AN INTELLIGENT DECISION-SUPPORT SYSTEM AND USE OF FUZZY SETS FOR RESERVOIR ANALYSIS

by

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A Thesis
presented to the University of Manitoba
in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy
in the Department of Civil Engineering

Winnipeg, Manitoba

October, 1990

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ISBN 0-315-71926-5

Canada

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A thesis submitted to the Faculty of Graduate Studies of the University of Manitoba in partial fulfillment of the requirements of the degree of

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ACKNOWLEDGEMENTS

The author wishes to express his sincere thanks to his advisor, Dr. Slobodan Simonovic, for his support throughout this research program and the preparation of the thesis. His guidance, advice, encouragement, and thoroughness are greatly appreciated. In addition, the author also thanks Dr. Caspar Booy, Dr. Ian Goulter, Dr. Donald Burn, and Dr. Witold Pedrycz who gladly obliged to serve on his advisory committee. Their valuable comments and helpfulness during the research program and, equally important, during lectures and informal discussions, are gratefully acknowledged.

A special thanks to the many students and faculty members, who were constantly offering support and encouragement.

Financial assistance for this research was provided by Natural Sciences and Engineering Research Council of Canada (NSERC), operating grant OGP0004416, and is gratefully acknowledged.

Appreciation is extended to Dr. J. Stedinger for the source codes and data for ILP and SDP models developed at Cornell University. The author also thanks Mr. K. Reznicek for the data, reports, source code, and personal observations about the EMSLP model developed at University of Manitoba.

Finally, to the author's family, a special note of thanks for their support and encouragement.

ABSTRACT

Use of mathematical models in water resource management has been plagued in the past by the lack of communication, understanding, and involvement of managers in the model development. Interactive modelling methods give managers an appropriate role in model use, calibration, and verification. This thesis extends the idea of interactive reservoir modelling using the engineering expert system approach. An advisory tool, REZES, which is developed using this approach, integrates formal reservoir models with reservoir expertise for making both numerical and logical inferences. This integration required special treatment, programming skills, and representations. Most of the objective functions and constraints employed in existing formal reservoir models, deterministic or stochastic in nature, are clear-cut, easy to formulate, and non-controversial. The presence of situations, characterized by lack of economic data and the involvement of a human factor, do not permit easy and correct system representations within the limits set up by existing models. With that difficulty in mind, a new approach is proposed for handling the uncertainty that is not statistical or random in nature. Fuzzy set theory is used to represent the imprecision which surrounds the probabilities and utilities in chance-constrained reservoir operation modelling. A new chance-constrained reservoir model is theoretically developed and encoded using this approach. Finally, this new model is added to the set of formal reservoir models within REZES.

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CHAPTER 1.

INTRODUCTION

1.1. GENERAL

The transformation of water regime by reservoir storage is used for regulating natural streams instead of adjusting water demands to unregulated random inflows. However, sizing, designing, and planning reservoir operation is a very complex problem. Matching water management requirements with topographic and hydrologic characteristics of water courses is a problem of searching for "the optimum" as a function of natural, economic, social, and environmental conditions and factors. Mathematical models have been used for this purpose for several decades. These formal tools, which range in sophistication from simple graphical techniques to complex computer programs, are used to help understand water resource characteristics and improve water resource management and planning activities.

A systems analysis approach and operations research provide the philosophical framework and quantitative techniques, respectively, for handling physical and socio-economic considerations within optimization processes. Use of systems analysis in reservoir problems (as above) is, in this work, referred to as "reservoir analysis". Over the past three decades the development and application of mathematical models for design, planning, and operation of water resources systems have attracted growing attention among engineers, planners, and managers. Many successful applications of optimization techniques have been made in reservoir studies, mostly for planning purposes [*Yeh*, 1985]. These techniques range from simple search and simulation to more advanced linear programming, dynamic programming and non-linear programming techniques. However, the complexity of the techniques and models, developed under the assumptions of probabilistic certainty or uncertainty, has proven to be a major obstacle for wider practical application of the models. One of the obvious reasons for this complexity and lack of acceptance is that some of the models have been developed for research purposes without consultations with practitioners in the field. Lack of information about available models, lack of communication and understanding, lack of manager involvement in model development, and involvement of a subjective and value-dominated human element are the most frequently cited constraints to effective model use. Another not so obvious, but nevertheless present reason [*Liebman*, 1976], is the presence of situations, in public systems decision-making, where the concept of so-called "classical" probability, alone, does not describe reality adequately.

Interactive water resources modelling, and model use coupled with use of graphics, have been introduced as a way of dealing with such problems [*Loucks et al.*, 1985]. This approach considers the interface between the model user and the models being used. Interactive methods can assist the user in controlling model calibration, model use, output form, and display. Integration of this approach with the expert systems approach leads to decision support systems with the potential for improving water resource management and planning.

1.2. RESEARCH OBJECTIVES

The intent of this work is to improve reservoir modelling and model use utilizing an integrated approach to developing engineering expert systems [*Simonovic and Savic*, 1989]. The approach, called the engineering expert system approach, may suit the needs of managers and planners better than classical expert systems or mathematical modelling alone. The main advantage of the approach over the pure expert system approach, or use of formal algorithmic routines alone, lies in its ability to combine both methods and better utilize their individual potentials for improved modelling of water resources related problems.

By adopting some of the ideas of interactive reservoir modelling and the engineering expert system approach, it was possible to combine/incorporate formal reservoir optimization models, experience in their use, heuristics, and common rules-of-thumb in an intelligent decision-support system (IDSS) named REZES. It will be shown that research efforts were concentrated on synthesis and structuring of the modelling knowledge necessary for the proper formulation, selection, and use of different mathematical models within REZES. The system is intended to help a user to select and use the proper formal (single-multipurpose) reservoir model(s) to improve the accuracy and effectiveness of information available to managers, decision makers, and researchers. REZES uses procedural and declarative (logic) programming methods, rather than using only one of them, to make both numerical and logical inferences.

Formal optimization models are the essential tools of systems analysis. Some representative reservoir optimization models, developed by different researchers, form a basis for reservoir sizing and short- and long-term planning optimization within REZES. These models are considered suitable for describing fairly complex aspects of physical systems and problems being modelled. Crucial elements of each model are a system performance indicator, i.e., the objective function, and a set of system constraints and boundary conditions. Depending on the purpose of the reservoir, different economic or social utility objectives may be quantified and integrated into a single objective function or presented through system constraints.

In spite of their strengths, there are concerns that models often display critical gaps in interpreting existing information and knowledge [*Rogers and Fiering*, 1986]. Most of the objective functions and constraints employed in existing formal models, whether deterministic or stochastic in nature, are clear cut, easy to formulate, and non-controversial. There is some doubt about the extent to which these models have been as useful as anticipated in adequately representing reality. Situations in public systems decision-making, characterized by a lack of economic data and the involvement of a human factor, do not permit easy and correct system representations within the limits set up by existing models. It will be shown by example that even using the expert system technology as a way to improve modelling, as suggested here, some informational gaps still exist and cannot be explained directly by conventional models. To counter this, a new approach is proposed for handling uncertainty that is neither statistical nor random in nature. Fuzzy set theory is used to represent the imprecision which surrounds the probabilities and utilities in chance-constrained reservoir operation modelling. A new chance-constrained reservoir model is developed using this approach and has been added to the set of formal models within REZES. The same reservoir problem used to illustrate the functionality of the developed tool is then used to show the merits of the proposed fuzzy-set-based methodology.

1.3. SCOPE OF WORK

This work emphasizes reservoir analysis through mathematical modelling and model use. The ultimate goal of the analysis in this thesis, is to identify, analyze, and provide appropriate solutions for reservoir design, planning, and development of operation plans and policies for single-multipurpose reservoirs.

A general review of major research contributions is presented in Chapter 2. This review includes reservoir management, mathematical modelling, and methods of analysis; advances in the artificial intelligence field with emphasis on the potential of artificial intelligence for water resources management applications; and the treatment of uncertainty and imprecision in water resources optimization with a special overview of fuzzy set theory and its applications to water resources systems.

In Chapter 3, theoretical considerations are established for the development of an intelligent decision support system for reservoir analysis. The expertise necessary for the development of REZES and the complex issues involved in reservoir analysis are also addressed. Reservoir analysis is introduced as a non-structured problem which can be treated using systems analysis and expert systems technology. In addition, specific areas and phases of reservoir analysis, where declarative and procedural components may outperform the present combination of human efforts and conventional programs, are identified and analyzed.

The development issues, from knowledge acquisition to organizing and representing reservoir analysis knowledge and expertise, are presented in Chapter 4. The structure and programming efforts necessary to enhance IDSS to include the identified reservoir analysis phases, are described. The formal mathematical optimization models for reservoir analysis, which constitute the procedural component of REZES, are then briefly presented. Finally, an illustrative example presents some of the potential benefits of the enhancement. As well, some unresolved problems related to the formal models are discussed. The example demonstrates the need for treating imprecise conceptual phenomena in modelling and decision making.

Chapter 5 gives an introduction to the theory of fuzzy sets and discusses necessary principles for the development of a fuzzy-set-based decision making model. These theoretical principles provide a mathematical framework for studying imprecise conceptual phenomena in modelling and decision making. The chapter presents a transition from rigorous, quantitative, and precise modelling to modelling which deals with vague, qualitative, and imprecise concepts.

The theoretical development of an original fuzzy-set-based methodology for selecting the risk levels in chance-constrained reservoir operation modelling is described in Chapter 6. Three different approaches to modelling of decision making in a fuzzy environment are investigated and presented. These are followed by an application of the developed model to the Gruza reservoir in Yugoslavia. Detailed results with explanations and sensitivity analysis are also presented.

Summary, conclusions, and recommendations for future research are included in Chapter 7.

CHAPTER 2.

LITERATURE REVIEW

Considerable research has been performed in the area of reservoir operations and design. Most of it is concerned with various systems analysis techniques utilized in and by the formal reservoir models. The emphasis has been on developing models which are more complex, which describe reality in a more satisfactory manner, and which require more computation. In this context, computers have been widely used to assist with numerical computations only. Limited utility of formal models and recent developments in artificial intelligence have encouraged research which is leading to an expanded role for computers in reservoir analysis.

This chapter reviews the various approaches to single reservoir operation and design modelling, the treatment of uncertainty and imprecision within formal reservoir models, and the use of artificial intelligence advances and potentials in water resources.

2.1. RESERVOIR DESIGN, PLANNING AND MANAGEMENT: MATHEMATICAL MODELLING AND ANALYSIS

In general, reservoir storage capacity may be divided into three components: (i) flood control storage capacity; (ii) active storage capacity; and (iii) dead storage capacity. These three components are usually determined separately and then added together, thereby constituting the total capacity of a reservoir. The following discussion of existing design models will be limited to several methods for estimating active storage requirements.

In addition to reservoir design, an optimal operating policy is needed for proper management of a reservoir system. The design of a reservoir and the design of its subsequent operation are interdependent. A separate review section considers mathematical models applied to reservoir planning and management.

Real-time decisions, regarding reservoir releases, for various purposes, often need to be made within a short time period. The last group of mathematical models discussed herein is concerned with these reservoir problems.

2.1.1. Single Reservoir Design Models

Before digital computers were introduced, reservoir design efforts were generally restricted to the group of, so-called, critical-period methods. These methods find the required reservoir active capacity to be the difference between the water released from an initially full reservoir and the inflows, for periods of low flow. The mass diagram analysis [*Rippl*, 1883] appears to have been the first rational method for estimating the amount of storage required to meet a sequence of specified reservoir releases. The original method does not take into account storage-dependent losses nor does it provide an estimate of the storage corresponding to a given probability of failure. *Alexander* [1962] augmented the critical-period approach by developing a series of drought curves for different probabilities of occurrence. From these he derived generalized storage-regulation-probability curves. A modification of Rippl's procedure, the sequent-peak algorithm [*Thomas and Burden*, 1963] resolves computational problems with the Rippl procedure but fails to take the probability of failure into account. *Simonovic* [1985] developed and applied a model based on the sequent-peak procedure and behaviour (simulation) analysis. The changes in storage content of a finite reservoir, using a mass storage equation with different reliability and vulnerability criteria, are calculated. Recently, *Lele* [1987] presented two improved algorithms based on the sequent-peak procedure that account for both storage-dependent losses and "less than maximum" reliability of water supply.

The second group of models, probability matrix models, are based on *Moran's* theory of storage [1959]. Moran derived an integral equation which relates the probability distribution of the inflow and the specified reservoir release rule to the probability distribution of the storage. Discretizing time and volume variables, reservoir states can be expressed in a transition matrix. The main limitation of this type of model is the assumption of independent inflows. *Gould* [1961] modified Moran's approach to account for both seasonality and autocorrelation of monthly inflows. This procedure, however, does not account for annual inflow autocorrelation nor for droughts longer than one year [*Haktanir*, 1989].

Mathematical programming methods applied to the reservoir sizing problem form the basis for the third group of models. These models are based on mass-balance or continuity equations for routing flows through the reservoir and have the advantage of easy incorporation of storage-dependent losses. *Loucks et al.* [1981, pp. 339-353] presented two yield models for reservoir design and operation based on the linear programming algorithm. These models, the complete and approximate yield model, arrive at the reservoir storage capacity necessary to provide yield with certain reliability for a given streamflow sequence.

These three groups of models are used mostly to screen preliminary estimates of reservoir capacities needed to meet specified release and reliability targets for water supply. Although they involve the same basic techniques, final design procedures are more complex and time-consuming. In practice, the use of most of these models has been combined with the use of synthetic streamflow data and detailed statistical analysis of the results. A recent study by *Savic et al.* [1989] showed that the decision of the appropriate streamflow generation scheme may significantly influence the identified storage capacity.

2.1.2. Reservoir Long-Term Operation Planning Models

In the optimum design of a reservoir system, determination of the optimum size and the optimum operating rules are necessary for the design and the subsequent use of the reservoir. The subproblem of planning the optimum mid- and long-term operation of a reservoir has been of major concern in the past twenty years and is the subject of this section. The models discussed here are those which are predominantly based on a monthly time period. In general, there are two basic approaches to the rational planning of reservoir release policies: deterministic and stochastic. In order to safeguard against extreme events, the model used to select the reservoir operating policy should include the stochastic nature of hydrologic parameters. However, some problems are still solved deterministically. Operations research quantitative techniques, such as linear programming, dynamic programming, nonlinear programming, and simulation, have been used within operation planning models to handle physical and socio-economic considerations of optimization problems [*Yeh*, 1985]. The following is a review of the most representative models and studies based on these techniques.

Linear Programming Models

Linear programming has been widely used in water resources optimization studies. It has become quite popular due to its ability to handle large numbers of variables and constraints and to provide global optimal solutions to problems which can be formulated to match the technique. *Dorfman* [1962] used linear programming for combined optimization of reservoir storage capacity and reservoir operation. His model considers the stochastic nature of inflows and treats reservoir capacities and target releases as decision variables. *Loucks* [1967] demonstrated how linear programming could be used to determine reservoir releases and the allocation of water to various uses. The management objectives considered were related to maximization of total expected benefits, minimization of total expected losses, and minimization of total expected deviations from each user's target.

Various linearization techniques are available for nonlinear problems to make them solvable using linear programming. However, it has to be noted that the solutions identified with the application of linearization techniques are not guaranteed to yield the global optimum. *Thomas and ReVelle* [1966] employed linear programming to determine optimal operating policies for the High Aswan Dam. considering benefits from hydropower and irrigation. Recent works by *Grygier and Stedinger* [1985] and *Reznicek and Simonovic* [1990] present the application of successive linear programming to optimizing hydropower generation. The first algorithm maximizes the value of energy generated over the planning period by an isolated hydropower system and the expected future benefit from the water remaining in the reservoir(s) at the end of the planning period. The second model is developed for an interconnected hydro utility with the objective of maximizing the energy export benefits, while minimizing the costs of satisfying the domestic power demand over the planning period.

Manne [1962] also adapted linear programs to the stochastic reservoir problem. He used a Markov process optimization with a hypothetical single reservoir example. *Loucks* [1968] developed a stochastic linear programming model for a single reservoir subject to random, serially correlated inflows. In his algorithm the joint probabilities of inflows and storage values are used to determine the optimal operating policy and the optimal "release joint probabilities" (as defined by *Loucks* [1968] and *Loucks et al.*, [1981]). The applicability of the model in real situations is limited somewhat by the dimensionality problem associated with this approach. Stochastic programming with recourse, sometimes called two-stage stochastic programming, is another variation of linear programming applied to the stochastic case. This modelling approach handles random variables in the constraint set of a linear problem. The solution is obtained by making decisions in multiple stages (usually two) [*Dorfman*, 1962].

Chance-constrained programming is another form of stochastic linear programming model. It is based on assigning fixed probability levels within the constraint set. These probability levels define the percentage of time that specified storage and/or release targets, defined by the constraints, can be violated. In the reservoir management context, chance constraints relate inflows (random variables with known distributions) to release and storage (random variables with unknown probability distributions). The defined stochastic problem can then be converted to a deterministic equivalent, if the cumulative probability distribution function of the inflow is assumed to be known. The application of the approach to reservoir system optimization was initiated by *ReVelle et al.* [1969]. Since then, many modifications, extensions, discussions and evaluations, of single- and multiple-decision rules have been reported for different single- and multi-reservoir model formulations. A different approach to use of chance-constrained programming in reservoir design and operation, which does not utilize the linear decision rule, has been introduced by *Curry et al.* [1973]. This approach can include releases in the objective function and can include stochastic as opposed to deterministic demands in problem formulation. The method used by *Curry et al.* [1973] converts a probabilistic constraint into an equivalent deterministic linear constraint by using the analytic convolution integral procedure. *Simonovic* [1979] applied the iterative convolution algorithm to the discretized inflow probability density function, thereby solving problems associated with integrating some complicated probability density functions. A feasibility analysis of chance constrained programming models for reservoir design and operations is presented in the paper by *Loaiciga* [1988].

Colorni and Fronza [1976] have employed reliability programming to find optimum reliability levels and reservoir operating rules, simultaneously. This approach is based on an extension of the chance-constrained formulation which, in their work, considers constraint reliabilities as decision variables. *Simonovic and Marino* [1980, 1981] applied reliability programming to a multipurpose reservoir and developed a methodology for estimating risk-loss functions, associated with the frequency and severity of failures in reservoir operation.

Dynamic Programming Models

Dynamic programming is a sequential decision-making procedure in which the optimization is done in steps (stages) employing a recursive equation. The procedure decomposes a multistage problem containing many related variables into a set of one-stage problems, each containing fewer variables. In optimizing reservoir operation by dynamic programming, the stages are the time periods and the state variables, which represent the state of the reservoir, are the storage volumes in the reservoir. The decision variables are the volumes to be released from the reservoir at each stage. Dynamic programming is particularly suitable for handling nonlinear problems of water resources systems. This technique can be used for problems having nonseparable objective functions. *Sniedovich* [1989] combined dynamic programming and c-programming techniques to alleviate the so-called "curse of dimensionality", caused in this case, by nonseparable objective functions.

Hall et al. [1968] developed an algorithm using the deterministic dynamic programming technique to obtain a release policy for a multipurpose reservoir system. Given the initial state of the system, price schedules, and sequences of critical period inflows, this model arrived at a set of release decisions. To reduce the amount of computation, *Hall et al.* [1969] adapted incremental dynamic programming to reservoir-operation problems. The generalization of incremental dynamic programming is systematized, and referred to as discrete differential dynamic programming, by *Heideri et al.* [1971]. This procedure starts from an assumed control state trajectory. The recursive equation is then used to examine the neighbouring states around the initial trajectory. If any neighbouring trajectory gives a better value of the objective function, it then replaces the initial trajectory, and the procedure continues until convergence takes place. This technique uses an iterative method, where the grid becomes progressively finer, until the desired accuracy is reached. Unfortunately, the technique does not guarantee that the global optimum will be found.

Parametric dynamic programming is a similar method. Its objective function is approximated by a multi-variate polynomial function over the entire state space. By defining the objective function in this way the burden of carrying over the information from one stage to another in tabular form is alleviated. To alleviate the "curse of dimensionality", *Larson and Keckler* [1969] have applied a technique which decomposes a multiple reservoir dynamic programming problem into a series of subproblems. The technique is called incremental dynamic programming with successive approximations. This technique is particularly useful for solving stochastic problems which can have large numbers of state variables [*Takeuchi and Moreau*, 1974]. *Opricovic and Djordjevic* [1976] proposed a three-level hierarchical deterministic algorithm for reservoir operation planning based on the dynamic programming procedure. The algorithm considered direct and indirect water users. The time distribution of available water was optimized on the first level; distribution to direct users, on the second level; and water was allocated to indirect users on the third level. An extensive list of dynamic programming computational procedures is given in *Esogbue* [1989].

