is based on the principle of progressive optimality. The feature of the approach is that it does not require the discretization of the solution space. It can also handle discontinuous return functions, and the objective function does not have to be linearized nor approximated by a quadratic function.

Trezos and Yeh [1987] have developed an SDP algorithm which addresses three issues: the potential of increasing the output from existing hydropower plants, the alleviation of the dimensionality problem for multistate DP, and the use of probabilistic forecast in a decision making process. The uncertainty in inflows is represented by specifying the first two moments of their probability distributions. The concluding remark of this paper is:

> *Much has been done in the area of deterministic optimization of reservoir operation. There is immense room for research in the area of stochastic optimization of water resources systems.*

Karamouz and Houck [1987] compared the performance of a deterministic and a SDP model. The deterministic model consists of an algorithm that cycles through three components: a dynamic program, a regression analysis, and a simulation. The SDP describes streamflows with a discrete lag-one Markov process. Real-time reservoir operation simulation models are constructed for a few hydrologically different sites and the comparison of the performance of the rules generated by the models is evaluated on the basis of three criteria: the efficiency of the derived operating rules to optimize a proposed objective function, the consistency of the rules or the probability that the actual release equals the operating rule in real-time operation, and the effect and adequacy of the number of characteristic inflows and the number of characteristic storages. Based on the test cases which include small, medium, large and very large capacity reservoirs located on rivers with different streamflow characteristics and hypothetical objective function, the SDP model performs better than the deterministic one for small reservoirs (capacity of 20% of mean annual flow), but for large reservoirs (capacity exceeding 50% of the mean annual flow) the deterministic model performs better. But the authors recommend at least 20-30 storage intervals for reservoirs with 20-50% of mean annual flow, at least 50 intervals for a capacity of mean annual flow and up to 150 intervals for a capacity more than the mean annual flow.

Paudyal et al. [1990] used the SDP approach to assess the optimal configuration of a system of reservoirs (two storage reservoirs and a run-of-the-river plant in series) on the basis of their joint long-term optimum operation policies. Their algorithm is a two-step process and in the first step, the Incremental DP technique is applied with the objective of maximizing monthly firm energy from the system as a whole ignoring the streamflow stochasticity. In the second step, an SDP model which incorporates the uncertainty in streamflows has been used to derive a long-term joint operation policy of the system of reservoirs in the configurations selected from the first step. The outcomes of this study imply that the SDP methodology (which defines the optimum operation policies based on expected system performance value for the set of available streamflow record) is not fully capable of dealing with such a severe constraint as constant monthly firm energy which is derived based on critical streamflow series within a deterministic context. The authors conclude by saying that the SDP could be used as ad hoc means to assess the hydrologic reliability of the system.

Li et al. [1990] have compared the performance of their Decomposition-Coordination approach with two other methods: SDP with Successive Approximation and the Aggregation-Decomposition method. SDP with Successive Approximation uses a local feedback control policy in which the successive approximation involves a 'one-at-a-time' stochastic optimization for each reservoir assuming an expected operation of the rest of the reservoirs. The Aggregation-Decomposition approach solves M 2-reservoir SDP problems (with M parallel reservoirs) in which one of the reservoirs in the system is retained and the remaining (M-1) are aggregated into an equivalent reservoir hydro plant model. The Decomposition-Coordination approach developed by Li et al. [1990] uses the Lagrangian relaxation techniques to break the original problem into M hydro subproblems and N thermal subproblems. The load is assumed to be deterministic in all the three approaches and incorporation of stochasticity will increase the complexity of the problem tremendously.

Sherkat [1990] pointed out that the Lagrangian Relaxation method applied to the hydrothermal dispatch optimization proposed by Li et al. [1990] with known unit commitments has an inherent problem, in that the usual pricing decomposition approach can result in bang-bang type non-convergent solutions; and the quality of the solutions to the stochastic optimization problem using the pricing decomposition approach is still dependent on: (a) the initial values for the expected multipliers; and (b) the expected hydro generation obtained from the DP solution of each hydro subproblem in the latest iteration.

Druce [1990] developed an SDP model to provide decision support for short-term energy exports and, if necessary, for flood control on the Peace River in Northern British Columbia. This model explicitly considers flood control along with energy production in operations planning. The complication arising from the difference in time periods corresponding to the two objectives is overcome by inputting contemporaneous monthly and daily inflow data. The operating policy established by the SDP model is passed on to a simulation model that determines a range of possible outcomes.

Braga et al. [1991] proposed an SDP model for the optimization of hydropower production of a multiple storage-reservoir system with correlated inflows. This model is developed focusing on the reduction in the computation requirement of the backward recursive algorithm for a complex multireservoir system developed by Arunkumar and Yeh [1973]. The basic difficulty arises from the fact that the backward DP proceeds from month to month with no known determinate quantities except the flow transition probabilities, which define the serial correlations. This becomes computationally unmanageable when a number of reservoirs are involved. The model of Braga et al. [1991] consists of two parts. An off-line, one-time-only deterministic DP computes the value of the stored water in all the reservoirs as a function of the several reservoir storages and the month of the year. The on-line program is formulated in terms of an SDP and conducted in real time for operational use.

Karamouz and Vasiliadis [1992] developed a Bayesian SDP model, which generates optimal operating rules for real-time reservoir operation. In this approach, the discrete Markov process is assumed to describe the transition of an inflow from one period to the next. The forecast for the next period's flow along with the actual inflow during the current period and the storage at the beginning of the period are the state variables in generating operating policies. In addition, this approach uses Bayesian decision theory to develop and continuously update prior to posterior probabilities to capture the natural and forecast uncertainty. Different probability models, flow and storage discretization schemes are also compared. Vasiliadis and Karamouz [1994] have expanded the concept of Bayesian SDP in their new approach called the Demand Driven SDP. This approach includes the uncertain demands for each month as an additional state variable. A comparison of three situations based on the demand characteristics in optimization-simulation models: (1) the ideal (demand is fixed in both optimization and simulation); (2) the pseudo-real (fixed demand in optimization, while in simulation it is a variable); and (3) the real (actual variable demand in both optimization and simulation), reveals the inappropriateness in the use of an assumed fixed demand in optimization when the demand is actually a variable.

The hydrologic reliability of the hydropower generation is very useful to the utility planners in making decisions regarding commitments to export power, contracts for importing power from other utilities. This is imposed because of the objective of the operation planning problem:

Choose among all possible operating strategies the one that maximizes the net benefit obtained as the difference between the benefits obtained from the reservoir operation and the losses accrued due to not meeting the reliability requirements.

The concept of a reliability-constrained DP aroused from the fact that long range reservoir operation has to tradeoff the return and the risk associated with not achieving it. A probabilistic DP model with discounting is formulated to solve the stated problem. The probabilistic term stands for independent stochastic character of the inflows in the model. The problem has been solved either using the Penalty Augmented approach or the Lagrangian Duality Theory of nonlinear programming.

In the Penalty Augmented approach, a deficit cost function is used as a parameter to ensure that the resulting operating strategies satisfy the target reliability constraints [Askew, 1974]. Rossman [1977] investigated the above problem in a slightly different context, in which the objective is to maximize the expected net benefits resulting from the operation of a single reservoir subject to a reliability constraint on the expected number of years in which the system fails to meet a target release. Through Lagrangian Duality Theory, it is shown by Rossman [1977] that: (1) the reliability constraint can be incorporated in a similar way as the Penalty Augmented approach (it is also shown that the adjustment of only one parameter in the penalty function is enough to ensure optimality); and (2) in terms of the reliability constraint, it does not matter in which stage of the planning period the failure occurs. This implies that the penalty function should not be affected by the discount factor used to evaluate the present value of the expected net benefit. The first result suggests that the Penalty Augmented approaches are valid as solution procedures. The second result indicates that the specific procedure does not lead to an optimal solution since the deficit costs are discounted in that formulation.

However, an unexpected result appears if the Penalty Augmented procedure is modified in accordance with the above conclusions. Since it does not matter in which stage of the planning period the failure occurs, the optimal strategy tends to distribute the majority of the allowed failures to the early years, when benefits are worth more, by following a more risky policy than that used in later years, when benefits are worth less [Rossman,1977]. This result is certainly not acceptable in terms of the operation planning studies. It should be noted, however, that the solution is optimal in terms of the objective of maximizing the net benefits. This implies that the modelling of the operation planning problem is not adequate.

The class of reliability constraints studied in Rossman [1977] is limited to the expected number of failures along the planning period. The results are extended to take into account the risk of any failure during the planning period [Sniedovich, 1980] which encompasses the reliability measure proposed in this research for operation planning studies. It is shown in Sniedovich [1980] that, if the reliability constraint has been violated in the early stages of the planning period, the operating strategy in the following stages becomes extremely risky and it is observed that:

> *it is rather unlikely that decision makers responsible for reservoir operation would be willing to implement strategies that sooner or later ignore the reliability constraint.*

It is also highlighted in Sniedovich [1980] that in an operation planning problem, the decision making process is repeated for each stage treating the reliability aspects in the same manner. In other words, what must be taken into account in each stage is the shortage risk from that point to the future, and the failures that occurred in the past should not affect decisions for the future. However, this is not true in operations planning during low-flow seasons when the decisions in future would certainly be influenced by the decisions taken during the past.

The author of this thesis is unaware of any work which deals with the evaluation of the hydrologic reliability explicitly through SDP algorithms. Neto et al. [1985] established a simulation criterion which modifies the hydro and thermal energy levels in order to achieve the target reliability specified by an explicit reliability constraint. However, Yeh [1985] pointed out that the reliability-based DP suffers greatly from the 'curse of dimensionality' which limits the number of reliability constraints that can be considered even for a single reservoir system.

To conclude, DP is capable of handling a large range of problems in reservoir systems. According to the literature [Yeh, 1985; and McLaughlin and Velasco, 1990], its major limitation is the curse of dimensionality and the approximations that are used in finding the solution with this approach.

2.1.3. Other Algorithms

A few applications of other optimization techniques are found in the literature for the mid-term operation planning of reservoirs for hydropower generation. These are discussed in the following subsections.

2.1.3.1. Nonlinear Programming

Nonlinear programming methods have not been applied to water resources systems analysis as often as LP or DP. This is primarily due to the fact that these methods are much less efficient in computer time and memory than the others. In addition, the mathematics is much more complicated, and the methods do not lend themselves easily to stochastic problem solutions. The remedial measure is to include a sensitivity capability in the algorithm. On the other hand, the application of these methods has its own advantages. Nonlinear programming can handle nonseparable and nonlinear functions (e.g., hydropower production function) in its formulation.

For the general problem where the objective and constraints are both nonlinear, the penalty or barrier solution methods could be one of the choices [Yeh, 1985]. Assuming convexity of the constraints, the problem can be solved by applying the Lagrangian Dual Procedure [Yeh, 1985].

If the problem is simpler in the sense that the constraints are linear functions of the decision variables and only the objective function is nonlinear, one of the appropriate solution techniques is the Gradient Projection Method proposed by Rosen [1960]. The key feature of this method is that it implements the feasible direction algorithm without solving an LP at each iteration. This is possible since the set of active constraints is changing at most by one element at a time and the required projection matrix can be calculated from the previous one by an updating procedure.

Another method for the same class of problems (i.e., linear constraints, nonlinear objective function) is the Reduced Gradient Method. The method is used by the Tennessee Valley Authority for scheduling weekly releases [TVA, 1976]. Rosenthal [1981] applied a modification of the Reduced Gradient Method to optimize a nonlinear nonseparable objective function with a linear network of flow constraints. An important feature of the algorithm developed by Rosenthal [1981] is the integer programming subproblem whose objective is to obtain the superbasic set and the search directions for the Reduced Gradient Method in order to improve the accuracy as well as the computational efficiency.

Marino and Loaiciga [1985 b] developed a quadratic optimization model to obtain operation schedules for hydropower systems. The model has the minimum possible dimensionality, treats spillage and penstock releases as decision variables, and takes advantage of system-dependent features to reduce the size of the decision space. The stability and convergence of the quadratic solution algorithm are ensured by the factorization of the reduced Hessian matrix and the accurate computation of the Lagrangian multipliers. The model is compared with that of Marino and Loaiciga [1985 a] and it is shown that the optimal release schedules are robust to the choice of the model, both yielding an increase of nearly 27% in the total annual energy production with respect to conventional operation procedures, although the quadratic model is more flexible and of general applicability. Relationships between energy output and reservoir storage are obtained through regression. The problem is, however, deterministic in terms of providing forecasted inflows and energy demands as inputs to the model.

Tejada-Guibert et al. [1990] have developed an implicit stochastic nonlinear programming model called CVPower Optimizer to determine how the Central Valley Project system might be operated to maximize the value of generated power and energy, subject to water, energy and power demand constraints. The optimization problem is solved using a commercially available nonlinear programming algorithm MINOS [Murtagh and Saunders, 1980]. The objective is to maximize the economic value of the generated energy, or of the project dependable capacity for each month (or a weighted combination of the two), based on the operating costs avoided. An important contribution of this work is that the value of energy and power is considered as a variable since it depends upon both the month in which it is provided and the generating unit's capacity factor; large storage reservoirs can regulate flows to take advantage of such variations in the value of energy and power. Convergence to an optimal solution cannot be guaranteed for this nonconvex problem and it depends partly on having good starting values for the decision variables. A comparison of computation time for planning horizons of 12, 24, and 36 months shows that the increase in the computational time requirement is roughly proportional to the square of the problem period length.

A summarizing comment on the nonlinear programming methods could be that the major obstacle for their application is the rate of convergence and the overall high computational requirements.

2.1.3.2. Simulation

Simulation is a mathematical modelling technique aimed at providing a response of the system to a certain input. The input includes decision rules which provide guidelines for the operation. The decision maker can examine the consequences of different operation scenarios for an existing or planned system. These methods can often be the only means of obtaining the solution to the system model, especially when the system studied is large and complex or when the effects of certain sequences of events are of a particular interest or when the probability distributions, rather than only the means and variances, are required.

A numerical solution is a process of selecting a set of values of system parameters and obtaining a solution of the system model for a selected set. By repeating the simulation process for different sets of system parameters, one obtains different sample solutions. The key activity in the simulation process is the selection of system parameters to obtain sample solutions. A numerical simulation procedure applied to problems involving random variables with known (or assumed) probability distributions is called Monte Carlo simulation. It involves repeating the simulation process, using in each simulation a particular set of values of the random variables generated in accordance with the corresponding probability distributions. A sample from a Monte Carlo simulation is similar to a sample of experimental observations. Therefore, the results of Monte Carlo simulations may be treated statistically, and the methods of statistical estimation and inference are applicable.

Simulation models are extensively used in water resources systems planning and management. Some of the known models are HEC-3, HEC-5, SIM-I and II. A detailed review of the simulation models is given in Yeh [1985]. The advantage of simulation is that it can be more flexible, versatile and detailed in the system description than the optimization techniques. On the other hand, optimization looks to all possible decision scenarios, while simulation is limited to a finite number of input decision alternatives.

The adopted operating rules that can be used as an input to the reservoir planning and management simulation models are summarized by Loucks and Sigvaldason [1982]. They suggest that the operating policies may include some of the following general concepts: target reservoir storage volumes, allocation zones within the reservoir, flow ranges, and conditional rule curves dependent on the expected natural inflows.

The combined use of optimization and simulation models is a common idea. Loucks et al. [1981] suggest the use of optimization to screen a great number of feasible plans in the water resources projects, and to explore the remaining ones in more detail by applying a simulation model. The general tendency in recent years is to incorporate an optimization scheme into the simulation model. One of these models is developed by Sigvaldason [1976].

Sabet and Coe [1986] developed a large-scale optimization and simulation model which provides schedules for operation of water and power for the California State Water Project. The department in charge provides water to municipal and agricultural users, and manages its electrical loads and resources. The model, therefore, performs hydraulic and electrical computations leading to optimal operation of the entire system. It consists of hydraulic network programming components to meet the storage objectives at all the reservoirs, an LP component to determine the schedules at pumping and generating plants, an electrical network programming component to balance electrical loads and resources, and a number of other simulation components.

The practical application of optimization techniques in water resources management is not so widespread due to the complexities of the water resources systems and the existence of noncommensurable objectives. In this regard, simulation is an effective tool for studying the operation of the complex water resources system incorporating the experience and judgement of the planner or design engineer into the model.

2.1.3.3. Optimal Control Algorithms

Since the operation of reservoirs largely depends on the ability to predict uncertain inflows, McLaughlin and Velasco [1990] suggest that it is more reasonable to put an added emphasis on the prediction aspects of the operations problem and less on the generality of the problem formulation. One of the ways to accomplish this is to adopt linear-quadratic formulations which have linear constraints, quadratic benefit functions, and no inequality constraints. Such problems are attractive because they have recursive analytical solutions that yield a globally optimal feedback control law if the benefit function is strictly concave or convex, for maximization or minimization, respectively. Linear-quadratic control algorithms do not require discretization of the state and control spaces and therefore do not suffer from the curse of dimensionality which is generally associated with DP techniques. They can, therefore, incorporate more complex models of hydrologic variability (spatial and temporal) than algorithms which require state and control discretization. The price paid for these benefits is a loss of generality, and, more specifically, an inability to accommodate inequality constraints.

A number of investigators have incorporated various aspects of linear-quadratic theory in their solutions to reservoir operations problems. Murray and Yakowitz [1979] used a constrained differential DP approach to develop a reservoir operations control algorithm. This algorithm imbeds a linear-quadratic solution in an iterative loop which continually refines an initial suboptimal solution. Since the algorithm is deterministic, it makes no provision for inflow uncertainty.

Mizyed et al. [1992] proposed two approaches for the deterministic operation of a very large multireservoir system in Srilanka. The first involves monthly application of the optimal-control algorithm to find an optimal policy for the next year, based on current storage and forecasted or historical inflows and demands. A partly heuristic approach is developed to correct violations in state variable constraints, thus handling some of the convergence problems that are common in optimal control. The second approach is an implicit stochastic algorithm that ultimately discards the mathematical representation of the physical system in favour of linear operating rules. A deterministic optimal-control algorithm produces an optimal monthly operation policy for the historical period of record, and this policy is, in turn, used to develop the linear operating rules via linear regression. The Conjugate Gradient Method is used to achieve faster convergence to an optimal solution. Constraints on the state variable, for example, the storage, can be treated successfully through a quadratic penalty function.

Hanscom et al. [1980] developed a deterministic discrete-time optimal control algorithm which comprises of linear transition equations, a highly nonlinear objective and bounds on both the state and control variables. The solution algorithm is of the Reduced Gradient type, with the control variables that are nonbasic to provide good conditioning. Because of the linear relationship between the state and control variables, the set of feasible directions at a point is a polyhedral convex cone and the bounds both on the state and control variables can be accounted for by means of an algorithm for the orthogonal projection of the gradient on the cone. Mid-term planning is carried out and the objective is to meet weekly loads at minimum cost which depends on weekly energy markets and on the reward for final reservoir storage.

Georgakakos and Marks [1987] used linear-quadratic concepts to develop an iterative search algorithm called the Extended Linear Quadratic Gaussian Controller which solves a stochastic real-time reservoir operations problem with strict inequality constraints. This controller accounts for system uncertainties, control and state reliability constraints, nonlinear dynamics, and general performance indices, and it is designed to display computational efficiency and reliability. The objective is to maximize energy generation subject to release and storage reliability constraints imposed from the operational requirements. The handling of state constraints is done via the penalty function which, in general, is less efficient than the treatment of control constraints via the projected Newton Method. Although their approach accounts for uncertainty, it relies on an open-loop solution which does not recognize that measurements will be available at future times. This solution is updated whenever new measurements become available.

Wasimi and Kitanidis [1983] and Loaiciga and Marino [1985] used true closed-loop stochastic linear-quadratic control algorithms in their studies of flood control reservoirs.

McLaughlin and Velasco [1990] have investigated the performance of a Linear-quadratic Control Algorithm applied to a system of hydropower reservoirs. The objective is to track a nominal trajectory that represents firm or contracted power output, i.e., to maximize the long-term hydropower benefit obtained from the complete reservoir system. The authors also proposed an approximate way of incorporating the inequality constraints in some parts of the control algorithm.

Georgakakos [1993] presented practical real-time operational tradeoffs common among reservoir systems, and a control model which avoids an all-encompassing problem formulation and distinguishes three operational modes (levels) corresponding to normal, drought and flood operations. The problem formulated in each control level is solved using the control scheme which includes an inflow predictor, and two control modules. The static module specifies turbine power loads based on turbine characteristics, net hydraulic head, minimum and maximum outflow rates, and power commitments (instantaneous quantities). The dynamic module optimizes system performance over time and determines energy generation schedules that satisfy minimum generation commitments during peak and offpeak periods, meet weekly average outflow constraints, balance reservoir drawdowns (for example, to provide equal recreation opportunities at the system reservoirs), and observe a certain order during refilling after droughts or emptying after floods. This module can utilize deterministic or stochastic inflow forecasts and the two modules periodically exchange information to ensure operational consistency.

Yao and Georgakakos [1993] proposed a new stochastic control approach which is based on the premise that the reservoir operator wishes to have a set of policies which are guaranteed to meet all system constraints rather than optimize specific objectives. The authors claim that this mode of operation is more meaningful under crisis situations. Relationships between discharges and storage for some constant level of power generation are estimated and used as inputs to the control problem. This work is an extension of the basic algorithm presented by Georgakakos and Yao [1993], in which the authors say that the product of two state variables cannot be explicitly handled in this control framework, but one can usually overcome this predicament by following a well-established engineering rule:

when faced with a nonlinear problem, linearize [Schweppe, 1973].

This basic algorithm is revised in Yao and Georgakakos [1993] first to accommodate for linearized hydropower function with energy demand constraints, and later to take into account the value of energy to avoid the cost of alternative energy sources. The case study involves a 3-reservoir system and is shown to take a reasonable computational effort to provide the operating policies.

Generally, this algorithm cannot use inequality constraints and hence, cannot account for physical limitations on reservoir storage or release. So this algorithm behaves as if the reservoir storage and release are unrestricted. Consequently, the releases it computes do not consider the effects of spills or overdrafts which may occur in the future. In applications where nonlinearities are significant, this algorithm may not be appropriate. For narrow storage variations, this will be useful.

2.1.3.4. Minimum Norm Formulation

Christensen and Soliman [1987] developed a new algorithm for solving the optimal long-term problem of a hydropower system for maximum expected benefits (benefits from energy generated by a hydropower system over the planning period plus the expected future returns from water left in storage at the end of that period). The problem is formulated as a minimum norm problem in the framework of a functional analytic optimization technique. The method uses the expected value of probabilistic inflows and a relationship between power generation and the corresponding discharge from reservoirs which is derived by least square curve fitting to typical data available. The advantage of this approach being its ability to deal with large scale coupled power systems and its negligible computational time requirement.

2.1.3.5. Min-Max Technique

Nardini and Montoya [1995] have developed the risk-averse Min-Max Technique for the management of a single multiannual reservoir aimed at hydroelectric generation and water supply. Inflows, energy demands, and water supply demands are assumed to be deterministic and several scenarios are given in order to make the problem implicitly stochastic for all the years. Pointwise indicators termed as 'performance indices' for these two purposes are developed based on the amount of actual release to the corresponding required release for each of the two purposes, and also on the amount of water losses such as spill and infiltration. The objective is to maximize these indicators which conflict with each other. A two-phase solution algorithm is presented and in the first phase, the minimum release policy problem is adopted and solved by the 'constraint method' by optimizing only with respect to a final required storage in the reservoir.

2.2. NEED FOR A NEW MODEL FOR OPERATION PLANNING

Many of the models developed for hydropower optimization are deterministic [Hall and Roefs, 1966; Daellenbach and Read, 1976; Murray and Yakowitz, 1979; Hansom et al., 1980; Bechard et al., 1981; Pereira and Pinto, 1985; Grygier and Stedinger, 1985; Allen and Bridgeman, 1986; and Reznicek and Simonovic, 1990]. Planning the operation of hydropower systems is essentially a stochastic problem. Results of Dagli and Miles [1980], Labadie et al. [1981], and Vasiliadis and Karamouz [1994] suggest that repeated optimization with a deterministic forecast may not yield as efficient a policy as simpler rules that are imposed to reflect the uncertainty in future inflows. The need for developing a stochastic optimization approach which could be used in reservoir management and other areas of water resources systems is well stated by Grygier and Stedinger [1985]. Also, the need for modelling uncertainty in the operation of a reservoir for hydropower generation is emphasized by Daellenbach and Read [1976].

At present, the need to represent uncertainties of future operating conditions in power system planning and operations is widely recognized by the utility industry. For example, the reliability evaluation methods, which assess the probability and severity of failures in load supply, are now routinely used in utility studies. Computational tools for probabilistic studies generally require sophisticated mathematical models, which have been classified as analytical and simulation techniques.

An example of an analytical model is Generation Reliability Evaluation, in which the probability distribution of the total available generating capacity is obtained by convolution of unit capacity distributions, and compared with the probability distribution of system load [Billinton and Allan, 1984]. The computational efficiency of these models can be further enhanced by the use of series expansion techniques to carry out the required convolutions. These models have several attractive features: they are accurate, computationally efficient, and, most importantly they provide the planner with insights regarding the relationships between input variables and final results. Their major limitations are related to the simplifying assumptions which may be required for analytical tractability. The extension of analytical models to incorporate additional features often leads to infeasible computational requirements [Breipohl et al., 1990].

Simulation methods, among which the Monte Carlo technique is the most common, are based on the random sampling of scenarios followed by the analysis of each sampled scenario. The expected system operation index is estimated as the mean over several scenarios. The advantages of the Monte Carlo sampling approach are its conceptual simplicity, that is, each sampled scenario can be seen as a possible history of system operation; and its flexibility, that is, it is easy to incorporate complex modelling features. One possible limitation of this method is related to the computational effort, which increases quadratically with the required accuracy of the estimates.

Pereira et al. [1992] proposed that the analytical methods and Monte Carlo simulation methods are not mutually exclusive approaches, as often mentioned in the technical literature. On the contrary, these methods have complementary features which, if properly exploited, can provide the decision maker with both an adequate system representation and acceptable computational requirements. The authors describe a general framework for combining analytical and Monte Carlo approaches by using a simpler analytical model as an approximation to a more detailed model in a Monte Carlo simulation scheme. The simulation then deals with the 'residual', that is, the difference between the results of the detailed model and of the approximation. Application of this hybrid approach has been demonstrated, along with other applications, for the operation of a multireservoir hydroelectric system.

Conceptually, there are two ways of incorporating the stochastic nature of inputs into an analytical mathematical programming model. One way is to incorporate the stochasticity implicitly in the model through sensitivity analysis [Pereira and Pinto, 1985; Grygier and Stedinger, 1985, and Reznicek and Simonovic, 1990]. Optimization has to be performed with different scenarios of stochastic data to evaluate their impact on the operation policy. To improve the operation policy, forecasted input is updated whenever additional information is available and the model is rerun. The second way is to incorporate the stochasticity explicitly through probability constraints. One of the explicit approaches is SDP [Little, 1955; Buras, 1963; Bras et al., 1983; Stedinger et al., 1984; Trezos and Yeh, 1987; Paudyal et al., 1990; Li et al., 1990; and Braga et al., 1991]. Based on the literature cited in Section 2.1.2, the observations of the author of this thesis are that SDP suffers from the following drawbacks: (1) the curse of dimensionality; (2) an inability to handle large water resources systems; (3) the implicit incorporation of uncertainty in energy demands; and (4) an inability to evaluate the reliability of the reservoir system explicitly.

All the SDP formulations developed for hydropower optimization presented to date consider the uncertainty in reservoir inflows through the transition probability matrices or the probability distributions. None of those formulations considers the uncertainty in energy demands. The energy demands are either assumed as deterministic [Stedinger et al., 1984; and Braga et al., 1991] or are treated as decision variables in the formulation [Trezos and Yeh, 1987; and Paudyal et al., 1990]. The task of incorporating the uncertainty in energy demand in these models appears to be complex and cumbersome. For example, the demand driven DP algorithm proposed by Vasiliadis and Karamouz [1994] for a single multipurpose reservoir, when extended to a system of reservoirs will be complex and computationally infeasible. Another explicit approach is the linear-quadratic method. As described in Section 2.1.3.3, this approach cannot represent the physical constraints on the reservoir system and also cannot handle a large variation in storages.

Yet another approach which has the capability of including risk directly in the optimization is CCP. In this approach, the uncertainty in inputs is modelled by considering them as stochastic variables. The stochastic nature of inputs is incorporated in the model through the use of cumulative probability functions of the stochastic variables. Furthermore, probabilistic constraints and preassigned tolerance levels are used to transform the stochastic optimization problem into its deterministic equivalent. The application of chance constraints to a reservoir system optimization is initiated by ReVelle et al. [1969]. CCP formulations neither penalize explicitly the constraint violations nor provide a recourse action to correct realized constraint violations as a penalty [Yeh, 1985]. The CCP approach has been criticized by Hogan et al. [1981], and has been reported to generate very conservative solutions. However, Yeh [1985] concluded that the intrinsic capability of CCP to incorporate the stochastic nature of inflow in a linear program offers an advantage over other stochastic models. Application of CCP to hydropower production has been attempted by Houck et al. [1980] in which the expected value of energy demand is included in a linear decision rule model. This work does not model the uncertainty in energy demand.

Linear CCP approach is one of the simplest ways to develop an operational measure of the reliability of the linear systems, under the assumption that only the right-hand side elements of the constraints of the system are random and mutually independent statistically. In this approach, a set of tolerance levels in terms of probability measures, one for each probability constraint, is preassigned by the decision maker to indicate the limit up to which constraint violations are permitted. This view of linear chance-constraints allows the interpretation of an LP model as a system where each probability constraint can be viewed as a system component with its reliability. This interpretation leads to the evolution of the systems reliability programming and hence the system reliability of the LP model can be defined in terms of the reliability of the individual components [Sengupta, 1972].

2.3. RELIABILITY PROGRAMMING MODEL

Application of a reliability programming (referred to as RP) approach, also referred to as a reliability model in this thesis, for reservoir management is first attempted by Colorni and Fronza [1976]. In their work, a single reliability constraint is used to represent the reliability of the single purpose reservoir and the goal is to determine the monthly contract volumes to be released by the reservoir. The approach has been extended by Simonovic and Marino [1980, 1981, 1982] to model a single multipurpose reservoir as well as reservoir systems without considering hydropower generation. The main contribution of their work is the incorporation of monthly downstream releases in the objective function with an aim of maximizing the benefits obtained from these releases. Simonovic and Orlob [1984] also used the reliability programming approach to water quality management.

One of the advantages of the reliability model is the consideration of risk-benefit analysis explicitly. Friedman et al. [1984] pointed out that the Office of Technology Assessment surveyed the water resources professionals in 22 federal agencies and offices and in all 50 states of the U.S. to determine: (1) how models are currently being used; (2) their present capabilities and limitations; and (3) constraints to further use. Their findings show a high potential for model usage to address economic and social issues (which includes the risk-benefit analysis). Another advantage of the reliability model is that the uncertainty in energy demand can, very easily, be incorporated in the formulation. This task is very complex and cumbersome in other formulations such as SDP.

In the next chapter, a reliability model is developed for planning the operation of a reservoir with hydropower generation as the major purpose [Srinivasan and Simonovic, 1994b]. Flood control is included as the secondary purpose in this study. The stochastic nature of reservoir inflows is incorporated in the model through the use of cumulative probability distribution functions. A set of probabilistic constraints associated with the reliabilities of the reservoir performance has been defined as the major component of the model. The approach considers the levels of these reliabilities as decision variables. In order to deal with the new decision variables, the objective function requires modification and hence, the concept of a risk-loss function is introduced. The formulation of a reservoir system management as a reliability program follows the recommendation of Hogan et al. [1981] by considering the reliability levels as decision variables.

Risk-loss functions in a reliability model evaluate the losses associated with the risk of choosing an infeasible solution. These losses may consist of penalties due to flood damages or deficit in energy supply and are difficult to interpret in the absence of a comparison with the net benefit obtained from the reservoir operation. These risk-loss functions aid in determining the trading offs between the benefits and the risk in the decision making process. The methodology for deriving the risk-loss functions for flood control and water supply has been proposed by Simonovic and Marino [1981]. A new methodology for deriving the risk-loss function for hydropower generation is discussed in Chapter 4, and also in Srinivasan et al. [1995].

3. FORMULATION OF THE RELIABILITY MODEL

One of the objectives of this research is to develop a mathematical model for planning the operation of a multipurpose multireservoir system for hydropower generation with uncertain inputs. In this chapter, a reliability model is developed and presented for a single multipurpose reservoir serving flood control and hydropower generation, which evaluates the values of reliabilities along with the optimal policy. Thus, the reliability model aids the planner in carrying out an explicit risk-benefit analysis. Risk-loss functions form an important component of this model, which are used in the model to explicitly represent the economic losses associated with not meeting the reliability requirements for the various purposes served by the reservoir. In the following section, the basic formulation of the reliability model is presented in which the uncertainty in reservoir inflows is incorporated using probability constraints by considering the inflows as stochastic variables. The energy demands are assumed to be deterministic, that is, the demands are assumed to be known for the entire planning period [Srinivasan and Simonovic, 1994b]. In the last section of this chapter, two approaches for incorporating the uncertainty in energy demand are discussed, namely, considering the energy demand as a stochastic variable or as a fuzzy variable.

3.1. BASIC FORMULATION

The variability in reservoir inflows is incorporated into the reliability model through a couple of probability constraints, which are derived from the physical characteristics of the reservoir as shown in Figure 3.1. The first constraint is derived based on the fact that the storage in the reservoir in any time period should not exceed the maximum storage which is usually taken as the physical capacity if the reservoir is not used for flood control purposes. Here, flood control is the secondary purpose and hence the maximum storage bound is computed after giving consideration to the flood control freeboard. Provision of a flood control freeboard will mitigate flood damages, and the probability of not violating the bound on maximum storage can be associated with the reliability of the reservoir system performance for flood control. The second constraint is based on the fact that the storage in the reservoir in any time period should not go below the minimum storage required in that time period as shown in Figure 3.1, which may be taken as the dead storage if there is no other storage requirement. In this case, hydropower generation is the primary purpose, and there is usually an elevation range in which the reservoir is allowed to operate for energy generation. This range is called the 'operating range' and is determined by the electrical utility responsible for operating the reservoirs. The lower bound of this range could be taken as the minimum storage requirement for hydropower generation, and hence the probability of not violating the minimum storage constraint can be associated with the reliability of reservoir system performance for hydropower generation.

The reliability model for planning the operation of a multipurpose reservoir is developed using the storage continuity equation:

$$S_t = S_{t-1} + I_t - R_t - SP_t - LO_t \qquad \forall\, t \qquad (1)$$

where S_t is the storage in the end of the time period t ; R_t is the average release through the turbines for energy generation in time period t ; SP_t is the average spill from the reservoir through the spillway (that is not used for energy generation) in time period t ; LO_t is the average loss of water from the reservoir such as evaporation and seepage in time period t ; and I_t is the uncertain inflow into the reservoir in the time interval *(t-1,t)*.

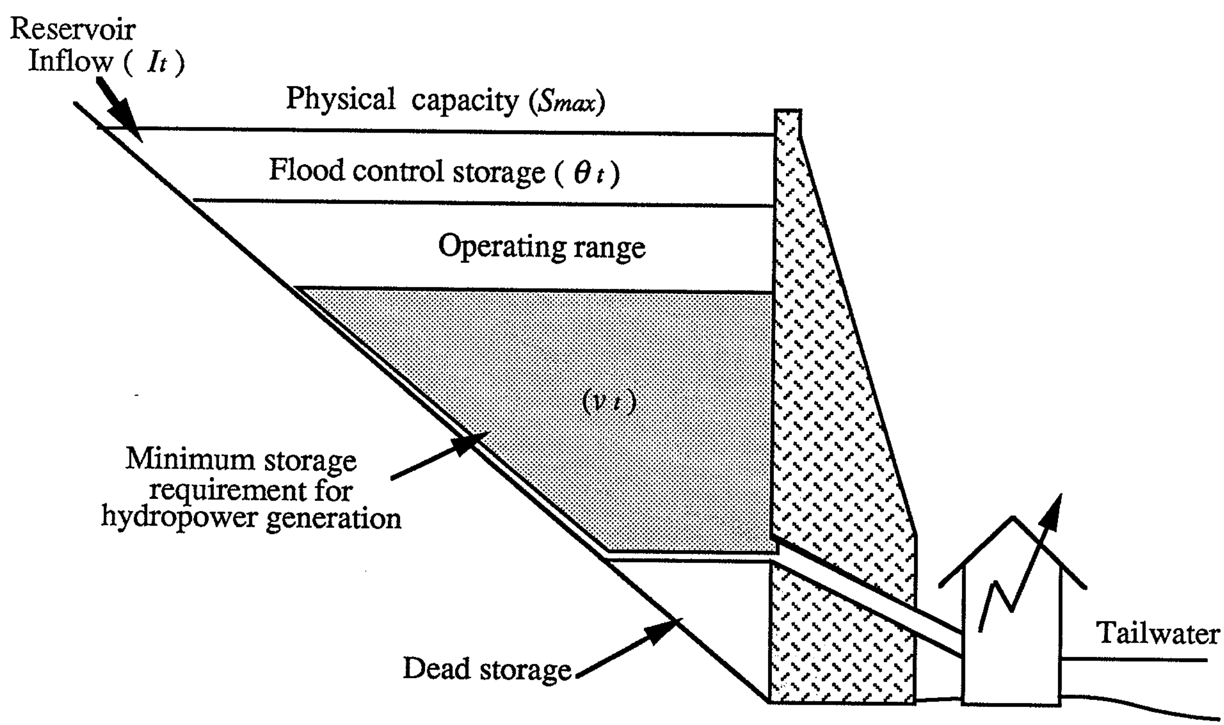


Figure 3.1. Conceptual Diagram of a Single Multipurpose Reservoir

All the terms in Equation (1) are expressed in volume units (for example, cubic meters) or in flow units (for example, cubic meters per second).

The reservoir loss in any time period t, LO_t, can be estimated from the surface area of water in the reservoir and the rate of evaporation per unit surface area. The storage-area curve of the reservoir, which relates the surface area and the storage, can be used to express the loss as a function of the storage in the reservoir. However, in the present formulation, the reservoir losses (LO_t) are ignored. Therefore, Equation (1) is rewritten as,

$$S_t = S_{t-1} + I_t - R_t - SP_t \qquad \forall\, t \tag{2}$$

Decision variables in the reliability model are: (1) the average release through the turbines in time period t, R_t; (2) the average head in the reservoir in time period t, h_t ; (3) the storage in the reservoir at the end of time period t, S_t ; (4) the average spill from the reservoir in time period t, SP_t ; (5) energy exported to other utility companies in time period t, E_t ; (6) the energy imported from other utilities in time period t, IM_t ; (7) the reliability of hydropower generation in the planning period, β ; and (8) the reliability of flood control in the planning period, α.

3.1.1. Set of Constraints

The reservoir operation is subject to physical, environmental, economic, and other constraints. In this section, the constraints in the reliability model are presented in the following order: (a) probability constraints; (b) constraints on reservoir elevations and releases; (c) constraints on energy demands; (d) constraints on reliabilities; and (e) constraints on reservoir storage.

a. Probability Constraints

The constraint on the maximum reservoir storage can be represented as:

$$P\ (\ S_t \ \leq\ S_{\max} - \theta_t\ )\ \geq\ \alpha \qquad \forall\, t \qquad (3)$$

where S_{max} is the maximum storage in the reservoir, and θ_t is the minimum flood control volume to be maintained in the reservoir in time period t, and α is the probability of exceedance of this constraint. This constraint ensures that the storage in the reservoir is less than $(S_{max} - \theta_t)$ in α*100% of time period t, and thus, the possibility of a flood is avoided in α*100% of the time. So the value of α is taken as the reliability of flood control.

Substituting Equation (2) in Equation (3) yields,

$$P\ (\ S_{t-1} + I_t - R_t - SP_t\ \leq\ S_{\max} - \theta_t\ )\ \geq\ \alpha \qquad \forall\, t \qquad (4)$$

Since I_t is a random variable, Equation (4) is rewritten as,

$$P\ (\ I_t\ \leq\ S_{\max} - \theta_t - S_{t-1} + R_t + SP_t\ )\ \geq\ \alpha \qquad \forall\, t \qquad (5)$$

The electrical utility companies often incorporate the temporal variation in load (and hence, the energy demand) through load duration curves, in the mathematical models. An example of a load duration curve for a given time period t is shown in Figure 3.2, which shows the variation of the load within the time period t. A horizontal straight line implies a uniform load in the entire time period t. This curve is approximated by a few linear strips (as fraction of the time period), as shown in Figure 3.2, and the load is assumed to be constant within each strip. Different energy prices may be assigned to each of these strips. The number of strips needed depends on the precision with which the load curve has to be specified in the planning model. Let nsl be the total number of strips in a unit time period and all the time periods have an equal number of strips.

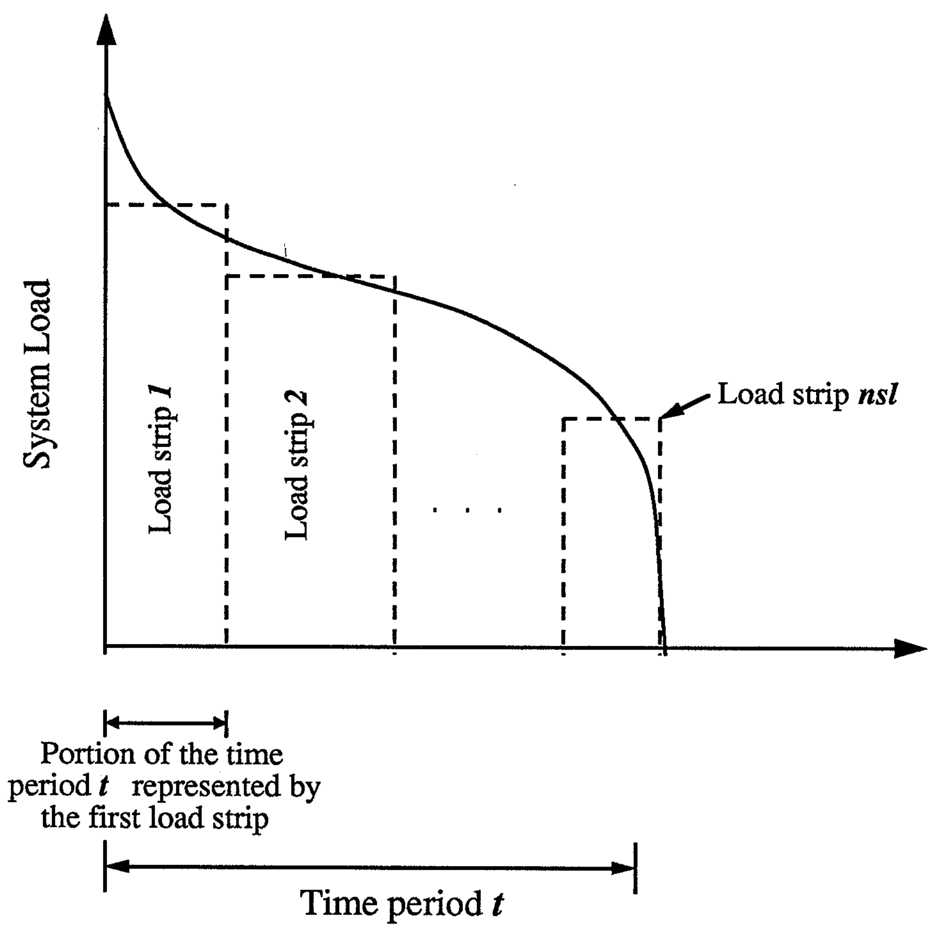


Figure 3.2. Representation of the Load-Duration Curve

For a given time period and a given load pattern in strip *ls*, the associated variables are: the average release from the reservoir for hydropower generation, R_t^{ls} ; the average hydraulic head on the turbines, h_t^{ls} ; the storage at the end of the strip, S_t^{ls} ; the energy export, E_t^{ls}; and the imported energy, IM_t^{ls}. Even though the variables such as releases, export energy, and the import energy in each load strip can be represented in this formulation, the storage (and hence, the reservoir elevation) has to be specified only at the end of time period *t*. The weighted average storage, S_t^{avg}, is assumed to represent the storage at the end of the time period *t* (weight for the load strip *ls* being equal to the fraction of the time period *t* represented by that strip), that is,

$$S_t = S_t^{avg} \qquad \forall\, t \qquad (6)$$

The deterministic equivalent of Equation (5) is written as:

$$S_{\max} - \theta_t - S_{t-1}^{avg} + \sum_{ls=1}^{nsl} R_t^{ls} + SP_t \geq F_{\Sigma t}^{-1}(\alpha) \qquad \forall\, t \qquad (7)$$

where $F_{\Sigma t}^{-1}(.)$ is the inverse value of the cumulative distribution function of the sum of inflows up to and including the time period t. A detailed explanation of the mathematical transformation is given in Appendix A.

The main use of the reservoir is hydropower generation. Many of the electrical utilities in North America which generate most of the energy requirements through hydropower generation have established a minimum reservoir storage requirement (also called a rule curve). This storage requirement is established based on the energy demand on the system as well as the anticipated inflow conditions in the river during the planning period. The second probability constraint is derived from the fact that the storage in the reservoir in any time period should not go below the minimum storage requirement in that time period.

The constraint on the minimum reservoir storage can be written as:

$$P\ (S_t \geq v_t) \geq \beta \qquad \forall t \tag{8}$$

where S_t is the storage at the end of the time period t, v_t is the minimum volume required for the purpose of hydropower production, and β is the probability of exceedance of this constraint. This constraint ensures that the reservoir storage is greater than v_t in β*100% of the time period t, and thus, the storage requirement for energy generation can be met fully in β*100% of the time. So the value of β is taken as the reliability of the reservoir for hydropower generation.

Analogous to Equation (7), the deterministic equivalent of Equation (8) is,

$$v_t - S_{t-1}^{avg} + \sum_{ls=1}^{nsl} R_t^{ls} + SP_t \leq F_{\Sigma_t}^{-1}(1-\beta) \qquad \forall t \tag{9}$$

The practical importance of the minimum storage requirement (v_t) for the Manitoba Hydro system is presented in Simonovic and Srinivasan [1993], and is also explained through an example in Chapter 6.

b. Constraints on heads and releases

Release from the reservoir may have a lower bound depending on the firm energy generation or the minimum flow requirement downstream of the reservoir, and an upper bound specified by the maximum allowable discharge downstream of the reservoir or the turbine capacity. Similarly, the reservoir elevation or the head will have upper and lower bounds depending on the storage requirements.

c. Constraints on energy

The constraints are developed based on the characteristics of the specific system under study, namely, the export energy commitments, available alternative energy, and the import energy commitments. The following constraints have been developed for Manitoba Hydro, the case study for this research. Manitoba Hydro is an interconnected utility and has the main goal of satisfying the energy demand described by the load duration curve in each time period of the planning period. As mentioned earlier in this chapter, the energy requirement ($ENMIN_t^{ls}$) is considered as a deterministic input in the basic formulation of the reliability model.

The firm energy demand is taken as the customer demand plus the firm export energy commitment to other utilities, minus any firm import energy commitments from other utilities. In Figure 3.3, the area ABCD represents the firm energy demand in load strip ls in time period t. There are three cases:

Case 1: If the reservoir storage and the external market conditions permit, the utility exports energy on an interruptible basis (E_t^{ls}) in order to increase its revenue, that is, the energy produced is given by the area ABF'E' and hence the excess energy over the firm energy demand as given by the area CDE'F' is exported,

Case 2: Energy produced is given by the area ABCD and hence the energy is neither imported to nor exported from the utility,

Case 3: The utility imports energy on an interruptible basis during the periods of deficits, i.e., when the energy produced is less than the firm energy demand. Referring to Figure 3.3, the energy produced is given by the area ABC'D' which is less than the firm energy demand and the deficit in energy as given by the area CDD'C' is imported from other utilities.

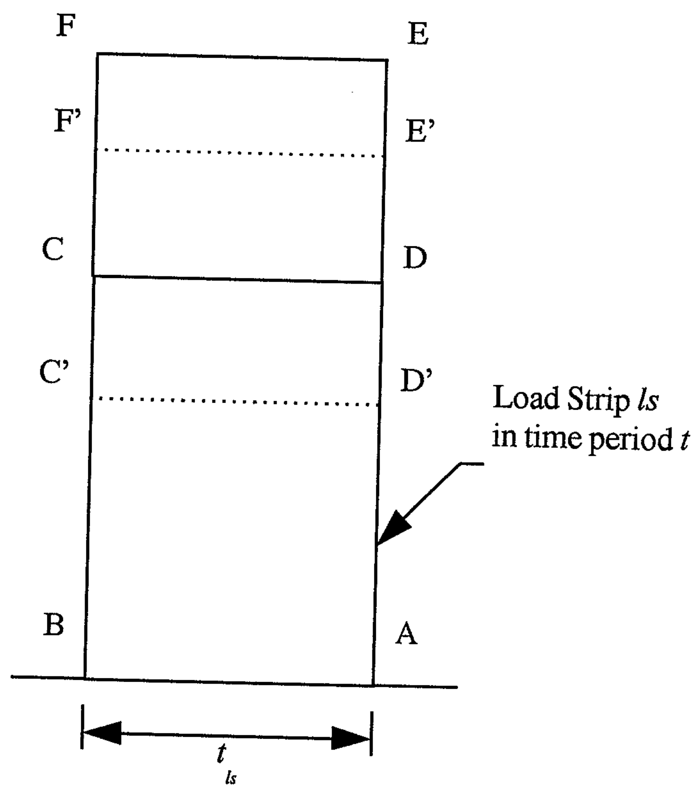


Figure 3.3. Energy Balance Diagram

The constraint which represents these three cases is,

$$C^{ls} * R_t^{ls} * h_t^{ls} - E_t^{ls} + IM_t^{ls} = ENMIN_t^{ls} \qquad \forall\ t,\ ls \tag{10}$$

where C^{ls} is the conversion factor in the energy equation given by:

$$C^{ls} = \frac{\underline{Energy\ Requirement\ within\ load\ strip\ ls}}{R_t^{ls} * h_t^{ls}} \tag{11}$$

Even though the utility can increase its net benefit by exporting energy to other utilities, there is a maximum bound on the interruptible energy export in each load strip *ls* in time period *t* ($EMAX_t^{ls}$). This bound is decided by the utility based on the factors such as water availability, export market conditions, and the capacity of the transmission network. This bound is represented by the area CDEF in Figure 3.3 and the mathematical form of the constraint is specified as,

$$E_t^{ls} \leq EMAX_t^{ls} \qquad \forall\ t,\ ls \tag{12}$$

However, depending on the goal to be achieved by the utility planners, the energy constraints given by Equations (10) and (12) can be modified accordingly.

d. Constraints on reliabilities

A reliability of 100% implies that the system will not fail and a reliability of 0% implies that the system will certainly fail. Constraints on the reliabilities of the system for flood control and hydropower generation respectively, are:

$$0 \leq \alpha , \beta \leq 1 \tag{13}$$

e. Constraints on reservoir storage

The hydraulic head on the turbines is the difference between the water level elevation in the reservoir and the water level immediately downstream of the generation station (referred to as the tail water level). The tail water level is a function of the flow through the turbines and the storage in the reservoir immediately downstream. At any time period t, the relation (represented by f_1) between the reservoir elevation (h_t) and the storage (S_t); and the relation (represented by f_2) between the tail water elevation (h_d) and the release through the turbines (R_t) in the generating station are expressed respectively as:

$$h_t = f_1 (S_t) \tag{14}$$

$$h_d = f_2 (R_t , S_{down}) \tag{15}$$

where S_{down} is the water storage downstream of the reservoir.

Discharge through the turbines raises the tail water and affects the hydraulic head. In the present formulation, the hydraulic head is assumed to be independent of the discharge through the turbines. This assumption can be justified in some practical situations such as a power plant across a river of very large width, where the tail water raises hardly by a few feet even when the discharge is high. This small raise is negligible when compared to a reservoir head on the order of several hundreds of feet. In the present formulation, the relation given by Equation (15) is ignored. The nonlinear stage-storage curve shown in Figure 3.4 and as given by Equation (14), is approximated using the piecewise linearization technique in the operating range. The average head in time period t (h_t) is computed using Equation (14) from the reservoir storage corresponding to the average of the storage values in the beginning of t and $(t\text{-}1)$. Therefore, Equation (14) is rewritten as,

$$h_t - \psi * \frac{(S_{t-1}^{avg} + S_t^{avg})}{2} = h^{\min} \qquad \forall\, t \tag{16}$$

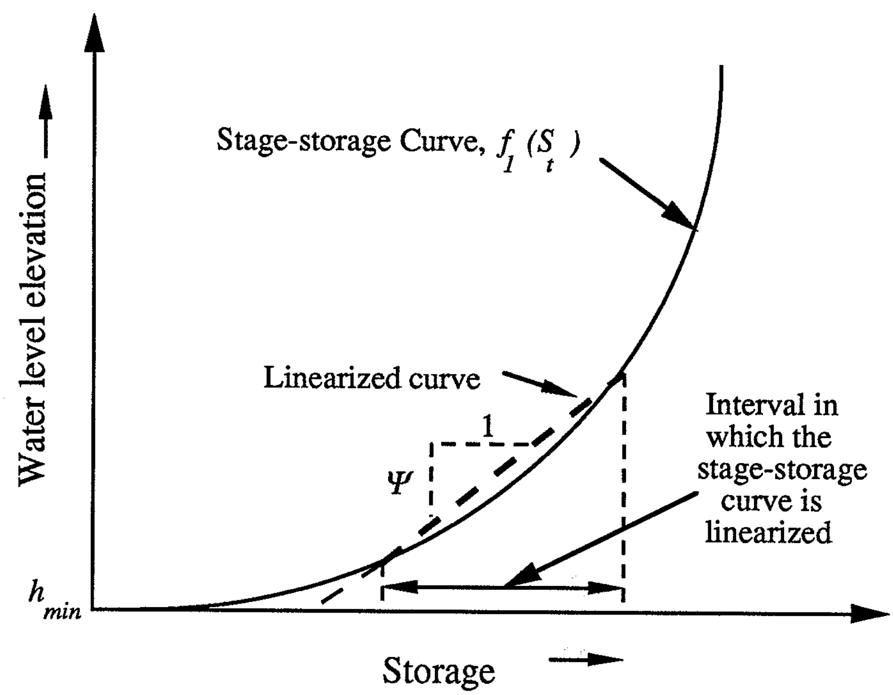


Figure 3.4. Stage-storage Relationship in the Reservoir

where h^{min} is the lower bound of the operating range; h_t is the average hydraulic head; and ψ is the slope of the linearized storage-stage curve, which can take a single value or multiple values depending on the number of linear segments used to approximate the nonlinear stage-storage curve.

The model tends to deplete the storage in the reservoir in the planning period as the objective is to maximize the net benefits. But, the storage available in the reservoir at the end of the planning period will be used for energy generation in the future. Hence, the storage at the end of the planning period is an important parameter, and is included as a decision variable in the objective function. Even though the storage term appears in Equation (16), there is some approximation involved in deriving the same. Hence, the flow continuity equation as given by Equation (2), is introduced as an additional constraint. Rewriting Equation (2),

$$I_t = S_t - S_{t-1} + R_t + SP_t \qquad \forall\, t \qquad \mathbf{(17)}$$

Since inflow (I_t) is a random component, the expression on the right-hand side of Equation (17) may lie anywhere in the range of variation of inflow. Lower and upper bounds of inflow in any time period (shown as points A and B respectively in Figure 3.5) are the deterministic equivalents corresponding to the lowest (P_l) and the highest (P_u) probabilities specified in the cumulative distribution function of the sum of inflows up to and including the time period t. In other words, the flow values $F_{\Sigma t}^{-1}(P_l)$ and $F_{\Sigma t}^{-1}(P_u)$, respectively, will be the upper and lower bounds on the right-hand side expression of Equation (17) which is rewritten as:

$$F_{\Sigma t}^{-1}(P_l) \leq S_t^{avg} - S_{t-1}^{avg} + \sum_{ls=1}^{nsl} R_t^{ls} + SP_t \leq F_{\Sigma t}^{-1}(P_u) \qquad \forall t \tag{18}$$

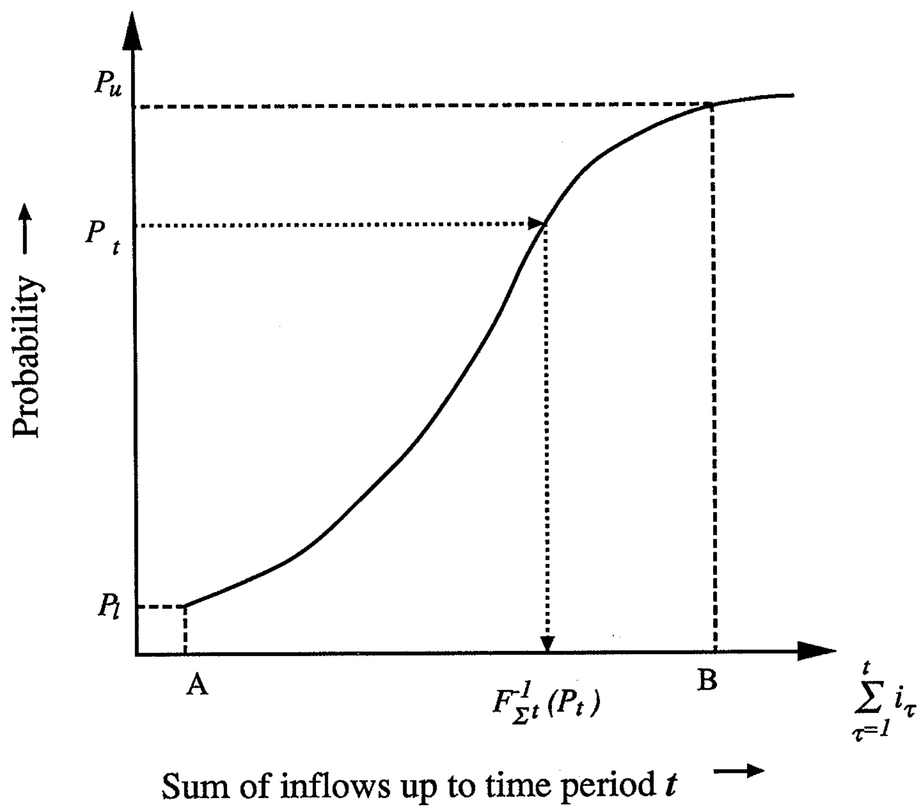


Figure 3.5. Cumulative Distribution Function of the Sum of Reservoir Inflows

3.1.2. Objective Function

The objective of this model is to maximize the benefits accrued from hydropower generation and flood control, and also to minimize the losses incurred due to not meeting the required reliability levels for each of the purposes served by the reservoir. The objective function, thus, has four components. The first and second components represent the benefits accrued from operating the reservoir for hydropower generation and flood control. The third component is used to describe the yearly risk loss for not meeting the reliability level associated with flood control, and the fourth, to describe the yearly risk loss for not meeting the reliability level associated with hydropower production. The mathematical form of the objective function is written as:

$$\max \Big[\Big[\sum_{t=1}^{T} \Big[\sum_{ls=1}^{nsl} r^{ls} * (C^{ls} * R_t^{ls} * h_t^{ls} - E_t^{ls}) + rexp^{ls} * E_t^{ls} - cimp^{ls} * IM_t^{ls}\Big] - LC_t * SP_t \Big] + B_T * S_T^{avg} \Big] + \sum_{t=1}^{T} BF_t\,(\theta_t) - L_1(\alpha) - L_2(\beta) \qquad \mathbf{(19)}$$

The first component in Equation (19) consists of the firm energy requirement which includes the firm export and import energy commitments ($C^{ls} * R_t^{ls} * h_t^{ls}$ - E_t^{ls}) with an associated revenue coefficient of r^{ls} (in $ per energy unit); interruptible energy export (E_t^{ls}) from the utility with an associated revenue coefficient of $rexp^{ls}$ (in $ per energy unit); cost incurred for importing energy (IM_t^{ls}) from other utilities with an associated cost coefficient of $cimp^{ls}$ (in $ per energy unit); the penalty for the water spilled (SP_t) from the reservoir with an associated loss coefficient of LC_t (in $ per unit storage spilled); and the expected benefits by keeping a storage (S_T^{avg}) at the end of the planning period (consisting of T number of time periods) for energy generation in the future with an associated benefit coefficient of B_T (in $ per unit storage retained in the reservoir). The second component in Equation (19) is the total benefit from flood control in the planning period T, which is computed as the sum of the benefit (BF_t in $ per unit storage) obtained when a flood control space, θ_t, is provided in the reservoir in time period t. The third and fourth components in Equation (19) evaluate the probability of system failure in terms of monetary losses. Values of α and β are the reliabilities of the reservoir system, and $L_1(.)$ and $L_2(.)$ are the yearly risk-loss functions for flood control and hydropower generation respectively.

The coefficients such as r^{ls}, $rexp^{ls}$, and $cimp^{ls}$, can easily be estimated for every load strip ls. The coefficient B_T influences the storage availability for future energy generation. The coefficient LC_t is the penalty for a spill from the reservoir during the time period t, which will possibly quantify the economic, social and environmental impacts of the spill on the downstream of the reservoir. The function $L_1(.)$ quantifies the impacts of flooding for the entire planning horizon. Many of the Canadian utilities use regression-based approaches to estimate B_T. However, the coefficients' LC_t can be specifically estimated *a priori* for the system under study, in conjunction with the function $L_1(.)$, to impose the consequences of spills (which are not used for energy generation) from the system.

The complexity of the nonlinear program given by Equations (3) through (19) can be reduced substantially by introducing a reasonable assumption that the net benefits and the risk losses are, respectively, concave and convex functions of their arguments [Colorni and Fronza, 1976]. Simonovic and Marino [1980] used logarithmic approximations of risk functions, which are convex functions of their arguments, namely, the risks.

Simonovic and Marino [1981] developed the methodologies to derive realistic risk-loss functions for flood control and water supply using the pertinent economic, hydrologic and hydraulic data. These risk-loss functions are also convex functions of the risks. A new methodology for deriving the risk-loss function for hydropower generation is developed in this research, and is presented in the next chapter.

3.1.3. Linearization of the Energy Function

The linearization procedure originally suggested by Can et al. [1982] is used in this formulation. It is found to be appropriate for a large storage reservoir with a small operating range. This results in the nonlinearity in the energy function to be not significant due to very small head variations. The linearization procedure is explained below:

Introducing two new variables X_t^{ls} and Y_t^{ls},

$$X_t^{ls} = 0.5 * (R_t^{ls} + h_t^{ls}) \tag{20}$$

$$Y_t^{ls} = 0.5 * (R_t^{ls} - h_t^{ls}) \tag{21}$$

the product term in Equations (10) and (19) is replaced by the expression,

$$R_t^{ls} * h_t^{ls} = [X_t^{ls}]^2 - [Y_t^{ls}]^2 \tag{22}$$

Each of the nonlinear single valued functions is approximated here by piecewise linear functions. The bounds on the new variables X_t^{ls} and Y_t^{ls} are set using the known bounds of the decision variables R_t^{ls} and h_t^{ls} as follows:

$$XMIN_t^{ls} = 0.5 * (RMIN_t^{ls} + HMIN_t^{ls}) \tag{23}$$

$$XMAX_t^{ls} = 0.5 * (RMAX_t^{ls} + HMAX_t^{ls}) \tag{24}$$

$$YMIN_t^{ls} = 0.5 * (RMIN_t^{ls} - HMAX_t^{ls}) \tag{25}$$

$$YMAX_t^{ls} = 0.5 * (RMAX_t^{ls} - HMIN_t^{ls}) \tag{26}$$

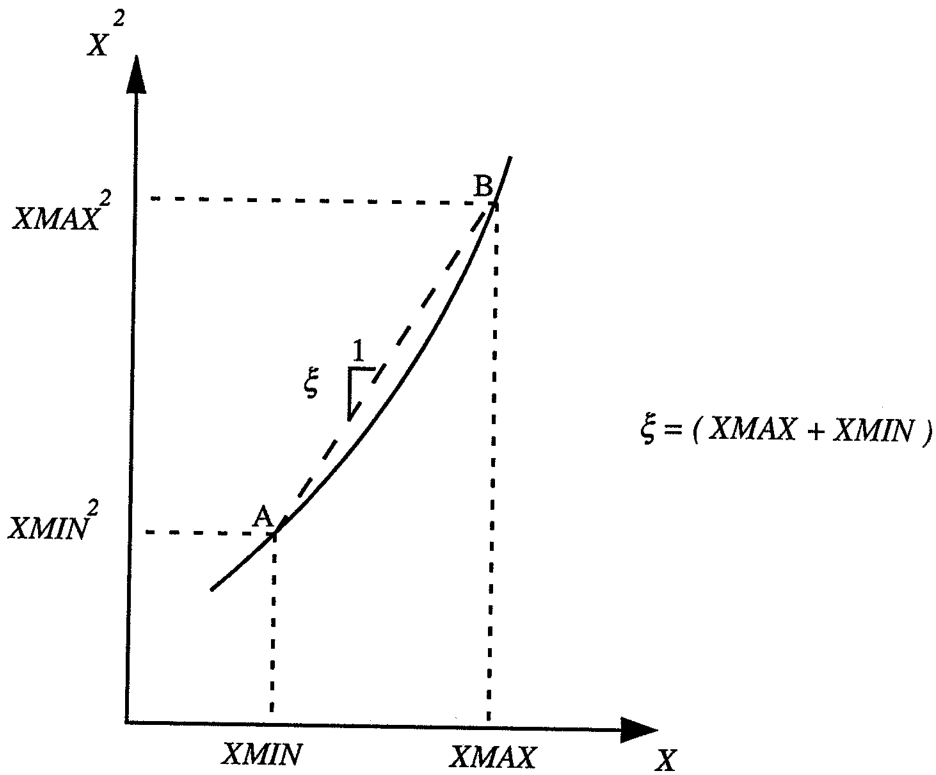


Figure 3.6. Linearization of the Energy Function

where $XMIN_t^{ls}$, $XMAX_t^{ls}$, $YMIN_t^{ls}$, $YMAX_t^{ls}$, $RMIN_t^{ls}$, $RMAX_t^{ls}$, $HMIN_t^{ls}$, and $HMAX_t^{ls}$ are the minimum and maximum bounds on the variables X_t^{ls}, Y_t^{ls}, R_t^{ls} , *and* h_t^{ls} respectively. Referring to Figure 3.6, the nonlinear curve for the variable X_t^{ls} is shown, and *AB* is the linearized segment in the range {*XMAX - XMIN*}. For a given load strip *ls*, and time period *t*, the equation of the line *AB* is:

$$[\,X_t^{ls}\,]^2 \;=\; -\,XMAX_t^{ls} * XMIN_t^{ls} + [\,XMAX_t^{ls} + XMIN_t^{ls}\,] * X_t^{ls} \tag{27}$$

Similarly the equation for the linearized curve for the variable Y_t^{ls} is written as,

$$[\,Y_t^{ls}\,]^2 \;=\; -\,YMAX_t^{ls} * YMIN_t^{ls} + [\,YMAX_t^{ls} + YMIN_t^{ls}\,] * Y_t^{ls} \tag{28}$$

When the ranges of linearization of X_t^{ls} and Y_t^{ls} , that is, $\{XMAX_t^{ls} - XMIN_t^{ls}\}$ and $\{YMAX_t^{ls} - YMIN_t^{ls}\}$, are small, better linear approximations can be obtained. Substituting Equations (27) and (28) in Equation (22),

$$\begin{aligned} R_t^{ls} * h_t^{ls} = & -XMAX_t^{ls} * XMIN_t^{ls} + YMAX_t^{ls} * YMIN_t^{ls} \\ & + (\,XMAX_t^{ls} + XMIN_t^{ls}\,) * X_t^{ls} - (\,YMAX_t^{ls} + YMIN_t^{ls}\,) * Y_t^{ls} \quad \forall\, t,\, ls \end{aligned} \tag{29}$$

Substituting the right-hand side of Equation (29) for the product term $(\,R_t * h_t\,)$ in Equations (10) and (19), the final form of the basic formulation of the reliability model is obtained. However, for the reservoirs with a very large operating range, better linearization techniques such as Successive Linear Programming [Grygier and Stedinger, 1985; Reznicek and Simonovic, 1990] could be adopted and incorporated in this formulation.

3.1.4. Solution Algorithm and Computer Program Architecture

3.1.4.1. Three Level Solution Algorithm

For solving the optimization problem represented by the objective function given by Equation (19) and the set of constraints (given by Equations 7, 9, 10, 12, 13, 16, 18, 20, 21, and 29), a three level algorithm has been developed. The algorithm combines: (i) a nonlinear search; (ii) a linearization of the energy function; and (iii) an optimization routine, which are shown in Figure 3.7 as Level 1, Level 2, and Level 3 respectively. Two-dimensional constrained nonlinear programming is used at the first level in order to determine the optimal values of the reliabilities α and β. Two additional levels, nested within the Level 1, are used to first linearize the nonlinear energy generation function (Level 2) and then evaluate the optimal value of the objective function (Level 3).

Before the solution algorithm is explained in detail, the theorem of concavity of the objective function [Simonovic and Marino, 1980; 1982] is introduced here. Let α' and β' are the lower bounds on the reliabilities defined in such a way that the shapes of $F_t(\alpha)$ and $F_t(\beta)$, respectively, are concave in the range $\alpha' \leq \alpha < 1$, $\beta' \leq \beta < 1$. Furthermore, let $Z^0(\alpha, \beta)$ be the optimal value of the objective function obtained from the basic formulation of the reliability model for a fixed set of reliabilities, α and β. Now, we can introduce the following theorem: the function $Z^0(\alpha,\beta)$ is concave in the domain,

$$\begin{aligned} DOM(\alpha, \beta) &= \alpha \qquad \alpha' \leq \alpha < 1 \\ DOM(\alpha, \beta) &= \beta \qquad \beta' \leq \beta < 1 \end{aligned} \tag{30}$$

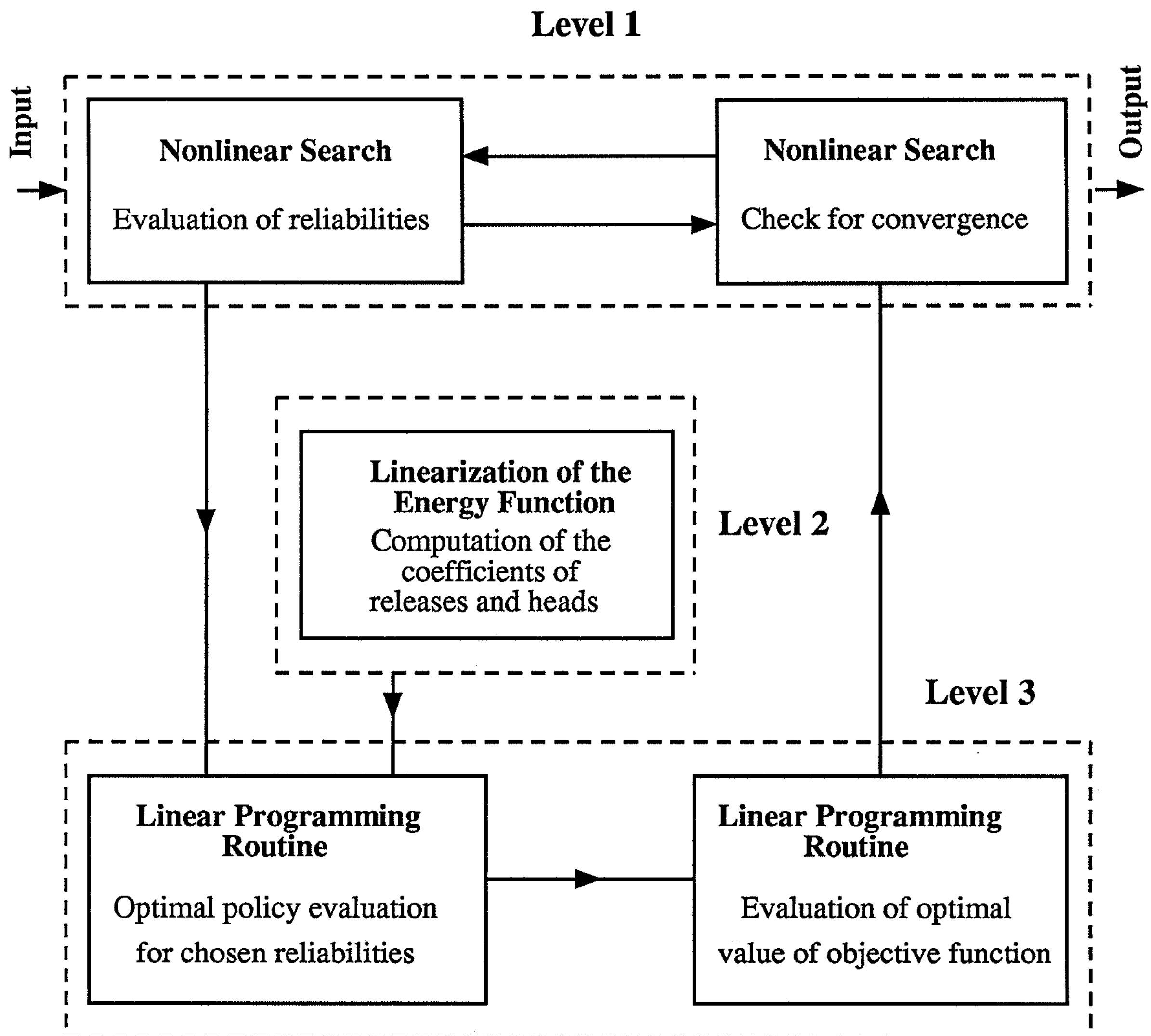


Figure 3.7. Three Level Solution Algorithm

The proof of the theorem is an extension to multiple dimensions of the proof by Colorni and Fronza [1976] and is not included in this thesis. In accordance with the above theorem, the reliability program can be rewritten as,

$$\textit{maximize} \quad Z^0 (\alpha, \beta) \tag{31}$$

subject to:

$$\alpha, \beta \in DOM \tag{32}$$

The solution algorithm uses the principle of a multidimensional search to find the values of reliabilities and a convenient mathematical programming technique to find the values of other decision variables. The computation is carried out using the following procedure:

1. In the search algorithm within the Level 1, an initial reliability pair α_0 and β_0, and the desired search accuracy are set. From this pair, two more pairs of reliabilities are computed using the two sets of random numbers generated by the algorithm.