In most reservoir operation problems, the system inflows are not known in advance. *Little* [1955] introduced a stochastic dynamic programming model for a mixed power-generation system that used inflow data described by probability distribution. The model identified an optimal water-use policy based on the present reservoir content and the inflow in the preceding period while it was minimizing the expected cost of meeting the power demand for the remainder of the planning horizon. *Butcher* [1971] presented an algorithm based on the storage volume and the reservoir inflow in the preceding period. The recursive equation was developed, using both the discounted and undiscounted approach. The model was applied, using different interest rates, to maximize returns from irrigation, hydropower generation, and recreation.

A different approach to reservoir optimization, using a nonstationary stochastic dynamic model, was employed by *Bras et al.* [1983]. This approach used a, so-called, real-time adaptive closed loop control scheme which made use of multilead real-time streamflow forecasts in reservoir operation. *Stedinger et al.* [1984] improved this model by employing efficient flow forecasts as hydrologic state variables in their predictive stochastic dynamic programming model. A study by *Goulter and Tai* [1985] reported on the effects of the number of storage state variables in stochastic dynamic programs on the estimated increase in the objective function (annual gain) and computational efficiency. Another model by *Kelman et al.* [1990] employed storage and forecast as state variables using a sampling stochastic dynamic programming approach. It utilizes a large number of generated streamflow scenarios to which conditional probabilities are assigned using a streamflow forecast. Unlike the implicit stochastic optimization approach, this model derives optimal decisions by considering all of the streamflow scenarios simultaneously, instead of using only one at a time to optimize reservoir operation. The large number of state variables in stochastic dynamic programming contributes to the computational barrier which is often found in deterministic multi-reservoir problems.

Other Reservoir Operating Models and Studies

Besides linear programming and dynamic programming models, used separately for reservoir management purposes, there have been some attempts based on the combined application of the two techniques. *Becker and Yeh* [1974] applied a linear programming model to obtain a set of alternative operating policies and a dynamic programming model to subsequently select a single optimal policy. The method was applied to the California Central Valley Project to derive optimal release control for a multiple reservoir system and hydropower utility.

Another mathematical programming approach, nonlinear programming, has been adapted for use in reservoir optimization. The consumption of large amounts of computer storage and time have made the application of nonlinear programming methods to the operation of reservoirs and reservoir systems impractical [*Yeh*, 1985]. Despite their capability to handle nonseparable objective functions and nonlinear constraints, these models have not been used as often as linear or dynamic programming models. *Rosenthal* [1981] reported on a study where a nonlinear network algorithm was used to optimize the benefits from a multi-reservoir hydroelectric power system for the Tennessee Valley Authority. He used deterministic inflows in conjunction with a nonseparable, nonlinear objective function.

Klemes [1979] reminded water resource researchers of the, so-called, "stretched-tread" method based on Rippl's storage mass-curve analysis. He concluded that for the deterministic formulation of the problem both linear and dynamic programming solutions converge to the same optimal reservoir policy as the method above. However, he unjustly kept both mass-curve analysis and the stretched-tread method from being classified in the systems analytic approach.

Simulation is a mathematical modelling technique which relies on trial-and-error to identify near-optimal solutions. It enables a decision-maker to examine the consequences of different operating scenarios for an existing, or future, system. As with optimization models, simulation may be used in the deterministic or stochastic manner. *Loucks et al.* [1981, pp. 21-22] suggested the combined use of optimization and simulation techniques. In this context, simulation models may be used to narrow down the search for a global optimum by identifying plans that may be close to it. At present, the general tendency is to incorporate an optimization scheme into the simulation model to take advantage of both approaches.

2.1.3. Reservoir Short-Term Operation Planning Models

Real-time (short-term) reservoir operation models determine optimal reservoir releases by using very short time steps, usually daily or even hourly increments. The performance of such a model depends greatly on a forecasting algorithm and forecasted information obtained. Most of the previously mentioned mathematical programming techniques have been used, within either a deterministic or a stochastic framework, for real-time reservoir operation models.

Houck [1982] developed the probabilistic balancing rule model for the optimal real-time (daily) operation of a reservoir system used both for water supply and flood damage mitigation. The model defines the optimal period-to-period operation decisions as those which maximize the non-exceedence probability values for the respective control variables, such as storage volumes or flows. *Nzewi and Houck* [1987] showed that it is possible to extend the approach to solve reservoir operation problems which involve hydropower generation.

In contrast to probabilistic balancing-rule models, the optimal decisions obtained from a penalty-based model are those which minimize the total assessed penalty (short-term losses) for non-ideal operations. This group of models uses economic criteria to derive optimal short-term operation of a reservoir system. *Datta and Burges* [1984] examined the importance of penalty functions (loss functions) and inflow forecast errors for effective short-term operation of a single multipurpose reservoir. They concluded that the actual losses, incurred, decrease substantially as the reliability of inflow predictions increases. *Can and Houck* [1985] pointed out problems, in short-term reservoir operation modelling, due to imperfect forecast information and the use of imperfect river routing models.

In general, forecasts, using streamflow and other input data, deteriorate with increase in forecast length. On the other hand, with perfect forecasting (the use of actual historical data as inflow predictions) the longer the operating horizon, the better the reservoir performance that can be expected. With this in mind, *Simonovic and Burn* [1989] proposed an improved modelling procedure that explicitly utilizes the trade off between forecast reliability, which decreases with the increase in forecast length, and the improvement in reservoir operation attributable to the longer inflow forecast. The model incorporates (i) a Kalman filtering technique within the forecasting algorithm; (ii) a linear programming real-time reservoir operation model which attempts to minimize cumulative penalties due to deviations from storage and release targets; and (iii) a multi-objective compromise programming algorithm, which minimizes the inflow forecast error variance as well as the total penalties associated with the reservoir operating horizon.

The combined use of short- and long-term operation models has been reported in the literature [*Yeh*, 1979]. Due to different objectives in the long- and short-term, the two types of models are run sequentially to account for the differences. Outputs from the first model are used as inputs into the next model, in an iterative manner, with updated streamflow forecasts.

2.2. TREATMENT OF UNCERTAINTY WITHIN FORMAL DECISION MODELS: IMPLICATIONS FOR RESERVOIR MODELLING AND ANALYSIS

Previous sections indicate that, in general, and according to the nature of input data, mathematical models may be classified into:

(i) **deterministic** models, in which parameters are considered to be known or fixed numbers for any set of conditions, and

(ii) **stochastic** models, in which data are expressed as a range of probable values.

In the case of reservoir planning and management, deterministic models which use the historical critical period or mean seasonal inflows to arrive at optimal decisions, do not encounter the hydrologic uncertainty associated with inflows or uncertainty in demand variability. Although, such models are very simple and easy to use, they may not lead to satisfactory results. Post-optimal analysis must follow deterministic optimization if the variability is to be incorporated in the analysis. Generally, these models represent physical system characteristics in more detail than stochastic models. However, simplifying the assumptions about reservoir inflows used for formulating them may result in overestimated benefits or underestimated costs and losses.

Stochastic procedures safeguard against the possibility that reservoir storage capacity may become insufficient during a drought longer than the historically critical one. They also take into account the possibility of experiencing flood conditions not observed in the period of record. Any model used to design a reservoir and select its operating policy must specifically incorporate the stochastic nature of inflows and demands. In order to do so, two stochastic approaches may be used: (a) explicit, and (b) implicit stochastic optimization. The explicit stochastic approach uses the probability distributions of streamflows at each stage directly in the stochastic optimization. Implicit stochastic optimization utilizes samples drawn in data generation procedures (synthetic inflow data) as input data for a deterministic reservoir optimization model. The optimum release policies, obtained for each generated sequence, are then studied through the use of multi-variate analysis. While some researchers maintain that a stochastic formulation is necessary for adequately addressing reservoir studies [*Turgeon*, 1980], others argue that, in some cases, deterministic models offer increased flexibility and reduced computer time and memory, without sacrificing much in performance or reliability, especially in the case of multi-reservoir studies [*Grygier and Stedinger*, 1985].

2.2.1. Adaptive and Predictive Methodologies

Each of the outlined approaches, deterministic or stochastic, may be augmented using an adaptive methodology, in which new information is incorporated into the decision problem as it becomes available. *Labadie* [1969] used Bayesian updating as a form of adaptive reservoir control. Closely related to the adaptive approach, is work that has been done in the forecasting field and its use in determining optimal operation of a reservoir system. *Dagli and Miles* [1980] used adaptive-planning methodology for deriving a reservoir-control policy with a one-year time horizon. They utilized long-range inflow and demand forecasts for determining releases for the first month only. At the end of the month, a new forecast was generated and a new control policy was determined for the actual state of the system, at the end of the month, as a starting condition.

The forecasting procedure developed by *Curry and Bras* [1980], which uses a multivariate autoregressive forecasting model for the Nile basin, was adopted by *Bras et al.* [1983] and used within an adaptive planning model. Using results of the stationary reservoir control problem as boundary conditions, they used dynamic programming to solve a finite horizon optimization problem using the multi-lead forecasts of reservoir inflows. This was an attempt to incorporate nonstationarity into the solution procedure.

Stedinger et al. [1984] discovered some inconsistency in this adaptive methodology, namely, that the use of all available flow information within the model requires the solution of a stochastic dynamic programming model of large dimensions. As an improvement they suggested employing flow forecast as a one-dimensional hydrologic state variable in, what they called, a predictive model. The improvement in the High Aswan Dam operation, observed with the predictive policy, shows the advantage of the adaptive methodology.

2.2.2. Fuzziness: Imprecision of Another Kind than Stochasticity and Randomness

The abundance and sophistication of all approaches, methods, and models available to water resources analysts, planners, and managers, implies that an appropriate model may be found for virtually every type of water resource problem. A study by the U.S. Office of Technology Assessment [*OTA*, 1982] revealed the high, current and potential, use of formal models by Federal and State agencies which "expanded the Nation's ability to understand and manage its water resources". However, as presented by *Rogers and Fiering* [1986], there are some problems that existing models are unable to address. These problems are related to vagueness or disagreement regarding objectives and constraints and to estimation error in model parameters. Even a study reported by *Austin* [1986], which offered a much more favourable view of models used in water resource management, acknowledges these problems.

Hipel [1981] recognizes the necessity for inclusion of, "nonquantitative OR (Operations Research) techniques" within formal models, mainly because information about the real world is often imprecise, ambiguous, difficult to interpret, and is not open to analysis by quantitative OR methodologies. Situations like these, where concepts of formal models and "classical" probability, alone, are not adequate to describe reality, are relatively common in engineering practice. Situations where some question arises about exactness of concepts, correctness of statements and judgements, degrees of credibility, etc., have little to do with probability of occurrence, the fundamental concept of the classical probabilistic framework. These situations warranted introduction of a fuzzy set concept [*Zadeh*, 1965] as a mathematical theory of vagueness. The theory of fuzzy sets attempts to provide a device for modelling a qualitatively different kind of uncertainty or imprecision, one which is not covered by any of the classical theories. This is modelling of inexactness, ill-definedness, vagueness, or simply: fuzziness. The key concept of fuzzy set theory is the membership function, which represents, numerically, the degree to which an element belongs to a fuzzy set. It should be noted that, when the quantity of available data is limited, Bayesian statistical theory provides another alternative to the classical approach. Bayesian relationships, that systematically combine new data with previous information, can be developed. The previous information can be either subjective or objective in nature. However, a large number of correlated variables can make the development of Bayesian relationships extremely complex.

Many methodologies, based on fuzzy set theory, have been developed for decision-making models which use quantitative and qualitative information simultaneously. Fuzzy mathematical programming was introduced by *Tanaka et al.* [1974] with extensions to some of the classical concepts in linear programming. The new approach was formulated for cases where coefficients need not be known precisely. *Zimmermann* [1976] clearly explained the idea of decision making under fuzzy conditions. He argues that a decision in a fuzzy environment can be viewed as the intersection of a fuzzy constraint and a fuzzy objective function. *Prade* [1980] adapted ordinary operations research algorithms treating PERT, assignment, travelling salesman, and transportation problems, which are appropriate to precise data, to data that are not precisely known. *Terano et al.* [1983] and *Esogbue* [1983] showed that dynamic programming, as a tool for planning and management, can be tailored to admit human interpretation and interference. This demonstration was performed using fuzzy set theory and the introduction of several new concepts: fuzzy state, fuzzy strategy, fuzzy constraints, etc.

In spite of the frequent and rather general claim of its applicability, little research in fuzzy sets has been directed toward solution of practical engineering problems. The predominant trend in early studies was toward examples sought out to show the capabilities of fuzzy set theory rather than to deal with real problems of application [*Kickert*, 1978]. However, the bibliography of fuzzy set application by *Maiers and Sherif* [1985] and the book by Kaufman and Gupta [1988] subsequently revealed considerable improvements in application of fuzzy mathematical models to engineering and management science.

Most of the applications of fuzzy set theory to water resources are related to multi-objective studies and conflict analysis. In his analysis of the Poplar River Basin conflict, *Hipel* [1981] advocates the use of fuzzy set theory, coupled with multi-criteria modelling, for a conflict analysis of the dispute over of water allocation. *Esogbue and Ahipo* [1982] developed a fuzzy-set-based model for measuring the effectiveness of public participation in area-wide water-resources planning. An heuristic algorithm for clustering the membership functions of the basic factors in the effectiveness model is also presented. *Dubois* [1983] analyzed the problem of optimal network design. As the problem belongs to the combinatorial field and an optimal solution is impossible, with practical-sized sets of data, he concluded that fuzzy set theory provides a basis for a more efficient methodology. The paper claims to present a methodology to provide a procedure for approximate network generation. *Chuang and Munro* [1983] discussed several ways in which imprecision may be incorporated into a linear program. The work includes comparisons of proximate programming, inexact programming, and fuzzy programming approaches. A simple illustrative example concerned with water quality is reworked using these techniques.

Bogardi et al. [1983] and *Nachtnebel et al.* [1986] have used fuzzy set membership functions to represent environmental objectives in a multi-objective framework. The first study concerns the conjunctive planning and operation of water and mineral resources extraction in the Bakony region of Hungary. The second work evaluated a small hydropower project with respect to both economic and environmental objectives. The existing hydropower scheme located on the Erlauf river (Austria) was selected as a case study. In their recent work, *Bogardi et al.* [1989] proposed a joint probabilistic and fuzzy set approach to treating stochastic uncertainty and imprecision in risk analysis.

2.3. ARTIFICIAL INTELLIGENCE AND WATER RESOURCES MANAGEMENT

The previous two sections presented a review of mathematical models and their use in the water resources field. The emphasis was mainly on new model formulations, improved solution techniques, improved computational efficiency, and addressing real situations within the formal models. However, the most frequently encountered problems relate the lack of communication between model users and developers, lack of documentation and support services, and involvement of a subjective and value-dominated human element [*Loucks et al.*, 1985; *Austin*, 1986].

As a consequence of emphasis on the development of progressively more sophisticated, more complex, and bigger models, their acceptance by planners and managers is limited. This trend prompted a new way of thinking about research [*Loucks et al.*, 1985]:

> We will need, and we will develop, better models, of course, as our knowledge of the system we model increases. However, equally important, we must devote some attention to the interface between the model user and the models being used. More effective communication is essential for increased effectiveness in model use.

Interactive water resources modelling and model use, as proposed by *Loucks et al.* [1985], gives the user an appropriate role in controlling model calibration, model use, and output display. *Goulter* [1990] identifies yet another problem, i.e., the lack of suitable "packaging", as the primary cause for the non-acceptance of optimization models. Goulter acknowledges also that "work is needed in packaging these optimization models before they can be used in practice". However, interface and "packaging" problems are addressed only marginally in this thesis. It concentrates on synthesis and structuring of the modelling knowledge necessary for the proper formulation, selection, and use of different mathematical models. In his summary, *Goulter* [1990] argues that "due to the nature of the packaging problem it appears that the packaging issue should be addressed by software experts rather than academic researchers who have formulated optimization algorithms". This diverges from Loucks' contention [*Loucks et al.*, 1985] and the one used in this work, with respect to the role of academic researchers (engineers) who have formulated and/or understand optimization algorithms. The development of a useable and marketable system requires the multidisciplinary approach, i.e., involvement of both engineering and software experts. But communication problems between the two groups, and the complex nature of engineering decision-making, require engineering experts to collect and structure the relevant engineering knowledge. Recent developments in Artificial Intelligence (AI) now make it feasible to expand, not only the role of computers in reservoir analysis, beyond numerical calculations, but to expand the role of academic researchers in improving the use of the models which they understand the best. This approach is demonstrated to be a possible direction for both research and practice in water resources [*Simonovic*, 1990; *Simonovic and Grahovac*, 1990; *Arnold and Rouve*, 1990; and *Fedra*, 1990].

The availability of inexpensive powerful hardware has enabled a major breakthrough in the field of AI, namely the introduction of expert systems (ES). These computer programs are capable of solving or helping to solve complex problems, in a manner similar to what a human expert would do if given the same task [*Waterman*, 1986]. Originally, engineering AI applications were primarily oriented toward study of vision perception, speech recognition, and movement (robotics). The science then began to address some other problems, gradually evolving into one of the more fertile research areas in engineering [*Kostem and Maher*, 1986; *Maher*, 1987]. The importance of AI lies in the fact that decision-making in engineering practice requires a high level of expertise, encompassing experience, judgment, heuristics, imagination, inventiveness, rules-of-thumb, etc.,- in short, a certain level of "intelligence".

There have been successful water-resources-related expert systems applications reported in the literature [*Simonovic and Barlishen*, 1987; *Weigkricht* *and Winkelbauer*, 1987; *Simonovic and Savic*, 1989]. From these publications, it is clear that the basic engineering tasks of planning, design, and operations management are addressed by the researchers in several water-resource subdisciplines. A detailed literature review of expert systems in environmental and structural engineering can be found in *Ortolano and Steinemann* [1987] and *Maher* [1987] respectively, and will not be covered in this thesis. A review of some attempts in developing expert systems in water resources follows.

Hydrology

One of the first of such attempts, HYDRO, is an expert system designed to help determine appropriate parameters of physical characteristics of a watershed [*SRI International*, 1981]. Recommended parameter values serve as input to the Hydrocomp HSPF simulation program, for evaluating various hydrological aspects of the region being analyzed. The system is intended to provide advice comparable to that of an expert hydrologist. Being one of the first expert systems in water resources, HYDRO was developed for a mainframe environment using INTERLISP. With the effect of the microcomputer "revolution" of the last decade, more expert systems are oriented toward the mini or micro, i.e., work station or personal computer (PC), environment.

A computer-based consultation system, FLOOD ADVISOR [*Fayegh and Russell*, 1986], has been developed to provide advice about the most suitable flood estimation technique. The advice is based on the availability of streamflow and rainfall data for the location being investigated or for nearby streams in the region. A hybrid-type expert system, WMS [*Palmer and Tull*, 1987],has been developed for the opposite problem, drought management planning. Integration of procedural computing, a linear programming model, declarative computation model, an expert system shell, and graphics is used to enhance their individual capabilities. Along the same lines, an expert system SID, has been developed for the Seattle Water Department, offering guidance for initiating water-use restrictions during drought conditions [*Palmer and Holmes*, 1988]. The expert system environment is used again for combining the advantages of linear programming, database management, and computer graphics. *Nishida et al.* [1990] presented an expert system, ESCORT, that guides water managers through the development of operational strategies for reservoir management by North West Water (Warrington, England) during droughts. ESCORT is a prototype rule-based system capable of interpreting control curves and selecting an appropriate management response using engineering expertise acquired from human experts.

The EXSRM computer system [*Engman et al.*, 1986] is designed to provide assistance in estimating parameters of a snowmelt-runoff simulation model (SRM). SRM needs satellite data and parameters that are not directly measurable. EXSRM is designed to provide the expertise necessary for estimating the appropriate values for these parameters. An expert system for a similar purpose has been developed to automate the calibration of the runoff block of the EPA's Storm Water Management Model (SWMM). It assists the user in the initial estimation of the parameter values, building the SWMM input files, interprets the results and suggests adjustments in the value of significant parameters [*Baffaut and Delleur*, 1989]. An early version of the system was written in the programming language PROLOG, but the final version was developed using an expert system shell KES written in C. The use of the shell allowed developers to concentrate on the development of a rule base without being concerned with programming search strategies.

The information about the following two expert systems is gathered through personal communications with the authors. Hydro-Quebec has been developing its own decision-support tool, ARIANE, with the aim of providing expert guidance to users of the multi-year operation planning process. It is intended to monitor data updating, consistency, and validation; to oversee the use of heuristics knowledge; and to control calling and use of mathematical models. Groundwater Branch of the U.S. Bureau of Reclamation uses DMWW, an expert system that works in a PC environment. The system is intended to assist the bureau personnel in the design of municipal water wells, water storage wells, observation wells, and dewatering wells.

A pilot expert system for advising on operation of the Jenpeg generation station during the freeze-up period, JOE [*Maxfield*, 1987] has been developed and tested by Manitoba Hydro. It is developed on a microcomputer using another expert system shell, GEPSE. The very complex operations expertise which involves many judgment calls, and is normally performed by an expert engineer, was successfully captured by the system. *Sieh and Strzepek* [1989] reported on the development of another advanced decision-support system for operations and maintenance. A prototype that explores embankment dam seepage was developed for the U.S. Bureau of Reclamation. An expert system has been developed to assist in selecting process units for upgrading small water supplies [*Knight, 1987*]. The system has undergone testing throughout the United Kingdom giving results comparable to those of human experts.

A prototype system has been developed to help organize and support operation of an integrated surface water quantity acquisition data network [*Simonovic*, 1990]. The developed prototype assists in selecting a suitable method for flow measurement in open channels. Two prototype expert systems; one for sewerage rehabilitation planning (SERPES), and a second for diagnosing a possible problem within a water distribution network (WADNES); have been developed. SERPES is focused on the use of a hydraulic model for an existing sewer network, while WADNES focuses on advising the controller on the best course of action to remedy problems in a water distribution network [*Ahmad et al.*, 1989]. *Armijos et al.* [1990] presented an interesting approach to real-time reservoir operation. A hybrid reasoning structure using both Bayesian and rule-based reasoning has been incorporated into a single decision-support tool. The authors claim that the system has learning capabilities an important consideration from the viewpoint of future use.

Nagy et al. [1989] addressed issues and problems in developing an expert system around the existing operating tool for Energy Management and Maintenance Analysis (EMMA) used by Manitoba Hydro. Conclusions from the investigation of the knowledge acquisition process [*Barlishen*, 1989] and the available programming tools were used by *Grahovac and Simonovic* [1990] as a starting point in the incremental development of the expert system. They concluded that permanent interaction between the expert, knowledge engineer, and the final user is critical for the development of an expert system.

Finally, based on a review of existing expert system applications, *Simonovic* [1991] concludes that expert systems have to play a significant role in the field of hydrology. He identifies various tasks, performed by hydrologists in collecting and using data and models, which may benefit from ES technology.

Water Quality

Several expert systems have been developed with environmental managers in mind. The RAISON expert system [*Swayne and Fraser*, 1986] performs analysis of acid rain data and examines the relationships between related acid rain parameters. The program, written in C, operates in a microcomputer environment. An expert system for extracting concise information from a large quantity of available historical water quality data, WATQUAS [*Allen*, 1986], is also capable of interpreting extracted information in a form useful for continuing analysis. WATQUAS is a prototype system that provides: (i) a user-friendly interface to water quality data; (ii) an interpretation of historical data; and (iii) a planning tool based on expert water quality assessment. It was developed for the Ontario Ministry of Environment and runs on a VAX machine. *Jenkins and Jowitt* [1987] describe potentials and problems in developing expert systems for river basin management. They describe work undertaken toward the development of an expert system for operational control of a wastewater treatment plant.

An heuristic computer program, PILOTE [*Lannuzel and Ortolano*, 1989], attempts to reproduce decisions of expert operators in scheduling outlet pumps at a water treatment plant near Paris, France. Although it is not considered an expert system by its authors, the program exhibits many expert systems characteristics and successfully combines mathematical models and heuristics. A knowledge-based expert system, DADEES [*Houck*, 1989], is being developed to support decision-making in the management of potentially hazardous or dredged materials. It is a completely menu-driven system and uses a three-tiered testing strategy to determine the aquatic disposal requirements for dredged material. The same report introduces the application of a knowledge-based system to aid in the calibration and use of the extended Streeter-Phelps BOD-DO model for a stream.

Other Research Areas

Two computer systems, HYSTOR and HYSIZE, were developed to determine the optimum layout for a particular hydroelectric site. The user is provided with alternative ranks according to economic priorities [*Dotan and Willer*, 1986]. HYSIZE is used for run-of-river type projects without storage and HYSTOR is used for sites with reservoir storage. These systems are a rare example of attempts to develop expert systems using FORTRAN. The SISES expert system was developed for use in the process of site selecting for specific uses [*Findikaki*, 1986]. The most impressive feature of the system is its ability to capture decision-makers' preferences without making a priori assumptions about them. The expert system RRA was designed for the U.S. Bureau of Reclamation to administer the acreage limitation provision of the Reclamation Reform Act. It provides a mechanism for determining the status of a landholder, as well as the number of acres on which subsidized reclamation water can be received. The system is designed using an expert systems shell, Personal Consultant Plus (*Strzepek*, personal communications).

The expert systems reviewed above cover a variety of topics and problems related to water resources planning and management. The extent of the work under way, or already completed, shows that ES technology has found a significant place in this engineering field. General conclusions about the status of current systems development, drawn by *Simonovic and Savic* [1989], still hold for the systems presented. The work on applying AI advances to water resources problems is mainly academic and, from the implementation point of view, in its starting stage. Very few of these systems are being used in practice, on a day-to-day basis, although several are undergoing thorough testing by practitioners. However, several papers presented at the recent research workshop on computer-aided support systems for water resources research and management [NATO, 1990] demonstrate that the expert systems technology is being increasingly accepted and trusted by decision makers. Due to cuts in funding, and scarcity of experts, affected water authorities or government agencies are focusing their attention on expert systems research. It is not surprising that most of the developed (or pilot) systems are intended for use by these organizations. The intended end users and the convenience and cost-effectiveness of using personal computers (PCs) have made the ES developers favour PC- or workstation-computing environments. Finally, it is important to note that computational aspects of water resources planning and management have influenced integration of knowledge-based and procedural programming for most of the decision-support system frameworks reviewed here.

Expert systems applying a knowledge-based approach are poised to take a more active role in water resources engineering practice. The technology is widely accepted by the research community and is gaining broader acceptance in the engineering community. However, the success of the new technology will be measured by the degree of its general implementation in practice.

CHAPTER 3.

RESERVOIR ANALYSIS EXPERTISE AND INTELLIGENT DECISION-SUPPORT SYSTEMS

In general, analysis of man-made lakes is a complex multi-disciplinary, multi-stage process comprising tasks from the design of a dam to impound the water to the day-to-day reservoir operations planning and management. The process involves specialists (structural, environmental, geomechanical, hydrological, and hydraulic engineers, among others) from various engineering and non-engineering, but related, fields (politics, economics, operations research, public participation, etc.). Difficulties related to integration of all the mentioned disciplines, modelling their interrelations, and policy implementation and decision-making issues make this analysis a very complex and difficult problem to model. Therefore, a somewhat restricted, yet very demanding, definition of reservoir analysis is introduced. The scope of "reservoir analysis", as used in this work, concentrates on expertise in using the systems approach as an effective means of advancing decision-making in reservoir planning, design, and operations. This definition serves as the framework within which an intelligent decision-support system is to be developed.

As pointed out by *Yeh* [1985], one of the most important advances made in water resources engineering is the development and adoption of optimization techniques for planning, design, and management of complex water resources systems. In fact, systems analysis, ranging from simple cost-benefit analysis to sophisticated simulation and use of optimization techniques, is considered to be the traditional decision-support instrument in water resources.

The decision-making process in reservoir management becomes more complex because of increasing water demands, increasing complexity of reservoir systems, and increasing public involvement. The development and analysis of water management plans and reservoir operating policies, and the subsequent selection of the most promising ones for consideration by managers/decision-makers requires considerable expertise. This expertise is provided by technical professionals, referred to as "experts" in this thesis, who use mathematical models to efficiently identify, formulate, and solve reservoir problems. Their expertise is typically gained through experience in developing and using mathematical models; interpreting their results; and consulting, and discussing operational policies and their consequences, with managers and others involved in decision-making. Expert systems promise to make this type of technical expertise readily available to managers and decision-makers having limited or no expert help. The use of expert systems makes expertise and knowledge transparent and allows the user to easily understand the reasoning of experts and the logic of the program.

The following sections present synthesis of existing expertise and knowledge regarding the non-structured reservoir analysis problem. The need for a tool encompassing this expertise is demonstrated through identified complexities of the reservoir analysis process. Further support for this need is demonstrated by the demonstrated inability of managers to make rational decisions without the help of technical experts. The expertise is structured in four steps/phases. Finally, an approach to developing intelligent-decision support systems is presented and recommended as a preferable alternative to the "classical" expert systems development approach.

3.1. RESERVOIR ENGINEERING AND ANALYSIS EXPERTISE

The engineering of a dam and reservoir goes far beyond the mathematics of structural, hydrologic, and hydraulic design, or the difficulties of construction. Even though a reservoir may be created to serve a single purpose, e.g., water supply, there will be some effects on the surrounding environment. A river basin normally contains a wide variety of aquatic and related wildlife, and may attract numerous recreational users. The changed flow regime of a river will not only affect the lives of people, but also those of fauna and flora, the weather patterns, and the landscape. The planning of a project is, therefore, a multi-disciplinary study in which the water resources engineer should be capable of playing a leading role.

There are a number of uncertainties and imprecisions involved in reservoir analysis, e.g., hydrological uncertainty associated with reservoir inflows and water demands; imprecision in subjective evaluation of changing objectives and values; and uncertainties in estimating future social or political impacts of recommended decisions. Reservoir inflows, together with other input data, including management objectives and assumptions concerning the representation of physical processes and their characteristics, are important factors in the reservoir analysis process. The following is a short summary of the most important features influencing this process and the expertise required to perform it.

For any reservoir analysis, streamflow data are considered to be of the greatest importance. Although streamflow is continuous in time, it is usually measured in discrete time intervals and is considered as a time series made up of discrete variables. In the reservoir analysis process, the length of the inflow time step varies from less than one day to a year or more, depending on purpose of the reservoir analysis. For example, problems involving floods require short time steps, sometimes even hourly or daily, to capture flow variability. As well as uncertainty resulting from its stochastic nature, the following characteristics of streamflow and streamflow data sources may cause difficulties:

(i) short and unreliable inflow records;
(ii) unreliable and inaccurate hydrometric measurements;
(iii) incompatible data;
(iv) differences in temporal and spatial resolution; and
(v) poor statistical quality.

Short inflow records may be extended by using the available techniques for estimating historical streamflow data. The selection of a technique depends on the characteristics of the river basin watershed and available streamflow and rainfall data sources.

In addition to inflow considerations related to reservoir analysis, the identification of relevant planning objectives, and subsequent definition of the relative importance of each of these objectives, is one of the most difficult aspects of the analysis. Many individuals, interest groups, and organizations are affected by, and concerned about, water and the environment. Each of them has a number of objectives which are usually conflicting, difficult to quantify, and often incommensurate. This complexity makes reservoir analysis an iterative, dynamic, and learning process during which goals may change or new objectives and constraints may emerge.

In attempting to improve reservoir analysis, it is worthwhile to examine issues and difficulties encountered in previous applications of the systems analytic approach (specifically, of formal models) to practical water resources problems. These issues placed burdens on decision-makers and reservoir operators who then became reluctant to use models for planning or for adjusting existing reservoir operation procedures. Although this work concentrates on single reservoir problems, which narrows the scope, a key characteristic of reservoir analysis is **the complexity of the reservoir problem itself**. Therefore, identifying and formulating the problem may not be as simple and straightforward task as it first appears. In formulating the problem, in terms of different measures of performance and constraints, a key player in the process is the expert, possessing highly developed technical capabilities, who relies mostly on experience and personal engineering judgment. A typical single reservoir system has many, equally important, physical components, each of which is related to the others (for example, spillway, emergency spillway, bottom outlets, turbines, turbine by-pass outlets, etc.). This complexity prevents engineers from evaluating all components in detail and requires them to break the analysis down into several stages. The process usually starts with the feasibility study, continues through the preliminary analysis, and ends with the detailed analysis.

Another important characteristic of reservoir analysis is related to **selecting the appropriate solution procedure** for the identified and formulated problem. Analytical and/or numerical procedures may be available to perform the required analysis. Since modelling is a rapidly advancing and highly specialized field, it is very difficult for managers to stay informed about new developments and models. Human experts (analysts), who are informed, experienced, and capable of making judgment in complex situations are not always available to managers. These technical experts are capable of making reasonable and accurate a priori evaluations of the problem-solving strategy and of making recommendations on the appropriate procedure for the particular situation.

Numerous reservoir models are currently used in water resources research laboratories or specialized agencies. Although the number of models is important and may be an advantage for a user, the **over-abundance of possible choices may increase the burden** on a water resources manager. The models may be difficult for users to identify, locate, and obtain. Even when different models require similar basic data, data selection and processing methods can vary greatly. The complexity associated with initial estimation or the adjustment of input parameter values emphasizes the need for a human expert to conduct or assist in the task [*Arnold and Sammons*, 1988; *Baffaut and Delleur*, 1989]

There is a long-standing concern about **difficulties inherent in using mathematical modelling techniques** and implementing them, especially for public-decision making [*Liebman*, 1976]. It has been pointed out that even multi-objective models have serious shortcomings and that no general technique which provides a definitive answer exists [*Brill*, 1979]. The review of reservoir operations models and applied optimization techniques by *Yeh* [1985] reached the same conclusion. Before applying optimization or simulation procedures to a specific problem, an expert should, therefore, contribute to the reservoir analysis by assessing potential weaknesses and limitations of the technique(s) employed in the model. For this task, knowledge, of both operations-research techniques and water resources related expertise, is essential.

Use of mathematical models as tools within a planning process requires the **objective evaluation and interpretation of the reservoir model outputs.** This output analysis should be done in a iterative manner, by adjusting parameters that need to be calibrated and then restarting the model with the changed parameters. The final solution is often unique, but sometimes many different answers to a given problem may achieve the objectives closely enough and satisfy the constraints.

An additional difficulty that is often encountered in decision-making related to reservoir planning is the **lack of communication and understanding between the experts/analysts and the decision-makers (DM)** [*Liebman*, 1976]. The involvement of the affected public, or stakeholders, is making the situation even more complicated. This deficiency can compromise all previous efforts exerted in the analysis. Different sources of complexity are summarized in Figure 3.1. Few decision-makers are familiar with the modelling process and even fewer are willing or able to get involved with it. Therefore, the transfer of quantitative and non-quantitative understanding of the problem from the expert to the DM, and vice versa, is of great importance. From this point of view, a computer may help in communication and learning.

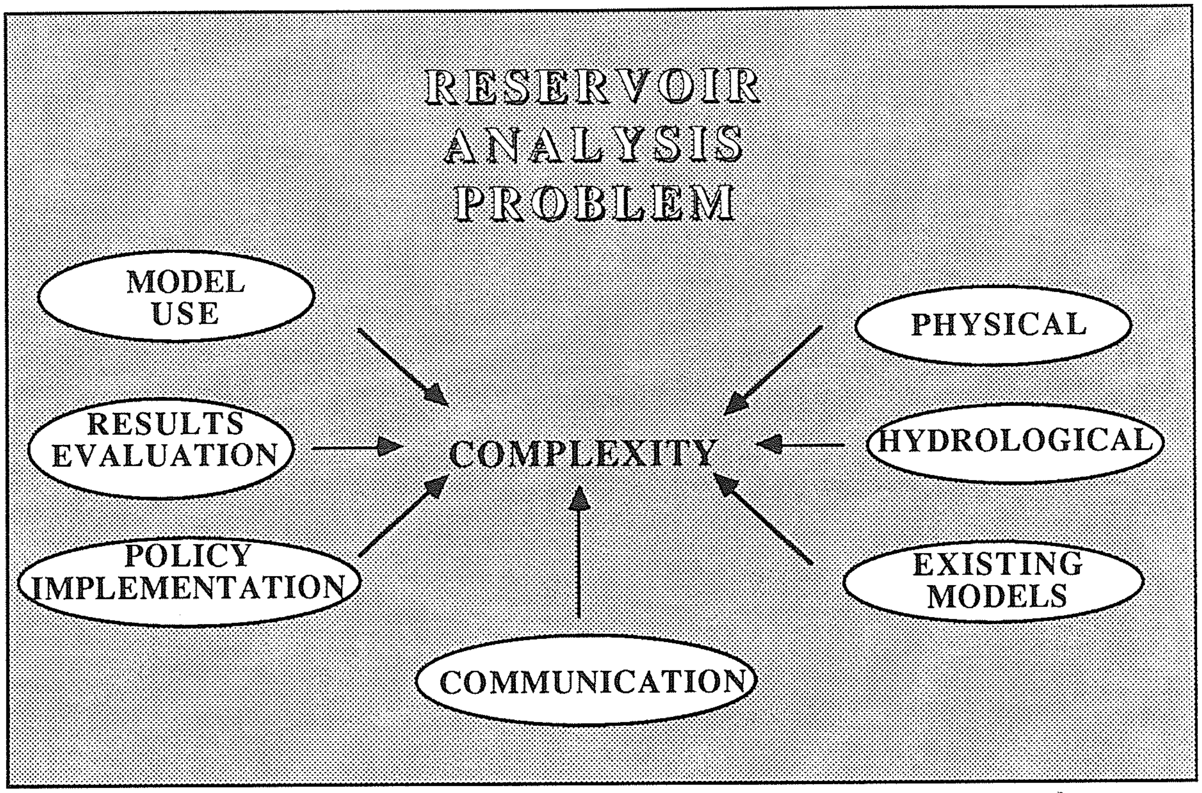

Figure 3.1. Sources of complexity in reservoir analysis problems

3.2. RESERVOIR ANALYSIS PHASES

The first step in implementing the EES approach to reservoir management problems is to identify specific areas in reservoir analysis where it may complement or out-perform the present combination of human expert involvement and use of conventional programs. In performing such an examination, it became obvious that a number of frustrating characteristics of public sector decision-making that require subjective evaluation and conflict resolution, cannot be formally represented in any generally acceptable way. Consequently, the scope of this work was narrowed down to improving reservoir mathematical modelling and model use for planning and management, i.e., the expertise from some engineering fields (geology, geomechanics, structures, etc.,) has been excluded from consideration here. However, even with the narrowed scope of study, all previously mentioned sources of complexity are addressed by the developed tool.

Once the scope of the work was decided upon, the task of reviewing and rationalizing the reservoir analysis process had to be performed. It was found that this complex dynamic task includes the following phases:

i) reservoir problem identification and analysis for establishing goals and objectives;

ii) mathematical formulation of the established objectives and physical and other constraints;

iii) selection of the formal mathematical solution procedure for analyzing the identified, and subsequently formulated, problem; and

iv) input data preparation, application of the formal mathematical procedure, and presentation, evaluation, and validation of the results.

In addition to these tasks, the process may be repeated, in an iterative manner, providing alternative solutions and more insight into the problem under consideration.

3.2.1. Reservoir Problem Identification and Analysis for Establishing Goals and Objectives

The initial step of every analysis is directed toward gathering preliminary information and identifying: i) important characteristics of the problem; ii) the scope of the problem; iii) the interrelationships among the components of a reservoir system; and iv) performing the analysis of the objectives. In the reservoir analysis process, this step is composed of defining the purposes of the analysis; acquiring information about the availability of historical records of relevant parameters; assessing involved risk; establishing goals and objectives, etc. This phase of reservoir analysis is not precisely defined, in a structured way, in the available technical literature. Rather, it is defined in general terms, giving users no guidelines but leaving them to rely on their individual experience in gathering relevant information about the problem.

One of the earliest decisions to be made concerns the purpose of the reservoir analysis. In discussing the problem with the DM or with members of the supporting staff the expert is usually expected to conclude whether reservoir design (sizing), or reservoir operation planning, or both are of interest and need consideration throughout the analysis process. If reservoir operation planning is inferred to be the primary concern, then a more detailed specification of the purpose of the analysis is needed. Using information about management needs and available data, the decision whether real-time reservoir operation or long-term planning is required, should be provided next.

To analyze a reservoir problem, an expert needs quantitative measurements of hydrologic data (streamflow, precipitation, evaporation rate, etc.), i.e., historical data records. These data records should be sufficiently long to properly define the statistical parameters and behaviour of hydrologic data. For example, a 3-4 year record is likely to be insufficient to provide a representative picture of long-term flow variability at the gauging station. The expert should also ensure that data are homogeneous over time and without systematic errors incurred in information gathering. Before proceeding further, an expert should also decide upon the optimization time step that should and can be used (given the purpose of the analysis and available data). If a planning study is needed, the number of time steps to be considered within a planning horizon must be determined.

Inadequacy of data is the most commonly identified factor inhibiting modelling efforts [*OTA*, 1982]. It may introduce significant bias into any water resources management evaluation. Therefore, it is often necessary to estimate short gaps of missing data, e.g., streamflow data, or even to increase the record length by using data extension techniques. Knowledge and experience in extending station records by regression with nearby gauging-station records, as well as knowledge of rainfall-runoff processes and models is essential for performing this task. It should be noticed that the reliability and credibility of formal models is only as good as the input data.