2. At Level 2, the linearization of the energy function is carried out. The coefficients of the decision variables (R_t^{ls} and h_t^{ls} written in terms of X_t^{ls} and Y_t^{ls}) in Equations (10) and (19) are computed.

At Level 3, for a given pair of reliabilities, the deterministic equivalents of the probabilistic constraints given by the Equations (7), (9) and (18) are obtained. These inputs along with other deterministic constraints of the reliability model are combined to construct the LP formulation which is solved using the IMSL LP solution routine [IMSL, 1987]. This routine evaluates the optimal values of the objective function and the decision variables for a given pair of reliabilities. The three objective function values corresponding to the three pairs of reliabilities are sent back to Level 1.

3. In the search algorithm, the three values of the objective function are compared.

A convergence criterion is defined such that the three objective function values computed in Step 2, are within the search accuracy (which is set as 0.1% in this study) to each other. The algorithm terminates if the desired accuracy is achieved. If not, the worst pair of reliabilities is dropped and a new pair is computed using a Box transformation of the simple multivariable search (termed as the Complex Box search) [Beveridge and Schechter, 1970], which is described in brief detail in the following paragraph. The new sets of reliabilities, consisting of three pairs, are sent in this iteration to Level 2 and 3 to compute the optimal values of the objective function corresponding to these three pairs. The objective function values are again compared, and this iterative procedure continues until either the objective function values computed from the three pairs of reliabilities converge to the desired accuracy or the number of iterations exceeds the maximum. The iterations are performed until convergence is achieved, and the optimal solution consists of the optimal values of the objective function and the decision variables corresponding to the final iteration.

The Complex Box search algorithm finds the maximum of a multivariable, nonlinear function subject to nonlinear inequality constraints where lower and upper constraint boundaries are either constants or functions of decision variables. This search handles constraints by using a flexible figure of more than $(n+1)$ vertices (where n is the number of decision variables), which can expand or contract in any or all directions and can extend around 'corners.' This search method is shown to be straightforward for concave regions. It can be proven that in the reliability program given by Equations (31) and (32), Z^0 is concave and that the constraint given by Equation (30) actually represents the upper and lower boundaries for the search.

3.1.4.2. Computer Program Architecture

Referring to the computer program architecture shown in Figure 3.8, the first component comprises of the following subroutines: CONSC, CHECK, CENTR, and CONST. The subroutine CONSC coordinates all the other subroutines in the nonlinear search level, and computes two additional reliability pairs from the initial reliability pair. Each pair of reliabilities is represented by a point and there will be three points in the search space in each iteration. The subroutine CHECK checks these three points against the explicit and implicit constraints and applies correction if violations are found.

The subroutine CENTR calculates the centroid of the three points. The subroutine CONST specifies explicit and implicit constraints on these points. Basically the Complex Box algorithm [Beveridge and Schechter, 1970] is incorporated in the three subroutines CHECK, CENTR, and CONST. The three reliability pairs thus computed, are transferred to the subroutine CCSP which coordinates all the subroutines in the Level 2 and 3, namely, the linearization of the energy function and the LP solution procedure.

There are four subroutines in Level 2 and 3: CCSP, PREV, CONVZ and LPS. In the subroutine CCSP, the deterministic equivalents of the probabilistic constraints (given by Equations 7 and 9) are computed from the cumulative distribution functions (CDFs) of inflows. The CDFs are given as input data in the program. Right-hand side coefficients of all the constraints of the reliability model are computed here. A linearization technique

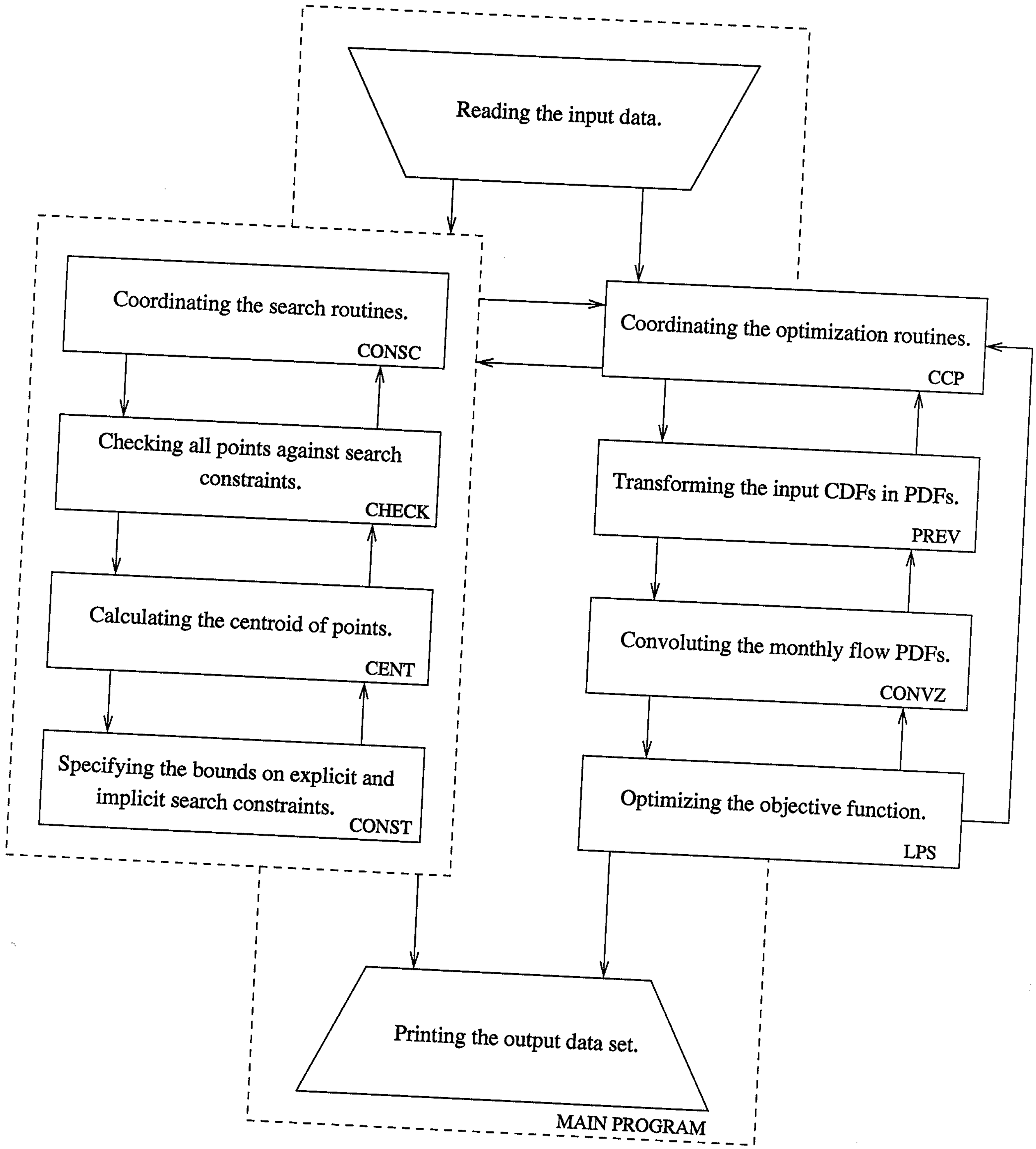


Figure 3.8. Program Architecture

is incorporated in the subroutine CCSP which computes the coefficients corresponding to the releases and the heads which are decision variables in the model.

Finding the sum of two monthly inflow random variables involves a convolution of their probability density functions (PDFs). So the PDF of the random variables must be derived from their corresponding CDFs. CDFs are first converted to their corresponding PDFs in the subroutine PREV. These PDFs are then convoluted in the subroutine CONVZ.

The subroutine LPS takes the coefficients of decision variables in the constraints and the objective function and the right-hand side coefficients as input from the subroutine CCSP. Then LPS solves this optimization problem using an LP solution subroutine [IMSL, 1987] which has been linked to LPS.

The three objective function values corresponding to the three reliability pairs are sent back to the subroutine CONSC where those values are compared.

3.2. INCORPORATING THE UNCERTAINTY IN ENERGY DEMAND

In the basic formulation of the reliability model (derived in Section 3.1) defined by Equations (7) through (19), energy demand in each time period is assumed to be deterministic. There are similar works available in the literature, for example, Stedinger et al. [1984] and Braga et al. [1991], which consider the uncertainty in reservoir inflows but the energy demand is treated as deterministic.

In this section, incorporation of the variability in energy demands in the formulation of the reliability model is discussed. Uncertainty in energy demand can be characterized either by a stochastic model (governed by the laws of probability) or by a fuzzy model (defined with vague boundaries).

3.2.1. Stochastic Approach

Most of the Canadian electrical utility companies forecast the future energy demands taking into account the uncertainties due to weather as well as due to the residential and industrial growth.

There is some degree of correlation between the two input parameters, namely, the energy demands and the reservoir inflows, imparted mainly by the factors which may influence both of these parameters. For example, the temperature increase due to global climate change may have a significant impact on the availability of water resources and also on the energy demand (which is influenced by the weather variations) in countries like Canada. However, the energy demands and the reservoir inflows are assumed to be independent in this study, similar to the other approaches presented in the previous literature.

The forecasters sometimes specify the PDF of the energy demand with corresponding parameters such as the mean and the variance. In the stochastic approach, the energy demands, $ENMIN_t^{ls}$, in Equation (10) are treated as random variables with known PDFs. A typical PDF of energy demand is shown in Figure 3.9. The probability of exceedance of energy demand in each time period (pe^{ls}) is specified *a priori*, and hence the value of $ENMIN_t^{ls}$ is constrained on either side of the distribution with an allowable probability of exceedance of (pe^{ls} /2). Therefore, Equation (10) is rewritten as:

$$F_E^{ls}\ (pe^{ls}/2\ ) \leq C^{ls} * R_t^{ls} * h_t^{ls} - E_t^{ls} + IM_t^{ls} \leq F_E^{ls}\ (1 - pe^{ls}/2\ ) \qquad \textbf{(33)}$$

where $F_E^{ls}(pe^{ls}/2\ )$ is the inverse of the cumulative distribution of $ENMIN_t^{ls}$, corresponding to a probability of exceedance of $(1\text{-}pe^{ls}/2)$. The final formulation of the reliability model using the stochastic approach contains Equation (19) as the objective function, subject to the constraints given by Equations (7), (9), (12), (16), (18), (29) and (33).

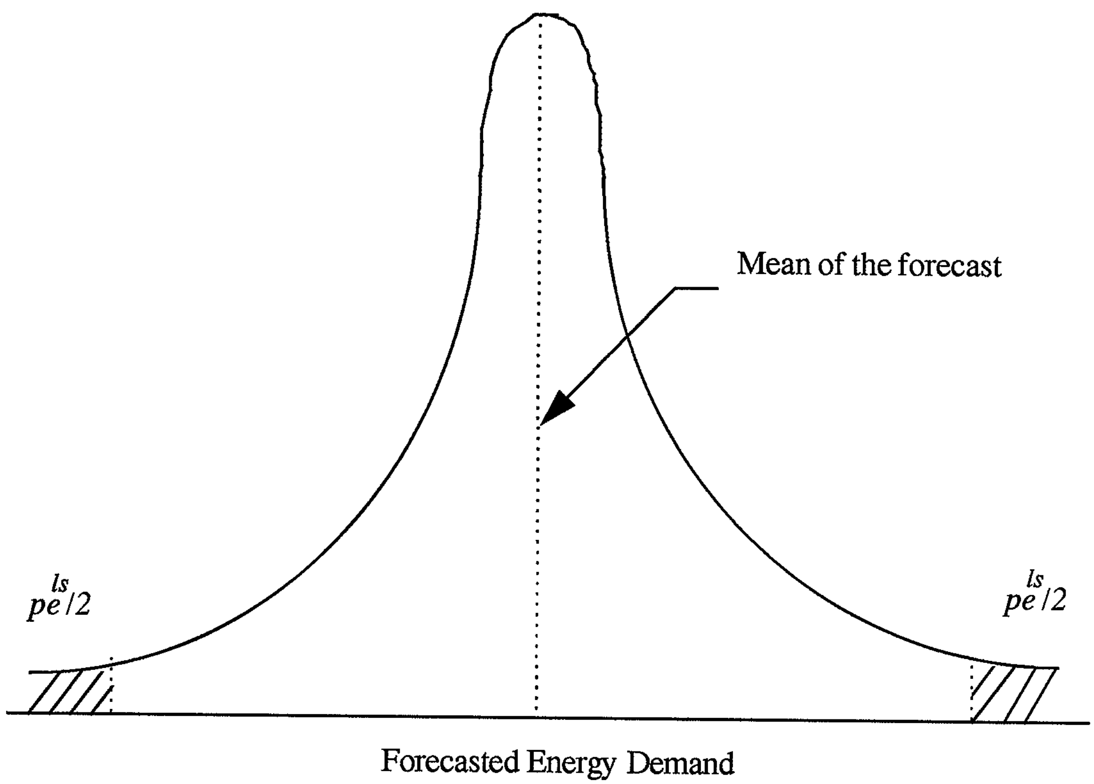


Figure 3.9. A Typical Probability Density Function of Energy Demands

3.2.2. Fuzzy Approach

The fuzzy constraint approach treats the energy demands as 'vaguely defined' or 'fuzzy', in which it is quite difficult to estimate the PDF of energy demands *a priori.* A brief review of the basics of fuzzy theory, and the mathematical formulation of the LP model with fuzzy constraints are given in Appendix B. An approximate methodology for deriving the membership functions (MSFs) of the fuzzy energy constraints is given in the next section followed by the revision of the basic reliability model with fuzzy energy demand constraints [Srinivasan and Simonovic, 1994a].

3.2.2.1. Development of Membership Functions for Energy Demand Constraints

A membership function is a subjective function that depends on the expert's or the decision maker's individual perception of degrees of membership. It is obvious that MSFs are context-dependent and should be carefully analyzed for each particular application. In general, there are three approaches to the estimation of a MSF. The first one is to simply ask the assessors to draw their MSFs or give thresholds for grades 0 and 1, and assume a functional relationship between the two grades [Bogardi et al., 1983; Sakawa et al., 1987]. The second approach is based on statistical data manipulation [Freeling, 1980; Bharathi and Sarma, 1985]. The third approach is a basic scaling method for priorities proposed by Saaty [1977]. In this section, an approximate method based on the statistical data manipulation, is proposed to derive the MSFs for the energy variables.

All utilities use some forecasting technique to determine the future energy demands on the system, and check the adequacy of the utility's generating capacity to meet the forecasted demands. For example, Manitoba Hydro uses regression analysis combined with an annual percentage increase in consumption to compute the future energy demand in the planning period [Manitoba Hydro, 1993]. These projected demands for all the time periods can be assumed to have a membership of 1 in the fuzzy environment, since they are the energy demands used in the basic formulation of the reliability model as deterministic inputs.

Deviations of the forecasted demands from the actual demands reflect the closeness of the forecasted values to the actual ones. MSF, which represents the degree of closeness of any given value of a variable to the fuzzy set describing that variable, can thus, be derived from the deviations [Srinivasan and Simonovic, 1994a]. Percentage deviations can be calculated as:

$$\%\ \textit{deviation} = \frac{(\textit{Forecasted demand} - \textit{Actual demand})}{\textit{Actual demand}} * 100 \qquad (34)$$

From the historical data of the forecasted and the actual demands in all time periods, the deviations can be divided into several intervals and a frequency plot of these deviations can be obtained. The frequency plots thus obtained are taken as the sample MSFs for energy demands.

Practical importance of both sides of the deviations plot is emphasized here. In the first case, when the actual demand is more than the forecasted demand, that is, the percentage deviations are negative in the sign, the energy needed in excess of the forecasted demand has to be either generated if the reservoir storage and the power plant conditions are favorable, or imported from other utilities. So this kind of a situation is critical, especially during low flow periods.

In the second case, when the actual power demand is less than the forecasted value, that is, when the deviations are positive in the sign, it reduces the expected revenue from hydropower generation prior to the planning period. If it is known before the planning period that the actual demand will be less than the forecasted demand, the excess energy could have been exported (for which the commitment has to be made well before generating that energy). So this kind of a situation results in improper and inefficient planning of the reservoir operation and thus, the economic consequences are quite severe.

So the MSFs in these two cases denoted by $\mu_t^{ls}(U)$ and $\mu_t^{ls}(L)$, respectively, are computed as:

$$\mu_t^{ls}(L) = \begin{cases} 0 & \text{if } (C^{ls} * R_t^{ls} * h_t^{ls} - E_t^{ls} + IM_t^{ls}) < ENMIN_t^{ls} - p_t^{ls} \\ 1 + \dfrac{(C^{ls} * R_t^{ls} * h_t^{ls} - E_t^{ls} + IM_t^{ls}) - ENMIN_t^{ls}}{p_t^{ls}} & \text{otherwise} \end{cases} \tag{35}$$

and,

$$\mu_t^{ls}(U) = \begin{cases} 0 & \text{if } (C^{ls} * R_t^{ls} * h_t^{ls} - E_t^{ls} + IM_t^{ls}) > ENMIN_t^{ls} + q_t^{ls} \\ 1 - \dfrac{(C^{ls} * R_t^{ls} * h_t^{ls} - E_t^{ls} + IM_t^{ls}) - ENMIN_t^{ls}}{q_t^{ls}} & \text{otherwise} \end{cases} \tag{36}$$

where p_t^{ls} and q_t^{ls} are the lower and upper bounds of the deviation of the forecasted demands from the actual demands.

3.2.2.2. Revision of the Basic Formulation of the Reliability Model

Let $\mu_D(x)$ be the MSF of the fuzzy set 'decision' of the reliability model. Equation (99) is the MSF of the objective function from Appendix B; Equations (35) and (36) are the MSFs of the energy constraint. Therefore, the decision space in a fuzzy environment is the intersection of fuzzy sets corresponding to the fuzzy objective function and the fuzzy constraints. Hence,

$$\mu_D(x) = Min \; [\; \mu_{OF}(x), \; all \;\; \mu_t^{ls}(x) \;] \qquad (37)$$

Assuming that we are interested not in a fuzzy set but in a 'crisp optimal solution', then, following Zimmermann [1988], we can obtain,

$$Max \;\; (\; \mu_D(x) = Min \;\; [\; \mu_{OF}(x), \; \mu_t^{ls}(x) \;] \;) \qquad (38)$$

subject to:

$$\mu_{OF} \geq \mu_D(x) \qquad (39)$$

$$\mu_t^{ls}(L) \geq \mu_D(x) \qquad \forall \; t, \; ls \qquad (40)$$

$$\mu_t^{ls}(U) \geq \mu_D(x) \qquad \forall \; t, \; ls \qquad (41)$$

along with other deterministic constraints of the reliability model.

Substituting λ for $\mu_D(x)$ and using the expressions for the MSFs μ_{OF}, $\mu_t^{ls}(L)$, and $\mu_t^{ls}(U)$, the formulation of the equivalent crisp problem is written as:

Maximize λ **(42)**

subject to:

A. Set of fuzzy constraints:

$$\lambda * (f_0 - f_1) - \Big(\sum_{t=1}^{T} \Big[\sum_{ls=1}^{nsl} r^{ls} * (C^{ls} * R_t^{ls} * h_t^{ls} - E_t^{ls}) + rexp^{ls} * E_t^{ls} - cimp^{ls} * IM_t^{ls} \Big] - LC_t * SP_t \Big) - B_T * S_T - \sum_{t=1}^{T} BF_t(\theta_t) + L_1(\alpha) + L_2(\beta) \geq -f_1 \tag{43}$$

with μ_{OF}, defined in Equation (99), as the MSF for the objective function;

$$(C^{ls} * R_t^{ls} * h_t^{ls} - E_t^{ls} + IM_t^{ls}) - \lambda * p_t^{ls} \geq ENMIN_t^{ls} - p_t^{ls} \tag{44}$$

with the corresponding MSF, $\mu_t^{ls}(L)$, as defined in Equation (35); and

$$(C^{ls} * R_t^{ls} * h_t^{ls} - E_t^{ls} + IM_t^{ls}) + \lambda * q_t^{ls} \leq ENMIN_t^{ls} + q_t^{ls} \tag{45}$$

with the corresponding MSF, $\mu_t^{ls}(U)$, as defined in Equation (36).

B. Other crisp constraints of the reliability model given by the Equations (7), (9), (12), (16), (18) and (29).

4. RISK-LOSS FUNCTION FOR ENERGY GENERATION

4.1. RISK IN A GENERATION SYSTEM

The reliability levels for hydropower generation and flood control are treated as decision variables in the reliability model and are incorporated in the objective function of the optimization problem through risk-loss functions, which evaluate the economic losses associated with the risk of not meeting the storage requirements for each of the aforementioned purposes. The losses associated with shortage of reservoir storage may consist of penalties due to flood damages or deficits in energy supply. These losses reduce the benefit obtained from reservoir operation. Due to the introduction of risk-loss functions, the tradeoffs between the system benefits and the risks corresponding to each of the purposes of the reservoir are considered explicitly.

Reliability, the complement of risk, is a measure of the overall ability of the system to perform its function. Electrical utilities consider reliability to be just as important as the economy of supply. A utility, even if one ignores the cost considerations, cannot provide absolute reliability for a number of reasons: (1) random system failures; (2) unexpected high load levels; (3) delays in manufacture or installation of new equipments; (4) legislative or legal impediments with regard to the installation of new units or lines or with regard to the operation of existing equipment; and (5) inadequate supply of fuel or water in hydroelectric system. Hydropower system reliability assessment, both deterministic and probabilistic, can be divided into two basic aspects of system adequacy and system security as shown in Figure 4.1. Adequacy relates to the existence of sufficient capacity and energy within the system to satisfy the consumer load demand or system operational constraints. Hence this term is associated with static conditions which do not include system disturbances. Security relates to the ability of the system to respond to disturbances arising within that system. Security is therefore associated with the response of the system to whatever perturbations it is subject to. These include the conditions associated with both local and widespread disturbances and the loss of major generation and transmission facilities.

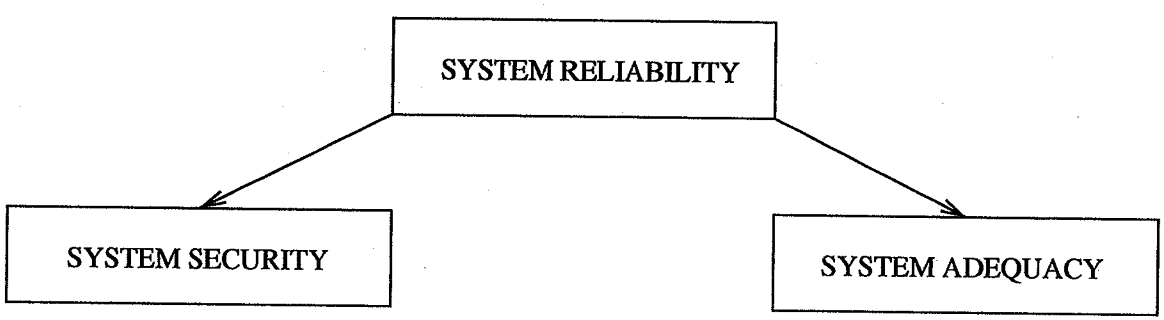


Figure 4.1. Components of System Reliability in a Power System

A power system consists of a set of components interconnected in some purposeful way. The reliability of the system will depend on the reliability of its components, on the configuration of the system, and on the system failure criteria. In system reliability studies, the goal is to predict suitable reliability indices for the system on the basis of component failure data and system design. The system indices may vary, depending on the application, but in essence, they are the probabilities, frequencies, or mean durations of some critical event or events by which the system failure is defined.

Several computational techniques have been developed for deriving system reliability indices from component reliability information. Four broad groups of approaches to compute system reliability have historically been applied in power system analysis. One is based on the solution of the state-space models; the second is based on the solution of logic diagrams; the third utilizes the Monte Carlo simulation technique; and the fourth is based on the fault tree analysis. The applications of the state-space approach have been ranging from the derivation of the reliability models for power systems components such as generators and transmission lines, through the analysis of maintenance models; to the evaluation of reliability indices of complex systems. This technique is usually applied for analysis of systems with repairable components and when both short-term and long-term predictions are required. The logic diagrams are usually applied to simple system configurations and are also used to obtain reliability indices for an equivalent component composed of several subcomponents to be used in reliability evaluation of complex systems. They are mostly used in evaluating reliability of nonrepairable systems with two-state independent components, or for systems with repairable components when long-run reliability indices are of interest. Monte Carlo simulation has been applied to reliability evaluation of composite power system models, where the presence of energy-limited hydraulic units and pump storage plants makes application of analytical techniques very difficult. The fault tree analysis has found numerous applications in safety analysis of nuclear generating stations.

Techniques for adequacy assessment are based on their application to components of a power system which are termed as functional zones of generation, transmission and distribution. As shown in Figure 4.2, there are four hierarchical levels used in adequacy assessment [Anders, 1990]. Hierarchical Level 1 (HLI) is concerned only with the generation facilities. Hierarchical Level 2 (HLII) includes both generation and transmission facilities, Hierarchical Level 3 (HLIII) considers, separately, station-originated outages in addition to the facilities analyzed in HLII. Hierarchical Level 4 (HLIV) includes all the four functional zones in an assessment of consumer load point adequacy. Adequacy at only the generation level (HLI) is dealt within this research.

In an HLI study, the total system generation is examined to determine its adequacy to meet the total system load requirement. This activity is usually termed as 'generating capacity reliability evaluation'. Referring to Figure 4.3, risk of energy shortage in a predominantly hydro system is imparted due to the following factors: (1) uncertainty in the hydrological variables; (2) uncertainty in the generation capability; and (3) uncertainty in the energy demand.

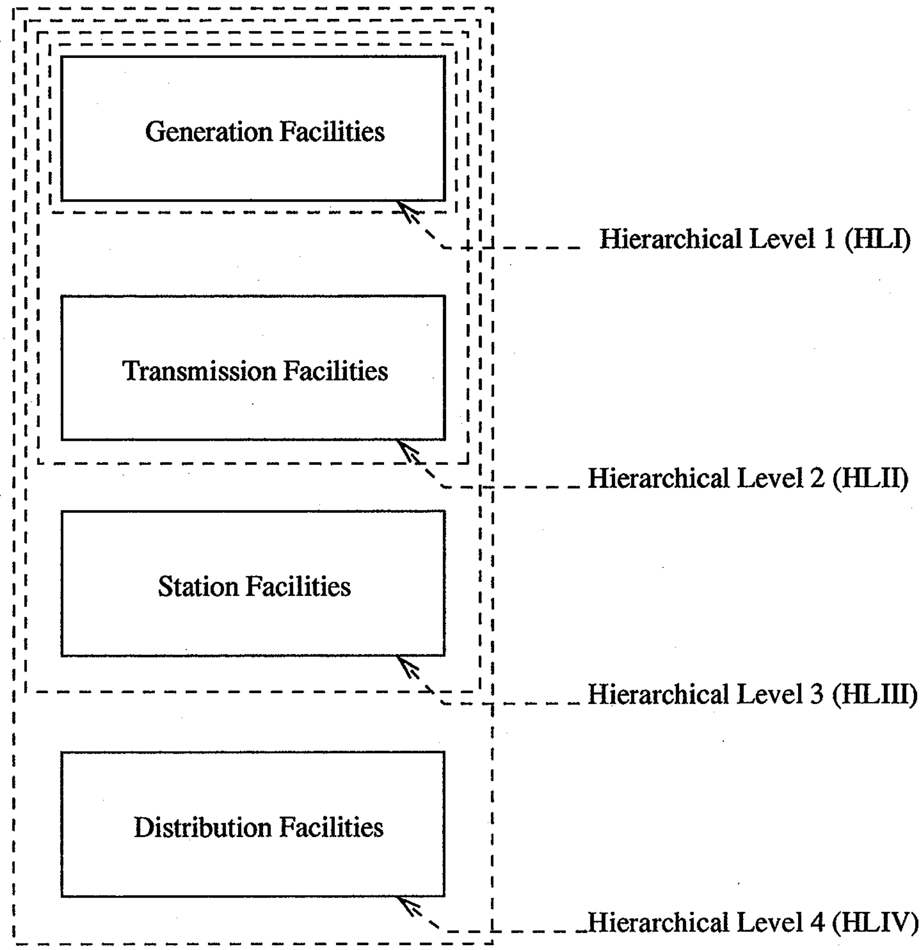


Figure 4.2. Hierarchical Levels in a Power System Analysis

The basic concern is to estimate the generating capacity required to satisfy the system demand and to have sufficient capacity to perform corrective and preventive maintenance on the generating facilities. The basic technique used in the past to determine

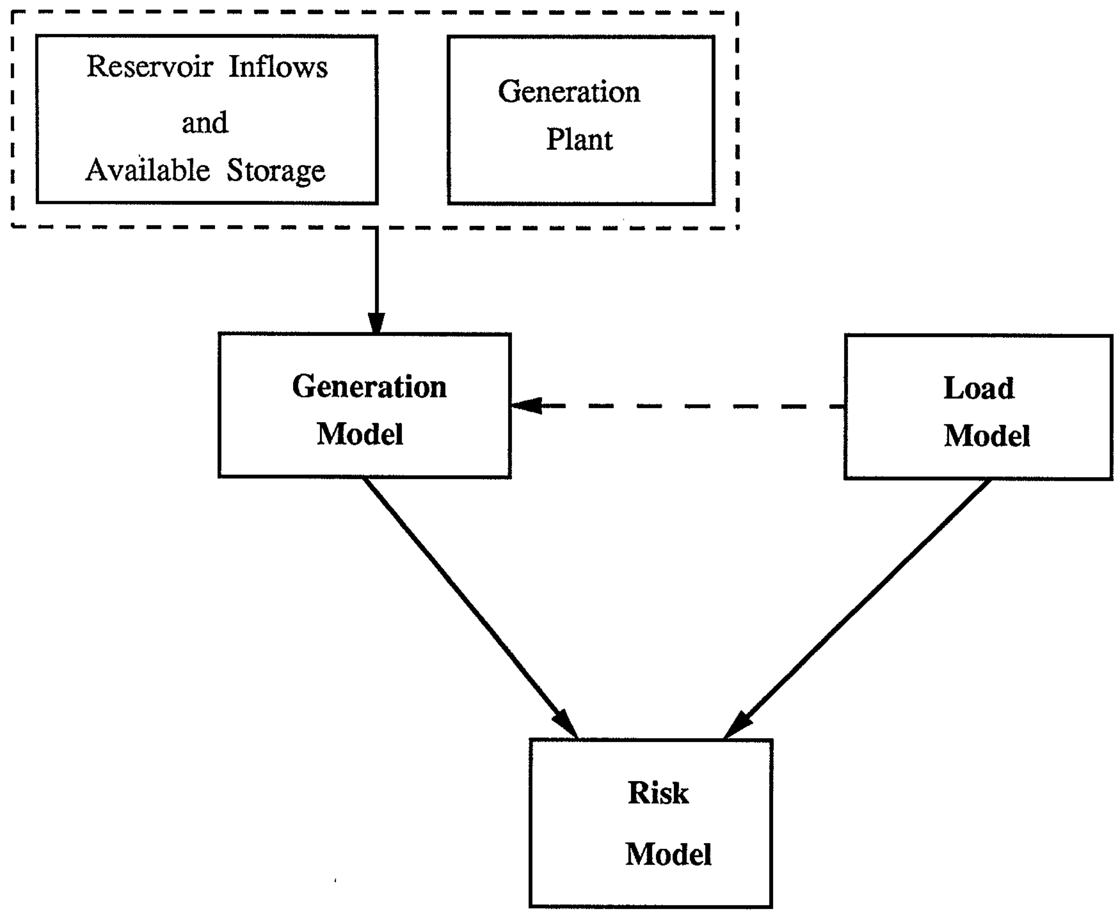


Figure 4.3. Components of Reliability in a Generation System

the capacity requirement was the percentage reserve method. In this approach, the required reserve is a fixed percentage of either the installed capacity or the predicted load. Other criteria, such as a reserve equal to one or more of the largest units, have also been used. These deterministic criteria have now been largely replaced by probabilistic methods which respond to and reflect the actual factors that influence the reliability of the system.

Criteria such as loss of load expectation (LOLE), loss of energy expectation (LOEE), frequency and duration (F&D), and expected energy not supplied (EENS) can be used [IEEE, 1975; Billinton and Allan, 1984].

The LOLE is the average number of days in which the daily peak load is expected to exceed the available generating capacity. It indicates the expected number of days in which a load loss or a deficiency will occur. It can be extended to predict the number of hours in which a deficiency may occur. It does not indicate the severity of the deficiency or the frequency or the duration of loss of load. Despite these shortcomings, it is, at the present time, the most widely used probabilistic criterion in generation planning studies.

The LOEE is the expected energy not supplied by the generating system due to the load demand exceeding the available generating capacity. This is an appealing index for two reasons. It measures the severity of deficiencies rather than just the frequency of energy shortage, and therefore the impact of energy shortfalls as well as their likelihood is evaluated. Because it is an energy-based index, it also reflects the basic fact that a power system is an energy supply system. It is, therefore, believed that this index will be used more widely in the future, particularly for situations in which alternative energy replacement sources are being considered. The complementary value of energy supplied, that is, energy actually supplied, can be divided by the total energy demanded to give a normalized index known as the energy index of reliability. This index can be used to compare the adequacy of systems that differ considerably in size.

The F&D criterion is an extension of the LOLE index in that it also identifies the expected frequency of encountering a deficiency and the expected duration of the deficiencies. It contains additional physical characteristics which makes it sensitive to further parameters of the generating system, and provides more information to power system planners. The criterion has not been used very widely in generating system reliability analyses, although it is extensively used in network studies.

Expected energy not supplied (EENS) is the expected energy not served to the customers as a result of bulk power system deficiencies. This index provides a relatively simple approach to production cost modeling.

These indices are generally calculated using direct analytical techniques although Monte Carlo simulation has also been used. Analytical techniques represent the system by a mathematical model and evaluate the reliability indices from this model using mathematical solution, while the Monte Carlo methods estimate the reliability indices by simulating the actual process and random behavior of the system.

In this study, the uncertainties in reservoir inflows and energy demand are considered, and a framework to evaluate the overall risk associated with the generation system is developed. The uncertainty in the capability of the generation plant (a forced outage) is not dealt within this study. However, this uncertainty in forced outages can easily be integrated into the framework for risk assessment described in this chapter.

The energy potential of a hydro system depends on the storage available in the reservoir for the purpose of energy generation. A deficit in the available storage will reflect a possible shortage of energy production, which indicates a failure in the generating system. This characteristic of the hydro system is used in defining the hydrologic risk level with respect to available storage in the reservoir for energy generation (referred to as risk level hereafter). Analyzing different storage levels and evaluating the economic impacts of the inability to supply the energy demand will help in quantifying the risk level from the point of view of a utility. Such a quantification can assist in determining the optimal risk level at which to operate the existing system or to adopt alternate management strategies.