Keeping in mind the purpose of the analysis, available data, data record sampling frequency, and data reliability, the next step in identifying a reservoir problem and performing analysis is to assess the potential consequences of a system failing to achieve established objectives. Generally, this type of risk depends on water use, land use, and population density downstream from the reservoir. According to the level of involved risk and data record characteristics, the decision about the level of detail and necessary simplifications of the physical system should be analyzed. The expert's task is to reduce the number of factors under consideration to a manageable size, and to select for modelling the most significant characteristics of the system.

3.2.2. Mathematical Formulation of Established Objectives, Physical and Other Constraints

A mathematical model uses numbers and/or symbols to represent relationships among the components of real-world systems. If these relationships can be meaningfully quantified, they can be included in a mathematical representation, i.e., formal model, of a reservoir system. As a result, along with gathering necessary data, a very important part of the analysis is formulation of the reservoir problem into a suitable mathematical form. Various simulation and optimization procedures require an explicit mathematical definition of the objective function, constraints, the governing equations, and the bounds on decision variables. Proper formulation is the first step in successful selection of an appropriate algorithmic procedure to solve the identified problem.

Decision Variables

Reservoir planning and management activities involve the selection of many engineering design and operating variables. When a mathematical model is used to describe a reservoir system, these design and operating variables are called decision variables. Often these variables represent decisions regarding physical quantities (e.g., storage capacity, release through turbines, release for irrigation, etc.), or system performance characteristics (e.g., probability of failure, resiliency, robustness, etc.). For example, if reservoir design is identified as the reason for analysis, reservoir capacity becomes the decision variable. Reservoir operation models may, on the other hand, include allocation of water to different users, release and storage targets, or reservoir releases as decision variables. In the mathematical notation used to describe a model, a set of decision variables is usually denoted as a vector:

$$\mathbf{x} = (x_1, x_2, \ldots, x_n)^T \tag{3.1}$$

Where n is the number of decision variables and T denotes transpose.

The expert's must often rank possible variable choices and decide which variable(s) is most important for the identified reservoir analysis objectives. This task requires experience and technical skill to fulfill the goal of including a high degree of reality within the model and analysis while keeping it manageable. For example, in considering hydropower generation, the decision should be made whether or not to distinguish between releases for on-peak and off-peak reservoir operation. If the distinction is not significant for the analysis, the dimensionality of the problem may be halved.

Objective Function

Reservoir system performance may be evaluated by assigning a value function to the system decision or output. For example, a reservoir operation within a time step may be judged in relation to the economic benefit realized from hydropower generation. Such a benefit depends on the reservoir storage, inflows, and releases of the current, and several previous, time steps. In optimizing reservoir operation usually more than one time step must be considered in the time horizon, thus generating a value vector during the optimization. The overall system performance may then be evaluated through the use of a single objective function. This objective function assigns a single total value of system performance to every possible value vector:

$$f\,[v_1(d_1),\, v_2(d_2),\ldots,\, v_t(d_t)] \tag{3.2}$$

Where f is the objective function; v_t represents the value function at the time step t, in the planning horizon t=1,2,...,T; and d_t represents the decision variable at the time step. If the objective function represents net benefits from operating the reservoir, then the expression (3.2) may be maximized with the decision variable representing release.

An alternative approach for optimizing the multi-purpose reservoir operation, is one often used in multi-objective analysis. The so-called weighting method may be used to reflect priorities assigned to each different goal of meeting release and/or storage targets. For the management of the High Aswan Dam, for example, *Bras et al.* [1983] considered irrigation, flood protection, and hydropower production. The objective function vector, consisting of separate goals, was converted to a scalar as the weighted sum of the individual goals:

$$\underset{\{\mathrm{r}\}}{\text{Minimize}} \sum_{i=1}^{3} w_i \cdot A_i\,(TAR,\, \mathbf{r}) \tag{3.3}$$

In the above equation, w_i represents the non-negative weights specified as constants, and A_i represents functions of the target vector TAR, and the release vector $\mathbf{r}$. The index i, i=1,2,3, is related to the three different goals contained within the optimizing model.

A different objective function, which incorporates net benefits, associated with monthly releases, and losses, associated with reliability levels for not violating storage targets, is reported by *Simonovic and Marino* [1980, 1981]. This approach requires deriving the so-called risk-loss functions, associated with violating storage targets and maximizing the following expression:

$$\underset{\{\mathbf{r}\}}{\text{Maximize}}\, f(r) - L_1(\alpha) - L_2(\beta) \tag{3.4}$$

where f represents the net benefit function associated with the release vector, $\mathbf{r}$, during a year, and L_1,L_2 represent yearly risk loss functions associated with reliability levels α, β for different parameters.

In the case of reservoir sizing, a simple objective function stated by expression 3.5, which achieves minimum active storage capacity under specified conditions (operating and/or physical constraints) may be used:

$$\text{Minimize } CAP \tag{3.5}$$

where *CAP* represents the active reservoir storage capacity. An example of the use of this objective (function) is determining the minimum active storage capacity for a given set of releases over a period of time.

The four objective function examples, cited, above illustrate the diversity in possible approaches to formulating reservoir analysis problems. An additional difficulty in identifying an appropriate objective function may be attributed to two types of benefit functions: long-run and short-run [*Loucks et al.*, 1981, pp. 203-205]. For long-run benefit functions, the target reservoir releases to different users are assumed to be unknown decision variables. For short-run benefit functions, the target storage and release levels have been fixed and reservoir operators try to satisfy them as closely as possible. Only when resources available in a short run, correspond to those anticipated when the long-run decisions were made, can estimated long-run benefits and actual short-run benefits be the same.

The choice of the objective function is highly influenced by the problem characteristics, the expert's preference for using specific technique(s), and the DM's willingness to co-operate. If formal models for improving reservoir management are to be implemented, the objective function should reflect both physical and economic reality, as well as the DM's perception of the system. *Houck* [1981] demonstrated the importance of the expert's understanding of the modelling problem to the correct identification of the objective function. In Houck's [1981] work the analysis was performed for the objective function of an optimization model used for real-time operation. By analyzing losses associated with deviations from ideal operations, he proved that the objective function should differ from the true measure of effectiveness of reservoir operation (i.e., penalty functions used in real-time operation should be different from the identified true penalty functions). These findings were attributed to the lack of reliable long-range inflow forecasts required to use true penalty functions in real-time reservoir operation. Other examples from the literature show that nonscientific aspects of the problem often dominate and reveal difficulties in achieving proper representation of real-world problems [*Schultz*, 1989].

Governing Equation

Every formal reservoir model must be based on the general principle of conservation of mass (mass balance or continuity). The conservation of mass for a reservoir may be simply expressed in terms of mass added by inflows, and mass removed by outflows (including losses). There are many ways to represent the components of the mass balance equation. One approach is to express the final storage volume S_t, in the time period t, in terms of the initial storage volume S_{t-1}, inflow i_t, release r_t, evaporation losses e_t, and seepage losses s_t:

$$S_t = S_{t-1} + i_t - r_t - e_t - s_t \tag{3.6}$$

Inflows are stochastic in nature and the proper collection of inflow data and their treatment is of crucial importance for reservoir modelling and model use.

A reasonably accurate estimation of the evaporation losses is necessary for reservoir analysis, at sites in arid regions having high rates of evaporation. For example, *Lele* [1987] reported a 30% increase in the required storage capacity when evaporation losses were included. A similar example by *Wurbs and Bergman* [1990] shows that the net evaporation losses in the Brazos River Basin (U.S.) were in the range of 20-60% of the firm yield of the reservoirs in the basin. Evaporation and seepage losses in the time period t, are functions of the storage volume in the reservoir during that period.Reliable estimation of the average evaporation (or seepage) rates for each period is required for a correct inclusion of losses.

Careful evaluation of the reservoir problem and basin hydrology is necessary for properly expressing the mass balance equation. A water resources expert, familiar with the problem and trade-offs between the problem representation and computational efficiency, is responsible for making decisions pertaining to this task. For example, the assessment of the quality of collected evaporation data may lead to a complete exclusion of evaporation terms, or the use of gross evaporation instead of calculated net evaporation. A common decision that must be made is whether to average monthly evaporation rates for all years in the planning period, or to use actual monthly rates which vary between years.

The nature of the mass balance equation, which represents an actual physical limitation which cannot be, usually requires that the equation be formulated as a constraint. The mass balance equation is analyzed before the other constraints because it is fundamental to the reservoir analysis problem.

Constraints

In addition to an objective function and the continuity equation, reservoir management problems incorporate a number of requirements which are formulated as constraints. As with the continuity equation, some of them may be expressed as rigid physical limitations, e.g., the capacity of the reservoir, the capacity of a spillway, etc. Other constraint types incorporate requirements that could be violated, although the losses associated with such violation may be high. These constraints include restrictions on minimum instream release for water quality reasons and restrictions on violating the reservoir flood control and minimal storage levels.

If a decision variable should be prevented from violating some physical boundary, a simple deterministic constraint may be appropriate to express the requirement. A typical deterministic constraint, regarding minimum instream release, may be expressed as:

$$r_t \geq r_{\min} \tag{3.7}$$

where $r_{\min}$ represents the minimum required volume to be released for low flow augmentation and water quality purposes. Sometimes, depending on a situation, the same type of requirement may be expressed as a probabilistic constraint:

$$P(r_t \geq r_{\min}) \geq \alpha \tag{3.8}$$

where P is the probability that the reservoir release r_t, in the time period t, is greater than the minimum required instream release $r_{\min}$. The expression allows violating the minimum required instream release, at most, $(1-\alpha)*100\%$ of the time.

In some cases, it is difficult to decide whether a requirement should be formulated as a constraint or an objective. A high level of modelling expertise and judgment is needed to decide which objectives of the problem can be modelled as constraints and how to formulate these constraints. For example, it is always an expert's responsibility to decide whether flood control requirements, in a particular case, should be included through an additional constraint or through the objective function. Different mathematical forms may be employed for this purpose [*Simonovic and Marino*, 1980; *Bras et al.*, 1983; and *Druce*, 1990].

3.2.3. Selecting Formal Mathematical Models for Analyzing Identified and Formulated Reservoir Problems

In practice, the outcome of this phase depends on the reservoir models available to managers and planners, or on the ability of their staff to develop a model. Developing reservoir models is a complex undertaking, requiring skilled personnel as well as adequate time and funding for computer facilities and collecting and processing data. It is, therefore, advantageous to use developed standard models that can be adapted to management needs. If possible, it is also important to use a tool with which the manager is familiar. *Ford and Davis* [1989] concluded that people would rather live with a problem they cannot solve than accept a solution they cannot understand. Therefore, any potential user needs a great deal of information about available models to select the proper one for his/her problems, to become familiar with running the selected model, and to interpret its results. Documentation is the primary mechanism for informed communication among those involved in developing a model and those interested in using it.

Even when documentation on different reservoir models is available, a great deal of experience and knowledge is needed to make an appropriate selection. In order to perform the analysis correctly, an expert user should be able to understand the simplifications and limitations of the model and modelling technique. For example, in sizing a reservoir, the expert should keep in mind which methods are suitable for preliminary design and which for final (detailed) analysis. It is also the expert's responsibility to choose the model having a programming technique that best fits all aspects of the reservoir problem and the computer facilities to be used.

It can be concluded, that there is no perfect match between reservoir problem characteristics and a model's capability to address them. A basic requirement that must be upheld in all analysis, namely the correct modelling of the problem at hand, is often difficult to achieve. The future uncertainty is a primary concern in all reservoir problems, but there is no unbiased approach to dealing with this. Therefore, a considerable amount of judgment is necessary when selecting the best tool for the circumstances. It is not surprising that the study by *OTA* [1982] came to the conclusion that "water resources models vary greatly in their capabilities and limitations and must be carefully selected and used by knowledgeable professionals".

3.2.4. Input Data Preparation, Model Use, and Results Presentation, Evaluation and Validation

An important aspect of reservoir modelling and model implementation is associated with preparing data for use by a formal model. This step deals with gathering and preparing necessary information and input data in a form recognizable by the selected model. Its success strongly depends on the user's knowledge of where to look for information and data as well as how to process them to get the desired output. Increasing numbers of hydrologic data collection networks and automated data retrieval systems make the first part of this task easier [*Call et al.*, 1989]. The second part, information and data processing, depends on the input data characteristics of a particular model.

For practical purposes, it is important to have a model that is designed for use by persons other than the model developers. This kind of model ensures that information and data needed for running the model can be introduced into the model with the least effort and with least possibility of errors. Such a model should perform data feasibility checks and verify data completeness. In the past, model developers concentrated their research efforts mostly on developing techniques and procedures; user interfaces and data checkers were neglected. These shortcomings are beginning to be addressed with the development and application of Computer Aided Design (CAD) and ES technologies.

A model's ease of use depends not only on the design of its input, but also on its output characteristics. The output of a good user-oriented model can be adjusted to provide the level of detail and organization of information that best suits the user. This may be quite different for different persons and if a model lacks these capabilities, it is expert's obligation to provide the end-user with systematized output. In that case, the modeller must instruct the user in interpretation of model results, otherwise, the conclusions may be misleading. Another approach is to hire an expert to be responsible for data analyzing and interpretation of results to managers and decision-makers. Common formats for presenting data to clients range from simple numerical tables to qualitative linguistic statements and colour graphics.

Most formal models are equipped with some kind of diagnostic mechanism for determining whether a model succeeded or failed to reach a solution. If a computer run cannot be completed due to errors or data incompatibility, there is usually no parameter or fault analysis to help a user trace the problem back to input data. Instead, a simple "diagnosis" indicating system failure is presented to the user.

Leaving a non-expert user with only this "diagnosis", for example, in the case of the solution infeasibility -- "solution infeasible", would not provide productive man-machine interaction. Instead the manager may choose to avoid using the model in the future. Managers and planners rely on human experts, or modellers to identify the parameters that cause problems and/or influence the solution most significantly. Again, a great deal of problem understanding and modelling experience is essential for performing diagnostic analysis and evaluating the effects of variation in parameters.

3.3. ENGINEERING EXPERT SYSTEMS APPROACH

Various definitions of an expert system may be found in the AI literature. A composite definition considers an expert system to be a computer system (program) that uses domain-specific knowledge to solve problems in a narrow domain at a level of performance that is comparable to that of a human expert [*Barr and Feigenbaum*, 1981; *Rich*, 1983; *Waterman*, 1986]. The key concept in expert systems development is the accumulation and codification of knowledge (expertise), particularly high quality knowledge used for solving so-called "hard" problems. The process of acquiring the knowledge needed to power an expert system and structuring that knowledge in a usable form, i.e., the process of building an expert system, is often referred to as "knowledge engineering". The advocates of this definition argue that the process should rely on specialists, i.e., knowledge engineers with a background in computer science and AI, to perform knowledge acquisition and knowledge structuring [*Waterman*, 1986]. In this context, a knowledge engineer is viewed, within the knowledge engineering process, as a crucial connecting link between the domain expert and the expert system (Figure 3.2). The role of the knowledge engineer is to interview the expert, to organize the knowledge, to decide upon knowledge representation within the expert system, and to develop a knowledge base.

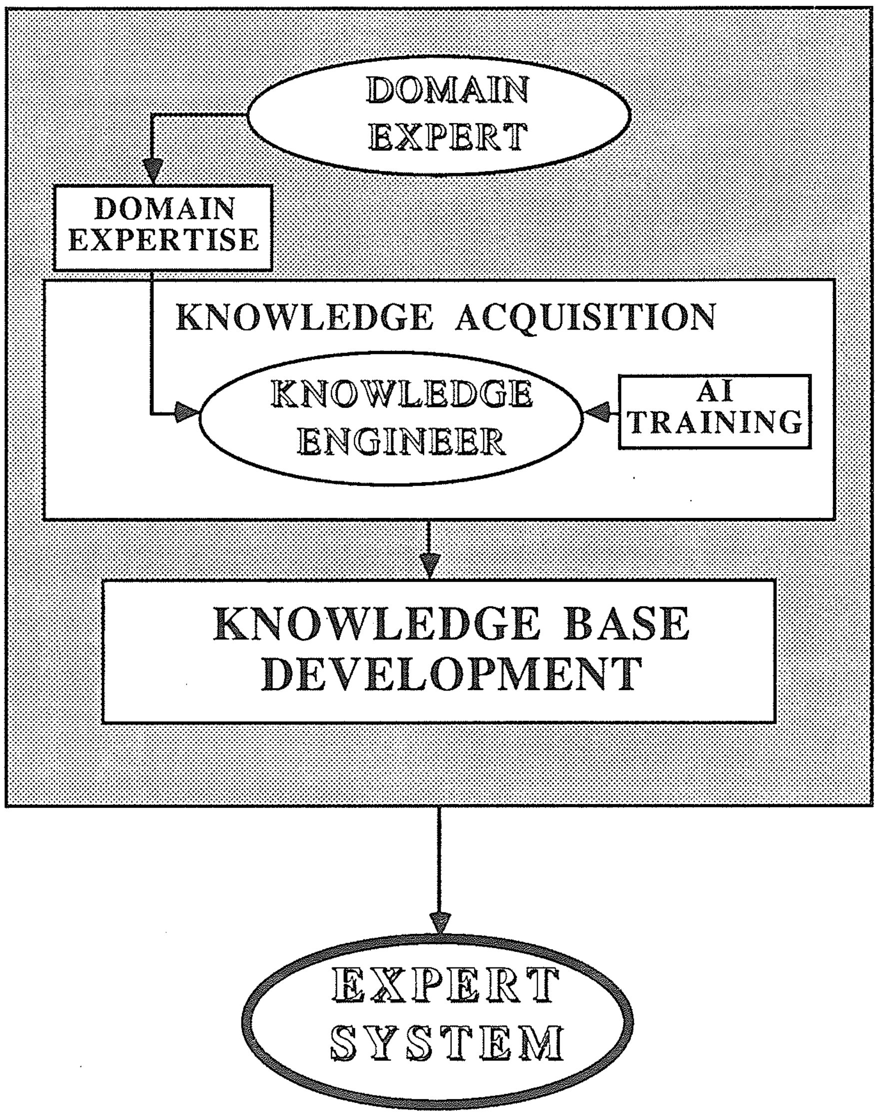

Figure 3.2. Standard approach to expert system development

Expert systems developed using this standard approach typically consist of two major components:

(i) knowledge base; and

(ii) inference engine.

The essence of an expert system is the explicitly encoded knowledge which has been organized to simplify decision-making. The most common way to store knowledge is in the form of facts and IF/THEN rules developed for a particular problem. Some systems make use of knowledge representations such as semantic nets and frames. These last two approaches group related facts and rules together to ensure consistency, modularity, and easier access to the knowledge [*Waterman*, 1986]. The problem of knowledge acquisition must be properly addressed to develop knowledge base that will promote a successful expert system. Depending on the type and source of knowledge relevant to the domain of the expert system, different approaches may be employed. Public knowledge [*Hayes-Roth et al.*, 1983], which is widely shared and agreed upon is contained mainly in textbooks, manuals, and references, is highly structured, may be easily accessed and acquired This type of knowledge is considered as a static knowledge category. The extraction of private knowledge, which is possessed by human experts and is therefore dynamic, is a much more difficult task. An important benefit of knowledge acquisition for modelling purposes is that it brings an understanding of how experts organize and use their knowledge to less experienced people [*Barlishen*, 1989].

The second important component of an expert system is the inference engine, i.e., a control strategy required for manipulation of knowledge. This control strategy determines how facts and rules are to be used for problem solving. Expert systems problem solving involves the search through the knowledge base for the set of rules that, when applied, provides a solution. The direction of a search through the knowledge base is determined by forward-chaining or backward-chaining strategy. A forward-chaining search works from an initial state of known facts to a goal state, while a backward-chaining search works in opposite direction. Each strategy has its own advantages and drawbacks. Effective engineering expert systems usually employ aspects of both strategies.

In addition to these two main components, a user interface, explanation facilities, a working memory, and a knowledge acquisition subsystem may also be distinguished within an expert system. The user interface is a vehicle for communication between the system and the user. The "friendliness" of a user interface should be as highly developed as possible, in order to give the user easy access to the information within the system. Explanation facilities are responsible for clarifying the reasoning leading to any conclusion the system reaches. They may provide a trace of the execution of the system, as well as facilities capable of answering WHY and HOW questions. The working memory contains information about the current subproblem a system is attempting to solve. As the system retrieves new data, facts may be added, modified, or even deleted from the working memory. The knowledge acquisition system is responsible for facilitating modifications and updating of the knowledge base. This system is closely related to the user interface.

The development and application of lower level as well as more advanced expert systems for helping water and environmental resource engineers and managers has been taking place for almost ten years [*SRI International*, 1981; *Kostem and Maher*, 1986; *Maher*, 1987; *Ortolano and Steinemann*, 1987; *Simonovic and Barlishen*, 1987]. The interest in technology is commensurate with its promises to help reduce complexities involved in decision making and implementation of water resources systems planning, design, and operations. Expertise and intuitive judgment form an important aspect of water resources engineering, making the development and application of expert systems highly appropriate.

A specific approach to developing expert systems by engineers and for engineering use, named Engineering Expert System (EES) approach by *Simonovic and Savic* [1989], evolved from the higher involvement of engineers in expert system construction [*Savic and Simonovic*, 1989; *Cohn et al.*, 1988; *Nagy et al.*, 1989; *Barlishen*, 1989]. The EES approach differs from classical knowledge engineering most significantly in the area of knowledge acquisition. In the EES approach civil engineers with a background in AI and ES techniques, and with the help of easy-to-use ES shells, assume the role of knowledge engineers (Figure 3.3). This approach simplifies the development of the knowledge base and helps engineers achieve more insight in the structure of the expertise. In addition, through this approach, the research concentrates on the application of the ES technology to specific engineering fields, rather than on problems in general AI.

Decision making within the reservoir analysis framework may be defined as choosing among alternatives which are generated for design, long-term, or short-term reservoir operation purposes. Alternatives are not always obvious, and the search for them can be a difficult task. Classical decision-support systems (DSS) provide a combination of tools which support the process of understanding and structuring a problem, generate alternative solutions, and help a decision-maker to evaluate them and to choose those that are acceptable. Decisions in water resources should be accepted with some reliability and within confidence limits because of the uncertainty and risk inherent in the area. In the past, decision-support tools were based mainly on mathematical modelling and use of graphics. Now, database and artificial intelligence techniques improve the capabilities of the classical tools.

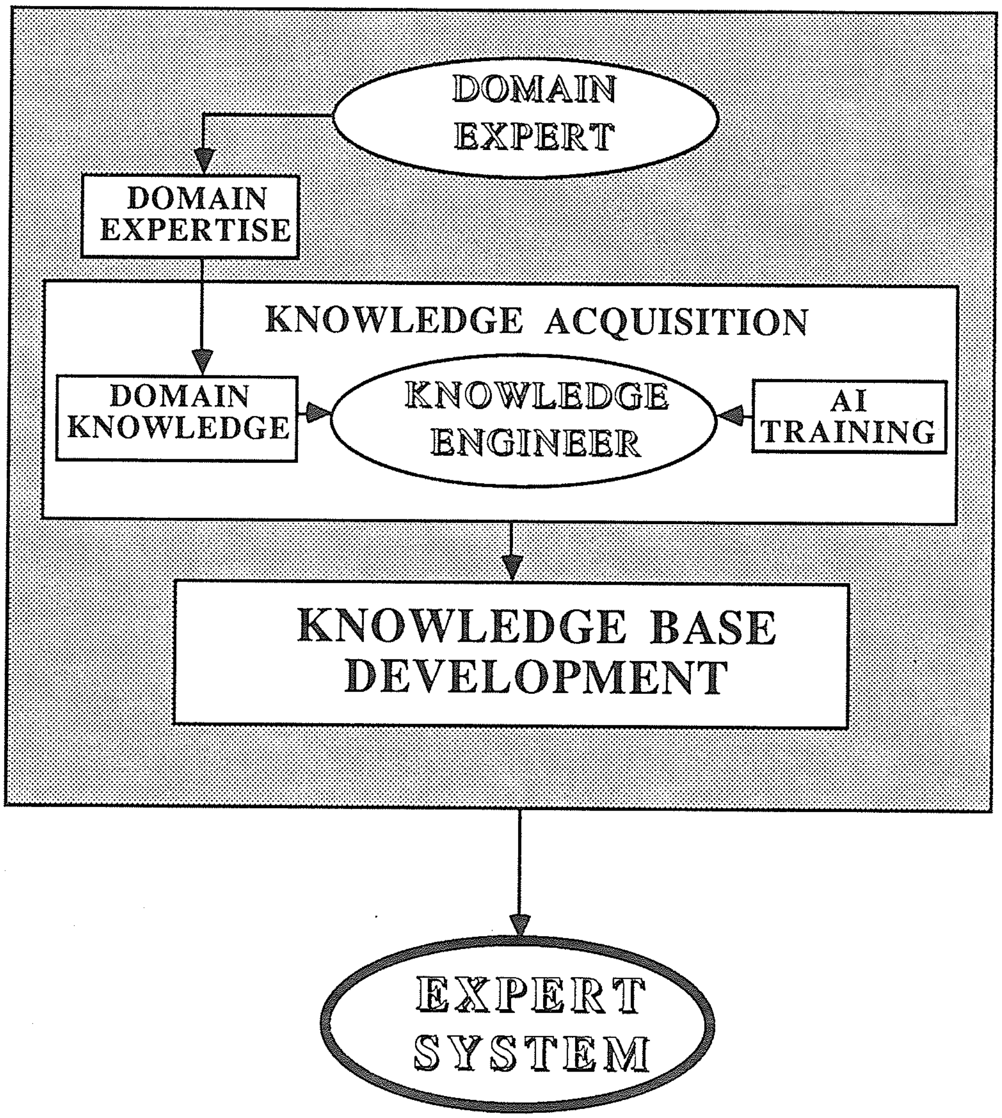

Figure 3.3. Engineering Expert System approach to expert system development

The EES approach should be widely applied in the development of DSS to be used by technical professionals as well as less experienced decision and policy makers and users. Thus computer becomes not only a vehicle for numerical analysis, but also a vehicle for communication, learning, and experimentation. This line of thinking initiated another definition of a computer system, called the intelligent decision-support system (IDSS), which differs from the classical definition of a DSS or expert system. An IDSS, particularly for water resources analysis, is a computer program that assists in understanding and solving complicated water resources problems by integrating engineering knowledge, principles of systems analysis, experience, intuition, creativity, and engineering judgment with formal procedural modelling. Therefore, the interaction between the declarative component and external procedural models, with efficient means of real-time data transfer, characterizes intelligent decision-support systems. To summarize, an IDSS is considered to be a result of applying the EES approach, within its philosophical framework, to the development of a computer system by and for engineers.

CHAPTER 4.

REZES: AN INTELLIGENT DECISION-SUPPORT SYSTEM FOR RESERVOIR ANALYSIS

This chapter describes how the expertise and knowledge in the area of reservoir analysis is structured by combining systems analysis and artificial intelligence technology in an intelligent decision-support system. The structure identified during the synthesis of the expertise (Chapter 3) is revised and transformed into decision rules. Examples of the rules for all four identified phases of the reservoir analysis process are then presented. Finally, an illustrative example is analyzed with help of the developed tool.

4.1. RESEARCH OBJECTIVES

The basic aim of the research leading to the development of REZES was to capture and formalize knowledge and expertise that has been implicitly rather than explicitly available. Careful analysis of research objectives preceded the system development because of the lack of detailed documentation of all the tasks normally undertaken in a reservoir analysis process. In addition to formalizing accumulated knowledge and expertise, this analysis revealed the following research objectives:

(i) to review and rationalize the general reservoir analysis process in order to permit it to be explicitly encoded;

(ii) to test the capabilities of knowledge-based (ES) technology in the field of reservoir analysis using domain experts in developing an IDSS themselves, rather than calling upon knowledge engineers;

(iii) to improve the application of different conventional procedures and formal models for the reservoir analysis, integrating them with advanced knowledge-based (ES) technology;

(iv) to provide an intelligent decision-supporting tool to advise and train different types of users of reservoir analysis;

(v) to equip the system with powerful explanation facilities and ensure that users are consistently informed of the reasoning employed by the system;

(vi) to provide a new type of automation using less experienced personnel (novice users), quicker solution procedures, and more reliable solutions;

(vii) to use a PC-based hardware environment for wider acceptance and applicability of the system.

The development of a complex decision-support system is not a uniquely defined task for a fixed time period. Rather, it is an iterative process, with frequent revisions as the work progresses. This revision aspect extends into the implementation phase. In addition to the objectives identified prior to the system development, some additional conclusions were drawn during the development of REZES. Several hidden objectives have also been identified:

(viii) not all areas in the reservoir analysis are suitable for declarative computation. Therefore, an additional objective was to identify specific areas (in the reservoir analysis) where ES technology may complement or out-perform conventional software; and

(ix) the scope of the general reservoir analysis as defined by all involved disciplines, and as described in the introduction to Chapter 3, was found to be too broad for the successful development and later effective implementation of an IDSS. The objective of the work was then confined mainly to expertise related to mathematical modelling and applying the systems analytic approach to reservoir management. This re-direction enabled the research to go more in depth rather than in breadth. For other related aspects of reservoir analysis not covered by REZES, the user is directed to literature dealing specifically with the given aspects of it.

In conjunction with the recognized research objectives, three potential user types have been identified for the software system being developed:

(i) An "assistant" user, with whom the system is intended to interact in order to encourage him/her to find a solution, or a range of solutions, for a problem at hand. This type of user needs directional advice from the system. He/she may have overall knowledge, but lacks experience in performing specific tasks.

(ii) A "client" user, for whom the system behaves as a consultant. The system is intended to offer answers to the client's reservoir problems. This user type is generally well aware of all aspects of reservoir problems, but is relatively ill informed about effective solution procedures.

(iii) A "student" user, for whom the system acts as an practical instructor and also provide a deeper insight into "expert" knowledge. This type of user possesses theoretical background in reservoir modelling approaches and techniques, but lacks practical experience and expertise in implementing them.

The underlying assumption for all the user types is that they all possess a certain amount of reservoir analysis knowledge or knowledge related to decision-making problems. The system requires user involvement in providing information on the reservoir problem. That information is used by the system to provide alternative solutions that ensure better understanding of management actions and can lead to rational decision making. This issue is in agreement with the purpose of REZES, which is not a decision-making, but a decision-supporting tool.

4.2. KNOWLEDGE ACQUISITION

The concept of building "skilled" expert systems by first extracting the domain expert's knowledge and then organizing it in an efficient manner is referred to as "knowledge engineering" in AI literature. The tasks of effectively extracting knowledge and operatively representing it are crucial for the building and ultimate success of expert systems. However, the transfer of knowledge from people and other sources to software systems is not simply an ad hoc procedure. During the course of this study the structure of the future system was defined and the reservoir analysis process was reviewed and rationalized as a result of the experience gained and increasing understanding of the problem. Development of the rule base uncovered additional problems related to knowledge encoding, as well as problems specific to the ES development tool being used. Initially developed strategies or intentions were modified to address problems emerging during the course of the research. The experience gained during the initial stages of knowledge acquisition and ES development was used for subsequent stages. Clearly, this is a benefit of building a knowledge base in stages and adopting the modular knowledge base structure.

The process of knowledge acquisition starts with the identification of all relevant sources of knowledge about the problem domain. A thorough review of the literature must be completed to ensure basic understanding of the domain. For the expertise structured in the REZES' knowledge base the following sources were identified:

(i) personal experience;
(ii) expertise available at the University of Manitoba;
(iii) expertise of other researchers in the field;
(iv) books, manuals, reports, journal articles, etc.

Technical literature, containing "static" knowledge on reservoir analysis, presents previously processed and partially structured knowledge. The other type of knowledge, dynamic knowledge, is that possessed by human experts. Acquired through personal experience and extracted through discussions with other researchers and through consultation with experts, it is less structured and therefore harder to represent and encode. The following section introduces some possible knowledge representation schemes considered during the development of REZES.

4.3. KNOWLEDGE REPRESENTATION

Conventional procedural programming can be defined as a set of techniques for specifying knowledge through algorithmic routines (procedures). These techniques specify the knowledge needed and the strategy to be used for solving a particular problem. The knowledge in an ES is organized so that the knowledge about a problem domain is separated from the techniques used to manipulate it. A kind of programming that supports a strict separation between the knowledge and the control strategy, known as declarative programming, uses a symbolic knowledge representation to give the knowledge a particular style and structure. Depending on how the knowledge is to be used, this representation can be quite simple or very complex. The three most common knowledge representation schemes are:

(i) production rules;
(ii) semantic networks; and
(iii) frames.

(i) **Production rules** are the elements of the simplest and most popular knowledge representation scheme. They take the form of IF-THEN statements consisting of one or more premises (conditions) and one or more actions or conclusions. Actions are performed if the premises are true:

IF	(premises)
THEN	(conclusion/action)

An application-independent inference procedure searches for the rules whose premises are true given the known facts contained in the working memory. The advantage of having an independent inference engine is that it allows incremental development. As new information in the problem domain is discovered, that information can be added to the knowledge base without requiring changes in the inference engine itself.

Closely related to the rule-based knowledge representation is the direction of search which the inference engine performs through the knowledge base.The characteristics of the problem domain should dictate the direction of search. As mentioned in Chapter 3, both forward- and backward-chaining search strategies exist. The forward-chaining search, also called a data-driven or bottom-up search, starts from an initial state and proceeds, applying rules, until a goal state is reached. This strategy is particularly useful in situations where a goal state is poorly defined. The main problem with this approach is that numerous search paths may be generated during a consultation. The backward-chaining search, also called a goal-driven or top-down search, starts from a goal state backward to the initial state. It is more useful in situations where the desired goal state is precisely known.

(ii) **Semantic networks** provide a transition from simple rules to more complex frames in the knowledge representation schemes. Semantic nets, as they are also called, provide a way of grouping rules into a structured knowledge base. Related rules and facts are structured as nodes in a network. Relations among facts and rules are represented as links between the nodes. The obvious advantage of using semantic networks is that they provide a mechanism for guiding the application of knowledge and protecting the consistency of the knowledge base.

(iii) Knowledge representation using **frames** is very similar to semantic nets. The frame representation is also defined as a network of nodes and relations organized in a hierarchy, where the top-most nodes represent general concepts and the lower nodes more specific instances of those concepts [*Waterman*, 1986]. Frames differ from nets in that all the properties of a concept or object, defined by a set of attributes and the values of these attributes, are grouped in a frame. Therefore, frames are used for more structured knowledge representation.

In general, water resources expertise contains different types of knowledge. Each of the representation schemes concentrates on a particular type of knowledge. While rules are suited to expressing heuristics and modular knowledge, structured representations are suited to expressing organized and hierarchical knowledge. Structured representations provide a powerful mechanism for organizing knowledge. They ensure more efficient consultation runs than a simple rule-based structure as a result of defined inheritance mechanisms and explicit paths for a search (along links). However, control of the search mechanism becomes less explicit and consequently the system becomes less understandable. Each of the schemes has shortcomings when representing knowledge that does not closely fit its focus. As a result, several representational approaches may be used concurrently. Combining the approaches provides increased flexibility and explicit separation of different types of knowledge.

4.4. INTELLIGENT DECISION-SUPPORT SYSTEM DEVELOPMENT TOOLS

A number of different development tools are currently available for developing IDSS. These tools vary widely in their characteristics, capabilities, price, and sophistication. The availability of powerful tools may greatly reduce the time required to develop expert systems. *Palmer and Mar* [1988] stated that some of the expert system software is sufficiently friendly that a domain expert can enter his/her knowledge directly into the knowledge base. That may eliminate the need for a knowledge engineer in the expert system development phase. Generally, ES tools can be grouped into three categories:

(i) **General-purpose programming languages**, such as LISP and PROLOG, have been very popular among AI researchers. These high-level languages offer great flexibility to knowledge engineers but lack knowledge representation guidance and support. This type of tool is useful for developing symbolic computing programs (as distinguished from numeric programming in FORTRAN or BASIC). With its built-in backward chaining inference engine PROLOG may be considered as a transition tool from pure languages to ES shells.

(ii) **Expert system shells**, provide the system developer with development support facilities, an inference mechanism, and a knowledge representation scheme. These tools are designed to facilitate the rapid development of expert systems. However, it is very important that the characteristics of the application match those offered by the shell.

(iii) **Expert system development environments**, generally include multiple knowledge representation schemes and reasoning mechanisms. These environments offer greater capabilities, but most of them require a LISP-based machine or a mini computer environment.

According to presented research objectives the IDSS development tool had to satisfy following criteria:

(i) to operate in the IBM PC or strictly compatible computer environment;

(ii) to have the ability to integrate formal (procedural) programming with ES (declarative) programming. The possibility of interacting with external FORTRAN programs, and efficient real-time data transfer were considered necessary features; and

(iii) to be easy to use for expert system development as well as consultations. The user-friendly developer interface and user-friendly user interface are considered very important.

In addition to the above, the development tool capabilities are required to match the following criteria as closely as possible:

(i) to have the capability of multiple knowledge representations (for example, rules and frames);

(ii) to be able to use its own graphics or to call other graphics procedures;

(iii) to have the ability to perform advanced mathematical calculations;

(iv) to be fast and ensure reasonably short execution times for knowledge bases developed with the tool; and

(v) to have good documentation and continuous vendor support, preferably on-line.

A prototype intelligent decision-support system was developed using the general-purpose programming language PROLOG. During the development of the prototype, it was found that forcing PROLOG to perform a forward-chaining task is a complex programming endeavour. After memory related problems were encountered with a moderately expanded knowledge base, and after problems in managing this comprehensive and flexible tool, it was decided to change to a friendlier expert system shell, Personal Consultant™ Plus (Texas Instruments). Personal Consultant Plus (PC Plus) is an expert system shell developed in the Scheme programming language, a dialect of LISP. PC Plus has very good graphics capabilities that are considered important for better use of IDSS.

Two basic knowledge representations, the rule-based and frame-based, are supported by PC Plus. Frames and rules organize a hierarchy of knowledge and information within an ES. A knowledge base, arranged in this way, ensures more efficient consultation runs. Thus the system is not slowed by searching for and processing knowledge and information that is currently irrelevant.

PC Plus is capable of handling uncertainty in user responses with the use of certainty factors and a built-in mechanism for processing them. However, this feature has not been used in REZES because a different approach to handling uncertainties was taken. In responding to a REZES' question, rather than expressing the level of confidence with a numerical value the user has the option of responding with the "DO NOT KNOW" or qualitative type of response. The questions and reasoning scheme, following this type of a user answer, are then modified accordingly.

The PC Plus capability to integrate procedural and declarative programming is very important for the interactive use of REZES. Necessary interaction between the knowledge base and the external formal models (FORTRAN subroutines), as well as real-time data transfer, are performed via data files.

4.5. MODULAR ARCHITECTURE OF THE KNOWLEDGE BASE

As shown in Chapter 3, in addition to being multi-disciplinary, reservoir modelling and model use represents a portion of a wider multistage and highly complex process. A major undertaking, in reviewing and rationalizing the reservoir modelling process was in identifying its phases. Accordingly, the REZES' structure is organized to resemble identified phases of the reservoir analysis process as closely as possible. It was found that a modular structure best suits the problem characteristics. However, the identified phases of the reservoir analysis and the developed REZES modules do not correspond one-to-one for several reasons. Firstly, several phases often employ the same information to arrive at their individual conclusions. In order to avoid duplication and unnecessary memory problems, phases that shared most of the information were modelled together. Secondly, although it constitutes a single entity, the phase encompassing input data preparation, model use and presentation, and evaluation and validation of results was found to be to large for one module. The proper adjustments were made and it was broken down into two separate modules.

Two basic knowledge representations, rules and frames, were used to facilitate the modular structure required for the development of REZES. The rule-based representation permitted declarative programming of the expert's rules and heuristics in the simple IF-THEN form. The frame-based representation, employed by PC Plus, enabled clustering of related rules into frames, to resemble one or more of the activities in reservoir analysis as performed by a human expert. For example, rules related to the historical inflow record, its length, sampling frequency, etc., were grouped into one frame to facilitate inferences that will lead eventually to the reservoir problem formulation. Furthermore, several related frames were grouped into a module designated to perform a specific phase in the reservoir modelling process. The graphical representation of the REZES' modular structure is represented in Figure 4.1.

The following sections provide detailed descriptions of the knowledge representation and knowledge use in different REZES' modules. These modules are developed to resemble identified reservoir analysis phases.