An example of such a quantification was provided by Lund [1995] for conservation measures in an urban water distribution system. Lund [1995] derives the estimates of customers' willingness-to-pay to avoid a particular, and complete, shortage probability distributions for water, given the estimates of consumer willingness-to-pay to avoid having to implement specific short- and long-term water conservation measures and a probability distribution of different water shortage levels. This derived approach can be used for estimating customer willingness-to-pay to avoid a set of probabilistic water shortages without the expense of situation-specific contingent valuation surveys, providing a check on the results of contingent valuation estimates of willingness-to-pay, and suggesting promising designs for short- and long-term water conservation programs suitable to local conditions. The cost values used by Lund [1995] can represent only the pure financial costs or can also include the costs of customer inconvenience or discomfort from implementing particular conservation measures. When the costs include these additional self-perceived costs to the customer, the implementation of this approach, requires some estimation of customer willingness-to-pay to avoid implementing particular water conservation measures, perhaps by contingent valuation.

The objective in this chapter of the thesis is to develop a methodology to derive a risk-loss function for hydropower generation which relates the risk level to the corresponding economic losses to the electrical utility due to deficits in energy supply. It must be noted that this function, represented by $L_2(\beta)$, is a deterministic input to the reliability programming model which is probabilistic.

Referring to Figure 4.3, the factors contributing to the risk level are the available storage in the reservoir, reservoir inflows and the energy demand. Different scenarios of these factors can be used in a simulation model to study their impact on the risk level.

In the reliability programming model formulation, a yearly risk-loss function is required to determine the tradeoff between the benefits from hydropower generation and the economic loss due to energy shortage. In order to derive a representative risk-loss function for any year, simulation of reservoir operation must be carried out over many years such that the annual risk level and the economic loss can be estimated from a statistical sample of sufficient size, which is termed as a simulation period.

4.2. SIMULATION ALGORITHM

A four-step simulation algorithm, as given in Figure 4.4, is developed to derive the risk-loss function for hydropower generation in a predominantly hydro system. The approach is as follows:

1. identification of the relationship between the risk and the storage level in the reservoir;

2. derivation of the relationship between the storage level in the reservoir and the

deficit in energy generation, expressed as EENS;

3. derivation of the cost of managing the expected deficit from the source of hydropower generation; and

4. combination of the three relationships derived in the previous steps to obtain the relationship between the risk level and the corresponding economic losses.

The procedures for developing each of these relationships are explained in the following subsections.

4.2.1. Relationship between Reservoir Storage and Risk Level

The minimum storage requirement for hydropower generation (v_t) is known for each time period, for example, the operating range (the desired elevation range in which the utility is constrained to operate its reservoirs) is fixed well in advance of the real-time operation. Knowing the inflows (I_t), the storage in the beginning of the simulation period (S_0), and the energy demand in each time period ($ENMIN_t$), the reservoir storages in the consecutive time periods are simulated using the flow continuity and the energy conversion equations. The storage in the end of each period is the storage in the beginning of the next period, and the stage corresponding to that storage is taken as the average head available for hydropower generation in that time period (h_t). Thus, from the energy conversion equation, the release requirement (R_t) from the reservoir in time period t is:

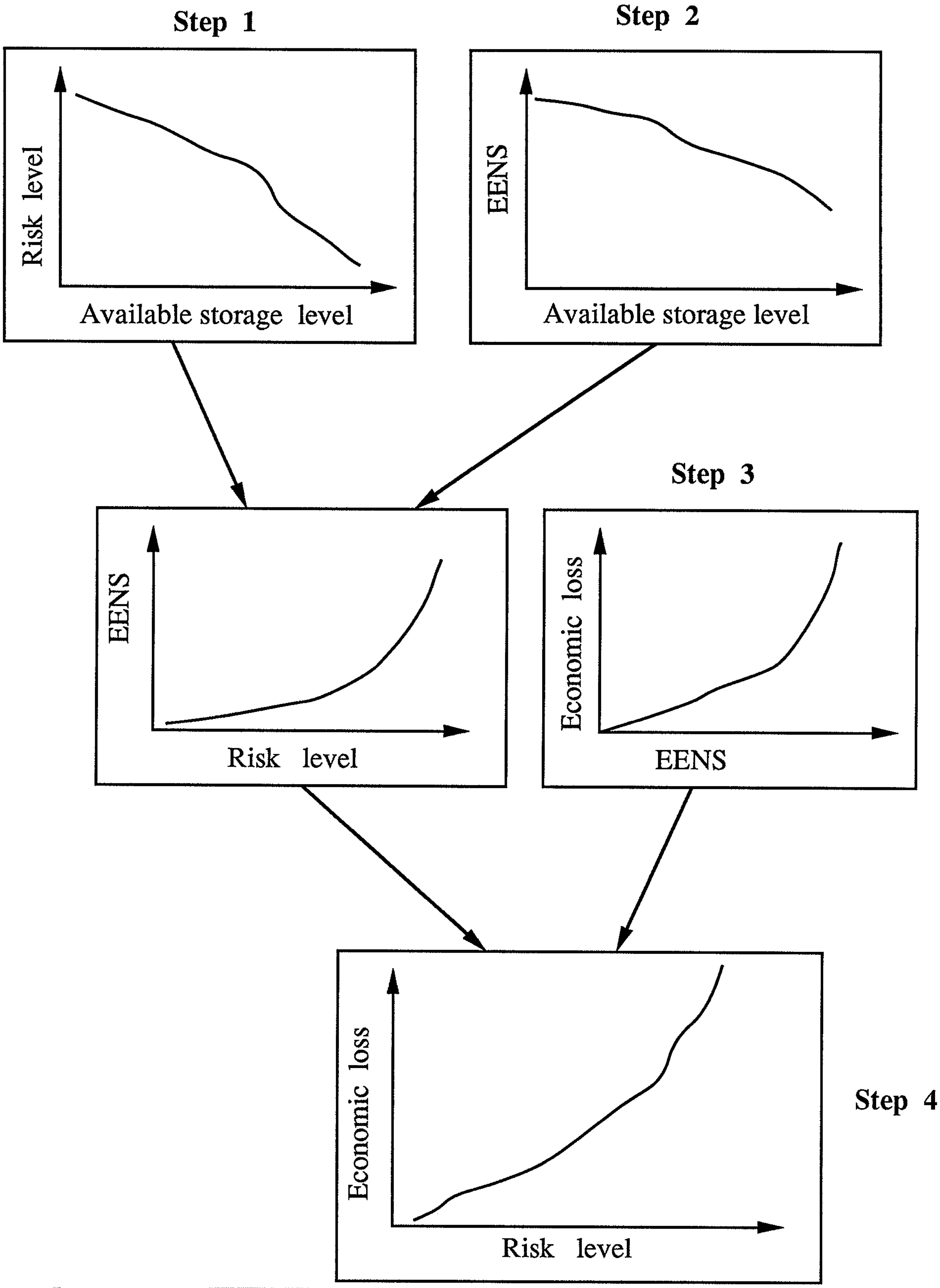


Figure 4.4. Simulation Algorithm for Hydropower Generation Risk-loss Function

$$R_t = \frac{ENMIN_t}{C_t * h_t} \tag{46}$$

This release requirement is constrained by the maximum allowable release through the generating units. From the known inflow and the release requirement, the simulated storage (S_t^s) in the end of time period t is calculated as:

$$S_t^s = S_{t-1} + I_t - R_t \tag{47}$$

The only constraint on this simulated storage is that it should not exceed the physical capacity of the reservoir taking the flood control requirement into account (S_{max} - θ_t). If the storage exceeds the maximum level, the excess water is spilled. Thus:

$$SP_t = (S_t^s - [S_{\max} - \theta_t]) \tag{48}$$

Otherwise, the spill is set to zero.

The simulated storage level is then compared with the minimum storage requirement (v_t) in each time period and the risk associated with hydropower generation is computed as:

$$\beta = \frac{n_f}{n} \tag{49}$$

where n_f is the number of time periods in which the minimum required storage bound is violated and n is the total number of time periods in the simulation period.

4.2.2. Relationship between Reservoir Storage and Energy Deficit

This is a critical step in which a deficit in storage must be related to a deficit in energy which is an indicator of failure in the generation system. The basic idea in this step is to find the energy potential from the generation system and compare it with the energy demands in order to find the corresponding energy deficit. The energy deficit can be expressed in terms of indices which are commonly used in electrical utilities, for example, the expected energy not supplied (EENS) which is the representative value of the magnitude of energy not supplied to the customers over a specified time period.

One of the approximate approaches for computing the energy potential from the available storage for hydropower generation in a reservoir, is a regression procedure [Tejada-Guibert et al., 1990]. The historic data for the storage level in the reservoir and the energy generated in the system in all the time periods are plotted and a nonlinear regression line is developed which is assumed to represent the functional relationship between the storage level in the reservoir and the energy potential. The other approach is to adopt storage depletion rules, and to compute the energy potential using the flow continuity and the energy conversion equations [Arvaniditis and Rosing, 1970 a and b; Terry et al., 1986].

In this study, the energy potential is calculated using the procedure developed by Terry et al. [1986] which is more accurate. The major components of the aggregate system model, as represented in Figure 4.5, are the equivalent reservoir and generating station. The equivalent reservoir is the aggregation of all the reservoirs in the generation

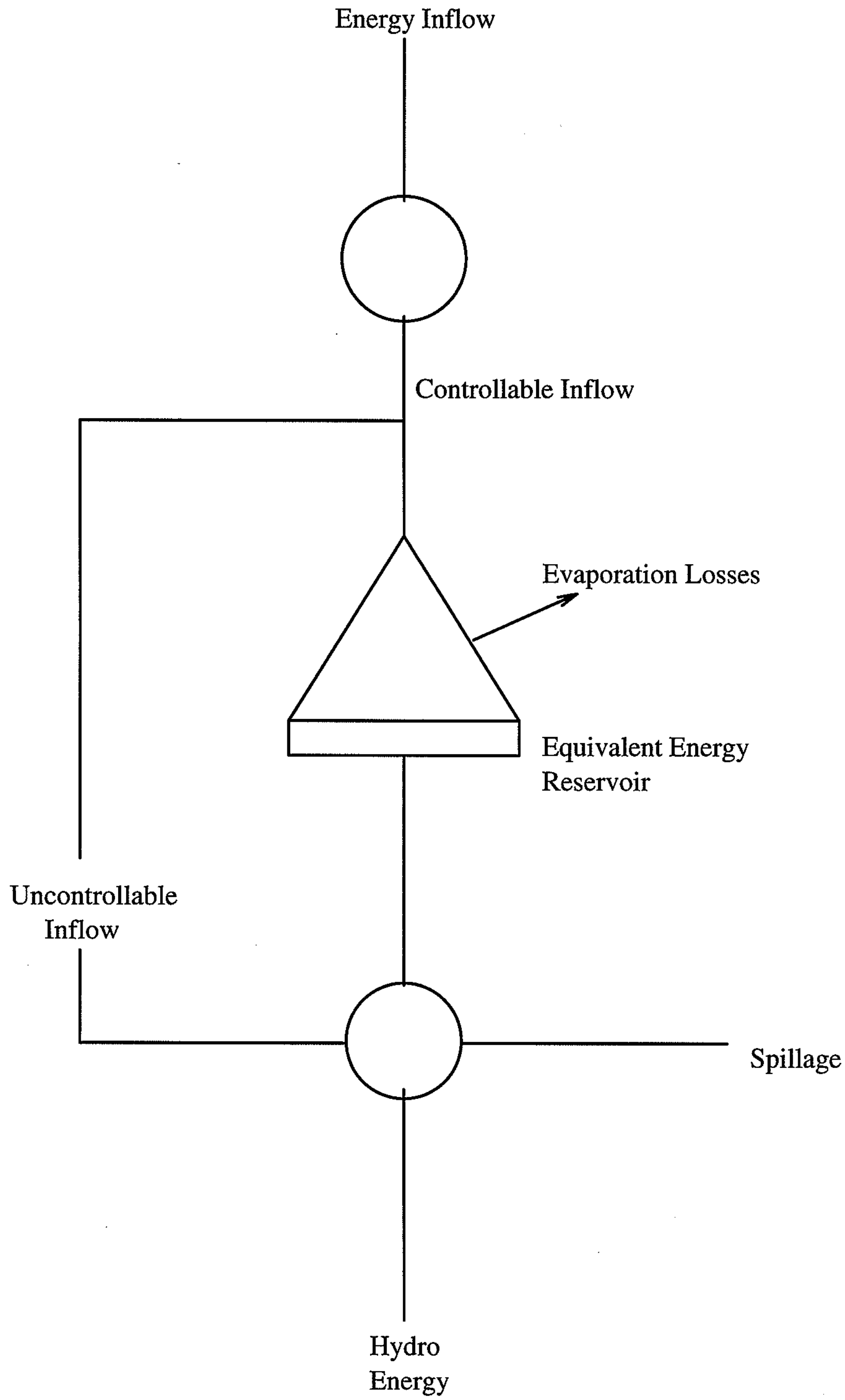


Figure 4.5. Components of an Aggregated Generation System

system. The total energy generation from the inflows is divided into two parts: (1) controlled inflow which is the volume that could be stored in the reservoir; and (2) uncontrolled inflow which represents local inflow volumes arriving at the run-of-the-river plants, which cannot be stored in the reservoir.

The energy output from the equivalent reservoir and the uncontrolled inflow is limited by the capacity of the generating units. Inflows exceeding these limits are spilled. Energy potential from the equivalent reservoir is estimated as the energy produced by the complete depletion of reservoir storage allocated for energy generation over the simulation period. However, the energy produced is a function of reservoir operating rules in this period.

The operating rules can be written in terms of the slope of the depletion curve at any time period. S_0 represents the initial storage, and S_{min} represents the storage unusable for hydropower generation. If $dS_0/dt \geq 0$, then the storage is either retained or increased for future generation while a negative slope indicates depletion over the period of time. Hence the energy potential from the reservoir storage (EP_{res}) can be calculated as:

$$EP_{res} = \int_{S_{min}}^{S_0} \frac{dS}{dt} z_t \; h_t \; C_t \tag{50}$$

where z_t is the function which converts a storage depletion to a corresponding release from the reservoir, h_t is the corresponding hydraulic head on the turbines, and C_t is the energy conversion factor.

Equation (50) can also be used to determine an inverse function. That is, for a given stored energy, EP_{res}* (obtained during a simulation, for example), it is possible to calculate the associated slope, dS/dt, and hence the reservoir storage S_t in each time period t. This has significant practical importance in that the utility company can determine the strategy to deplete the reservoir depending on the stored energy, for example, base on a strategy which minimizes the overall deficit in energy supply.

Energy potential from the controlled inflow (referred to as CE) is estimated as:

$$CE = \sum_{t=1}^{n} I_t^c \; h_t \; C_t \tag{51}$$

where I_t^c is the controlled inflow at the reservoir in time period t.

The uncontrolled inflow (UI_t) is the local flow which cannot be controlled by the reservoir. The energy potential from this inflow (referred to as UE) is limited by the capacity of generating units, and is given by:

$$UE = \sum_{t=1}^{n} Min \; (\; UI_t \; , \; [\; I_t^{\lim} - I_t^c \;] \;) \; h_t \; C_t \tag{52}$$

where I_t^{lim} is the limit on the total inflow (controlled and uncontrolled together) which could be used for hydropower generation. Depending on the capacity of the generation plant, this limit can be computed for each time period.

The total energy potential at a given level of minimum storage requirement (v_t) is the sum of the energy potential from the utilization of this storage and the energy potential from the controlled and uncontrolled inflows. This total energy potential (EP_{res} + CE + UE) in each time period is then compared with the total energy demand on the system. The deficit in energy generation is taken as the difference between the energy demand and the energy potential if the former is greater than the latter; or taken as zero if the potential is greater than the demand. Dividing the cumulative deficit in energy by the number of years in the simulation period, the EENS in any year can be computed.

4.2.3. Cost of Unsupplied Energy

The costs associated with component failure, namely, not being able to supply the required energy, depend on the severity of the failure and on the corrective action undertaken to remedy the situation. In most of the cases, there will be some costs associated with the use of manpower and equipment. In some situations, the energy replacement cost may be quite significant (for example, when a supply from a hydraulic station has to be replaced by activating oil fired generators). Since a major goal of any electric utility company is to supply uninterrupted power to the customers of minimal cost, prevention of power system failures is of paramount importance during the design and operation of the system.

The deficit in energy can be managed by: (1) planning additional generating capacity; (2) demand side management strategies; (3) alternate sources of energy; or (4) absorbing the cost of interruption in energy supply to the consumers. Each of these alternatives involves a cost which could be associated with the magnitude of the deficit in energy.

This study utilizes customer cost analysis carried out by Billinton et al. [1992; 1993] for a number of Canadian jurisdictions through the use of customer surveys. The reader is referred to Billinton et al. [1992; 1993] for the specific factors investigated in the surveys, details about the development of questionnaires, mailing out procedures, and the analysis of survey results. Neudorf et al. [1995] suggest that the customer cost functions derived from surveys are only applicable to local random interruptions rather than large wide scale ones, that is, distribution rather than generation interruptions. The reason is that the survey estimates do not take into account indirect economic and social effects which would tend to be significant for the large interruptions. Neudorf et al. [1995] quote an example, namely, the Ontario Hydro generation expansion study which overcomes this limitation to a certain extent by using macroeconomic models to determine indirect economic costs in addition to the customer survey estimates of direct effects.

However, the customer cost survey data are used in this study as the cost of unsupplied energy at the generation level as an approximation.

4.2.4. Risk-loss Function for Energy Generation

In this final step, the three relationships derived in the previous steps are combined to arrive at the relationship between the risk and the corresponding economic loss. For a given minimum storage requirement, a risk level is chosen from the first relationship, and an expected energy not supplied from the second relationship. Knowing the relationship between the EENS and the corresponding cost from the third step, the relationship between the risk and the economic loss is obtained. Combining the relationship between the risk and the economic loss for all possible minimum storage levels, a complete risk-loss function is developed, as shown in Step 4 of Figure 4.4. The function, thus developed, is given as a deterministic input, $L_2(\beta)$, in the reliability model.

The next chapter deals with the implementation of the reliability model to planning the operation of a single as well as a system of reservoirs with hydropower generation as the major purpose and flood control as a secondary purpose.

5. IMPLEMENTATION OF THE RELIABILITY MODEL

5.1. SINGLE RESERVOIR

The deterministic forms of the two probability constraints derived for the purposes of flood control and hydropower generation are rewritten as:

$$F_{\Sigma t}^{-1}(\alpha) + S_0 - [S_{\max} - \theta_t] \leq \sum_{ls=1}^{nsl} R_t^{ls} + SP_t \leq F_{\Sigma t}^{-1}(1-\beta) + S_0 \qquad \forall\, t \qquad (53)$$

where $F_{\Sigma t}^{-1}(.)$ is the inverse value of the cumulative distribution function of the sum of inflows up to and including the time period t; S_t is the storage at the end of the time period t; v_t is the minimum storage to be maintained in the reservoir for hydropower production; θ_t is the minimum flood control storage requirement in time period t; R_t^{ls} is the release from the reservoir for hydropower generation in the load strip ls in time period t; SP_t is the spill from the reservoir not used for hydropower generation; and α and β are the reliability levels for the purposes of flood control and hydropower generation respectively.

In the formulation of the reliability model developed in Chapter 3, the marginal PDFs of monthly inflows are assumed to be independent of each other. To give an example, derivation of the CDF of inflows in the first two time periods is discussed here. As described in the program architecture of the reliability model (Section 3.1.4.2), the subroutine PREV converts the CDFs corresponding to the inflows in the two time periods into their PDFs. Under the assumption of independence between these two PDFs, the subroutine CONVZ uses the convolution procedure to derive the PDF of the sum of inflows. The CDF of the sum of inflows can now be derived, and can be used to find the values of $F_{1+2}^{-1}(\alpha)$ and $F_{1+2}^{-1}(1\text{-}\beta)$.

Since the marginal distributions are considered to be independent, the variance of the estimates obtained from the resultant CDF of the sum of inflows will be lower than the one obtained taking into account the cross correlation between the inflows in these two time periods. Let I_1 and I_2 be the random variables corresponding to the flows in the two time periods. The expected value or the mean of the distribution of the sum of inflows, namely, (I_1+I_2) is given by:

$$E[I_1 + I_2] = E[I_1] + E[I_2] \tag{54}$$

and the variance of (I_1+I_2) is given by,

$$VAR[I_1 + I_2] = VAR[I_1] + VAR[I_2] + 2 * COV[I_1, I_2] \tag{55}$$

where $E[I_1]$, $VAR[I_1]$, and $E[I_2]$, $VAR[I_2]$ are the means and variances of the marginal distributions of I_1 and I_2, respectively. $COV[I_1, I_2]$ is the covariance between I_1 and I_2, which is written as a function of the cross correlation coefficient between I_1 and I_2 (designated as ρ_{12}) as:

$$COV[I_1, I_2] = \rho_{12} * \sqrt{VAR[I_1] * VAR[I_2]} \tag{56}$$

When the marginal distributions are considered independent, the third component of the right-hand side of Equation (55), namely, $\{2 * COV[I_1, I_2]\}$ is ignored, and hence the variance of the distribution estimated using the convolution procedure is smaller compared to the scenario when the correlation is taken into account. Statistically, the reduction in variance results in a distribution which gets compressed toward the mean from either side of the distribution compared to the distribution that would be obtained taking into account the cross-correlation. The effect on the CDF of the sum of inflows in the independent and the correlated cases are illustrated in Figure 5.1, which suggests that

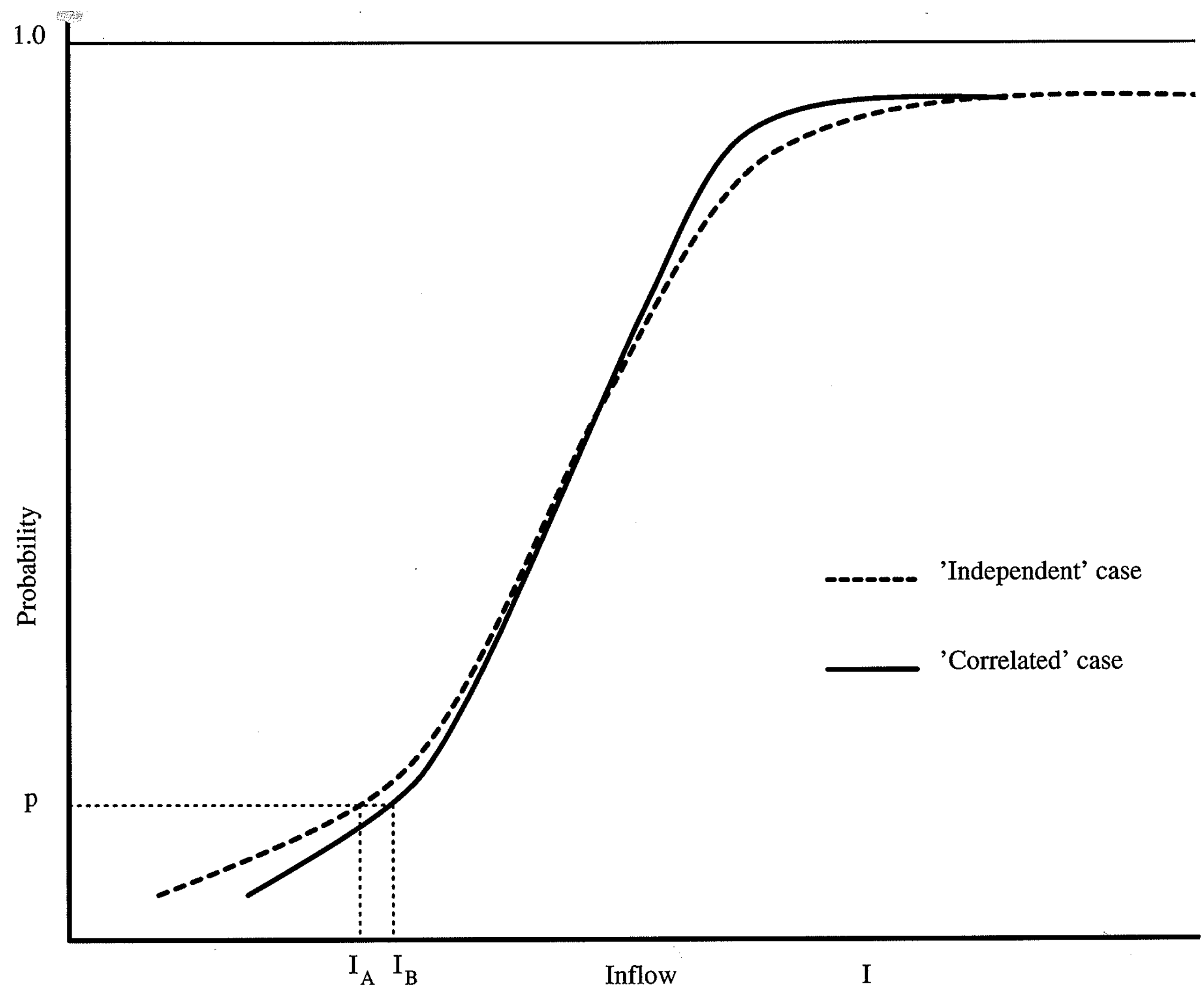


Figure 5.1. Comparison of CDF of independent and correlated cases

the lower quantiles of the distribution are underestimated, and the higher quantiles are overestimated in the independent case compared to the correlated case.

In the application of the reliability model, the values of $F_{1+2}^{-1}(\alpha)$ and $F_{1+2}^{-1}(1-\beta)$ are taken from the lower end of the CDF of $(I_1 + I_2)$ for the corresponding reliability levels of α and β for flood control and hydropower generation respectively. The estimates of the sum of inflows obtained from the independent case are lower than those for the correlated case, and hence, the values of the storage levels (which are decision variables in the reliability model) computed using the independence assumption are conservative estimates.

The influence of a positive correlation on the optimal solution is pointed out by Strycharczyk and Stedinger [1987]. A reservoir design problem in which the reservoir storage required to meet the demand with a certain reliability level is computed with the independent and correlated cases. The authors have shown that the independent case is quite conservative to the extent that the storage required is enormous compared to that obtained from the correlated case in order to provide the same level of reliability.

Three new approaches are proposed in this research to alleviate the problem of conservative operation of the reservoirs, which are illustrated in the following subsections.

5.1.1. Windows Approach

Considering the deterministic equivalents of the probabilistic constraints corresponding to the first time period,

$$F_1^{-1}(\alpha) + S_0 - [S_{max} - \theta_1] \leq \sum_{ls=1}^{nsl} R_1^{ls} + SP_1 \leq F_1^{-1}(1-\beta) + S_0 \qquad (57)$$

where the values $F_1^{-1}(\alpha)$ and $F_1^{-1}(1\text{-}\beta)$ are taken from the marginal distribution of inflow in the first time period, which are not affected by the assumption of independence. As shown in Figure 5.2, the probability constraints for the first month constrain the values taken by the decision variables, namely, S_1, R_1^{ls} and SP_1.

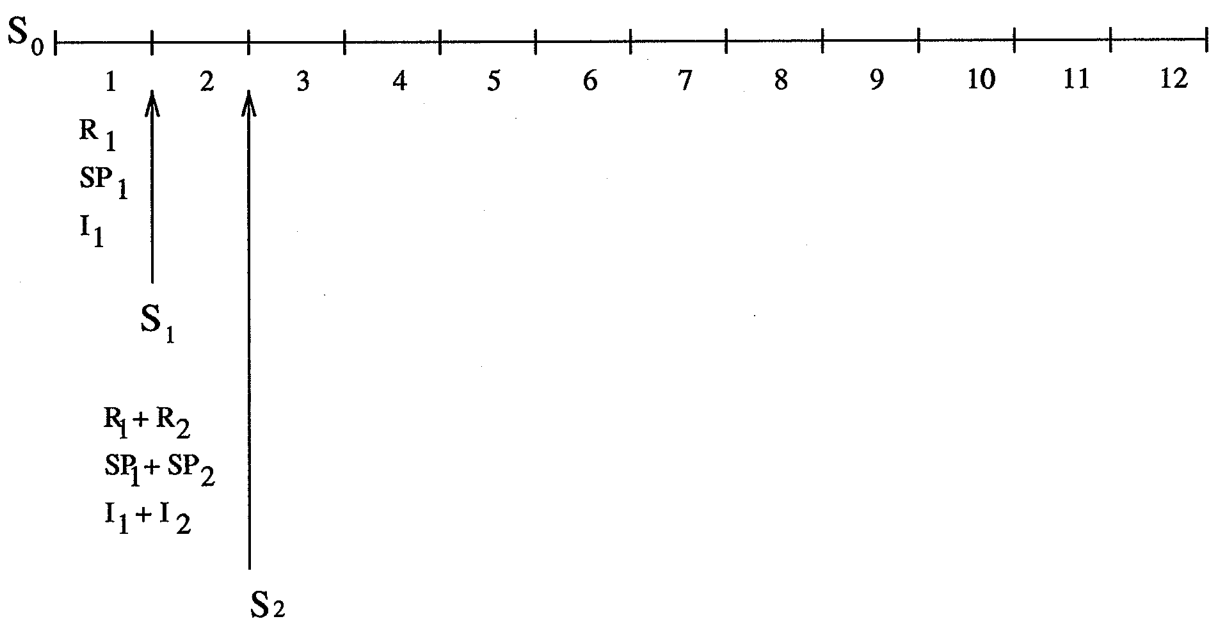


Figure 5.2. Concept of Windows Approach

In the second time period, the values $F_{1+2}^{-1}(\alpha)$ and $F_{1+2}^{-1}(1\text{-}\beta)$ are taken from the CDF of $(I_1 + I_2)$ obtained by convoluting the marginal PDFs of I_1 and I_2 with the assumption of independence between them. These values, in turn, are used in the deterministic equivalents of the probability constraints corresponding to the second time period, which constrain the values of decision variables in the first as well as the second periods. Hence, the values of the decision variables in the first time period must be least affected by the assumption of independence. This characteristic of the analytical model is the basis of the Windows Approach, in which the information obtained in the first time period, that is, in the first window, is carried over as the initial information for the second window as shown in Figure 5.3.

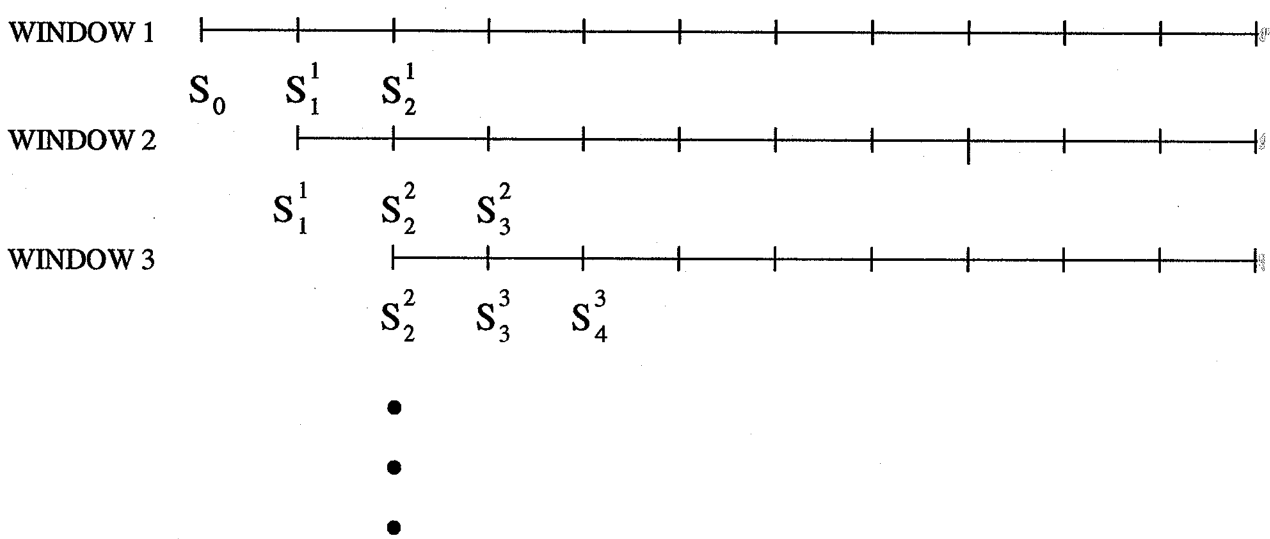


Figure 5.3. Implementation of the Windows Approach

Let S_t^k, $R_t^{ls,k}$, and SP_t^k represent the values of reservoir storage, release for hydropower generation in the load strip *ls*, and the spill from the reservoir in time period *t*, in the window *k*. The optimal values of the decision variables for the planning problem are obtained as the set of the decision variables in the first time period of each of the windows. So, the sets of optimal decision variables are written as:

$$S = [\, S_1^1,\ S_2^2,\ S_3^3,\ \dots,\ S_{12}^{12} \,] \tag{58}$$

$$R^{ls} = [\, R_1^{ls,1},\ R_2^{ls,2},\ R_3^{ls,3},\ \dots,\ R_{12}^{ls,12} \,] \tag{59}$$

$$SP = [\, SP_1^1,\ SP_2^2,\ SP_3^3,\ \dots,\ SP_{12}^{12} \,] \tag{60}$$

The economic benefits due to the operation of the reservoirs are computed using these sets of decision variables. The reliability levels for flood control and hydropower generation are obtained as the minimum of the sets of reliabilities obtained from the twelve optimization problems formulated for all the twelve windows.

5.1.2. CUSUM Approach

In this approach, the PDFs of the sum of inflows are derived *a priori* from the historical reservoir inflow data, and are given as an input to the reliability model. The basic assumption in this approach is that the correlation or the seasonal trend in the data, for example, between the first and the second time period, is implicitly captured by constructing a new time series of the sum of inflows in these two time periods from the historic data.

For illustration, let $CUSUM_2$ be a new random variable which represents the sum of random inflows in the first and second time periods in any given year is written as:

$$CUSUM_2 = I_1 + I_2 \tag{61}$$

Similarly, for any time period t in the planning period, the cumulative sum is written as,

$$CUSUM_t = I_1 + I_2 + \ldots + I_t \qquad \forall\, t \tag{62}$$

Let $CUSUM_1$, $CUSUM_2$, ... , $CUSUM_{12}$ be the new sets of data constructed from the historical reservoir inflow data. The CDFs of the new sets of data are derived, and are given as an input to the reliability model.

In the program architecture of the reliability model discussed in Section 3.1.4.2, the subroutines PREV and CONVZ which perform the conversion of the CDFs to the corresponding PDFs, and convolving the PDFs respectively. Since the CDFs of the sum of inflows are given as an input in the cumulative sum approach, these two subroutines are eliminated and the revised program architecture is given in Figure 5.4.

5.1.3. RISKSUM Approach

This approach is similar to the CUSUM approach in that the CDF of the sum of inflows is derived *a priori* and is given as an input to the reliability model. However, the CDFs are derived using a decision analysis tool called *@risk*, a brief description of which is given here.