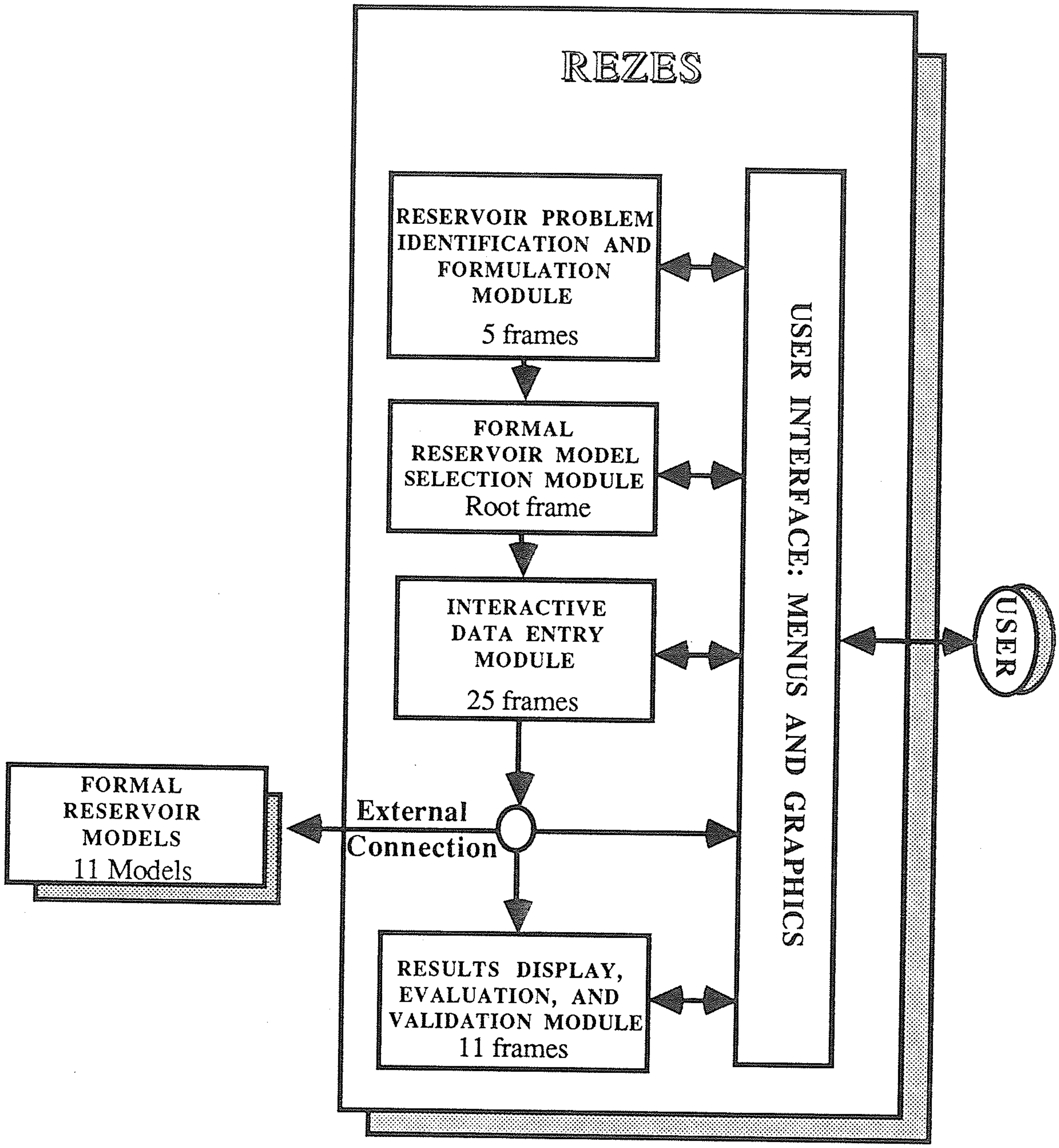

Figure 4.1. Organizational chart of REZES modular structure

4.5.1. REZES: Reservoir Problem Identification and Formulation Module

Two closely related reservoir analysis phases, problem identification and mathematical formulation, are arranged to share five frames. These five frames constitute one programming entity, a module, which contains the knowledge base portion designated for identification and formulation tasks. The module and frames within it are graphically represented in Figure 4.2.

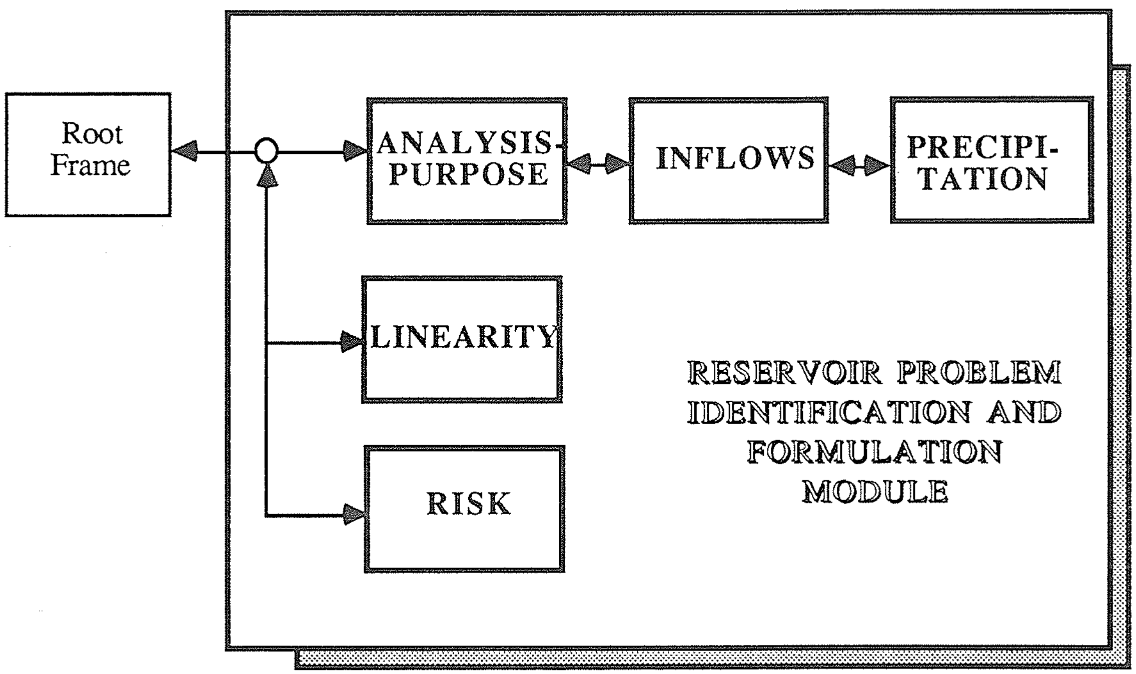

Figure 4.2. Reservoir problem identification and formulation module

The frames are named to suggest the task they perform and to agree with the PC Plus syntax:

(i) ANALYSIS-PURPOSE

(ii) INFLOWS

(iii) PRECIPITATION

(iv) LINEARITY

(v) RISK

(i) The ANALYSIS-PURPOSE frame is created to identify the purpose of performing the reservoir analysis, i.e., whether to identify or define a possible reservoir design or management plan. The identification is performed in one or two stages depending on the answers supplied by the user. At the first level, REZES distinguishes between analysis for reservoir sizing and reservoir planning. The second level, where a more detailed specification of the purpose is derived, is invoked only if planning is deduced at the first level. The decision is then rendered whether real-time reservoir operation, or long-term planning is required. The identification process is carried out in REZES through a set of rules and related questions. The following are two rules from the first level identification that exemplify the set:

Rule 1:

IF	(RESERVOIR does not exist)
AND	(PROJECT DOCUMENTATION is not available)
THEN	(PURPOSE OF THE ANALYSIS is to determine the reservoir size)

Rule 2:

IF	(RESERVOIR does not exist)
AND	(PROJECT DOCUMENTATION is available)
AND	(REASSESSMENT OF RESERVOIR SIZE is needed)

THEN (PURPOSE OF THE ANALYSIS is to determine the reservoir size)

These two and the following rules in this chapter are given in a pseudo-English form. The premise and action parts of each rule are given following IF and THEN indicators.

Rules 1 and 2 are backward chaining rules. They both conclude that only reservoir sizing, not operation planning, can be recommended and performed. If one of these rules is fired, then the reservoir storage capacity is determined to be the decision variable. The inference engine starts by searching for a goal state (parameter), in this case, PURPOSE OF THE ANALYSIS. In order to evaluate rules, the rule premises are checked and questions related to their parameters (RESERVOIR and PROJECT DOCUMENTATION) are asked.

The following is another rule from the same set of identification and formulation rules, but this time from the second level of identification:

Rule 3:

IF (PURPOSE OF ANALYSIS is planning in general)

AND (user cannot identify OPTIMIZATION TIME STEP)

AND (STRATEGIC GOAL is to help short-term operation of the reservoir)

THEN (DETAILED PURPOSE OF ANALYSIS is real-time reservoir operation planning)

It should be noted that if this rule is fired, then the objective function minimizing the reservoir storage capacity, in the form of Eq.(3.5), is eliminated from the mathematical formulation. These rules are developed to work without direct questions being asked. This helps the user to expose the facts relevant to the decision without knowing particular terminology. The consultation is based on gradual refinements of the analysis parameters, e.g., from the general purpose of the reservoir analysis to the detailed decision about the mathematical model needed.

Another rule from the same frame, this time used in a forward-chaining manner, looks like this:

Rule 4:

IF	(DETAILED PURPOSE OF ANALYSIS is real-time reservoir operation planning)
THEN	inform the user of the conclusion

The THEN part of the rule is an action that should be performed whenever a conclusion that DETAILED PURPOSE OF ANALYSIS is real-time planning, has been reached.

The parent frame for the ANALYSIS-PURPOSE sub-frame is the root frame. The only child frame is the INFLOWS sub-frame (see Figure 4.2).

(ii) The INFLOWS gathers initial information about the streamflow historical data record. The availability, characteristics, sampling frequency, and the length of data records are of special interest to the analyst (who is to determine whether data are sufficient to proceed with the analysis or not). Depending on available data, the request for additional investigation or data preparation may emerge from this specific investigation. For example, it is often necessary to estimate or fill in short gaps of missing streamflow data. The parent frame for INFLOWS is ANALYSIS-PURPOSE, and its child frame is the PRECIPITATION frame (Figure 4.2).

A characteristic rule from this frame is:

Rule 5:

IF	(HISTORICAL STREAMFLOW RECORD is available)
AND	(STARTING YEAR OF THE RECORD is known)
AND	(LAST YEAR OF THE RECORD is known)
AND	(RECORD EXTENSION is impossible)
THEN	{RECORD LENGTH is [(LAST YEAR OF THE RECORD minus STARTING YEAR OF THE RECORD) plus 1]}
AND	inform the user about the record length and advise him/her about analysis reliability in relation to the record length

This rule is an example of how PC Plus performs mathematical operations (subtraction).

(iii) Simple processing on precipitation data and record availability is taken care of in the PRECIPITATION frame. Although REZES cannot use this information for extending the inflow record, it is capable of giving advice about procedures and citing references in the literature. The PRECIPITATION frame does not have any child frames. The following is a rule extracted from that frame:

Rule 6:

IF (HISTORICAL RAINFALL RECORD is not available)

THEN (EXTENDING INFLOWS RECORD is impossible)

The user supplies answers to precipitation-related questions, as well as information on available nearby gauging stations at REZES's request. Again, procedures for multivariate analysis are not available within REZES, but REZES can advise the user on locating more details about them.

(iv) Knowledge translated into rules, related to the linearity of the mathematical problem being formulated, is stored in the LINEARITY frame. This frame is directly involved in both the identification and formulation phase of the analysis. According to the purpose of the analysis and intended future reservoir use, it discriminates between linear and non-linear problems. The root frame is its parent frame and it has no child frames. Next, the rule that concludes non-linearity is given. A typical rule in this frame is

Rule 7:

IF	[(DETAILED PURPOSE OF ANALYSIS is long-term planning)
OR	(DETAILED PURPOSE OF ANALYSIS is real-time planning)]
AND	(RESERVOIR FUNCTION is to generate electricity)
THEN	(RESERVOIR PROBLEM is non-linear)

In this particular rule, only one potential reservoir purpose is explicitly mentioned (hydropower). However, the user is required to supply information about every possible use of the reservoir and, often, several conflicting purposes may be selected.

Information about other possible reservoir purposes is used for formulating the objectives and constraints of the reservoir problem. This process is done in agreement with the available mathematical models so that one of them matches the formulated problem.

(v) Lastly, REZES should decide to what degree of detail the analysis is to be performed. Often, it is difficult to justify a detailed analysis for screening alternative plans. Similarly, it is not appropriate to use preliminary techniques for cases where detailed analysis is necessary and where consequences of a wrong decision may be devastating. This type of decision also depends on the available formal models. For example, if an explicit stochastic analysis matches the problem requirements and the appropriate model is not available, the analysis may be performed using a deterministic model. In such a case utilizing synthetic streamflow sequences in the implicit stochastic manner can give comparable results to those of the explicit stochastic optimization approach. The last frame in this module, RISK, determines whether a deterministic or stochastic procedure is to be used. The following two rules illustrate the outlined methodology as it is used by REZES:

Rule 8:

IF	(DOWNSTREAM AREA is highly populated municipality)
AND	(DOWNSTREAM AREA is predominantly industrial)
THEN	(RISK LEVEL is high)

Rule 9:

IF	(RISK LEVEL is high)
OR	[(RISK LEVEL is medium)
AND	(REQUIRED ANALYSIS is detailed)]
THEN	(MODELLING APPROACH is stochastic)

The conclusion about the modelling approach to be used directly influences the form of some of the problem constraints. In the case where Rule 9 is applicable, some of the constraints, like that in Eq. (3.8), may be reliability based. A different recommendation may be expected if one of the problem characteristics used for evaluation of the premises changes. For example in Rule 9, if analysis is required for preliminary or screening purposes, the conclusion will be that a deterministic modelling approach be used.

Many parameters which influence the identification phase were investigated throughout the research. Each of them identifies or contains a piece of information that REZES uses to arrive at a conclusion or to give a recommendation. Table 4.1 lists some of the parameters used in the identification and mathematical formulation phases. Conclusions or recommendations from these parameters are used for making inferences in the later phases.

The parent frame for RISK is the root frame. The root frame uses information provided by RISK and other sub-frames in the identification and formulation module, to determine the appropriate formal reservoir model for performing the analysis. Only information used to render this conclusion is transferred from these five frames to the model selection module.

Table 4.1. Parameters used in the identification and formulation phases

Supplied Information		Conclusions/Recommendations	
Parameters	**Options**	**Parameters**	**Options**
•Reservoir identification	user defined	Analysis purpose	sizing planning
•Reservoir existence	exists undeveloped		
•Previous project documentation	available not available	Detailed planning purpose	short-term long-term
•Reservoir sizing	yes/no		
•Planning objective	strategic short-term	Analysis feasibility	can be done cannot be done
•Historical inflow record	available not available		
•Starting/last year of the inflow record	numerical input	Record length	numerical result
•Display detailed statistical requirements of the record	yes no		
•Historical rainfall record	available not available	Record extension	possible not possible
•Gauging station in the same or nearby watershed	yes no		
•Overlap period of the two records (for calibration)	exists does not exist	Record length appropriateness	very likely long enough unlikely long enough not long enough
•Optimization time step	less than hour hour day week month season unknown	Reservoir problem	linear non-linear
•Input data time step	month and less season		
•Reservoir functions	municipal water supply industrial water supply irrigation wild life preservation recreation flood control low flow augmentation hydropower generation	Risk level	high medium low
•Land use specification of the downstream area	industrial farming unpopulated	Modeling approach	deterministic stochastic
•Downstream population density	scarcely populated medium populated heavily populated		
•Required analysis	preliminary detailed		

4.5.2. REZES: Formal Mathematical Model Selection Module

The module which selects the appropriate reservoir model renders its conclusions based on the interactively collected information about the reservoir system and on the conclusions derived in the identification and formulation phases. If selecting the model is not possible given the existing information, additional refinements are stimulated. It should be noted that the decision on which model to use is highly dependent on the models available. As not every model is appropriate, in all contexts, inclusion of different techniques and approaches to reservoir analysis ensures the best match between problem characteristics and one of the formal models. Special attention was, therefore, paid to choosing a wide range of comprehensive models for improving the accuracy and effectiveness of the analysis.

This module consists of only one frame, RESERVOIR-MODEL, which is simultaneously the root frame of the IDSS. Having this feature, the RESERVOIR-MODEL frame does not only recommend the formal reservoir model to be used, but also controls the rest of the system. The root frame performs control functions by making an appropriate sub-frame active at the appropriate time, and/or by transferring necessary information from frame to frame. Being the root frame, RESERVOIR-MODEL does not have a parent frame. Its child frames are: ANALYSIS-PURPOSE, LINEARITY, RISK, and INPUT-PREPARATION frames (Figure 4.3).

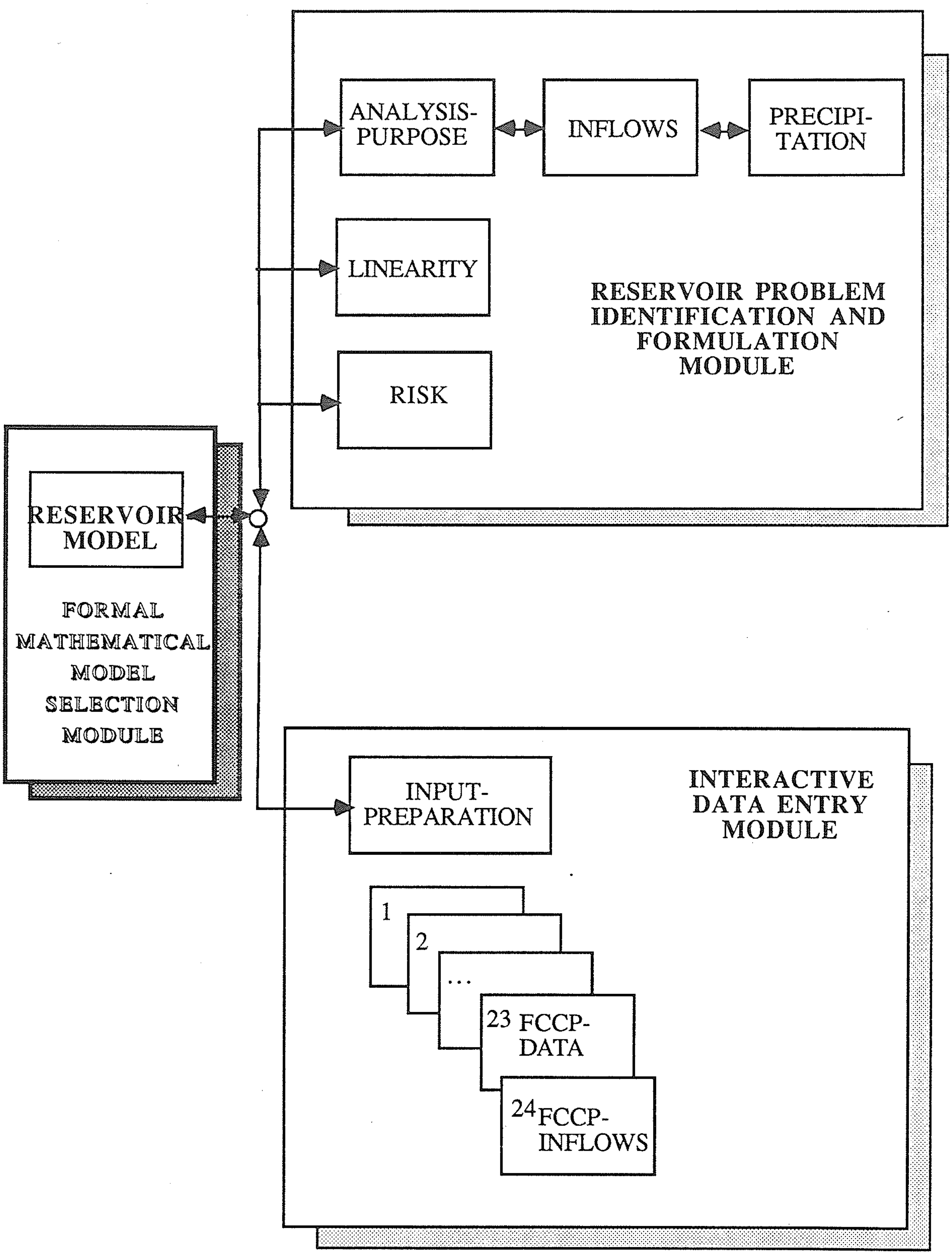

Figure 4.3. Formal mathematical selection module with root frame

Rules of the Selection Module

Twenty three rules accommodated by this frame may be grouped into three rule categories:

(i) rules rendering advice or giving an explanation;

(ii) rules activating a sub-frame; and

(iii) model selection rules.

These rule types will be described below and examples illustrating each of the rule types will be presented:

(i) Rules rendering advice or giving an explanation: in general, these are antecedent rules used in a forward chaining manner to render advice or a warning. The following rule informs the user that further analysis is impossible without inflow data. Although this analysis cannot be completed,as a record is not available, the consultation can proceed until the missing information is actually required.

Rule 10:

IF	(MODEL is known)
AND	(HISTORICAL INFLOW RECORD is not available)
THEN	inform the user that none of the methods and formal procedures can work without this information
AND	proceed with consultation

(ii) Rules activating a sub-frame: these types of rules are antecedent rules, activated when a set of conditions is already being traced and satisfied. They usually ensure proper ordering of reservoir analysis activities. In the following example, the INFLOWS frame may be activated only after the detailed purpose of the analysis is known, regardless of whether it is sizing, real-time planning, or long-term planning:

Rule 11:

IF	(DETAILED PURPOSE OF ANALYSIS is known)
THEN	consider activating frame: INFLOWS

(iii) Model selection rules: this type of rule uses previously gathered information to choose the appropriate mathematical modelling technique and the reservoir model. Additional information to distinguish between possible model choices may be required at this point. The final choice of the model to be employed, as pointed out by *Rogers and Fiering* [1986]:

> ... depends upon the use to which the model is put; what sort of questions the problem poses; and how detailed the analysis is to be.

The formal models included within REZES cover a wide range of reservoir problems, thereby ensuring that the model chosen provides a good fit to the problem at hand. The following rules demonstrate the reasoning used to choose one of these models:

Rule 12:

IF	(PURPOSE OF ANALYSIS is sizing)
AND	(REQUIRED OPTIMIZATION TIME STEP is month or less)

AND (INFLOW DATA is collected and recorded on monthly basis)

AND (RELIABILITY OF WATER SUPPLY is to be maximized)

THEN (MODEL to be used is APPROXIMATE YIELD MODEL)

Rule 13:

IF (DETAILED PURPOSE OF ANALYSIS is long-term reservoir operation planning)

AND (RESERVOIR PROBLEM is non-linear)

AND (MODELLING APPROACH is deterministic)

AND (PRIMARY WATER USE is for electricity generation)

AND (GENERATION SYSTEM is considered isolated)

THEN (MODEL to be used is ITERATIVE LINEAR PROGRAMMING MODEL)

Table 4.2. lists mathematical model selection parameters and their values arrived at, or obtained from the user during a consultation. Selected models and their main characteristics are also provided. A list of all formal mathematical models included in REZES, with short explanations, is given at the end of this chapter.

4.5.3. REZES: Interactive Data Entry Module

This module, which contains 172 rules, helps the user to prepare necessary input data to suit the particular reservoir problem, in a form recognizable by the selected formal model. The transfer of information between the IDSS knowledge

Table 4.2. Parameters used in the model selection phase

Supplied Information and Previous Conclusions		Selection	
Parameters	**Options**	**Model**	**Characteristics**
Analysis purpose	sizing planning	RESER	sizing, simulation-optimization, monthly, linear, reliability criteria, and vulnerability criteria
Detailed planning purpose	short-term long-term	CYIELD	sizing, linear programming, seasonal, and linear
Reservoir problem	linear non-linear	AYIELD	sizing, linear programming, monthly, and linear
Reservoir functions	municipal water supply industrial water supply irrigation wild life preservation recreation flood control low flow augmentation hydropower generation	ILP	long-term planning, deterministic, iterative linear programming, monthly, nonlinear, isolated generation system, variable energy price, constant demand, and one year planning horizon
Planning horizon	less then a year one year	EMSLP	long-term or mid-term planning, deterministic, successive linear programming, month or less, nonlinear, interconnected generation system, variable energy demand, and a year or less planning horizon
Demand reliability	maximum possible user defined	DP	long-term planning, deterministic, three level dynamic programming, monthly, nonlinear, direct and indirect users, and one year planning horizon
Priority of the generation of electricity over the other users	primary secondary	CCLP	long-term planning, stochastic, chance-constrained linear programming, monthly, linear, flood control, and minimal storage reliability levels
Energy generation system characteristics	isolated interconnected	RPORC	long-term planning, stochastic, reliability programming, monthly, nonlinear, flood control and minimal storage reliability levels
Energy price throughout the time period	constant variable	SDP	long-term planning, stochastic, dynamic programming, monthly, nonlinear, and a year planning horizon
		PROFEXI	real-time planning, daily, linear programming, compromise programming, and linear.
		FCCP	long-term planning, stochastic, fuzzy sets, chance-constrained linear programming, search, monthly, linear, flood control, and minimal storage reliability levels

base and the library of formal (procedural) models is performed via data files. For this purpose, a floppy disk drive is used as a file communication vehicle.

The INPUT-PREPARATION frame, together with 24 additional frames, forms the basis for the input data preparation tasks (Figure 4.4).This frame contains over 60 rules which control data-export and data-import procedures. These procedures, easy to incorporate into rules, ensure data completeness for each of the formal reservoir models. Each of the 11 formal models has its own 5-8 rules associated with the INPUT-PREPARATION frame. These rules enable control over gathering inflow data, demands, losses, and other physical and computational parameters necessary for the reservoir analysis.

Two characteristic types of rules are employed by this frame:

(i) rules which warn the user of the action(s) to be performed; and

(ii) rules which control presence of file(s) with the necessary data.

(i) Rules which warn the user of the action(s) to be performed: To provide a "non-modeller" with better understanding of the system and to improve REZES-user communication, this type of rule provides necessary information about the system's subsequent actions. Usually, graphics capabilities of PC Plus are employed to highlight important facts or user actions required to proceed with a consultation. The following rule warns the user to place the correct floppy disk, with the selected formal model, into the floppy disk drive:

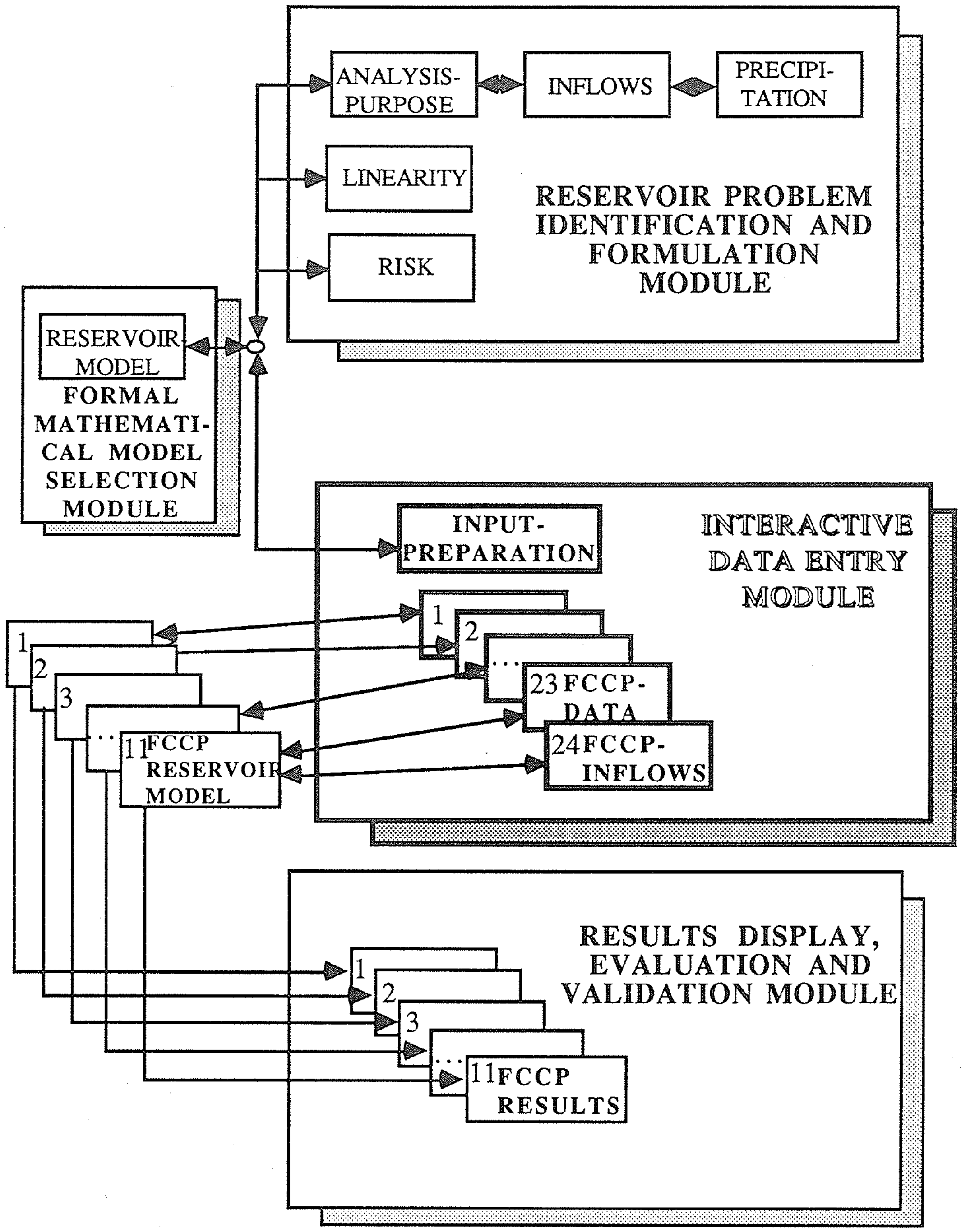

Figure 4.4. Interactive data entry module

Rule 14:

IF	(MODEL is RELIABILITY PROGRAMMING RESERVOIR MODEL)
THEN	print warning and inform the user about necessary action

(ii) Rules which control presence of file(s) containing necessary data: once a formal reservoir model is chosen, model runs with different inputs are usually performed several times. REZES contains this type of rule in order to check whether data files already exist. A user is allowed to override an existing file and change input data if another model run with changed parameters is needed. Each of the 11 formal models has a rule similar to the following to check whether some or all data files are already present:

Rule 15:

IF	(MODEL is RELIABILITY PROGRAMMING RESERVOIR MODEL)
AND	[(INFLOW DATA FILE is prepared)
AND	(HYDROLOGIC/PHYSICAL DATA FILE is prepared)]
OR	[(INFLOW DATA FILE is not prepared)
AND	(PREPARE INFLOW DATA FILE)
AND	(HYDROLOGIC/PHYSICAL DATA FILE is prepared)]
OR	...
THEN	(INPUT PREPARATION is done)

The remaining 24 frames associated with the interactive data entry module, are closely related to 11 mathematical models. Each formal model has 1-5 frames for handling the laborious task of input data preparation and data export to an external medium so it can be used with the formal model.

Although all the REZES modules use PC Plus graphics capabilities, the input data preparation module uses them most extensively. It is advantageous to include graphics with a model designed for use by persons other than the model developers, because users are more comfortable with pictures than with text. Static pictures enhance REZES "prompt" or "help" capabilities, while background pictures are combined with active image(s) to create a user-friendly input environment. These pictures cannot take in or display parameter values. Active images can accept values from the user and display parameter values set as a result of conclusions reached during a consultation. These standard images, like dial image, thermometer image, selection boxes, etc, are associated with parameters from the knowledge base. Figure 4.5 shows a horizontal bar graph image, used for data input necessary for running one of the formal models. For this image type the user selects the desired value from the numeric range displayed on the horizontal bar graph. The cursor keys move the bar to the left or to the right, indicating the value a model will use. It is also possible to group two or more active images in a cluster to give a better view of the multiple parameter values. A background picture added to a cluster can provide additional guidance and supplementary details for data input. In REZES, image clusters and background pictures have often been used for multi-valued input, for example, average monthly inflows, demand levels, evaporation rates, etc. An example of an integrated background picture and active images is shown in Figure 4.6. Boxes with explanations are part of the background picture and the shaded box is an active image for data input. Over 450 active images, together with 46 background pictures, have been created for REZES.

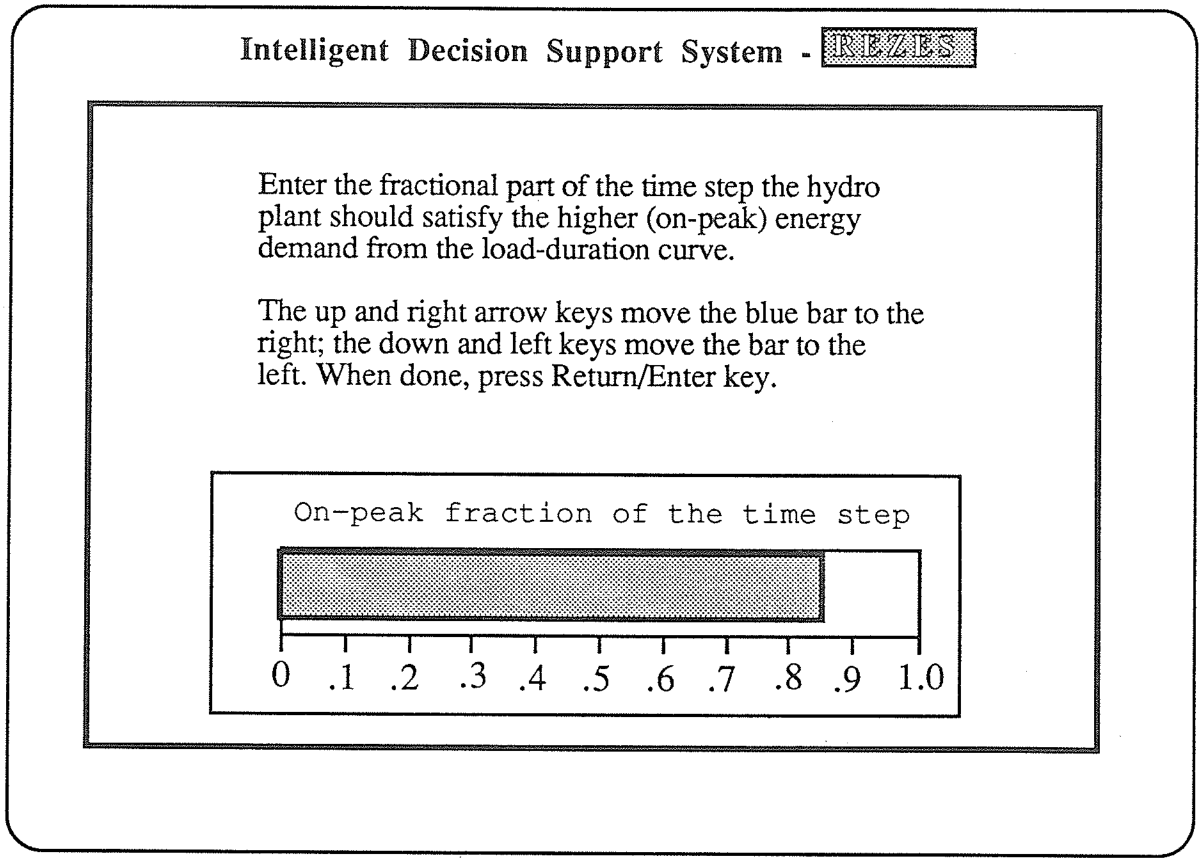

Figure 4.5. Example of a horizontal bar graph image

In conjunction with graphical aids, REZES provides a user with default parameter values, and with information about acceptable parameter value ranges in two ways: explicitly and implicitly. The explicit approach provides a user with the parameter value range by displaying it on the screen as the question is asked. In the implicit approach, REZES prompts a user to answer whether to accept a value falling outside of the prespecified range.

The following rules exemplify interactive data entry module use in gathering and exporting input data:

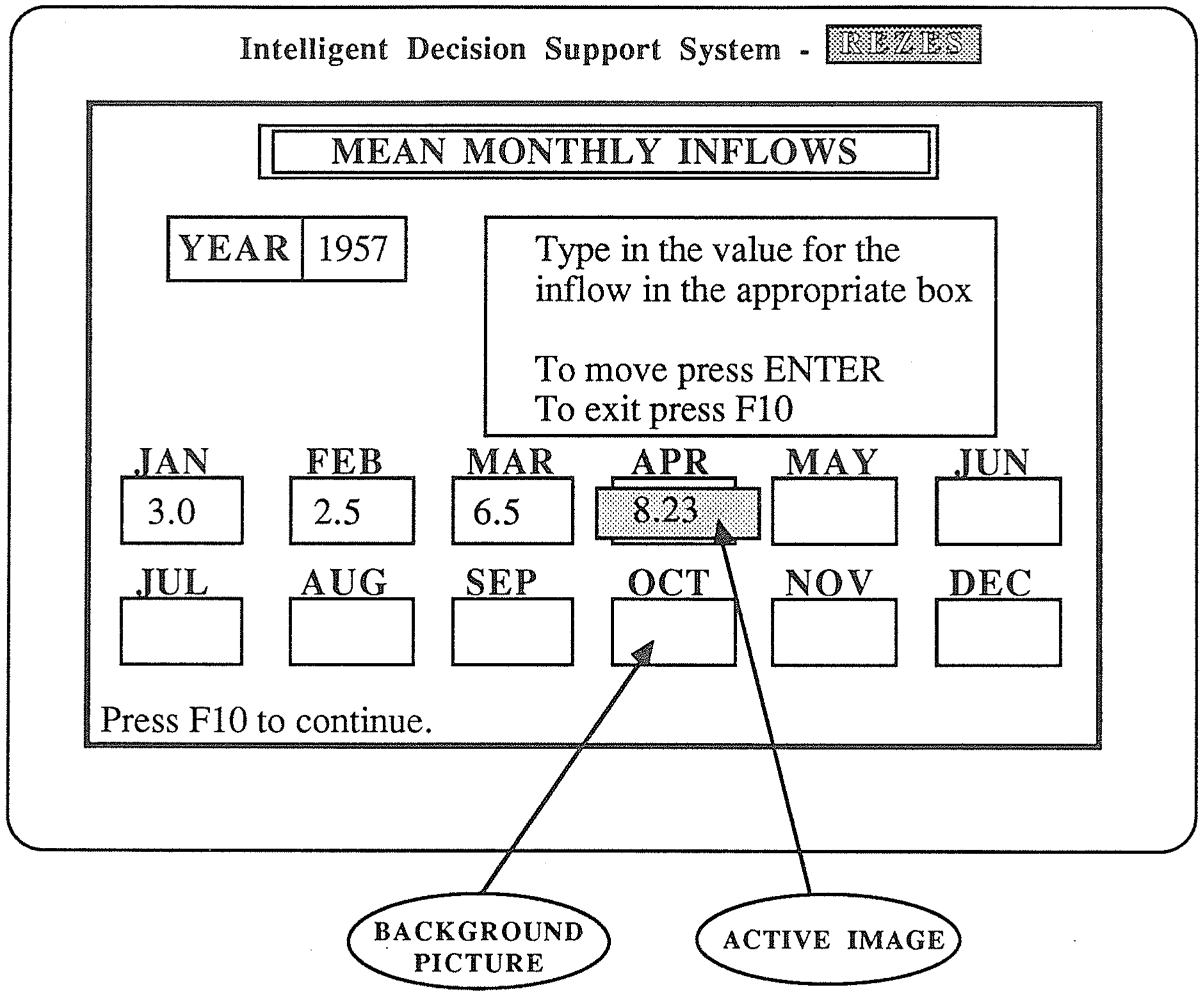

Figure 4.6. Integrated background picture and active images

Rule 16:

IF	(INFLOW FOR JANUARY is known)
AND	(INFLOW FOR FEBRUARY is known)
AND	...
AND	(INFLOW FOR DECEMBER is known)
THEN	export data and change the counter value for frame instantiation

Rule 17:

IF	(EVAPORATION DATA are stored)
AND	(STAGE-STORAGE RELATIONSHIP is stored)
AND	(STORAGE-AREA RELATIONSHIP is stored)
AND	(WATER DEMAND DATA are stored)
AND	(COMPUTATIONAL DATA are stored)
THEN	(INPUT DATA PREPARATION FOR RESERVOIR DYNAMIC PROGRAMMING MODEL is finished)

The same input preparation module may be used several times in a single consultation. If the model run is interrupted, or adjustment of some parameter values is needed, REZES proceeds with all, or just a part, of the input preparation process.

4.5.4. REZES: Results Display, Evaluation and Validation Module

There are several important aspects of the utilization of the optimization model regarding its output results. The first is related to the format and output characteristics of the formal models within REZES. The output module is designed to display a brief summary of results immediately after running the particular formal model. For example, after a consultation with a sizing model, information on required storage capacity and computed water supply reliability is presented to the user. In addition to the summarized results, each model stores detailed output results in a data file accessible to REZES. These results may be displayed to the user automatically, or upon request, during the consultation. The information is clearly presented, i.e., tables with short explanations, to permit rapid comprehension and to improve the user understanding of the solution. After a consultation, the summary files remain on the floppy disk and may be analyzed or printed using some other software.

The second aspect of using output results is diagnostic, i.e., the ability of the model to determine whether computation has reached the optimum. REZES is capable of detecting malfunctioning of a model and can advise the user of possible remedies and courses of action. This is accomplished by enabling each model to produce a diagnostic data file, which REZES processes in addition to presenting the results. Often, due to an internal error, or wrong or inadequate input data, a computation may be interrupted. In this case the user is left without any explanation about what actually went wrong. Mathematical models incorporated within REZES are tailored to generate clear diagnostic messages whenever an important step in the computation is performed. These messages are stored in the file accessible by REZES, which is then capable of interpreting them and informing the user of the terminating conditions. The following are examples of two rules from this module that are used for the purposes described above:

Rule 18:

IF (DIAG #1 is "optimum is reached")
AND (USER REACTION is "satisfied")
THEN inform the user that optimal solution is reached, invoke text editor to display detailed output results, and conclude consultation.