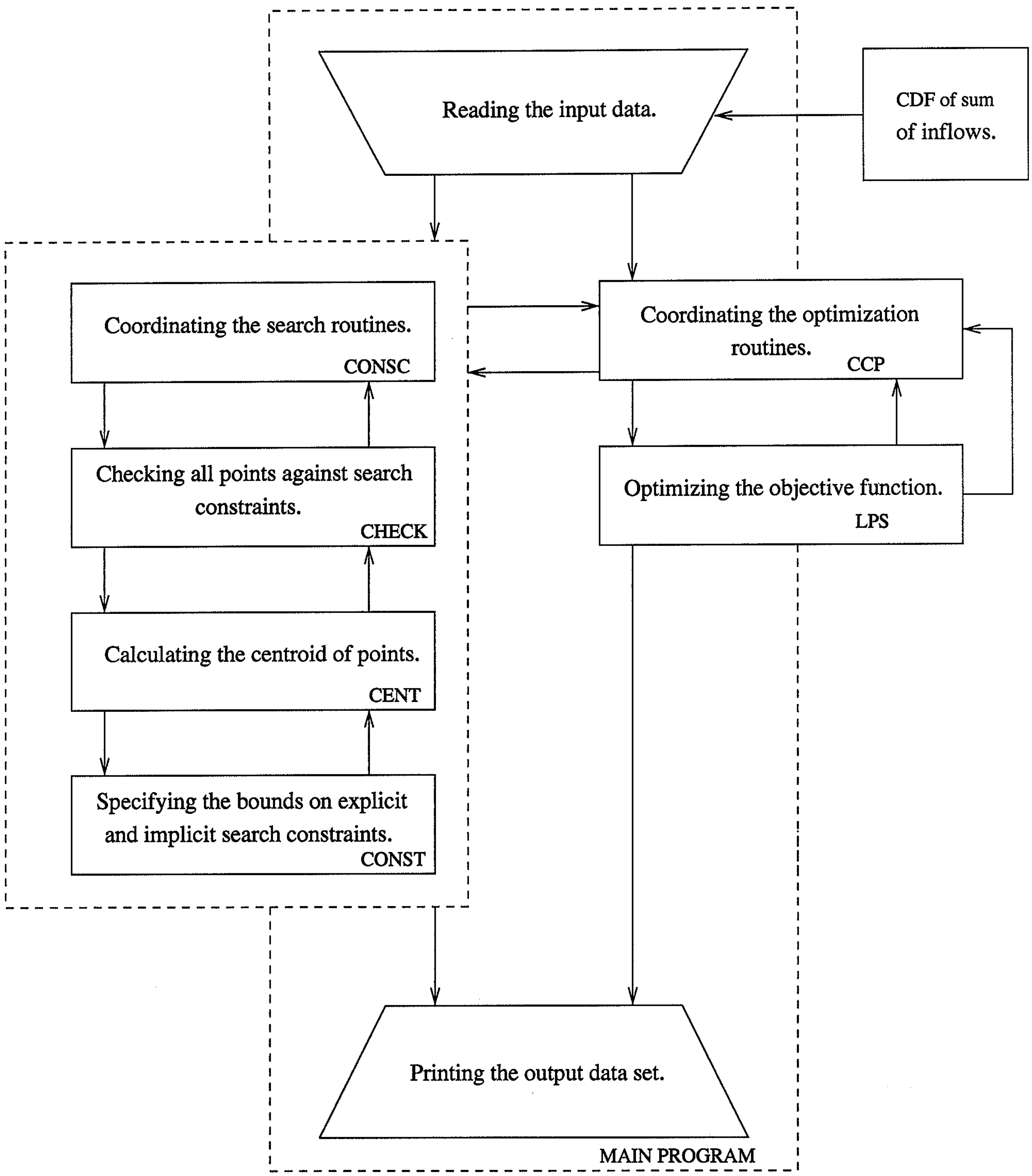


Figure 5.4. Program Architecture for the CUSUM Approach

The program *@risk* is a decision analysis tool which allows a user to perform simulations with correlated inputs using standard sampling techniques such as Monte Carlo or Latin Hypercube methods. The parameters such as the PDFs of inputs, correlation between the inputs, number of simulations, sampling technique, number of iterations of the experiments to be performed in order to obtain the desired accuracy, and convergence criteria are specified by the user.

For the purpose of deriving the CDFs of the sum of inflows, the marginal PDFs of the monthly inflows are specified in *@risk* along with the cross correlations between the monthly flows. Simulations are performed to find the PDF of the sum of inflows. As an example, I_1 and I_2 be the random variables representing the reservoir inflows in the first and second time periods respectively, whose marginal PDFs are known. A new random variable, $RISKSUM_2$, is defined as

$$RISKSUM_2 = I_1 + I_2 \tag{63}$$

specified with a correlation matrix given by,

$$\rho = \begin{bmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{bmatrix} \tag{64}$$

This information along with specified simulation parameters is given as an input to *@risk*. However, the resultant distribution will be a bivariate distribution because of the cross correlation. One of the features of *@risk*, namely, finding the expected value of the distribution, is used in order to find the resultant distribution along with the values of the quantiles of the distribution.

Similarly, the sum of the inflows up to and including any time period t is defined as a new random variable, $RISKSUM_t$, defined as:

$$RISKSUM_t = I_1 + I_2 + \dots I_t \tag{65}$$

with a correlation matrix of:

$$\rho = \begin{bmatrix} 1 & \rho_{12} & \dots & \rho_{1t} \\ \rho_{21} & 1 & \dots & \rho_{2t} \\ \cdot & & & \\ \cdot & & & \\ \cdot & & & \\ \rho_{t1} & \rho_{t2} & \dots & 1 \end{bmatrix} \tag{66}$$

The CDFs of the sum of inflows thus derived using *@risk* simulation software, are given as an input to the reliability model similar to the CUSUM Approach. This approach also uses the program architecture shown in Figure 5.4.

5.2. SYSTEM OF RESERVOIRS

Management of a reservoir system is very complex and involves several factors such as the number of reservoirs, the system configuration, treatment of inflows and purposes involved in the system. The reliability model can be applied to any multipurpose multiunit reservoir system, and the model is made as general as possible by assuming two general types of linkages: normal channel flow for reservoir releases and pipelines, or pumping canals [Curry et al., 1973; and Simonovic and Marino, 1982]. Thus, each reservoir could be connected to every other reservoir, and each could receive releases from any or all other reservoirs as dictated by a particular system configuration.

The multipurpose reservoir system is modeled based on continuity equations. Each reservoir in each time period could receive random inflow, regulated inflow from upstream reservoir releases, spill from the upstream reservoirs, and inflow from pumping. The release from a reservoir combined with any uncontrolled inflow into the channel from the catchment area downstream of that reservoir and in the upstream of the energy generating station, will be used to generate hydropower in that station. A schematic of the connected multipurpose reservoir system is shown in Figure 5.5.

5.2.1. Model Formulation

The *reliability model* for planning the operation of a system of multipurpose reservoirs is developed using the following flow continuity equation:

$$S_t^j = S_{t-1}^j + I_t^j - R_t^j - SP_t^j + \sum_{k=1}^{m} [R_t^k + SP_t^k + PU_t^k + UI_t^k] \quad \forall\ t,j,k(\neq j) \qquad (67)$$

where S_t^j is the storage in the end of the time period t in reservoir j ; R_t^j is the average release from reservoir j through the turbines for energy generation in time period t ; SP_t^j is the average spill from reservoir j through the spillway (and not used for energy generation) in time period t; I_t^j is the inflow into the reservoir j in the time interval $(t-1,t)$. R_t^k, SP_t^k, and PU_t^k are the release, spill, and the pumped water from any reservoir k respectively; and UI_t^k is the uncontrolled inflow which gets into reservoir j. It should be noted that the R_t^k, UI_t^k, and SP_t^k for any reservoir k downstream of reservoir j is zero, however, PU_t^k, R_t^k, and SP_t^k will take positive or zero values depending on the system configuration.

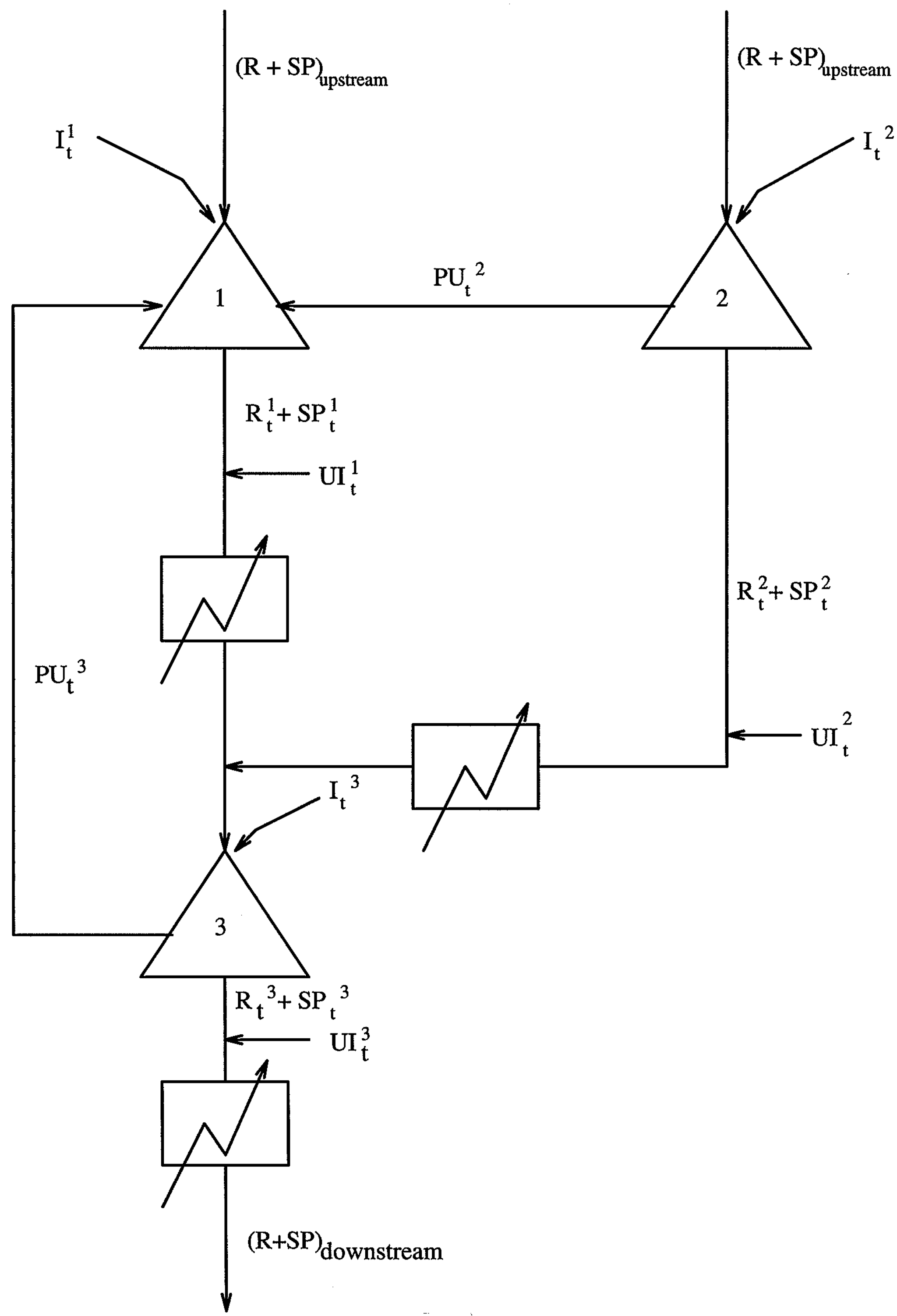


Figure 5.5. Conceptual Diagram of a System of Reservoirs

Total energy generation in the system is achieved through accumulated energy generation in all the hydropower generating stations. Unless the utility company has a highly localized supply and demand network, the utility planners are concerned about the possible energy deficit in the whole system in order to plan about alternate energy management strategies. Since the smallest time period considered is a month, the lag in time for the water to reach from one reservoir to another is ignored. Hence, the total energy generation is obtained as the sum of the product of energy conversion factor, quantity of water available (release from the immediate upstream reservoir plus any local inflow), and the hydraulic head available in the immediate upstream reservoir, for all the reservoirs in the system.

Therefore, the decision variables in the reliability model are: (1) the average release through the turbines from reservoir j in time period t, R_t^j; (2) the average head in the reservoir j in time period t, h_t^j; (3) the storage in the reservoir j at the end of time period t, S_t^j; (4) the average spill from the reservoir from reservoir j in time period t, SP_t^j; (5) the total energy exported to other utilities from the reservoir system in time period t, E_t; (6) the energy imported from other utilities to the reservoir system in time period t, IM_t; (7) the reliability of hydropower generation for the entire system in the planning period, β; (8) the reliability of flood control in each reservoir j, γ^j, and (9) the reliability of flood control for the entire system of reservoirs in the planning period, α.

The 'reliability constraint' for the probability of not exceeding the maximum allowable storage in reservoir j, which is defined as the difference between the total reservoir capacity and the required freeboard volume in reservoir j.

$$P\ ([S^j_{\max} - S^j_t] \geq \theta^j_t) \geq \gamma^j \qquad \forall j, t \tag{68}$$

where S_{max}^j is the storage capacity, and θ_t^j is the minimum flood control volume to be maintained in reservoir j in time period t.

The 'reliability constraint' for the probability of not exceeding the system storage reserved for flood protection when more than one reservoir is assumed to be used for protection. The system storage, θ_t , is defined as a sum of the differences between total reservoir capacities and freeboard volumes (θ_t^j), over the number of reservoirs acting together as one storage whose purpose is to protect the downstream area from flooding.

$$P\ (\sum_{j=1}^{m} [S^j_{\max} - S^j_t] \geq \theta_t) \geq \alpha \qquad \forall t \tag{69}$$

where θ_t is the minimum total flood control volume to be maintained in the reservoir system in time period t, and α is the probability of exceedance of this constraint.

The 'reliability constraint' for the minimum storage to be maintained in the entire system of reservoirs for the purpose of hydropower generation is given as the sum of the minimum storages maintained in all the reservoirs for this purpose. Hence,

$$P\ (\sum_{j=1}^{m} S^j_t \geq v_t) \geq \beta \qquad \forall t \tag{70}$$

The deterministic equivalents of the probability constraints given by Equations (68) through (70) are written as:

$$S^j_{\max} - \theta^j_t - S^j_{t-1} - UI^j_t + \sum_{ls=1}^{nsl} R^{ls,j}_t + SP^j_t$$
$$- [\sum_{k=1}^{m} [\sum_{ls=1}^{nsl} R^{ls,k}_t + SP^k_t + PU^k_t] \geq F^{-1}_\tau (\gamma^j) \qquad \forall\ t,j \quad \forall\ k \neq j \tag{71}$$

$$\sum_{j=1}^{m} [S^j_{\max} - S^j_{t-1} - UI^j_t + \sum_{ls=1}^{nsl} R^j_t + SP^j_t$$
$$- [\sum_{k=1}^{m} [\sum_{ls=1}^{nsl} R^{ls,k}_t + SP^k_t + PU^k_t] - \theta_t \geq F^{-1}_\tau (\alpha) \qquad \forall\ t \tag{72}$$

$$v_t - \sum_{j=1}^{m} [S^j_{t-1} - UI^j_t + \sum_{ls=1}^{nsl} R^j_t + SP^j_t$$
$$- [\sum_{k=1}^{m} [\sum_{ls=1}^{nsl} R^{ls,k}_t + SP^k_t + PU^k_t]] \leq F^{-1}_\tau (1-\beta) \qquad \forall\ t \tag{73}$$

where F_τ^{-1} *(.)* is the inverse value taken from the CDF of the sum of inflows from the beginning of the planning period through the end of time period τ .

The 'constraints on the minimum energy requirement and the maximum exportable energy' for the entire system in load strip *ls* in their deterministic form can be written as:

$$(\sum_{j=1}^{m} C^{j,ls}_t * R^{j,ls}_t * h^{j,ls}_t) - E^{ls}_t + IM^{ls}_t = ENMIN^{ls}_t \qquad \forall\ t,\ ls \tag{74}$$

$$E^{ls}_t \leq EMAX^{ls}_t \qquad \forall\ t,\ ls \tag{75}$$

However, depending on the goal to be achieved by the utility, the energy constraints given by Equations (74) and (75) can be modified accordingly.

The 'constraints on the reliabilities' are:

$$0 \leq \alpha , \beta \leq 1 \tag{76}$$

$$0 \leq \gamma^j \leq 1 \qquad \forall j \tag{77}$$

The formulation also contains constraints on the maximum allowable releases through the turbines, elevation levels in the reservoirs, and the stage-storage relationships.

The objective function maximizes the benefits accrued from hydropower generation and minimizes the losses incurred due to not meeting the required reliability levels for each of the purposes served by the reservoir.

$$\begin{aligned} \max \Big[\Big[\sum_{t=1}^{T} \Big[\sum_{ls=1}^{nsl} r^{ls} * \Big(\Big[\sum_{j=1}^{m} C_t^{ls,j} * R_t^{ls,j} * h_t^{ls,j} \Big] - E_t^{ls} \Big) + rexp^{ls} * E_t^{ls} \\ - cimp^{ls} * IM_t^{ls} \Big] - LC_t^j * SP_t^j \Big] + B_T^j * S_T^j \Big] \\ + \sum_{t=1}^{T} \Big(BF_t \, (\theta_t) + \sum_{j=1}^{m} BF_t \, (\theta_t^j) \Big) - L_1(\alpha) - L_2(\beta) - \sum_{j=1}^{m} L_1^j \, (\gamma^j) \Big) \Big] \end{aligned} \tag{78}$$

Analogous to the single reservoir case, the linearization of energy functions in each of the reservoirs can be adopted if the operating ranges of all the reservoirs are small in comparison to the hydraulic head in those reservoirs. In reservoirs with large operating ranges, energy potential can be considered as a system parameter based on which the system risk is defined, instead of the reservoir storage. Consideration of energy potential as a criterion in the planning of hydropower reservoirs has been done by Arvaniditis and Rosing [1970 a; b], Turgeon [1980; 1981], Tejada-Guibert et al. [1990], Valdes et al. [1992] and many other researchers. A new reliability constraint can be incorporated to define the system risk in terms of the energy potential.

6. APPLICATION OF THE RELIABILITY MODEL

6.1. DESCRIPTION OF THE CASE STUDY

The case study of Manitoba Hydro (MH), the electrical utility company for the Province of Manitoba, Canada, is used in this research. MH and Winnipeg Hydro operate an integrated power system to supply energy to Manitoba. The MH Integrated system consists of 14 hydropower and two thermal power generating stations. The hydropower stations lie on the Winnipeg, Laurie and Nelson Rivers. There are six generating stations on the Winnipeg River which drains into Lake Winnipeg, the largest lake in Manitoba. There are four generating stations downstream of Lake Winnipeg on the Nelson River. A schematic diagram of the MH Integrated system is given in Figure 6.1.

Since Lake Winnipeg is very wide and shallow, a small change in stage results in considerable storage that greatly influences the inflow to the Nelson River. Lake Winnipeg is controlled at Jenpeg for power generation and flood control. The hydro capacity of the plants downstream of Lake Winnipeg is 3900 MW which accounts for nearly 80% of the total hydro capacity (5000 MW) of the MH system. Similarly, the annual dependable energy capability of those plants is 17000 GWh which amounts to nearly 80% of the total capability for the system of 21000 GWh.

MH is an interconnected utility and has firm power and diversity exchange agreements with its neighbouring utilities. In addition, MH exports interruptible energy to neighbouring utilities when the reservoir storage and power plant conditions permit

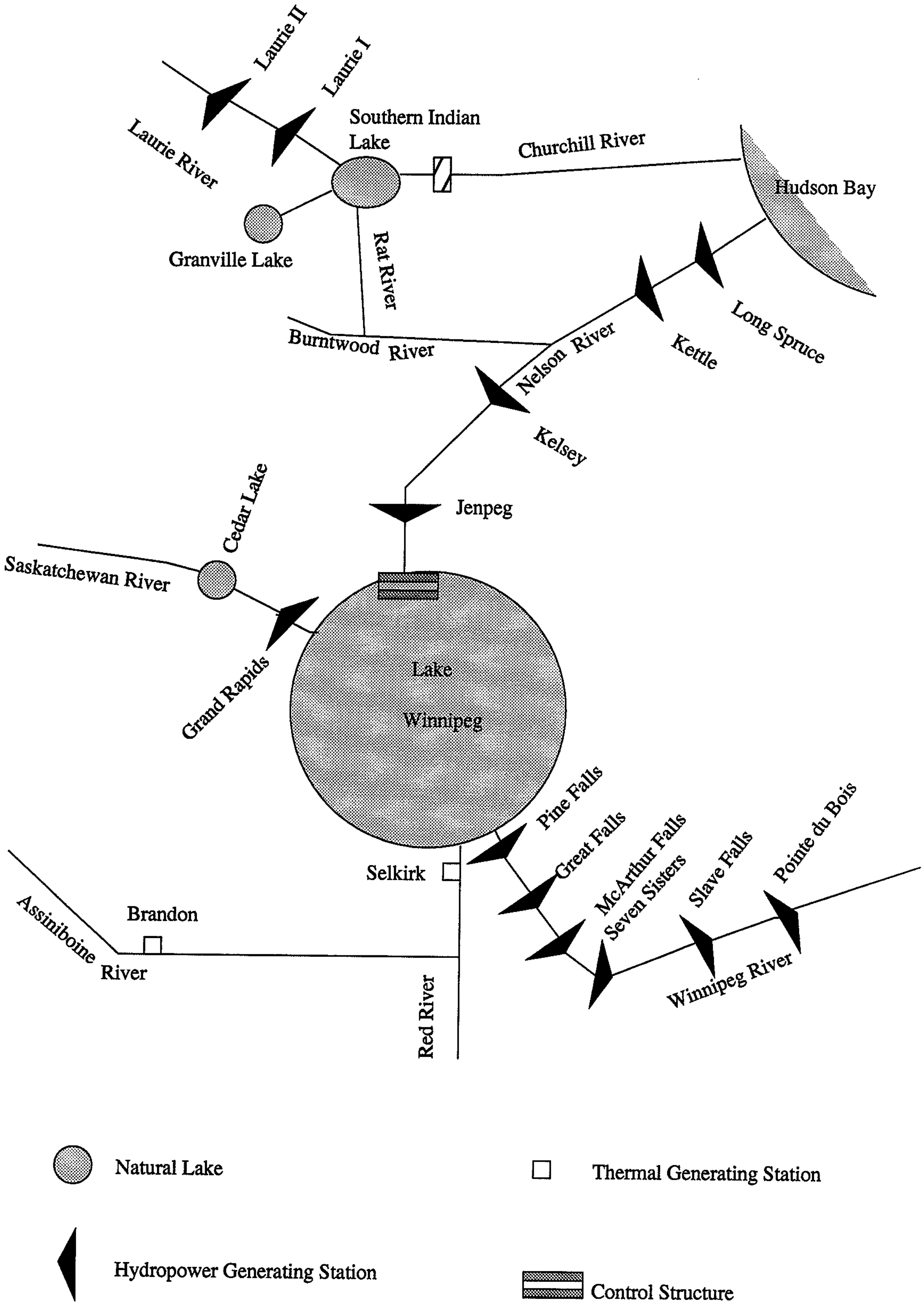


Figure 6.1. Schematic Diagram of Manitoba Hydro Generation System

excess energy production, and imports energy from these utilities during deficit periods.

MH operates the system in such a way to generate energy to satisfy the entire system demand, including firm export commitments. Therefore, the demand on any single reservoir in the MH system is unknown. Due to this characteristic of the MH system, a single equivalent reservoir is used to represent all the reservoirs in the system. Since most of the energy generated in the system is from the power stations located downstream of Lake Winnipeg, the equivalent reservoir is assumed to have physical characteristics similar to those of this lake. However, this limitation of a single reservoir will be relaxed for other generation systems which are operated on a local basis in which the hydrologic and generation characteristics of all the reservoirs and the generating stations in the system are known.

The stage-storage relationship of Lake Winnipeg is given in Table 6.1. The stage-storage relation of Lake Winnipeg provided by MH is linear in the operating range.

Stage (ft.)	***Storage (kcfs*month)***
527.56	***0.0***
546.36	***1905.33***

Table 6.1. Stage-storage Relationship in Lake Winnipeg

A single hydroelectric plant is assumed downstream of the equivalent reservoir to represent all hydraulic generating stations in the MH system. The effect of tail water level on the hydraulic head of the turbines is neglected. The tail water level is a function of the flow through the turbines and the storage in the reservoir immediately downstream. In the MH system, this influence is negligible due to the distance from a plant to the following reservoir. Therefore, the forebay elevation is considered fixed. For zero discharge conditions, the tail water level is 168.64 feet (referred to as ft.) and even for a maximum permissible discharge of 170 kilo cubic feet per second (which is the commonly used unit in MH and is referred to as kcfs), the tail water level varies by at most 10 ft. Therefore, the tail water elevation of 168.64 ft. is assumed, and the head is derived using this level (the range of hydraulic head is 527.56 ft. to 546.36 ft).

The inflow component is the sum of inflows into all the catchments of the MH system. Monthly flow records from 1913 and 1992 are used for deriving the CDFs of the monthly inflows which need to be given as input to the reliability model. CDFs of inflows are computed using the Hydrologic Frequency Analysis software [Bobee and Ashkar, 1991]. Four kinds of Gamma and its derived distributions are fit for each historical monthly flow data, and the best distribution which fits this data is selected and the corresponding CDF is derived. The parameters of the fitted distributions, along with the method of estimating the parameters are tabulated in Appendix C for all the twelve months.

The load pattern for each month in the entire MH system is known. The energy demand in each month is computed from the corresponding load curve for the onpeak and offpeak strips and is given in Table 6.2.

Month	*Demand in GWh*		*Month*	*Demand in GWh*	
	Onpeak	*Offpeak*		*Onpeak*	*Offpeak*
October	*1788.9*	*1117.1*	*April*	*1770.0*	*1096.0*
November	*2040.0*	*1314.0*	*May*	*1692.5*	*949.6*
December	*2339.9*	*1608.1*	*June*	*1596.4*	*895.6*
January	*2486.6*	*1675.4*	*July*	*1571.1*	*856.9*
February	*2135.4*	*1432.6*	*August*	*1624.1*	*885.9*
March	*2099.7*	*1398.3*	*September*	*1631.0*	*915.0*

Table 6.2. Monthly Energy Demand

The amount of energy to be exported is determined by the utility company based on the availability of water, firm energy commitments, etc. The maximum bound on the export power is taken as 1500 MW per month, and the proportion of time in a month for the onpeak and offpeak periods are 0.55 and 0.45 respectively, in this study [Personal

Communication, 1994]. So the maximum exportable energies in each month t $(24*DN_t$ *hours*) in these strips are $0.55*24*DN_t *1500$ *MWh* and $0.45*24*DN_t *1500$ *MWh* respectively, where DN_t is the number of days in month t.

The energy generated (in MWh) in the load strip *ls* in time period t is given by,

$$Energy = \frac{(R_t^{ls} + UI_t^{ls}) * h_t^{ls} * e * t^{ls}}{11.8} \tag{79}$$

where R_t^{ls} is the release through the turbines and UI_t^{ls} is the uncontrolled inflow from the Churchill River Diversion (kcfs) in the load strip *ls* in time period t; h_t^{ls} is the hydraulic head over the turbines (ft.); t^{ls} is the proportion of the time period t for the load strip *ls* (hours); e is the efficiency of the turbines (taken as 0.9 here); and 11.8 is a constant. So the monthly energy conversion factors for the onpeak and offpeak strips, namely, C_t^1 and C_t^2, can be written from Equation (79) as, $(0.9*0.55*24*DN_t/11.8)$ and $(0.9*0.45*24*DN_t/11.8)$, respectively.

6.2. DISCUSSION OF RESULTS

6.2.1. Basic Formulation

In the basic formulation of the reliability model, the energy demands are assumed to be deterministic, and are as shown in Table 6.2. The expected benefit from the storage retained in the reservoir for future energy generation, B_T, is taken as \$ 100,000 per kcfs*month [Personal Communication, 1994]. Lake Winnipeg is the major storage reservoir for energy generation in the MH system, and a spill from such a system is activated only when the reservoir storage exceeds the maximum allowable storage in the lake. The release from the reservoir is only used for hydroelectric energy generation downstream of the reservoir, and hence a spill from the lake is not considered as an economic loss to the system. Therefore, the coefficients in the formulation which penalize a spill from the reservoir, LC_t, are set to zero. However, these penalty coefficients will play an important role when a spill from the reservoir affects the downstream purposes such as erosion control and fish and wild life habitats.

The pertinent economic data to compute the benefits accrued from providing a flood control space, $BF(\theta_t)$, in each time period t are not known for the MH system. Split Lake Community is the only community downstream of Lake Winnipeg which is likely to be affected due to flooding. However, MH has an agreement with this community about the operational requirement for Lake Winnipeg during the flood seasons.

Flood control storage is set as 55.33 kcfs*month for all the time periods, and the starting storage in the reservoir is set as 1400 kcfs*month. The minimum storage requirement for hydropower generation is set as 500 kcfs*month for all the time periods.

The risk-loss functions form an important component of the reliability model, and this function for the purpose of flood control can be derived using the procedure developed by Simonovic and Marino [1981]. However, the economic, hydraulic and the hydrologic data required to derive this function are not available for the MH system. The risk-loss function for the purpose of hydropower generation, developed in Section 6.2.4, is not incorporated in the basic formulation. Hence, logarithmic shapes of risk-loss functions, which are convex functions of the reliabilities for the purposes of flood control and hydropower generation, are assumed in this formulation as shown below:

$$L_1 (\alpha) = CALFA1 * LOG(\alpha) \qquad \textbf{(80)}$$

$$L_2(\beta) = CALFA2 * LOG(\beta) \qquad \textbf{(81)}$$

where α and β are the reliabilities of the reservoir system for flood control and hydropower generation, respectively, and *CALFA1* and *CALFA2* are the coefficients of risk-loss functions for these two purposes, which are assumed to be 1000 and 1000, respectively.

The basic formulation is run with the aforementioned data, and the optimal release policy computed by the model is shown in Figure 6.2. The optimal value of the net benefit is $ 1313.05 M (Cdn). In addition to the optimal release policy, the model explicitly evaluates the optimal reliabilities of reservoir system performance for the purposes of flood control and hydropower production, respectively, as 0.8777 and 0.9899.

The interpretation of the results of the reliability program is that the benefit obtained from operating the reservoir for hydropower generation and flood control is traded off with the economic losses due to not meeting the required reliability levels for these two purposes. Traditionally, the water resources systems are designed to minimize the failure of those systems. The performances of the system are evaluated using simulation procedures after designing the systems. The reliability program is an innovative tool which allows the planner to use the quantified cost of failure of the system *a priori* so that the model identifies an optimal level of failure or risk level that is acceptable to the planner. The acceptability criterion is that the net benefits computed as the difference between the total benefits and the economic losses achieves its maximum, and the model yields the optimal release policy and the reliability levels corresponding to this situation.

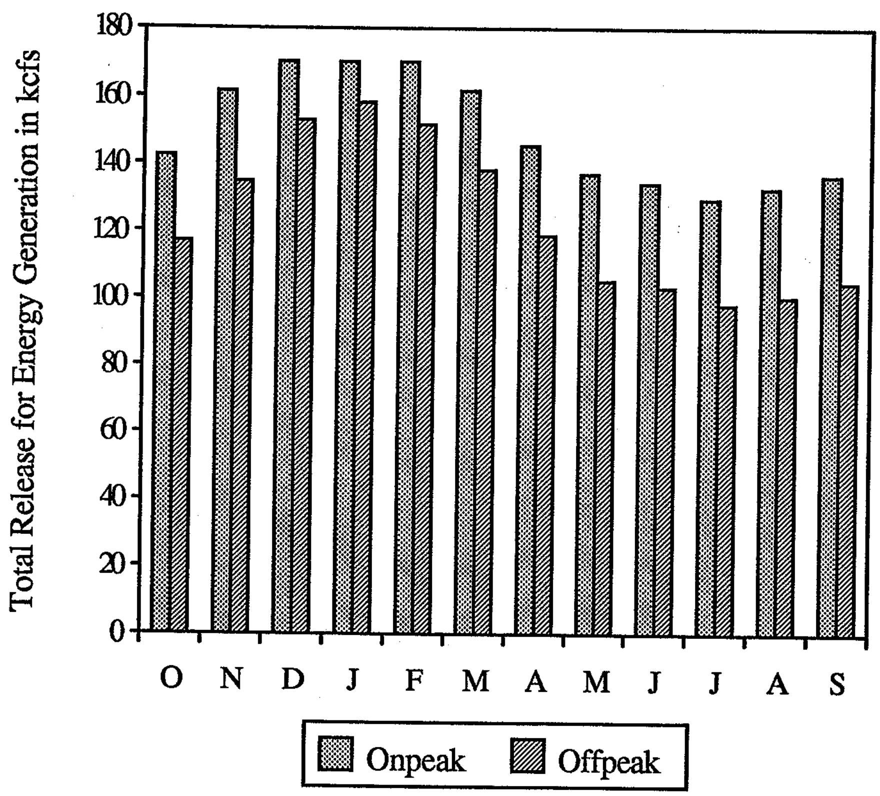


Figure 6.2. Optimal Release Policy

To study the impact of the risk-loss function for energy generation on the decision-making process, the coefficient, *CALFA2*, which controls the shape of this function is changed from 1000 to 2000. An increase in *CALFA2* results in a steeper risk-loss function, and a violation in the minimum storage requirement for energy generation is penalized to a larger extent compared with the case when *CALFA2=1000*. A comparison of the optimal values of the reliability for energy generation, export energy from the system, and the benefits from the end storage in these two cases is given in Table 6.3.

	CALFA2=1000	***CALFA2=2000***
Net benefits (M \$ Cdn.)	***1313.05***	***1340.00***
Reliability for hydropower generation	***0.9899***	***0.9989***
Benefits from Export energy in On-peak period (M \$ Cdn.)	***67.918***	***67.932***
Benefits from Export energy in Off-peak period (M \$ Cdn.)	***47.304***	***41.325***
Benefits from End storage (M \$ Cdn.)	***131.30***	***134.00***

Table 6.3. Sensitivity of the Optimal Solution to Risk-loss Function Coefficient

The model conserves more water in the reservoir when *CALFA2* is set to 2000, due to a higher penalty imposed for violating the minimum storage requirement, as can be seen from Table 6.3. This results in a decreased export energy from the system during the off-peak period, and an increased end storage available for future energy generation.

Another parameter which influences the optimal solution is the minimum storage requirement for energy generation, v_t [Simonovic and Srinivasan, 1993]. A higher value of the minimum storage requirement imposed on the reservoir reduces the storage available for energy generation in the planning period. In order to meet the same energy demand, a higher value of a storage requirement is likely to be violated more frequently than a lower value of the minimum storage requirement. Assuming the values of *CALFA1* and *CALFA2* as 1000 and 1000, the basic formulation of the reliability model is run with different values of the minimum storage requirement ranging from 500 kcfs*month to 1500 kcfs*month. The reliability of energy generation obtained from these runs are plotted against the minimum storage requirement in Figure 6.3. As can be seen from this figure, the reliability level decreases with higher values of minimum storage requirements. This sensitivity analysis is useful to the decision maker in multi period planning, as the decision taken during one period affects the performance of the system in the following period. In practice, a decision maker can compare the risk level, that is, the failure of the reservoir performance in the planning period as well as in the future, and develop a 'balanced' rule curve to provide guidelines for operating the reservoir system.

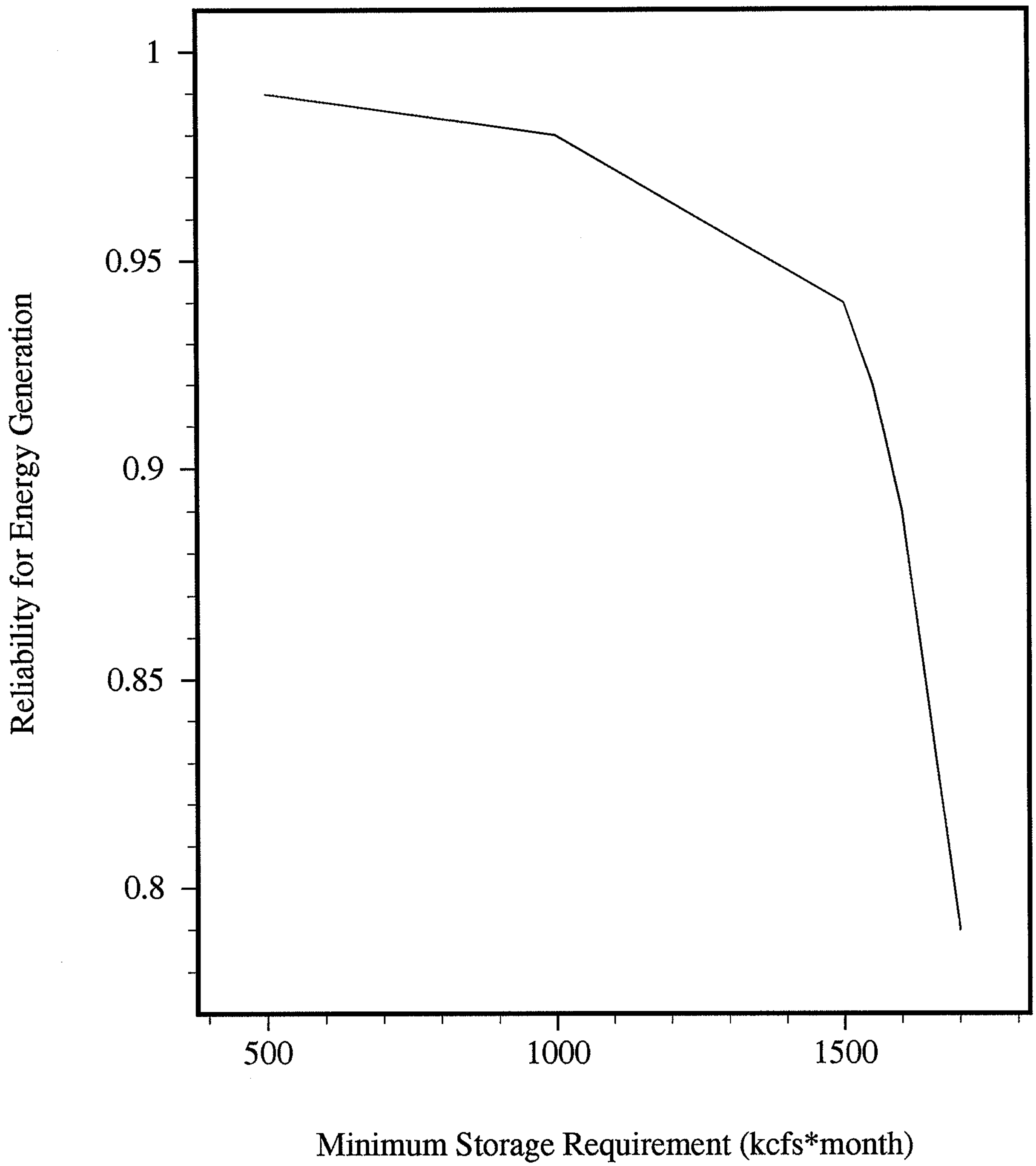


Figure 6.3. Sensitivity of Optimal Reliability to Minimum Storage Requirement

6.2.2. Incorporating the Uncertainty in Energy Demand

The variability in energy demands is incorporated in the basic formulation of the reliability model by treating the energy demands as stochastic (governed by the laws of probability) or as fuzzy (defined with vague boundaries). The results obtained using these two approaches are presented and compared with those obtained from the basic formulation in the following subsections.

6.2.2.1. Stochastic Formulation

Based on the formulation presented in Section 3.2.2, Equation (10) alone needs to be modified in the basic formulation, in order to derive the stochastic formulation of the reliability model. The stochastic formulation, thus contains the modified energy constraint along with other constraints given by Equations (7), (9), (12), (16), (18) and (29), and the objective function defined by Equation (19). The probabilistic form of Equation (10) is written as:

$$F_E^{ls}\ (pe^{ls}/2) \leq C^{ls} * R_t^{ls} * h_t^{ls} - E_t^{ls} + IM_t^{ls} \leq F_E^{ls}\ (1 - pe^{ls}/2) \qquad \textbf{(82)}$$

where $F_E^{ls}(pe^{ls})$ is the inverse of the CDF of the energy demand in time period t in the load strip ls, $ENMIN_t^{ls}$, with a probability of exceedance of $(1\text{-}pe^{ls})$. However, the PDFs of the energy demands must be known *a priori* to convert Equation (82) into its deterministic form. Manitoba Hydro [1993] suggests that the forecasted energy demands are normally distributed, and also provides the estimated values of the means and standard deviations of forecasts for all the months, depending on the variability in weather forecast and the anticipated growth in residential and industrial customer demands. The energy demands are assumed to be serially uncorrelated, and the statistics of the suggested normally distributed demands are given in Table 6.4.

	Onpeak		***Offpeak***	
Month	***Mean (GWh)***	***Standard Deviation (GWh)***	***Mean (GWh)***	***Standard Deviation (GWh)***
October	***1788.9***	***200.0***	***1117.0***	***200.0***
November	***2040.0***	***500.0***	***1314.0***	***500.0***
December	***2339.9***	***600.0***	***1608.1***	***600.0***
January	***2486.6***	***700.0***	***1675.4***	***700.0***
February	***2135.4***	***500.0***	***1432.6***	***500.0***
March	***2099.7***	***400.0***	***1398.3***	***400.0***
April	***1770.0***	***200.0***	***1096.0***	***200.0***
May	***1692.5***	***100.0***	***949.55***	***100.0***
June	***1596.4***	***200.0***	***895.64***	***200.0***
July	***1571.1***	***200.0***	***856.94***	***200.0***
August	***1624.1***	***250.0***	***885.88***	***250.0***
September	***1631.0***	***250.0***	***915.05***	***250.0***

Table 6.4. Statistics of Energy Demand Forecast

The exceedance probability, pe^{ls}, is assumed to be 5% for both onpeak and offpeak load strips for all the time periods in the planning period. Hence the probabilistic constraint for energy demand is rewritten as:

$$\mu_t^{ls}(E) - 1.85*\sigma_t^{ls}(E) \leq C^{ls}*R_t^{ls}*h_t^{ls} - E_t^{ls} + IM_t^{ls} \leq \mu_t^{ls}(E) + 1.85*\sigma_t^{ls}(E) \qquad (83)$$

where $\mu_t^{ls}(E)$ and $\sigma_t^{ls}(E)$ are the mean and standard deviation of the energy demand forecast in the load strip ls in time period t.

The stochastic formulation is solved with an assumed risk-loss coefficient of 1000 for flood control, a minimum storage requirement of 500 kcfs*month, and a starting storage of 1400 kcfs*month in the reservoir. In addition, a typical risk-loss function developed for the MH system, as described in Section 6.2.4, replaces the assumed risk-loss function for energy generation in the basic as well as in the stochastic formulation. The optimal values of the net benefit accrued from hydropower generation, the reliability for energy generation (β), the export energy, and the end storage obtained using these two formulations are given in Table 6.5. It can be seen from this table that the stochastic formulation yields a flexible policy, in which it is able to generate more energy without violating the minimum storage requirement to a greater extent. This results in an increased use of reservoir storage in the planning period leaving lesser storage for future energy generation. A higher benefit coefficient, B_T, can however, be incorporated in the stochastic formulation if the decision maker wishes to retain more water for future energy generation.

The basic formulation may also provide a more flexible policy through the implicit stochastic approach in which a large number of scenarios of energy demands are generated for all the time periods, and a policy is derived from the results of all such scenarios.

	Basic Formulation	*Stochastic Formulation*
Net benefit (M $ Cdn.)	*1437.06*	*1520.97*
Reliability for Energy Generation	*0.9899*	*0.9885*
Benefits from Export energy during onpeak periods (M $ Cdn.)	*67.918*	*72.270*
Benefits from Export energy during offpeak periods (M $ Cdn.)	*47.304*	*47.304*
Benefits from End storage (M $ Cdn.)	*131.305*	*107.716*

Table 6.5. Comparison of the Results of Basic and Stochastic formulations

6.2.2.2. Fuzzy Formulation

This formulation can be used when the PDFs of energy demands cannot be defined *a priori*. However, as explained in Section 3.2.2, the variation in energy demand needs to be vaguely defined by experienced planners using the membership functions (MSFs). These MSFs represent the degree of belongingness of different values of energy demands to a fuzzy set. Please refer to Appendix B for more details about the MSFs.

MH uses a regression analysis combined with an annual percentage increase in consumption to compute the future energy demands in the planning period [Manitoba Hydro, 1993]. These projected demands for all the time periods will have a membership of *one* in the fuzzy formulation, since these values are used in the basic formulation as deterministic inputs.

Based on the methodology proposed in Chapter 3 for deriving the MSF of energy demands, the frequency plot of the deviations of the forecasted demands from the actual demands is taken as the sample MSF for energy demands [Srinivasan and Simonovic, 1994a]. Data for the forecasted demands 5-years preceding the forecast, and the actual energy consumption are obtained from Manitoba Hydro [1993] for a 20-year period (1973-74 through 1992-93). Percentage deviations are computed for each year using Equation (34). The deviations are divided in steps of 5%, and the number of years in which the deviations are in certain interval, say between 5% and 10%, are plotted in the middle of this interval, as shown in Figure 6.4.

Two cases need to be analyzed from Figure 6.4 in which the first case represents a scenario when the actual demand is more than the forecast, and the second case represents a scenario when the actual demand is less than the forecast. From Figure 6.4, the maximum deviation in the first case is 10% (taken as the value of q_t^{ls} in the fuzzy formulation), and the MSF is set at *zero* for any deviation more than this value. Hence the MSF decreases from *one* (at 0%) to *zero* (at 10%) linearly. Similarly, for the second case, the maximum deviation is 25% (taken as the value of p_t^{ls}), and the MSF is set to *zero* for any deviation more than this value. The MSF decreases from *one* (at 0%) to *zero*

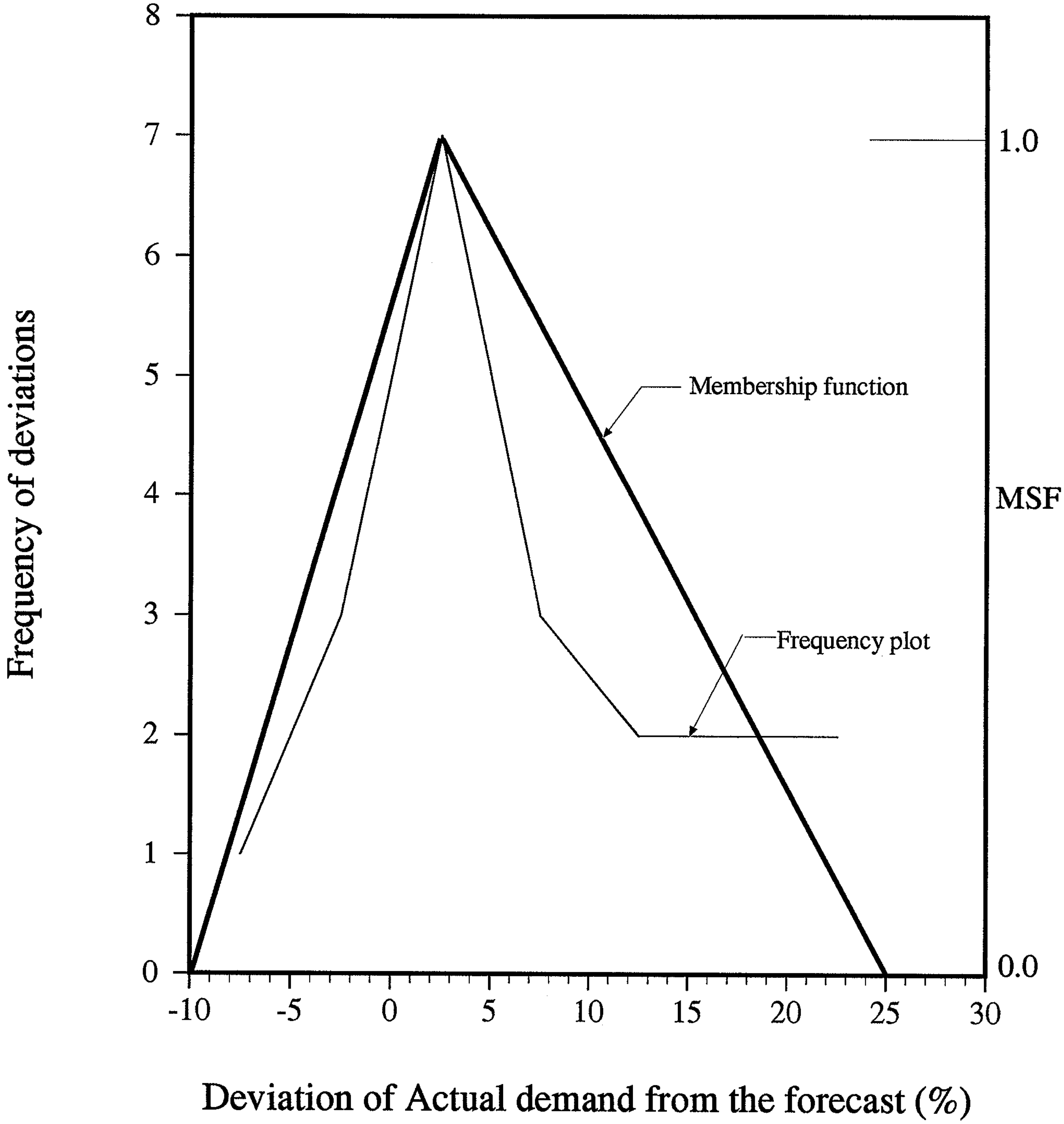


Figure 6.4. Frequency Plot of the Deviations of Actual Demands from Forecasts

(at 25%) linearly. Graphically, the MSF for these two cases are indicated by thicker lines in Figure 6.4, in which the membership scale is marked on the right side of this figure.

Since the energy demands are treated as fuzzy variables, Equation (10) is written as a fuzzy constraint for all the time periods. However, there is no 'vagueness' in defining the objective function in the formulation. Based on the description provided in Appendix B, the formulation is unsymmetric and hence, the objective function must be converted into its fuzzy form. Referring to Equations (97) through (101) in Appendix B, the basic formulation of the reliability model can be used to define the values of the objective function, f_0 and f_1 . These objective function values, respectively, are the net benefits obtained from the basic formulation with a typical risk-loss function for energy generation, using the forecasted energy demands and the lowest possible energy demands (75% of the energy demands, from Figure 6.4). The parameters of the model are set as follows: *CALFA1* of 1000, a minimum storage requirement of 500 kcfs*month, and a starting storage of 1400 kcfs*month. The MSF for the objective function is defined in the fuzzy formulation as shown in Figure 6.5.

The fuzzy formulation is solved using the MSFs defined for the energy demands and the objective function using the Equations (42) through (45) along with the constraints given by Equations (7), (9), (12), (16), (18), and (29). The optimal values of the net benefit accrued from hydropower generation, the reliability for energy generation, benefit from export energy, and the benefit from end storage obtained as a crisp solution to the fuzzy formulation are presented in Table 6.6 along with the corresponding results from the basic formulation. The MSF of the crisp decision space is 0.4559, which is the minimum of the MSFs of fuzzy energy constraints and the fuzzified objective function.

As can be seen from Table 6.6, the fuzzy formulation yields a 'flexible' policy compared with the basic formulation.

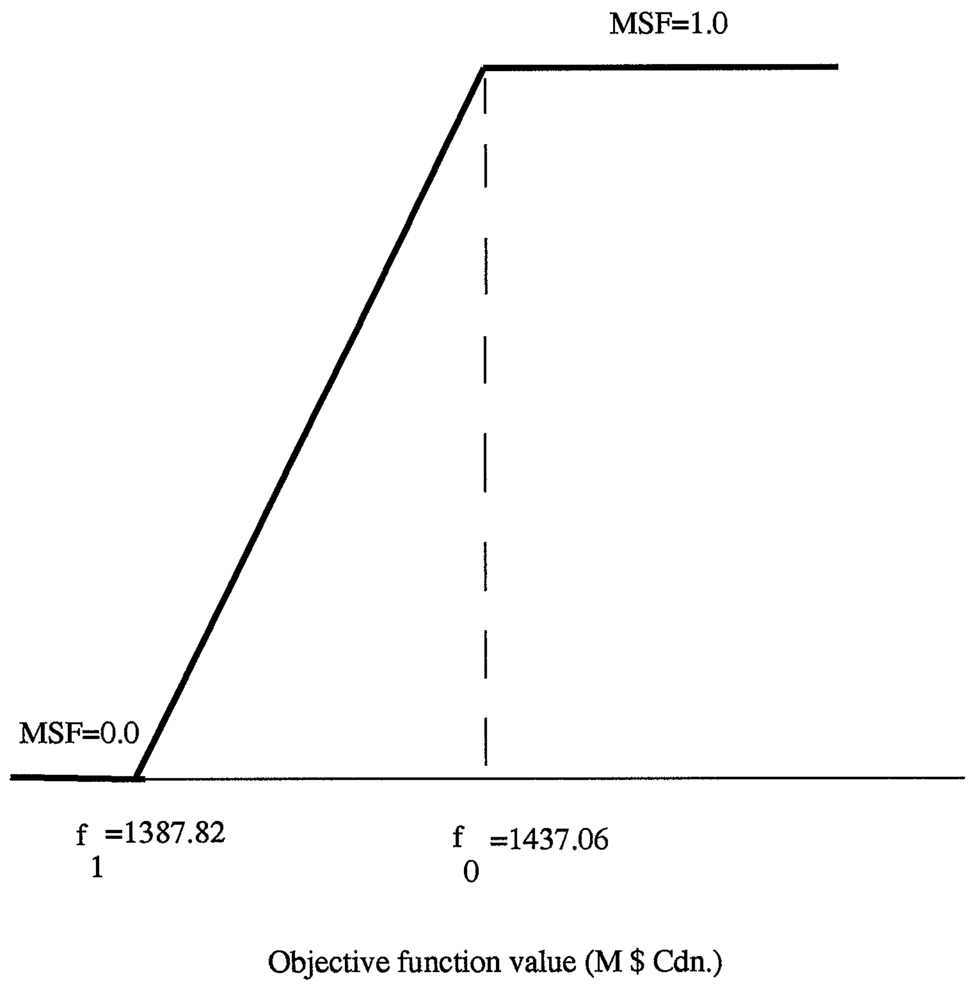


Figure 6.5. Membership Function of the Objective Function

Comparing the results obtained from the stochastic and fuzzy formulations in Tables 6.5 and 6.6, the stochastic formulation yields a higher energy generation, and hence a higher value of net benefit compared with the fuzzy version. However, this is a direct consequence of the upper bound on energy demands defined in both formulations. In the stochastic formulation, the upper bound is defined by $[\mu_t^{ls}(E)+1.85*\sigma_t^{ls}(E)]$ as in Equation (83), while the bound is defined by *110% of* $\mu_t^{ls}(E)$ in the fuzzy formulation.

	Basic Formulation	*Fuzzy Formulation*
Net benefit (M $ Cdn.)	*1437.06*	*1462.15*
Reliability for Energy Generation	*0.9899*	*0.9899*
Benefits from Export energy during onpeak periods (M $ Cdn.)	*67.918*	*72.270*
Benefits from Export energy during offpeak periods (M $ Cdn.)	*47.304*	*47.304*
Benefits from End storage (M $ Cdn.)	*131.305*	*125.829*

Table 6.6. Comparison of the Results of Basic and Fuzzy Formulations

Choice of the approach for explicitly considering the variability in energy demand depends entirely on the accuracy of forecasted energy demands. Some utilities in North America (including MH) use PDFs to define the variation in energy demand, and some other utilities use judgment based on experience to define the variability, and adopt an implicit stochastic approach to study the sensitivity of the optimal solution. The fuzzy formulation developed in this research can be used as a robust technique in the situations which use judgment based on experience. On the other hand, the stochastic formulation has fewer constraints compared to the fuzzy formulation, and hence requires less computational time.

6.2.3. Hydropower Generation Risk-loss Function

The risk-loss functions form an important component of the reliability model since they quantify the costs of deviations from the goals, and thus, influence decision making during planning the operation of reservoirs. A four-step simulation algorithm, proposed in Chapter 4, is used to derive the risk-loss function for energy generation. Prior to explaining the components of risk in a predominantly hydro system, the data for the MH system used in the simulation algorithm is detailed.

The simulation period is taken as 30 years consisting of 360 monthly time periods. The physical capacity of Lake Winnipeg is 1905.33 kcfs*month, which includes a minimum flood control requirement of 55.33 kcfs*month [Personal Communication, 1994], and the operating range of the reservoir is between 527.56 ft. and 546.36 ft. The aggregated generation system for MH is presented in Figure 6.6. Referring to this figure, the uncontrolled flows result from the Churchill River Diversion; the controlled flows are the inflows into Lake Winnipeg; and the outflow from the lake is regulated by the Jenpeg Generating Station.

The components of risk in a predominantly hydroelectric generation system are the reservoir inflows, the maximum depletable storage in the reservoir for the purpose of energy generation, and the energy demands. Different scenarios of simulation data are generated based on the variation in each of these components for the MH system as follows.

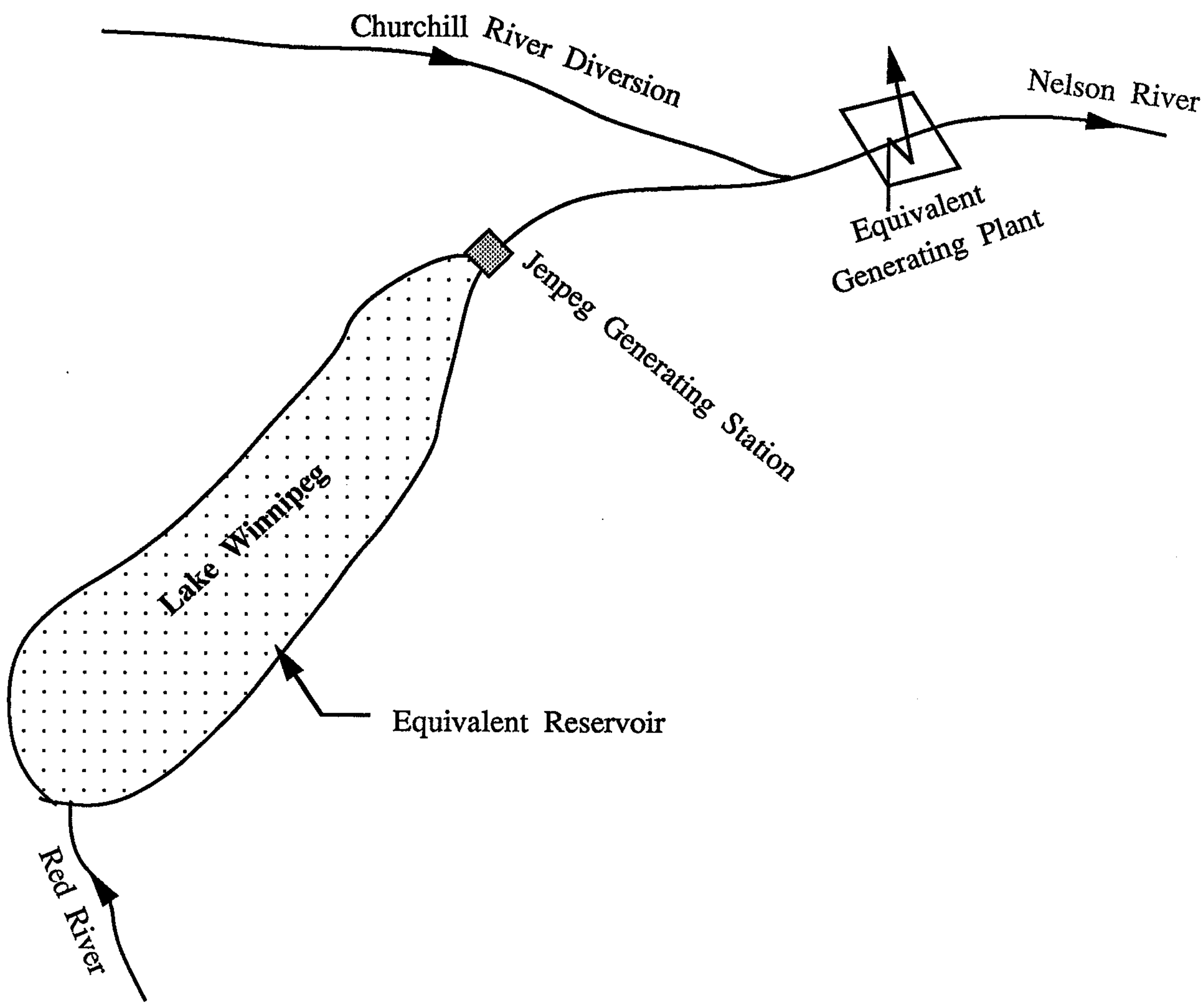


Figure 6.6. Aggregated Generation System for MH

MH uses the criterion of *critical period* for planning studies [Manitoba Hydro, 1990]. A *critical period* is the duration of time which has the lowest reservoir inflows observed in the historical data. This period is identified for the years 1938-41 from the historical inflows into Lake Winnipeg. The inflow scenarios are chosen to include the *critical period* in the beginning, the middle or end of the simulation period, because the impact of initial reservoir storage diminishes over time. Four such scenarios, termed as Inflow Scenarios 1 through 4, are generated from the historical inflow data such that the *critical period* appears in the beginning, in the end, in the later half, and in the first half of the simulation period, respectively. Hence the simulation period consists of the following years: 1938-69; 1912-41; 1931-1960; and 1921-1950, for these four scenarios, respectively.

The second component, namely, the available storage, is the maximum depletable storage for hydropower generation in the reservoir system. This component is used to find the stored energy potential in the system. The operating range of Lake Winnipeg is between 527.56 ft. and 546.36 ft., corresponding to storage levels of zero and 1905.33 kcfs*month, respectively. The lowest storage available for hydropower generation is assumed to be zero which corresponds to 527.56 ft. After deducting the minimum flood control storage of 55.33 kcfs*month from the maximum capacity of 1905.33 kcfs*month, several possible minimum storage intervals (20 discrete storage intervals in this study) are chosen in the range between zero and 1850.00 kcfs*month. The twenty storage intervals considered in this simulation algorithm are: 0, 100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200, 1300, 1400, 1500, 1600, 1700, 1800, and 1850 kcfs*month storage requirement based on the available storage for energy generation. Knowing the energy demands on the system, and the initial condition in the reservoir, the storages in all the 360 months are simulated using Equations (46) and (47). The simulated storage levels are then compared with the minimum storage requirement to compute the frequency of violation of this requirement.

The second step involves depleting the available storage linearly over the entire simulation period, and finding the total energy potential in the system using this available storage and the inflows (both controlled and uncontrolled) in each month. This energy potential, which is constrained by the capacity of the turbines, is compared with the energy demand in all the months of the simulation period. The energy deficit in any year is computed as the yearly average deficit in the simulation period, corresponding to a certain available storage level.

For Step 3, namely, the evaluation of the cost of unsupplied energy, MH suggested that a cost between $ 5.00 and $ 15.00 (Cdn.) per kWh be used [Chu, 1994]. A representative value of $ 8.00 (Cdn.) is used in this study. The cost of unsupplied energy varies linearly with the magnitude of energy not supplied.

In the final step, the three relationships obtained in the first three steps are combined to derive the risk-loss function for energy generation. An example risk-loss function obtained using the Inflow Scenario 2, Energy Scenario 1, and a minimum storage requirement of 1500 kcfs*month is shown in Figure 6.7 (indicated as 2:1:1500 for identification purposes).

As can be seen from Figure 6.7, the risk level of violating a minimum storage requirement of 1500 kcfs*month, as well as the magnitude of energy not supplied seem to increase (shown in Figure 6.7 in terms of the cost of unsupplied energy) when the available storage in the reservoir is varied from 1850 to zero kcfs*month. The risk levels and the costs of unsupplied energy for these two storage bounds, respectively, represent the starting and the ending points of the risk-loss function curve. In the MH system, the

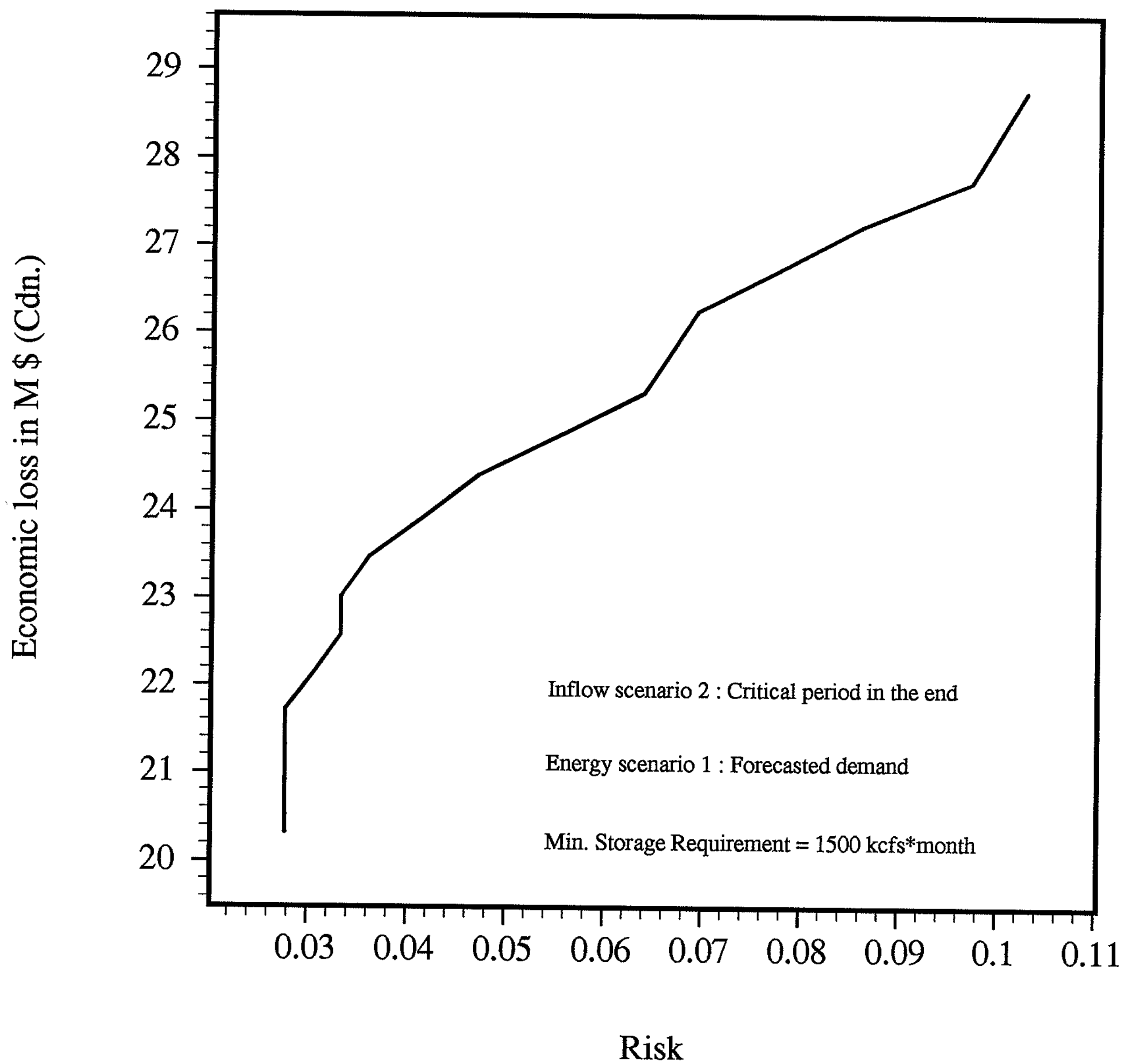


Figure 6.7. Risk-loss Function (Scenario 2:1:1500)

cost data suggested by Chu [1994] is the compensation given to the residential and industrial customers for the energy not supplied. However, if alternative strategies are adopted to manage the energy deficit in the system such as, thermal energy generation and demand side management, new cost data must be incorporated in the third step of the simulation algorithm.

Referring to Figure 6.7, the vertical increase in the cost of unsupplied energy from \$ 20.2 M (Cdn.) to \$ 21.7 M (Cdn.) for the same risk level, is due to the same frequency of violation of a minimum storage requirement of 1500 kcfs*month for different available storage levels. However, the energy potential in the system varies depending on the available storage level. The risk level varies from 2.8% to 10.4% for the available storages from 1850 kcfs*month to zero kcfs*month, with corresponding costs of unsupplied energy varying from \$ 20.2 to \$ 28.8 M (Cdn.).

The interpretation of the risk-loss function is that the reliability model will tend to use more reservoir storage from the system, since the objective function maximizes the benefits from energy generation. However, depletion of more water in the planning period indicates a possible failure in the reservoir system for not providing a certain minimum requirement. Since the risk-loss function is also in the objective function, a larger violation from the minimum storage requirement is penalized to a larger extent, thus forcing the reservoir storage not to be used excessively for energy generation in the planning period. Depending on the magnitude of the benefits and the losses specified by the risk-loss function, the reliability model finds the compromise values of the storage levels.

For reservoirs with a very large operating range and with multiple uses, it may be possible to obtain a complete description of the risk-loss function for risk levels varying from near zero to near 100%.

A comparison of the risk-loss functions obtained using different scenarios along with the sensitivity of the reliability model in providing decisions using different risk-loss functions are discussed in the following section.

6.2.3.1. Sensitivity of the Reliability Model to Risk-loss functions

The influence of the first component of energy generation risk, namely, the reservoir inflow is discussed here. A minimum storage requirement of 1500 kcfs*month, and the Energy Scenario 1 are used in this sensitivity analysis. Each simulation scenario is represented by Z_1: Z_2: Z_3, where Z_1, Z_2 and Z_3 are the indices corresponding to reservoir inflow, energy demand, and the minimum storage requirement scenarios, respectively. The three risk-loss functions obtained from the reservoir inflow scenarios 2, 3, and 4 are presented in Figures 6.7, 6.8, and 6.9, respectively. Inflow Scenario 2 represents a situation in which the *critical period* appears at the end of the simulation period, and Inflow Scenarios 3 and 4 represent situations in which the *critical period* appears in the middle of the simulation period. Due to the linear depletion of the available storage, lesser water is available in the reservoir towards the end of the simulation period, and when the reservoir inflows are lower, the energy potential of the reservoir decreases considerably. This situation possibly represents a 'worst-case' scenario. As can be seen from Figures 6.7 through 6.9, the risks and the corresponding economic losses are quite high (2.8% to 10.4%; and \$ 20.2 to \$ 28.8 M Cdn) in the Scenario 2:1:1500, compared to the situations when the Scenario 3:1:1500 (0.1% to 10.8%; and \$ 9.8 to \$ 17.6 M Cdn.) or the Scenario 4:1:1500 (0.1% to 7.8%; and \$ 13.8 to \$ 22.2 M Cdn.) is used.

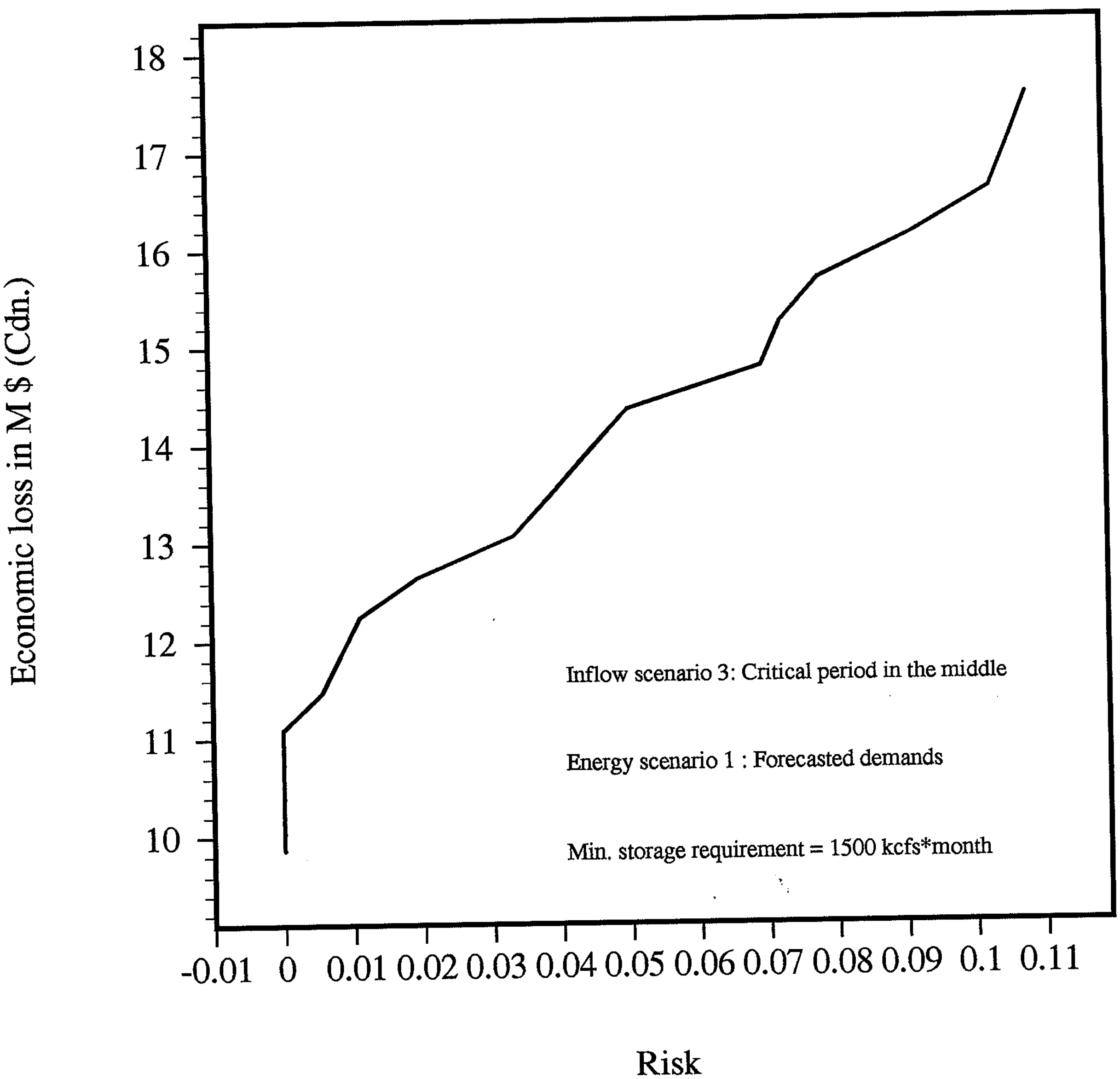


Figure 6.8. Risk-loss Function (Scenario 3:1:1500)

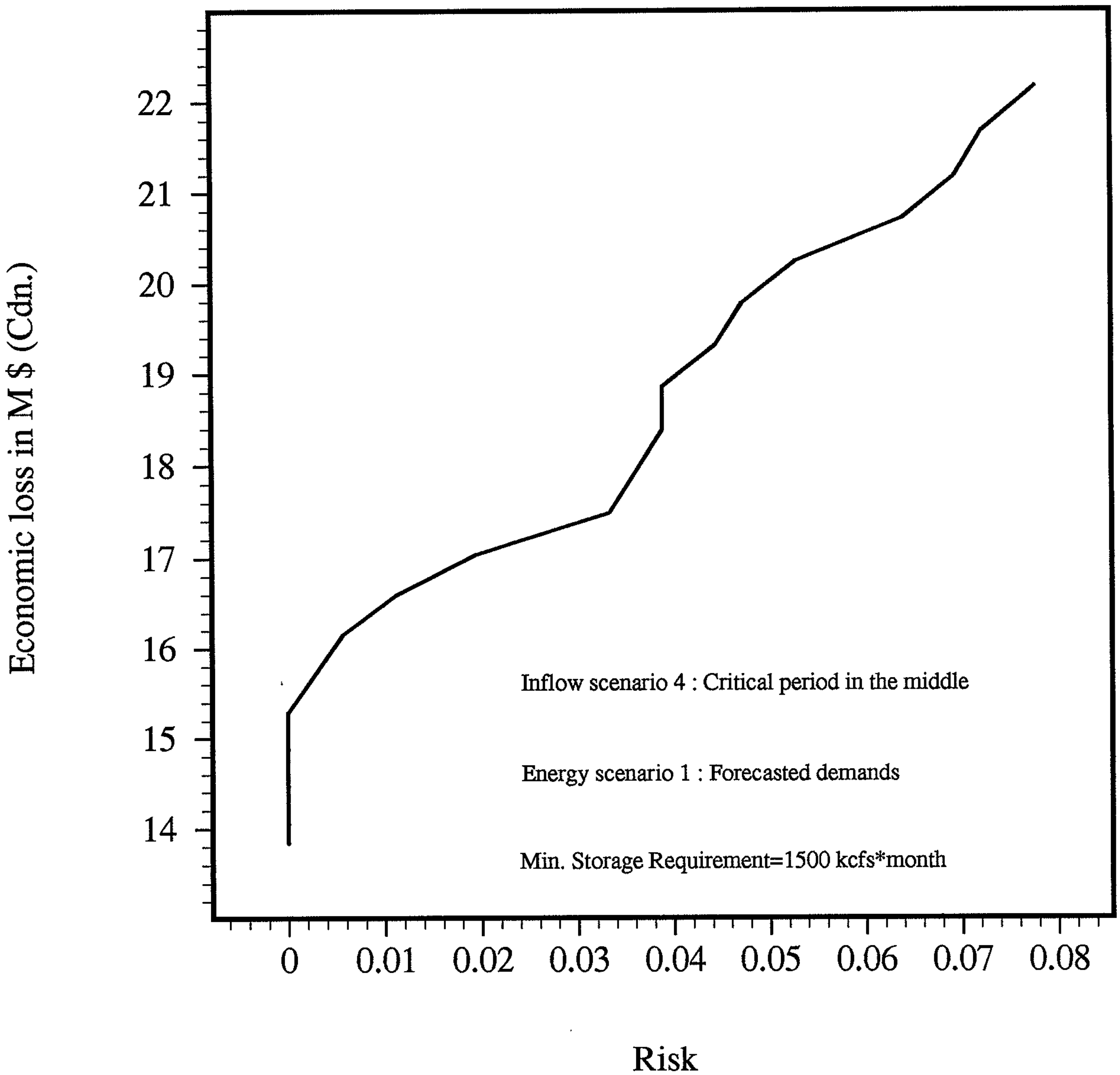


Figure 6.9. Risk-loss Function (Scenario 4:1:1500)

The variation in the second component of the energy generation risk, namely, the minimum storage requirement has a similar influence as the reservoir inflow scenarios. A higher storage requirement implies that a 'low flow' situation is anticipated, and the planner wishes to retain as much water as possible in the reservoir for future energy generation. Using the Energy Scenario 1 and the Inflow Scenario 2, the risk-loss functions obtained for minimum storage requirements of 1500 kcfs*month and 1000 kcfs*month respectively, are presented in Figures 6.7 and 6.10.

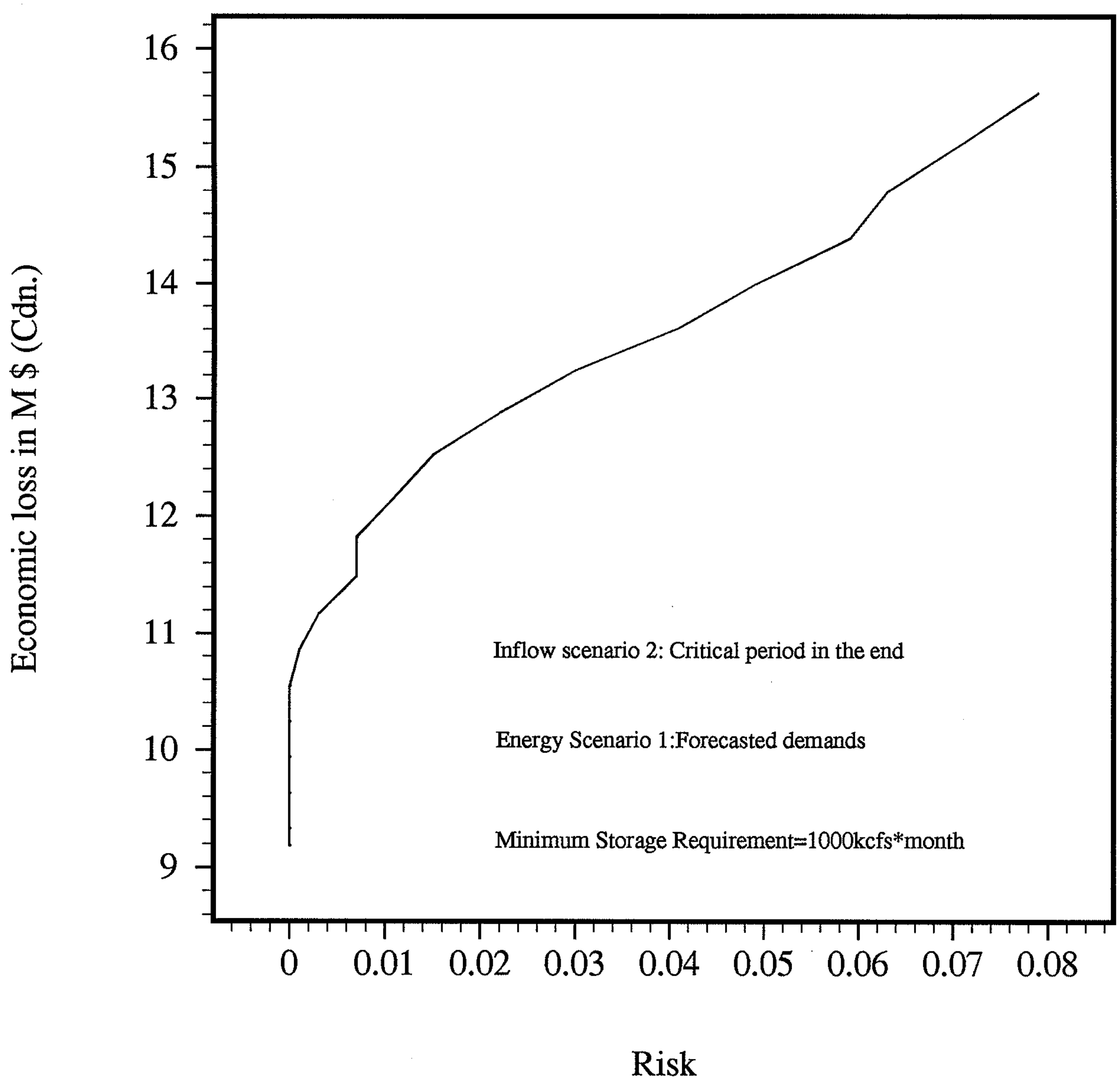


Figure 6.10. Risk-loss Function (Scenario 2:1:1000)

A lower minimum storage requirement must provide more water for energy generation during the simulation period and consequently, the energy deficit and the risk level must be smaller compared to a higher value of the storage requirement. Comparing the risk-loss functions presented in Figures 6.7 and 6.10, the risk levels and the energy deficits are reduced from (2.8% to 10.4%; $ 20.2 to 28.8 M Cdn) for Scenario 2:1:1500, to (a maximum of 7.8%; $ 9.2 to $15.6 M Cdn) for Scenario 2:1:1000.

A variation in the third component of energy generation risk, namely, the energy demands, will have a significant impact on the shape of the risk-loss functions. For illustration, a minimum storage requirement of 1500 kcfs*month and the Inflow Scenario 2 are used in this sensitivity analysis. The risk-loss functions are obtained using the Energy Scenarios 1, 6, 8, and 10 which represent 100%, 110%, 130%, and 150% of the forecasted energy demands, and are presented in Figures 6.7, 6.11, 6.12 and 6.13 respectively.

A comparison of the starting and the ending points of these functions which correspond to an available storage levels of 1850 kcfs*month and zero kcfs*month, respectively, show a dramatic increase in the risk level and the corresponding cost of unsupplied energy when the energy demands are increased.

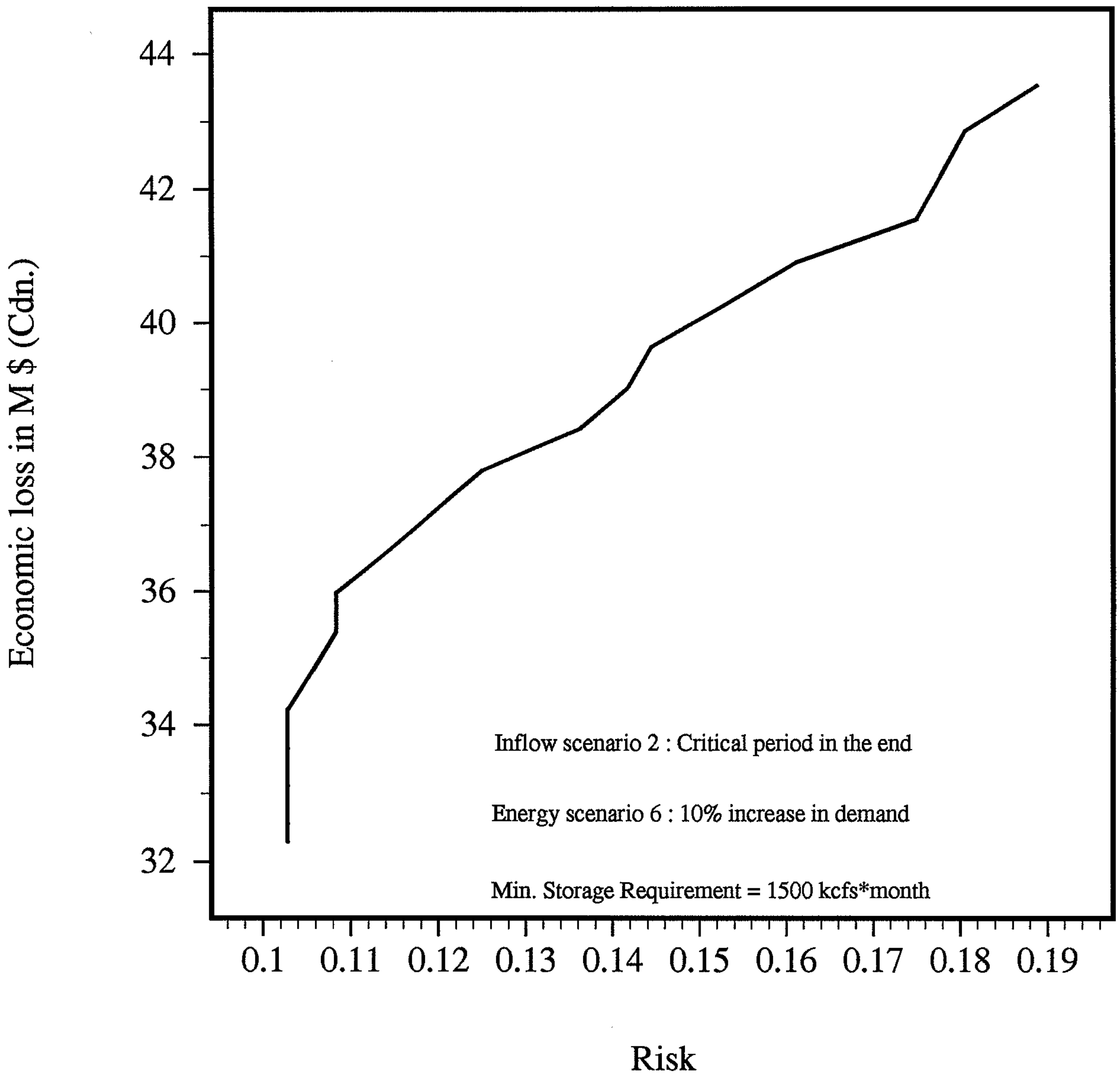


Figure 6.11. Risk-loss Function (Scenario 2:6:1500)

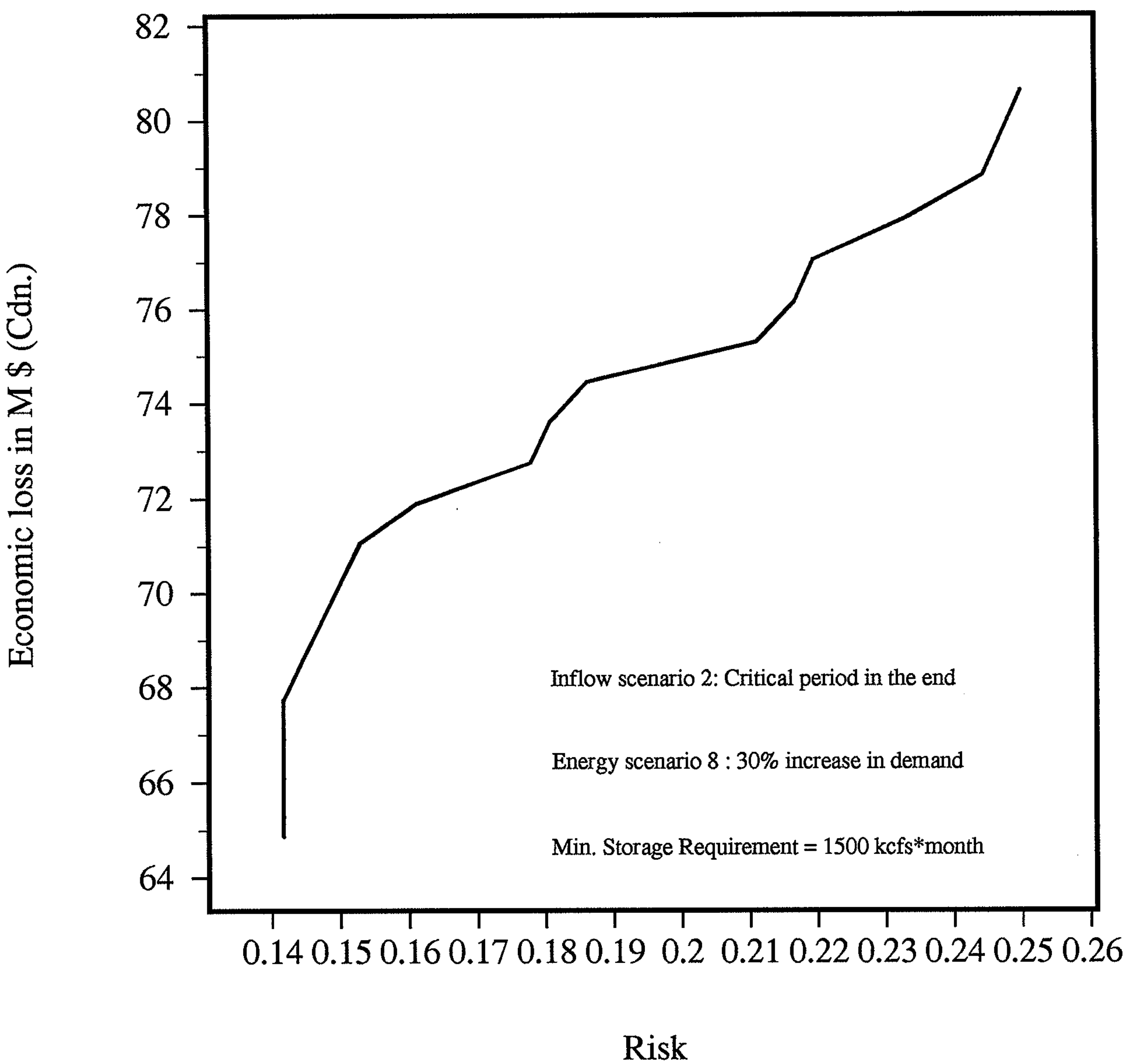


Figure 6.12. Risk-loss Function (Scenario 2:8:1500)

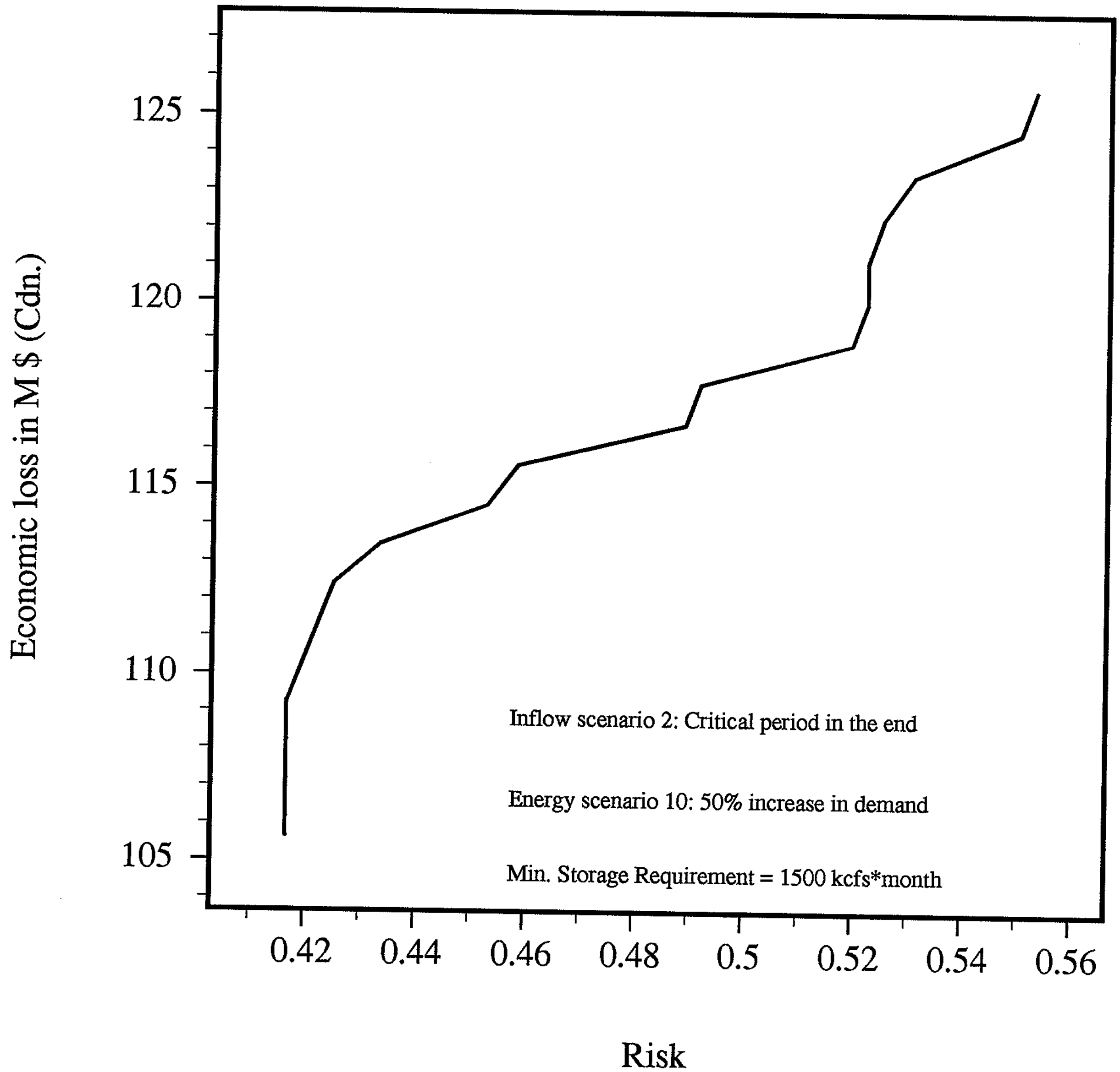


Figure 6.13. Risk-loss Function (Scenario 2:10:1500)

Some of the aforementioned scenarios are used in the reliability model, and the optimal value of the reliability of energy generation along with the benefit from end storage, and the benefit from export energy are presented in Table 6.7.

Scenario Description	*β*	*Benefit from end storage (M $ Cdn.)*	*Benefit from Export Energy*	
			Onpeak (M $ Cdn.)	*Offpeak (M$ Cdn.)*
1:1:1500	*0.9899*	*131.305*	*67.92*	*47.30*
1:2:1500	*0.9721*	*132.220*	*67.00*	*39.56*
2:6:1500	*0.8971*	*138.080*	*57.52*	*32.45*
2:8:1500	*0.8582*	*142.965*	*40.34*	*24.59*

Table 6.7. Sensitivity of the Optimal Solution to the Shape of Risk-loss Functions

As can be seen from Table 6.7, the optimal reliability level computed by the reliability model decreases with an increase in energy demand on the system. The model also reduces the export energy when a higher energy demand and/or a lower inflow situation is anticipated. Depending on the anticipated hydrologic conditions and the load growth during the planning period, the decision maker can choose a suitable risk-loss function and incorporate it in the reliability model.

6.2.4. Implementation of the Reliability Model

The probabilistic constraints corresponding to any time period t, given by Equations (3) and (8) are converted into their deterministic equivalents in the formulation of the reliability model, using the CDF of the sum of reservoir inflows up to and including the time period t. The model assumes that the reservoir inflows in consecutive months are independent of each other, and uses a simple convolution procedure to derive the CDF of the sum of inflows in those two months from their marginal PDFs. This assumption of independence between inflows in consecutive months results in ignoring the covariance component which actually exists due to the cross-correlation between the flows in those two months. Hence the variance of the parameters estimated from the CDF obtained in the 'independent' case will be smaller compared to those estimated from the CDF obtained by taking the correlation into account. Hence, the sum of future reservoir inflows is underestimated in the 'independent' case, and thus, results in a conservative operating policy for the reservoir. The only obstacle in implementing the reliability model in its present form for the operation of reservoirs is that of 'conservative planning'. Three approaches, namely, the 'Windows Approach', 'CUSUM Approach', and the 'RISKSUM Approach' are developed in this research, as discussed in Chapter 5, to alleviate the problem of 'conservative planning'.

The minimum storage requirement is set as 500 kcfs*month, and the storage in the beginning of the planning period is taken as 1400 kcfs*month.

a. Windows Approach: The problem of the decrease in the variance of the estimates due to the 'independent' assumption worsens when the number of marginal PDFs of monthly inflows involved in the convolution process increases. In the first month, the marginal CDF of that month alone is used to constrain the values of the decision variables in that month. From the results presented for the basic formulation in Table 6.3 and Figure 6.2, the values of the decision variables are: the storage in the end of first month is 1440 kcfs*month; releases from the reservoir are 142.3 and 117.0 kcfs in the onpeak and offpeak periods, respectively; export energy from the system are 502 and 486 MWh in the onpeak and offpeak periods respectively; and the spill from the reservoir is zero. These values are predominantly controlled by the constraints of the first month in which the CDF of the first month alone is used to convert the probabilistic constraints corresponding to this month to their deterministic equivalents. Hence, these values are least affected by the 'independent' assumption, and are given as the input to the second window. The planning period for the second window extends from the second through the thirteenth month (the data is assumed to be cyclic and the data for the first month is repeated for the thirteenth month). The windows are updated and continued until the policy for the twelfth month is computed with lesser influence from the 'independent' assumption. The optimal values of the benefits from the storage in the end of the planning period, the net benefits, and the benefits from export energy are given in Table 6.8.

b. CUSUM Approach: In this approach, the CDF of the sum of inflows is derived *a priori* from the historical data, and is given as an input to the reliability model. The historical inflow data for Lake Winnipeg are available for the period from 1913 to 1992. New time series data are constructed consisting of the flow in the first month alone, sum of flows in the first and second months together, and so on, from the historical data. Each of these time series data represents the sample space for the new random variables $CUSUM_1$, $CUSUM_2$, and so on. The CDFs of these random variables, which represent the sum of historical inflows, are computed using the Hydrological Frequency Analysis package [Bobee and Ashkar, 1991]. The CDFs, thus derived, are used in the reliability model and the optimal values of the benefits from end storage in the reservoir, net benefits, and benefits from export energy are computed and are shown in Table 6.8.

Approach	*Net Benefits*	*End Storage Benefits*	*Benefits from Export*		β
			Onpeak	*Offpeak*	
	M \$ Cdn.	*M \$ Cdn.*	*M \$ Cdn.*	*M \$ Cdn.*	
Independent	***1437.06***	***131.305***	***67.92***	***47.304***	***0.9899***
CUSUM	***1482.05***	***161.36***	***68.00***	***47.30***	***0.990***
Windows	***1498.55***	***185.00***	***71.20***	***48.00***	***0.990***

Table 6.8. Comparison of the Windows and CUSUM Approaches with the 'independent' case

Figure 6.14 shows a comparison of storage levels in the reservoirs using the 'independent' case, Windows Approach, and the CUSUM Approach. The results shown in Figure 6.14 and Table 6.8 reveal the importance of considering the temporal correlation between monthly inflows.

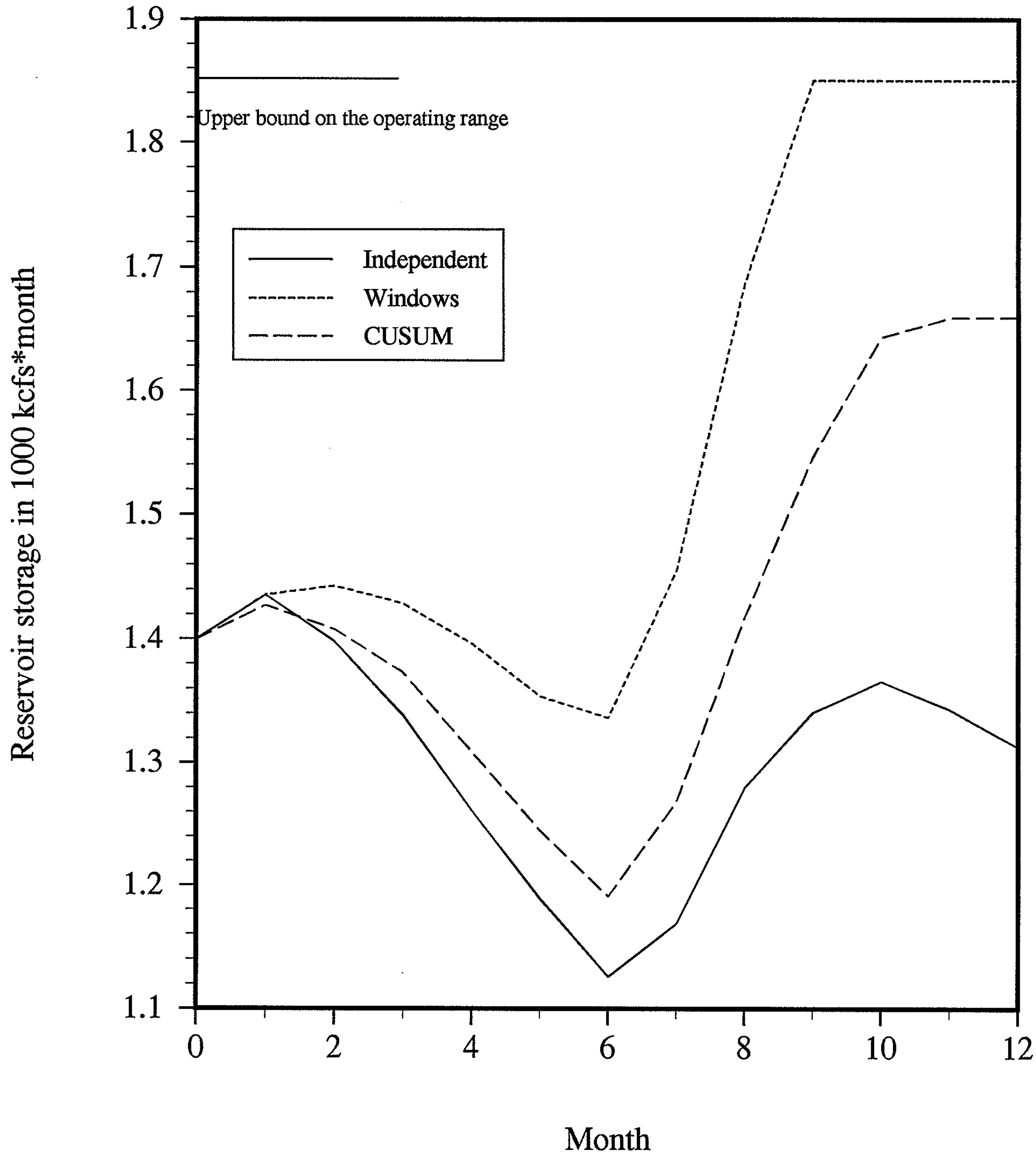


Figure 6.14. Comparison of Reservoir Storage Levels

Comparing the storage levels in the reservoir from Figure 6.14, the Windows Approach seems to overestimate the inflows into the system compared to the CUSUM Approach. However, the correlation between monthly inflows is partially built in the CUSUM Approach and the estimates from this approach are more 'reliable'.

c. *RISKSUM Approach:* This approach is similar to the CUSUM approach in which the CDF of the sum of reservoir inflows is derived *a priori*, and is given as an input to the reliability model. The marginal PDF of monthly inflows along with the cross-correlation coefficients between them are given as inputs to the *@risk* software, the decision analysis tool which is capable of simulating the distribution of the sum of correlated inputs. The Monte Carlo technique is used for sampling the correlated inputs. The tolerance level for convergence of the simulation results is specified as 1.5%, and the number of iterations in the simulation experiment is set as 3000. Due to the memory limitations of the personal computer used for simulation, the experiments could be carried out up to a maximum of 8 input variables specified with a cross-correlation matrix of size [8 * 8]. That is, the CDF of the sum of inflows up to 8 time periods could be simulated using *@risk*. Hence, a comparison of the storage levels in the reservoir computed using this approach with those obtained using other approaches could not be made. However, the CDFs of the sum of inflows up to the eighth time period obtained from the 'independent' case, the CUSUM Approach and the RISKSUM Approach are compared in Figure 6.15.

Referring to Figure 6.15, the CDFs obtained using the 'independent' assumption are shifted towards the left, thus, predicting lower inflows for the same probability level compared to the CUSUM and RISKSUM Approaches, and hence, resulting in a 'conservative operation'. Both the CUSUM and RISKSUM Approaches predict better CDFs due to the consideration of the temporal correlation between the monthly inflows. However, the correlation structure heavily influences the sampling for simulation in the RISKSUM Approach and hence it is preserved better when compared with the CUSUM Approach. So, the RISKSUM Approach will be the best choice if sufficient computational facilities are available to perform the simulation. The CUSUM Approach is the next best choice for deriving the CDFs of the sum of inflows.

The sum of inflows, as pointed out by Takeuchi [1986], is an important hydrological parameter useful for decision making especially during low flow or drought situations. However, very little research has been done on this parameter due to the statistical complexity involved in deriving the PDF of the sum of inflows. The approaches proposed in this research can easily be extended for other hydrological studies involving the sum of inflows, such as water supply reliability and water quality management.

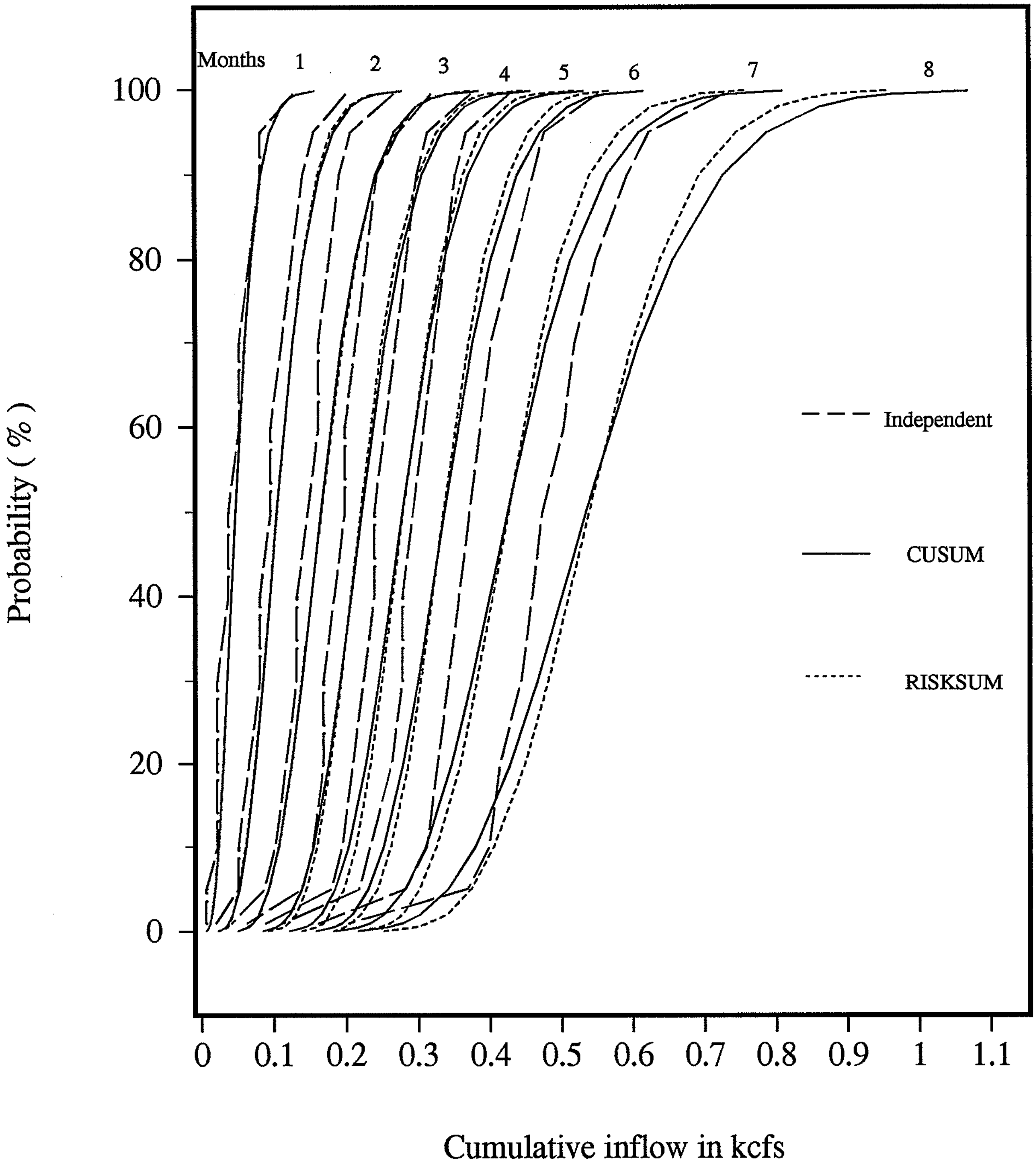


Figure 6.15. Comparison of CDFs in the 'independent', CUSUM and RISKSUM Approaches

in the reliability model leads to the underestimation of future reservoir inflows, and hence results in conservative planning. Three new approaches are proposed in this research which are shown to alleviate the problem of conservative planning, thus, making the reliability model developed in this research a robust tool for planning the sustainable operation of reservoirs for hydropower generation.

7.2. RECOMMENDATIONS

The linearization technique used in this research is quite accurate for the systems with a smaller operating range such as the case study of Manitoba Hydro. When the operating range is larger, more accurate techniques such as successive linear programming could be incorporated in the reliability model.

Application of the reliability model is demonstrated for a single reservoir in this report. However, the model can be extended for the reservoir system in which the hydrological and the generation system data for all the individual reservoirs and the generating units are available.

7.3. FUTURE WORKS

Risk assessment and management is one of the important components of sustainable development of interdisciplinary water resources systems. The capability of the reliability model to explicitly tradeoff the benefits and the costs of goal deviations, can be explored to quantify and incorporate the complex multiobjective parameters of water resources planning into a decision making framework.

The hydrological risk, quantified in this research as the inability of a reservoir(s) to provide adequate storage for energy generation in predominantly hydroelectric systems can be integrated with other uncertain parameters in a generation system such as the generating capacity, and also with alternative sources of energy such as thermal generation, in order to evaluate the overall performance of the generation system.

The methodology developed for finding the possible energy deficit in the generation system, can be combined with different cost evaluation studies to evaluate and to choose a suitable management strategy such as thermal generation, demand side management, and turbine capacity expansion.

The cumulative hydrological index, for example, the cumulative inflow in summer months, is an important parameter in many water resources studies such as water quality management, and water supply reliability during drought periods. The approaches proposed in this research, namely, CUSUM and RISKSUM can be applied to such studies to obtain and provide more information about the hydrology to the decision makers.

REFERENCES

Allen, R.B., and S.G. Bridgeman (1986), Dynamic programming in hydropower scheduling, Journal of Water Resources Planning and Management Division, American Society of Civil Engineers, 112 (3), 339-353.

Anders, G.J. (1990), Probability concepts in electric power systems, Wiley (New York).

Arunkumar, S., and W.W-G. Yeh (1973), Probabilistic models in the design and operation of a multipurpose reservoir system, Contribution 144, California Water Resources Centre, University of California, Davis, USA.

Arvaniditis, N.V., and J. Rosing (1970 a), Composite representation of a multireservoir hydroelectric power system, IEEE Transactions on Power Apparatus and Systems, PAS-89 (2), 319-326.

Arvaniditis, N.V., and J. Rosing (1970 b), Optimal operation of multireservoir systems using a composite representation, IEEE Transactions on Power Apparatus and Systems, PAS-89 (2), 327-335.

Askew, A.J. (1974), Optimum reservoir operating policies and the imposition of a reliability constraint, Water Resources Research, 10 (1). 51-56.

Bechard, D.I., I. Corbu, R. Gagnon, G.A. Nix, L.E. Parker, K. Stewart, and M. Trinh (1981), The ottawa river regulation modeling systems (ORRMS), Proceedings of the International Symposium on Real-Time Operation of Hydrosystems, University of Waterloo, Ontario,Volume 1, 179-198.

Beveridge, G.S.G., and R.S. Schechter (1970), Optimization: Theory and practice , McGraw Hill Book Company, 453-456.

Bharathi, D.B., and V.V.S. Sarma (1985), Estimation of fuzzy memberships for histograms, Information Sciences, 43-59.

Billinton, R., and R. Allan (1984), Reliability evaluation of power systems, Plenum Press, New York, 1984.

Billinton, R., G. Wacker and G. Tollefson (1992), Worth of power system reliability, Workshop report of Power Systems Research Group, University of Saskatchewan, Canada.

Billinton, R., G. Wacker, and G. Tollefson (1993), Assessment of reliability worth in electric power systems in Canada, Report prepared by the Power Systems Research Group, University of Saskatchewan, Canada.

Bobee, B., and F. Ashkar (1991), The gamma family and derived distributions applied in hydrology, Water Resources Publications, Water Resources Centre, Fort Collins, USA.

Bogardi, I., A. Bardossy, and L. Duckstein (1983), Regional management of an aquifer for mining under fuzzy environmental objectives, Water Resources Research, 19(6), 1394-1402.

Boshier, J.F., and E.G. Read (1981), Stochastic single reservoir models for long term scheduling of hydrothermal power systems, Planning division internal report, Planning Division, New Zealand, Ministry of Energy, Wellington.

Braga, B.P.F., W.W-G. Yeh, L. Becker, and M.T.L. Burrows (1991), Stochastic optimization of multiple-reservoir-system operation, Journal of Water Resources Planning and Management Division, ASCE, 117 (4), 471-481.

Bras, R.L., R.B. Buchanan, and K.C. Curry (1983), Real time adaptive closed loop control of reservoirs with the high aswan dam as a case study,Water Resources Research, 19 (1), 33-52.

Breipohl, A., F.N. Lee, J. Huang, and Q. Feng (1990), Sample size reduction in stochastic production simulation, IEEE/ Power Engineering Society 1990 Winter Meeting, Paper 90, WM 122-2 PWRS.

Bryson, A.E. Jr., and Y.C. Ho (1975), Applied optimal control, John Wiley, New York.

Buras, N. (1963), Conjunctive operation of dams and aquifers, Journal of Hydraulics Division, ASCE, 89 (HY6), 111-131.

Can, E.K., M.H. Houck, and G.H. Toebes (1982), Optimal real-time reservoir systems operation: Innovative objectives and implementation problems, Purdue University Water Resources Research Centre, Technical Report No. 150.

Caselton, W.F., and S.O. Russell (1976), Long-term operation of storage hydro projects, Journal of Water Resources Planning and Management Division, ASCE, 102 (WR1), 163-176.

Christensen, G.S., and S.A. Soliman (1987), On the application of functional analysis to the optimization of the production of hydroelectric system, IEEE Transactions on Power Systems, PWRS-2 (4).

Chu, K.C.H. (1994), Estimating the worth of reliability using customer interruption costs, Internal report of Manitoba Hydro.

Colorni, A., and G. Fronza (1976), Reservoir management via reliability programming, Water Resources Research, 12 (1), 85-88.

Curry, A.T., R.E. Kalaba, and K. Spingarn (1973), Chance-constrained model of system of reservoirs, Journal of Hydraulics Division, ASCE, 99, HY12, 2353-2366.

Daellenbach, H.G., and E.G.Read (1976), Survey on optimization for the long-term scheduling of hydro-thermal power systems, presented to the ORSNZ Conference, New Zealand.

Dagli, C.H., and J.F. Miles (1980), Determining operating policies for a water resource system, Journal of Hydrology, 47 (34), 297-306.

Draper, D.W., and K. Adamowski (1976), Application of linear programming optimization to a northern ontario hydropower system, Canadian Journal of Civil Engineering, 3 (1), 20-31.

Dreyfus, S.E., and A.M. Law (1977), The art and theory of dynamic programming, Academic press, Orlando, Florida.

Druce, D.J. (1990), Incorporating daily flood control objectives into a monthly stochastic dynamic programming model for a hydroelectric complex, Water Resources Research, 26 (1). 5-11.

Ellis, J.H., and C.S. ReVelle (1988), A separable linear algorithm for hydropower optimization, Water Resources Bulletin, 24 (2), 435-447.

Freeling, A.N.S. (1980), Fuzzy sets and decision analysis, IEEE Transactions on Systems, Man, and Cybernetics, SMC-10(7), 341-354.

Friedman, R., C. Ansell, S. Diamond, and Y.Y. Haimes (1984), The use of models for water resources management, planning, and policy, Water Resources Research, 20 (7), 793-802.

Georgakakos, A.P. (1993), Operational trade-offs in reservoir control, Water Resources Research, 29 (11), 3801-3819.

Georgakakos, A.P., and D.H. Marks (1987), A new method for the real-time operation of reservoir systems, Water Resources Research, 23 (7), 1376-1390.

Georgakakos, A.P., and H. Yao (1993), New control concepts for uncertain water resources systems, 1. Theory, Water Resources Research, 29 (6), 1505-1516.

Gjelsvik, A. (1982), Stochastic seasonal planning and multireservoir hydroelectric power systems by differential dynamic programming, Model Identification Control of Environmental Systems, 3 (3), 131-149.

Grygier, J.C., and J.R. Stedinger (1985), Algorithms for optimizing hydropower system operation, Water Resources Research, 21 (1), 1-10.

Gustafsson, L. (1968), Optimization of the production in a hydro-thermal power system, Paper presented at the VII World Power Conference, Moscow.

Hall, W.A., and T.G. Roefs (1966), Hydropower project output optimization, Journal Power Division, ASCE, 92 (PO1), 67-79.

Hanscom, M.A., L. Lafond, L. Lasdon, and G. Pronovost (1980), Modelling and resolution of the midterm generation planning problem for a large hydroelectric system, Management Science, 26 (7), 659-668.

Heidari, M., V.T. Chow, P.V. Kokotovic, and D.D. Meredith (1971), Discrete differential dynamic programming approach to water resources systems optimization,Water Resources Research, 7 (2), 273-282.

Hogan, A.J., J.G. Morris, and H.E. Thompson (1981), Decision problems under risk and chance constrained programming: Dilemmas in the transition, Management Science, 27 (6), 698-716.

Houck, M.H., J.L. Cohon, and C.S. ReVelle (1980), Linear decision rule in reservoir design and management, 6. Incorporation of economic efficiency benefits and hydroelectric energy generation, Water Resources Research, 16 (1), 196-200.

IEEE Committee Report (1975), Definitions of customer and load reliability indices for evaluating electric power system performance, IEEE PES Summer Meeting, Paper No: A 75 588-4.

Ikura, Y., and G. Gross (1984), Efficient large-scale hydro system scheduling with forced spill conditions, Paper presented at the Winter meeting of IEEE Power Engineering Society, Dallas, Texas.

IMSL (1987), Math/ Library, FORTRAN Subroutines for Mathematical Applications, IMSL Problem-Solving Software Systems, Version 1.0.

Jacobson, D., and D. Mayne (1970), Differential dynamic programming, Elsevier, New York.

Kaplan, S., and B.J. Garrick (1981), On the quantitative definition of risk, Risk Analysis, 1 (1), 11-27.

Karamouz, M., and M.H. Houck (1987), Comparison of stochastic and deterministic dynamic programming for reservoir operating rule generation, Water Resources Bulletin, 23 (1), 1-9.

Karamouz, M., and H.V. Vasiliadis (1992), Bayesian stochastic optimization of reservoir operation using uncertain forecasts, Water Resources Research, 28 (5). 1221-1232.

Kelman, J., J.R. Stedinger, L.A. Cooper, E. Hsu, and S-Q. Yuan (1990), Sampling stochastic dynamic programming applied to reservoir operation, Water Resources Research, 26 (3), 447-454.

Labadie, J.W., R.C. Lazaro, and D.M. Morrow (1981), Worth of short-term rainfall forecasting for combined sewer overflow control, Water Resources Research, 17 (5), 1489-1497.

Lalonde, R. (1993), Energy reliability planning for a hydroelectric power system, Presentation material for the workshop on 'Planning and operating electrical power systems with energy uncertainty', Canadian Electrical Association.

Larson, R.E., and W.G. Keckler (1969), Applications of dynamic programming to the control of water resources systems, Automatica, 5 (1), 15-26.

Li, C-A., R. Yan, and J-Y. Zhou (1990), Stochastic optimization of interconnected multireservoir power systems, IEEE Transactions on Power Systems, 5 (4), 1487-1496.

Little, J.D.C. (1955), The use of storage water in a hydroelectric system, Journal of Operations Research Society of America, 3, 187-197.

Loaiciga, H.A., and M.A. Marino (1985), An approach to parameter estimation and stochastic control in water resources with an application to reservoir operation, Water Resources Research, 21 (11), 1575-1584.

Loucks, D.P., and O.T. Sigvaldason (1982), Multiple-reservoir operation in north america, Operation of Multiple Reservoir Systems, edited by Z.Kaczmarek and J.Kindler, International Institute for Applied Systems Analysis, Laxenburg, Austria.

Loucks, D.P., J.R. Stedinger, and D.A. Haith (1981), Water resource systems planning and analysis, Prentice Hall, Englewood Cliffs, NY, USA.

Lund, J.R. (1995), Derived estimation of willingness to pay to avoid probabilistic shortage, Water Resources Research, 31(5), 1367-1372.

Manitoba Hydro (1990), Report for the Public Utilities Board in respect of Major Capital Projects.

Manitoba Hydro (1993), System Load Forecast 1992/93 to 2012-13, Report No. CP93-2A, Winnipeg, MB, Canada.

Marino, M.A., and H.A. Loaiciga (1985 a), Dynamic model for multireservoir operation, Water Resources Research, 21 (5), 619-630.

Marino, M.A., and H.A. Loaiciga (1985 b), Quadratic model for reservoir management: Application to the Central Valley Project, Water Resources Research, 21 (5), 631-641.

McLaughlin, D., and H.L. Velasco (1990), Real-time control of a system of large hydropower reservoirs, Water Resources Research, 26 (4), 623-635.

Mizyed, N.R., J.C. Loftis, D.G. Fontane (1992), Operation of large multireservoir systems using optimal-control theory, Journal of Water Resources Planning and Management Division, ASCE, 118 (4), 371-387.

Murray, D.M., and S.J. Yakowitz (1979), Constrained differential dynamic programming and its application to multireservoir control, Water Resources Research, 15 (5), 1017-1027.

Murtagh, B.A., and M.A. Sanders (1980), MINOS/ Augmented Users Manual, Technical Report SOL 80-14, Systems Optimization Laboratory, Stanford University.

Nardini, A., and D. Montoya (1995), Remarks on a min-max optimization technique for the management of a single multiannual reservoir aimed at hydroelectric generation and water supply, Water Resources Research, 31 (4), 1129-1135.

Neto, T.R.A., M.V.F. Pereira, and J. Kelman (1985), A risk-constrained stochastic dynamic programming approach to the operation planning of hydrothermal systems, IEEE Transactions on Power Apparatus Systems, PAS-104 (2), 273-279.

Neudorf, E.G., D.L. Kiguel, G.A. Hamoud, B. Porretta, W.M. Stephenson, R.W. Sparks, D.M. Logan, M.P. Bhavaraju, R. Billinton, and D.L. Garrison (1995), Cost-benefit analysis of power system reliability: two utility case studies, IEEE Transactions on Power Systems, 10(3), 1667-1675.

Nopmongcol, P., and A.J. Askew (1976), Multi-level incremental dynamic programming, Water Resources Research, 12 (6), 1291-1297.

Palicios-Gomez, F., L. Lasdon, and M. Engquist (1982), Nonlinear optimization by successive linear programming, Management Science, 28 (10), 1106-1120.

Paudyal, G.N., D.L. Shrestha, and J.J. Bogardi (1990), Optimal hydropower system configuration based on operational analysis, Journal of Water Resources Planning and Management Division, ASCE, 116 (2), 233-246.

Pereira, M.V.F., and L.M.V.G.Pinto (1983), Application of decomposition techniques to the mid-and short-term scheduling of hydrosystems, IEEE Transactions on Power and Apparatus Systems, PAS-102 (11), 3611-3618.

Pereira, M.V.F., and L.M.V.G. Pinto (1985), Stochastic optimization of a multireservoir hydroelectric system : A decomposition approach, Water Resources Research, 21 (6), 779-792.

Pereira, M.V.F., M.E. Maceira, G.C. Oliveira, and L.M.V.G. Pinto (1992), Combining analytical models and monte carlo techniques in probabilistic power system analysis, IEEE Transactions on Power Systems, 7 (1), 265-272.

Personal Communication (1994), Discussions with technical staff from Manitoba Hydro.

ReVelle, C., E. Joeres, and W. Kirby (1969), The linear decision rule in reservoir management and design, 1. Development of the stochastic model, Water Resources Research, 5 (4), 767-777.

Reznicek, K.K., and S.P. Simonovic (1990), An improved algorithm for hydropower optimization, Water Resources Research, 26 (2), 189-198.

Rogers, P.P., and M.B. Fiering (1986), Use of systems analysis in water management, Water Resources Research, 22 (9), 146S-158S.

Rosen, J.B. (1960), The gradient projection method for nonlinear programming; 1. Linear constraints, Journal of Society of Industrial Applications Mathematics, 8 (1), 181-217.

Rosenthal, R.D. (1980), The status of optimization models for the operation of multireservoir systems with stochastic inflows and nonseparable benefits, Report 75, Tennessee Water Resources Centre, Knoxville.

Rosenthal, R.D. (1981), A nonlinear network flow algorithm for maximization of benefits in a hydroelectric power system, Operations Research, 29 (4), 763-786.

Rossman, L.A. (1977), Reliability-constrained dynamic programming and randomized release rules in reservoir management, Water Resources Research, 13 (2), 247-255.

Saad, M., and A. Turgeon (1988), Application of principal component analysis to long-term reservoir management, Water Resources Research, 24 (7), 907-912.

Saad, M., A. Turgeon, P. Bigras, and R. Duquette (1994), Learning disaggregation technique for the operation of long-term hydroelectric power systems, Water Resources Research, 30 (11), 3195-3202.

Saaty, T.L. (1977), A scaling method for priorities in hierarchical structures, Journal of Mathematical Psychology, 15, 234-281.

Sabet, M.H., and J.Q. Coe (1986), Models for water and power scheduling for the california state water project, Water Resources Bulletin, 22 (4), 587-596.

Sakawa, M., H. Yano, and T. Yumine (1987), An interactive fuzzy satisficing method for multiobjective linear programming problems and its application, IEEE Transactions on Systems, Man, and Cybernetics, SMC 17(4), 654-661.

Schweppe, F. (1973), Uncertain dynamic systems, Prentice-Hall, Englewood Cliffs, New Jersey.

Sengupta, J. U. (1972), Stochastic programming methods and applications, North-Holland, Amsterdam.

Sherkat, W.R. (1990), Discussion on 'Stochastic optimization of interconnected multireservoir power systems - Li et al.', IEEE Transactions on Power systems, 5 (4), 1495.

Sigvaldason, O.T. (1976), A simulation model for operating a multipurpose multireservoir system, Water Resources Research, 12 (2), 263-278.

Simonovic, S.P., and M.A. Marino (1980), Reliability programming in reservoir management, 1.Single multipurpose reservoir, Water Resources Research, 16 (5), 844-848.

Simonovic, S. P., and M. A. Marino (1981), Reliability programming in reservoir management, 2. Risk-loss functions, Water Resources Research, 17 (4), 822-826.

Simonovic, S. P., and M. A. Marino (1982), Reliability programming in reservoir management, 3. System of multipurpose reservoirs, Water Resources Research, 18 (4), 735-743.

Simonovic, S.P., and G.T. Orlob (1984), Risk-reliability programming for optimal water quality control, Water Resources Research, 20 (6), 639-646.

Simonovic, S. P., and R. Srinivasan (1993), Explicit stochastic approach for planning the operation of reservoirs for hydropower production, IAHS Publication No: 213, Extreme Hydrological Events: Precipitation, Floods and Droughts, 349-360.

Sniedovich, M. (1979), Reliability-constrained reservoir control problems 1. Methodological issues, Water Resources Research, 15 (6), 1574-1582.

Sniedovich, M. (1980), Analysis of a chance-constrained reservoir control model, Water Resources Research, 16 (5), 849-854.

Srinivasan, R., and S.P. Simonovic (1994 a), Incorporating uncertainty in energy demand in a reservoir reliability planning model, Effective Environmental Management for Sustainable Development, Volume 4 of the Proc. on 'Stochastic and Statistical Methods in Hydrology and Environmental Engineering,' Kluwer Academic Publishers, 397-409.

Srinivasan, R., and S.P. Simonovic (1994 b), A reliability programming model for hydropower optimization, Canadian Journal of Civil Engineering, 21, 1061-1073.

Srinivasan, R., H.M. Surminski, and S.P. Simonovic (1995), Practical application of reliability programming model to hydropower planning, Accepted for publication in the Special issue of Journal of Water Resources Planning and Management, ASCE.

Stedinger, J.R., B.F. Sule, and D.P. Loucks (1984), Stochastic dynamic programming models for reservoir operation optimization, Water Resources Research, 20 (11), 1499-1505.

Strycharczyk, J.B., and J.R. Stedinger (1987), Evaluation of a 'reliability programming' reservoir model, Water Resources Research, 23 (2), 225-229.

Takeuchi, K., and D.H. Moreau (1974), Optimal control of multi-unit interbasin water resource system, Water Resources Research, 10 (3), 407-414.

Takeuchi, K. (1986), Chance-constrained model for real-time reservoir operation using drought duration curve, Water Resources Research, 22 (2), 551-558.

Tanaka, H., T. Okuda, and K. Asai (1974), On fuzzy-mathematical programming, Journal of Cybernetics, 3 (4), 37-46.

TVA (1976), Tennessee Valley Authority Water Resource Management Methods Staff, Weekly release scheduling by REDGRAD, Report B-27, Knoxville.

Tejada-Guibert, J.A., J.R. Stedinger, and K. Staschus (1990), Optimization of value of CVP's hydropower production, Journal of Water Resources Planning and Management Division, ASCE, 116 (1), 52-70.

Terry, L.A., M.V.F. Pereira, T.A. Araripe Neto, L.F.C.A. Silva, P.R.H. Sales (1986), Coordinating the energy generation of the brazilian national hydrothermal electrical generating system, Interfaces, 16 (1), 16-38.

Toebes, G.H., M.H.Houck, and H. Yazicigil (1981), Difficulties in using dynamic programming for real-time operations that use forecasting, Proc. of the International Symposium on 'Real-Time Operation of Hydrosystems,' University of Waterloo, Canada.

Trezos, T., and W.W-G. Yeh (1987), Use of stochastic dynamic programming for reservoir management, Water Resources Research, 23 (6), 983-996.

Turgeon, A. (1980), Optimal operation of multireservoir power systems with stochastic inflows, Water Resources Research, 16 (2), 275-283.

Turgeon, A. (1981), Optimum short-term hydro scheduling from the principle of progressive optimality, Water Resources Research, 17 (3), 481-486.

Valdes, J.B., J.M-D. Filippo, K.M.Strzepek, and P.J. Restrepo (1992), Aggregation-disaggregation approach to multireservoir operation, Journal of Water Resources Planning and Management Division, ASCE, 118 (4), 423-444.

Vasiliadis, H.V., and M. Karamouz (1994), Demand-driven operation of reservoirs using uncertainty based optimal operating policies, Journal of Water Resources Planning and Management Division, ASCE, 120 (1). 101-114.

Wacker, G., R.K. Subramaniam, and R. Billinton (1984), Using cost of electric service interruption surveys in the determination of a composite customer damage function, Proceedings of the International Association of Science and Technology for Development (IASTED), Energy Symposia, San Francisco, CA, USA.

Wasimi, S.A., and P.T. Kitanidis (1983), Real-time forecasting and daily operation of a multireservoir system during floods by linear quadratic gaussian control, Water Resources Research, 19 (6), 1511-1522.

Yakowitz, S. (1982), Dynamic programming applications in water resources, Water Resources Research, 18 (4), 673-696.

Yao, H., and A.P. Georgakakos (1993), New control concepts for uncertain water resources systems, 2. Reservoir management, Water Resources Research, 29 (6), 1517-1526.

Yeh, W. W-G. (1985), Reservoir management and operation models: A state of-the-art review, Water Resources Research, 21 (12), 1797-1818.

Young, G.K. (1967), Finding reservoir operating rules, Journal of Hydraulic Division, ASCE, 93 (HY6), 297-321.

Zadeh, L.A. (1965), Fuzzy sets, Information and Control, 8 , 338-353.

Zimmermann, H.-J. (1988), Fuzzy set theory and its applications, Kluwer-Nijhoff Publishing Inc.

APPENDIX A : Transformation of Chance Constraints into Deterministic Equivalents

This section details the description about transforming the probabilistic constraints into their deterministic equivalents. Recalling from Section 3.1, the reliability model is developed from the continuity equation:

$$S_t = S_{t-1} + I_t - R_t - SP_t \tag{84}$$

The probabilistic constraint written for flood control in the first time period is:

$$P\,(\ S_1 \le S_{max} - \theta_1\ ) \ge \alpha \tag{85}$$

Substituting (84) in (85) yields,

$$P\ (\ S_0 + I_1 - R_1 - SP_1 \le S_{max} - \theta_1\ ) \ge \alpha \tag{86}$$

Since I_1 is a random variable, (86) is rewritten as,

$$P\ (\ I_1 \le S_{max} - \theta_1 - S_0 + R_1 + SP_1\ ) \ge \alpha \tag{87}$$

The probabilistic constraint for the second time period is,

$$P\,(\ S_2 \le S_{max} - \theta_2\ ) \ge \alpha \tag{88}$$

Rewriting S_2 in terms of S_1 using Equation (84), and then expressing S_1 in terms of S_0, Equation (88) is rewritten as:

$$P\ (\,(\,I_1 + I_2\,) \le S_{max} - \theta_2 - S_0 + (\,R_1 + R_2\,) + (\,SP_1 + SP_2\,)\,) \ge \alpha \tag{89}$$

Similarly, for time period t ,

$$P\ \left(\sum_{1}^{t} I_t \ \leq\ S_{\max} - \theta_t - S_0 + \sum_{1}^{t} R_t + \sum_{1}^{t} SP_t\right)\ \geq\ \alpha \qquad \textbf{(90)}$$

Referring to Figure 3.5 in Chapter 3, the above probabilistic constraint can be satisfied when,

$$S_{\max} - \theta_t - S_{t-1}^{avg} + \sum_{ls=1}^{nsl} R_t^{ls} + SP_t \geq F_{\Sigma t}^{-1}(\alpha) \qquad \forall\, t \qquad \textbf{(91)}$$

where $F_{\Sigma t}^{-1}(.)$ is the inverse value of the CDF of the sum of inflows up to and including time period t .

APPENDIX B: Basics of Fuzzy Set Theory

B.1. CONCEPT OF FUZZINESS

A few concepts of fuzzy set theory which will be used in formulating the fuzzy version of the reliability model are introduced in this section. For more details, the reader is referred to Zadeh [1965] and Zimmermann [1988].

Theory of fuzzy sets is basically a theory of graded concepts. A central concept is that it is permissible for an element to belong partly to a fuzzy set. Let X be a space of points or objects, with a generic element of X denoted by x. Thus X = {x}.

a. Fuzzy set: Let $x \in X$. A fuzzy set A in X is characterized by a membership function (referred to as MSF) $\mu_A(x)$ which associates with each point in X, a real number in the interval [0,1], with the value of $\mu_A(x)$ at x representing the 'grade of membership' of x in A. Thus, the nearer the value of $\mu_A(x)$ to *one*, the higher the grade of belongingness of x in A.

In classical (crisp) set theory, $\mu_A(x)$ takes only two values *one* or *zero* depending on whether the element belongs or does not belong to the set A.

Therefore, if X = {x} is a collection of objects denoted generically by x, then a fuzzy set A in X is a set of ordered pairs,

$$A = [\, x, \mu_A(x)], \qquad x \in X \tag{92}$$

where $\mu_A(x)$ maps X to the membership space [0,1]. Because fuzzy sets are represented by their respective MSF's, these two terms are considered equivalent and are referred to interchangeably.

b. Union of fuzzy sets: Union of two fuzzy sets A and B with corresponding MSF's, $\mu_A(x)$ and $\mu_B(x)$ is a fuzzy set C whose MSF is given by:

$$\mu_C\,(x) \;=\; Max\;[\;\mu_A\,(x),\;\mu_B\,(x)\;], \qquad x \in X \tag{93}$$

c. Intersection of fuzzy sets: Intersection of two fuzzy sets A and B with corresponding MSF's $\mu_A(x)$ and $\mu_B(x)$ is a fuzzy set C whose MSF is given by:

$$\mu_C\,(x) \;=\; Min\;[\;\mu_A\,(x),\;\mu_B\,(x)\;], \qquad x \in X \tag{94}$$

In the following subsections, a classical LP model is taken and the formulation of the fuzzy version of this model will be dealt with; a methodology will be proposed for deriving the membership function for the energy demand; and the basic formulation of the reliability model will be modified.

B.2. FUZZY VERSION OF A CLASSICAL LP MODEL

All the constraints and the objective function of the basic reliability model are either linear or linearized ones. Incorporation of energy demand as a fuzzy variable, thus, results in a fuzzified version of this LP model, which could be solved using a fuzzy LP approach. Conceptual formulation of the fuzzy LP proposed by Tanaka et al. [1974], and developed by Zimmermann [1988], is briefly described here.

The classical LP model characterized by its feasible region in the decision space (defined by the constraints) and the goal (specified by the objective function), may be stated as follows:

$$\textit{Maximize} \qquad z = c^T . x \tag{95}$$

subject to

$$A . x \leq b \tag{96}$$

$$D . x \leq b' \tag{97}$$

$$x \geq 0 \tag{98}$$

where X is a given space of alternatives, x $\in$ (X = DOM^n); c $\in$ DOM^n ; b and b' $\in$ DOM^m ; A and D are the coefficient matrices such that A, D $\in$ $DOM^{m,n}$; DOM^k, k -dimensional real space; *DOM* denotes the *domain*; *n* is the number of decision variables; and *m* is the number of constraints. According to this formulation, the violation of any constraint renders the solution infeasible. Also, it should be noted that the solution to this problem lies in the corner of the feasible region, that is, the intersection of the two or more constraints and the objective function.

If it is assumed that decision making (modelled by LP) has to be made in a fuzzy environment, and both objective function and constraints become ambiguously defined (with vague boundaries), the problem can be reformulated in terms of the fuzzy set theory. The objective function and constraints may be represented, then, by fuzzy sets with their corresponding MSF's and there is a standard algorithm proposed by Zimmermann [1988] to solve this symmetric problem. It should be noted that the LP formulation requires that all MSF's of the fuzzy objective function and fuzzy constraints are given in linear form.

In practice, it is very rare that the objective function is initially expressed in fuzzy terms. Usually, a decision maker wants the objective function maximized or minimized, subject to the set of constraints, where some of them (say, the set of constraints defined by Equation (97)) are well defined and some (say, the set of constraints defined by Equation (96)) are vaguely defined. Accordingly, the roles of objective function and fuzzy constraints are different and the symmetric approach is not applicable. In order to make the problem symmetric again, the following transformation procedure is proposed by Zimmermann [1988], to normalize the MSF of the original objective function:

$$\mu_{OF}(x) = \begin{cases} 1 & f_o \le c^T . x \\ \dfrac{c^T . x - f_1}{f_0 - f_1} & f_o < c^T . x < f_1 \\ 0 & c^T . x \le f_1 \end{cases} \qquad \textbf{(99)}$$

where μ_{OF} is the MSF of the fuzzified objective function $f(x)$, f_o is the optimal solution of the standard LP problem without any allowed violation of the original constraint set (96), and f_l is the optimal solution of the relaxed standard LP problem with introduced relaxation terms $\mathbf{p}_i$'s on the constraint set (96):

$$f_1 = \mathit{Maximize} \;\; f(x) \qquad \textbf{(100)}$$

subject to:

$$(A . x)_i \le b_i + p_i \qquad i=1,2,...,m \qquad \textbf{(101)}$$

along with other constraint sets given by Equations (97) and (98).

Graphical representation of the MSF of the objective function is given in Figure

B.1. Due to the transformation, the problem is symmetric with respect to the objective function and constraints. Its equivalent crisp LP formulation (which will be dealt within detail, in section 3.2.2.3) may be obtained, following Zimmermann [1988], by introducing a new variable λ :

$$\textit{Maximize} \qquad \lambda \tag{102}$$

subject to:

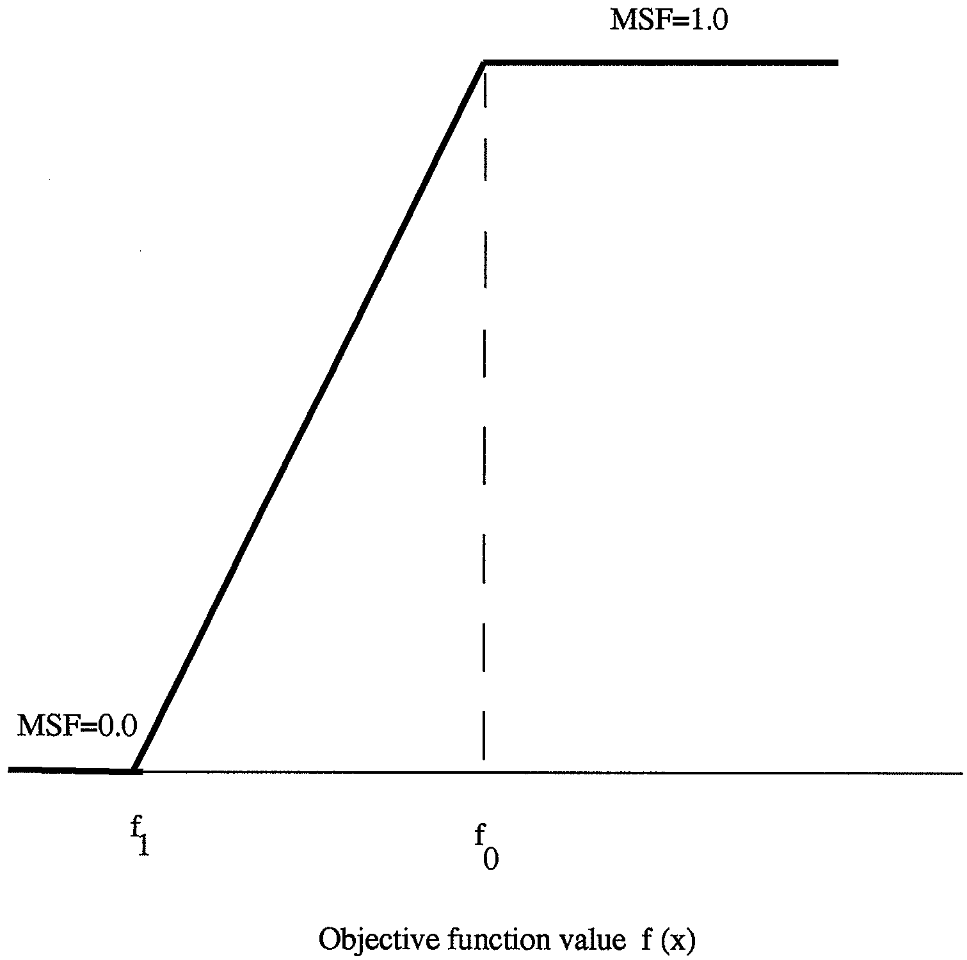
$$\lambda\ (f_o - f_1) - c^T . x \ \leq \ -f_1 \tag{103}$$

$$\lambda\ .\ p_i - (A\ .\ x)_i \ \leq \ p_i - b_i \qquad\qquad i=1,2,\ldots,m \tag{104}$$

$$0 \ \leq \ \lambda \ \leq \ 1 \tag{105}$$

along with other constraint sets given by Equations (97) and (98).

This is the fuzzy formulation of the classical LP model, and requires the MSFs of the fuzzy variables to derive the final formulation.



B.1. Membership Function for the Objective Function

APPENDIX C: Probability Density Functions of Monthly Reservoir Inflows

The distributions that fit the reservoir inflow data of Lake Winnipeg are presented in Table C.1 for all the twelve time periods in the planning period along with the method of estimating the parameters of the distribution.

Month	*Distribution*	*Method of Estimation*
October	$\Gamma(4.36,11.42)$	*Method of Moments*
November	$\Gamma(7.47,7.82)$	*Method of Moments*
December	$\Gamma(12.49,4.92)$	*Method of Moments*
January	$\Gamma(14.99,3.76)$	*Method of Moments*
February	$\Gamma(20.38,2.77)$	*Method of Moments*
March	$\Gamma(16.49,3.55)$	*Method of Moments*
April	$\Gamma(6.34,14.27)$	*Maximum Likelihood*
May	$\Gamma(5.09,22.30)$	*Method of Moments*
June	$\Gamma(7.28,14.95)$	*Method of Moments*
July	$\Gamma(6.29,14.20)$	*Method of Moments*
August	$\Gamma(3.80,13.45)$	*Method of Moments*
September	$\Gamma(2.99,14.31)$	*Method of Moments*

Table C.1. PDFs of Monthly Reservoir Inflows