Rule 19:

IF (DIAG #1 is "optimum is not reached)

THEN (import DIAG #2 from the file: CYIELD.DGN and interpret the error message stored in the file)

Note, that "DIAG #1" and "DIAG #2" are parameters generated by the particular model (in this case COMPLETE YIELD RESERVOIR MODEL) which are transferred to the REZES knowledge base via the diagnostic (CYIELD.DGN) file. The parameter USER REACTION calls for user opinion about recommended storage or reservoir release policy, and depending upon this opinion, the appropriate course of action is recommended.

The third aspect is related to estimating the effect of model parameter change, commonly known as "sensitivity analysis". Water resources practitioners, which utilize the systems approach in their professional practice, know that it is important to consider the effects of changes in the model parameter on the optimal policy. Most computer codes do not display the non-optimal solutions through which an algorithm passes on its way to the optimum. It may be beneficial for the user to explore the near-optimal solutions that give similar values of the objective function but substantially different operating policies. Through its 11 frames and over 60 rules, employed in the result evaluation and validation module, REZES advises the user about the parameters that are mostly likely to change the performance of the formal model. The following is a rule illustrating this IDSS capability:

Rule 20:

IF (DIAG #1 is "optimum is reached")

AND (USER REACTION is "storage is too large")

OR (USER REACTION is "reliability is too high)

THEN (inform the user on which parameter influences the solution most significantly)

AND restart the input preparation phase

This rule is taken out from the RESER-EXE frame and causes the next iteration in preparing input data. By changing the parameters identified by REZES, the user may get a better understanding of the solution sensitivity to parameter variation or may even obtain a more suitable solution to the problem at hand.

4.6. RESERVOIR FORMAL MODELS: MATHEMATICAL OPTIMIZATION PROCEDURES

This section provides a brief description of the formal models for reservoir analysis that are incorporated in the REZES knowledge base. The REZES system includes formal mathematical models selected to cover three basic areas of reservoir analysis:

(i) reservoir design;
(ii) short-term reservoir operation planning; and
(iii) long-term reservoir operation planning.

The selected set of models includes optimization methods that use classical calculus, linear programming, non-linear programming, dynamic programming, and simulation techniques. To represent all possible input situations as well as possible, both deterministic and stochastic modelling approaches have been incorporated.

These models have proved to be acceptable decision-support tools for handling a variety of reservoir related problems.

However, careful analysis, of the reservoir mathematical modelling and its theoretical background, unveiled an existing gap between available models and reservoir management problems. Even with using the expert system technology to improve modelling, as suggested in this thesis, the gap still appears to exist. The objective functions and constraints employed by existing models are required to be well-defined and are not always easy to formulate. As the library of formal models within REZES grew, the need for a model capable of coping with fuzzy situations became more apparent. That is why efforts were also directed to the analysis of decision making and modelling in a fuzzy environment. A fuzzy set model has been developed for this purpose and it is included with the rest of the formal reservoir models.

Most of the models, deterministic or stochastic in nature, were developed by different researchers well before REZES development started. Each of them had to be modified to allow for specific input-output processing employed by REZES. For some, the theoretical foundations were set in the literature, but the algorithms still had to be adapted for use within REZES. These models constitute an important segment of the expertise contained in REZES. The theoretical background, detailed development, and an example application of the fuzzy set reservoir model are presented in Chapters 5 and 6.

The following is a list of all formal mathematical models included in REZES, with a short explanation of the model capabilities.

1. RESER - a reservoir sizing model based on the improved Rippl procedure [*Rippl*, 1883; *Simonovic*, 1985]. At present the model includes storage dependent losses and uses different reliability levels of water supply.

2. CYIELD (Complete Yield) - employs a linear programming technique for minimizing total reservoir capacity with regard to set of system constraints [*Loucks et al.*, 1981]. It is used with seasonal hydrological data.

3. AYIELD (Approximate Yield) - is a simpler reservoir sizing model [*Loucks et al.*, 1985] than CYIELD, in that it requires a smaller number of constraints in the formulation of an LP model. It minimizes the total active storage capacity necessary to provide the within-year yield.

4. ILP - uses a technique called Iterative LP [*Grygier and Stedinger*, 1985] for solving nonlinear reservoir operation problems. The algorithm attempts to maximize the value of hydropower generated over the planning period of one year.

5. EMSLP - employs successive LP in optimizing long-term planning of an interconnected hydro utility for a deterministic future [*Reznicek and Simonovic*, 1990]. The operation involves scheduling reservoir releases to generate hydro power, and managing energy transfer through the interconnections (i.e., system,import, and export).

6. DP - considers the optimal long-term control of a multipurpose reservoir which could supply water to both direct and indirect users [*Opricovic and Djordjevic*, 1976]. The model uses the dynamic programming (DP)

technique for optimizing hydro-power-plant operation as a direct user and as the only source from which indirect users may receive water.

7. CCCP - a chance-constrained LP model determines operating policies which maximize expected benefits when the system is constrained to achieve fixed minimal storage and flood control reliability levels [*Simonovic*, 1979]. The model uses the specific approach for converting stochastic problem formulation into its deterministic equivalent one.

8. RPORC - a model developed by *Simonovic and Marino* [1980], uses the reliability programming approach where reliability levels are not fixed, a priori. A nonlinear problem resulting from using this approach is solved using a multi-dimensional Complex search by Box.

9. SDP - a predictive stochastic dynamic programming approach [*Bras et al.*, 1983; *Stedinger et al.*, 1984] served as a basis for this reservoir model. This nonstationary model employs the solution of the steady state stochastic DP as a boundary condition. The model makes use of efficient flow forecasts as hydrologic-state variables.

10. PROFEXI - employs the concept of optimizing short-term operation of a multi-purpose reservoir. It performs optimization on the basis of inflow forecasts provided by an external forecasting algorithm [*Simonovic and Burn*, 1989]. However, due to the nature of real-time reservoir operation REZES uses this procedure only for demonstration purposes.

11. FCCP - a fuzzy-set-based chance-constrained model that determines the reservoir operating policy which maximizes system reliability and returns from release. The model accepts both quantitative and qualitative input. The model transforms qualitative information about a decision-maker's preferences toward the system's operations reliability and releases, into numerical data. The model employs LP and search techniques for solving the non-linear problem.

4.7. AN ILLUSTRATIVE CONSULTATION

The Gruza reservoir (in Yugoslavia) case study has been employed to illustrate the application of REZES and its potential benefits. The reservoir is intended to provide water for a large municipal settlement (the town of Kragujevac) 10km from the reservoir site and to release minimal contracted volume downstream from the reservoir (Figure 4.7). Flood control and sediment deposition control were two additional purposes, considered in the study done by the *Jaroslav Cerni Institute* [1976] and implemented in modelling reservoir operation. According to this study the storage of the Gruza reservoir is 64.6×10^6 m^3. Currently, this capacity is divided into three zones: the dead storage of 8.5×10^6 m^3, the active storage of 48.4×10^6 m^3, and the flood control storage of 7.7×10^6 m^3. Reservoir storage, and the long-term planning reservoir-management policy have been developed to provide firm water supply discharge of Q_g=0.816 m^3/s with very high reliability. Mean monthly evaporation (potential) ranges from 19.2 mm in January to 119.0 mm in July. The most recent hydrologic report [*Energoprojekt*, 1988] showed that demand and reservoir releases for water supply stayed at the average level of Q_d=0.550m^3/s during the period 1985-1988 (the reservoir began operating in 1983). This low value of Q_d relative to Q_g raised a question of how to improve utilization of the reservoir storage. The potential of rural water supply has been considered for the utilization of available excess water.

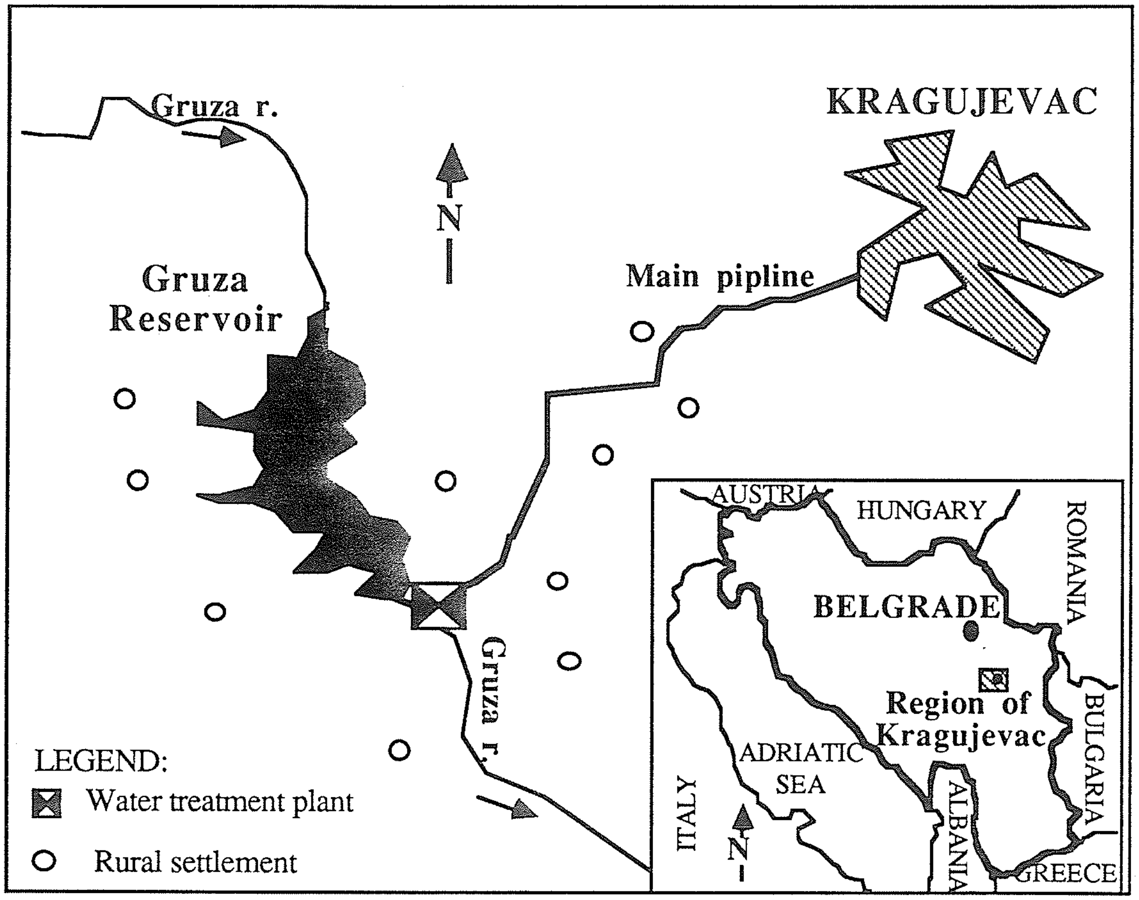

Figure 4.7. Gruza reservoir system

The following is an illustrative consultation session performed by the author, using information available on the Gruza reservoir system. It is suggested here that a planner or manager (the "client" type of user), having limited knowledge about the most appropriate model in the given context, but having access to the mentioned project documentation and reservoir characteristics, may benefit from interacting with REZES. However, this interaction should involve an analyst as well (the "assistant" type of user).

Figure 4.8 represents the problem identification steps for the Gruza reservoir system operation study. The problem description is made up using information supplied by the user. Logical inferences are then made based on the problem description and modelling experience. Partial decisions and inference flow respectively are represented by the shaded ellipses and arrows between them.

A more complete description of the logic in Figure 4.8 is as follows:
Using the fact that the reservoir exists and the previous project documentation is available, REZES concludes that reservoir operation planning rather than sizing of the reservoir is appropriate for this problem. The strategic goals and optimization time step foreseen by the user suggested a long-term reservoir operation planning approach and eliminated the real-time operation planning approach which would need streamflow data with a shorter time step, and a good forecasting algorithm. For this study, historical streamflow data for the years 1926 to 1977, recorded on a monthly basis at the dam site, are used. Using rules, generally accepted by practitioners, REZES concluded that this inflow record provides enough information about inflow variability.

The next task is to determine risk levels, from the user's qualitative description of the downstream land use and population density, involved in choosing wrong methodology. Due to the conclusion of high risk, data record length of 52 years, and available procedural models, an explicit stochastic optimization approach is chosen. Finally, water supply, flood control, and low flow augmentation purposes, identified for Gruza reservoir use, determined that a

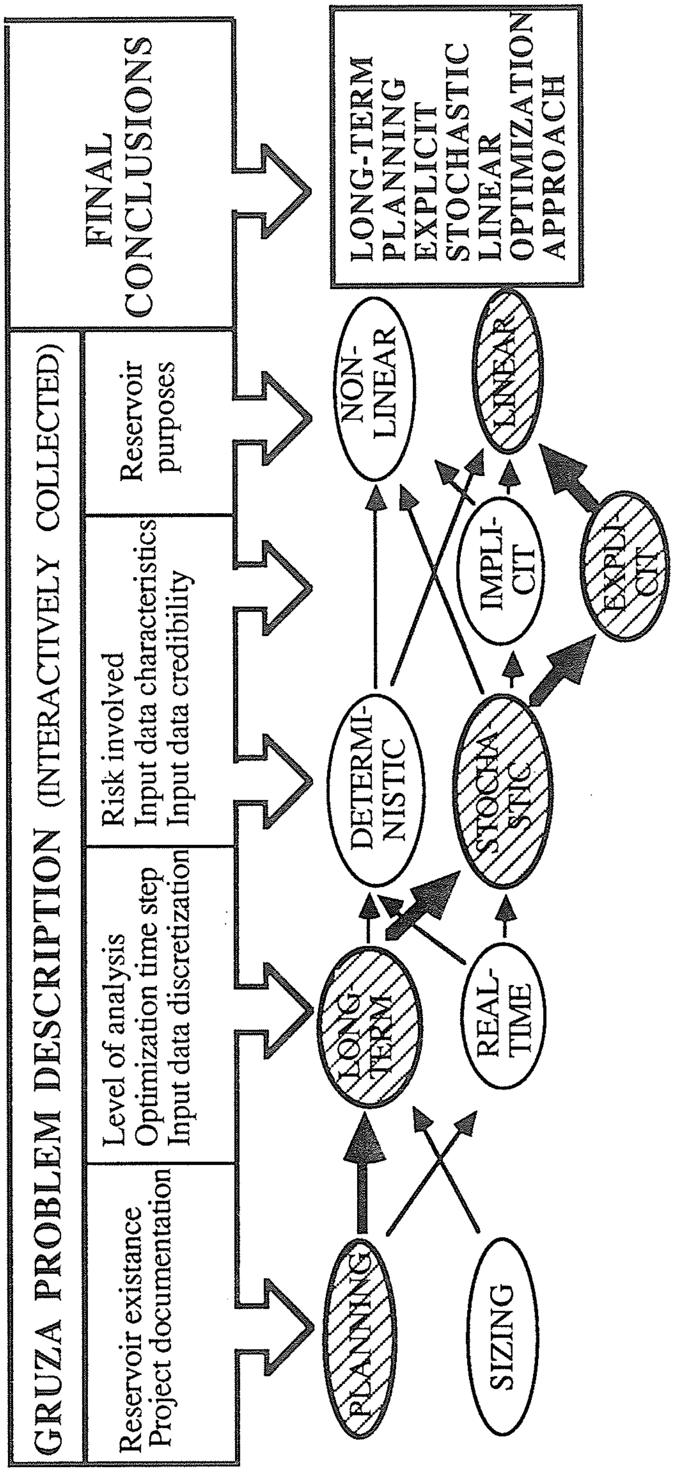

Figure 4.8. Gruza problem identification phase

linear programming approach is appropriate for modelling of the functional relationships. It is worthwhile mentioning that at each step of the analysis, the "explanation" and "help" facilities are available to the user of REZES.

The mathematical formulation phase of the Gruza reservoir problem is represented schematically in Figure 4.9. For long-term planning purposes and available streamflow record characteristics, reservoir storage was eliminated as a decision variable and only monthly releases were selected as decision variables. In addition, current and future reservoir use dictated selecting a linear form of the objective function. The form of the storage constraints is decided upon, using the information available on reservoir storage zones. Finally, from the previous documentation about the reservoir and its surroundings, minimal and maximal allowable release levels are chosen to account for required instream release quantities and the acceptable river channel erosion respectively. Certain restrictions to the formulation phase are applied to assure that the formulated model is available among the 11 reservoir optimization models included in REZES.

Gruza problem characteristics (supplied by the user or derived during the consultation) are matched next against characteristics of the 11 models available in REZES. Reservoir sizing and real-time models are eliminated first. Among the long-term planning models, those that capture stochastic variability of the inflows are next examined, and a chance-constrained linear programming (CCCP) model is chosen.

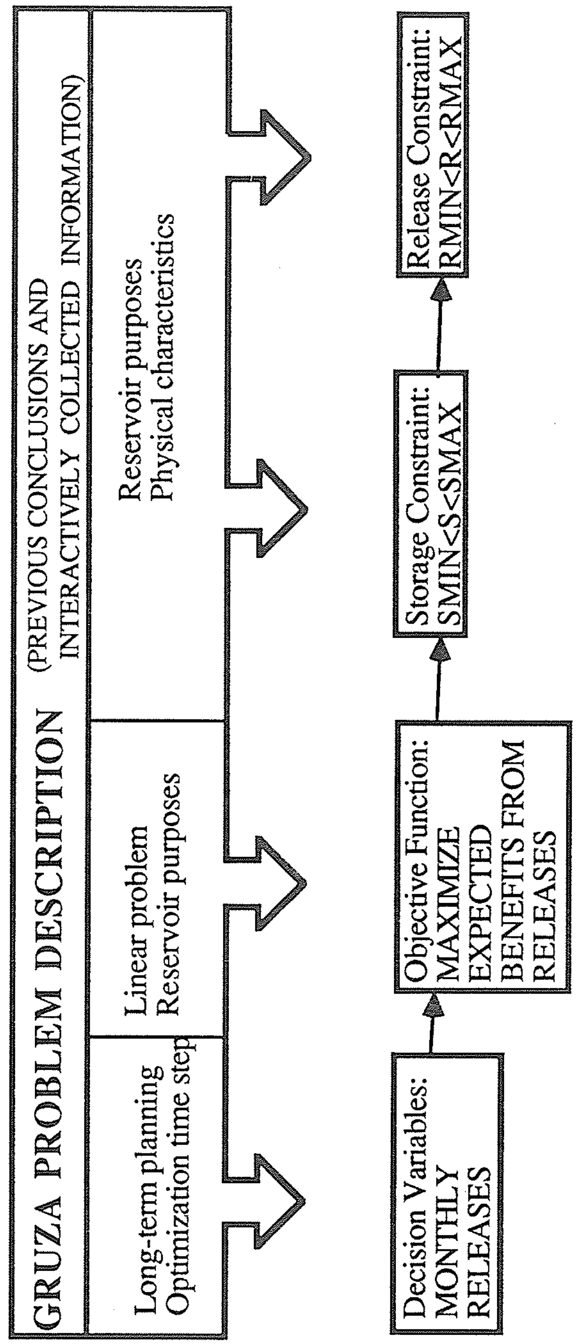

Figure 4.9. Mathematical formulation of the Gruza reservoir problem

Figure 4.10 shows a good agreement between the reservoir characteristics and the CCCP model. A short explanation about the model's main features is then presented to the user. This is a final instruction before proceeding to the input data preparation and following phases of the reservoir modelling and model use process.

Through the use of active images and background pictures (Figure 4.6) data necessary to run the formal mode are collected. Physical data, reservoir model specific computational data as well as hydrological data are supplied by the user.

To ensure accurate numerical results, REZES provides the user with default parameter values and/or their acceptable ranges. Again, "explanation" and "help" facilities are used for ensuring correct information input and subsequent model use. After the model is run and the optimal solution is reached, a concise presentation of numerical results is shown to the user and he/she is given the option to comment on it. Based on this, further advice about the most influential parameters, or a more detailed numerical output is provided. In the Gruza reservoir case, the specified reliability levels were identified as being important, and it was suggested that they be changed in the next run. In addition to the reliability levels, the user is supposed to supply the coefficients of the objective function in the form of unit benefits per cubic meter of released water. However, this information was not available as it would have required precise economical evaluation and considerable information on the future. Therefore, only rough estimates were used in the analysis. It should be noted, also, that required reliability levels α (of not exceeding the flood control storage) and β (of not violating the minimal storage) are not known or strictly regulated by water authorities and

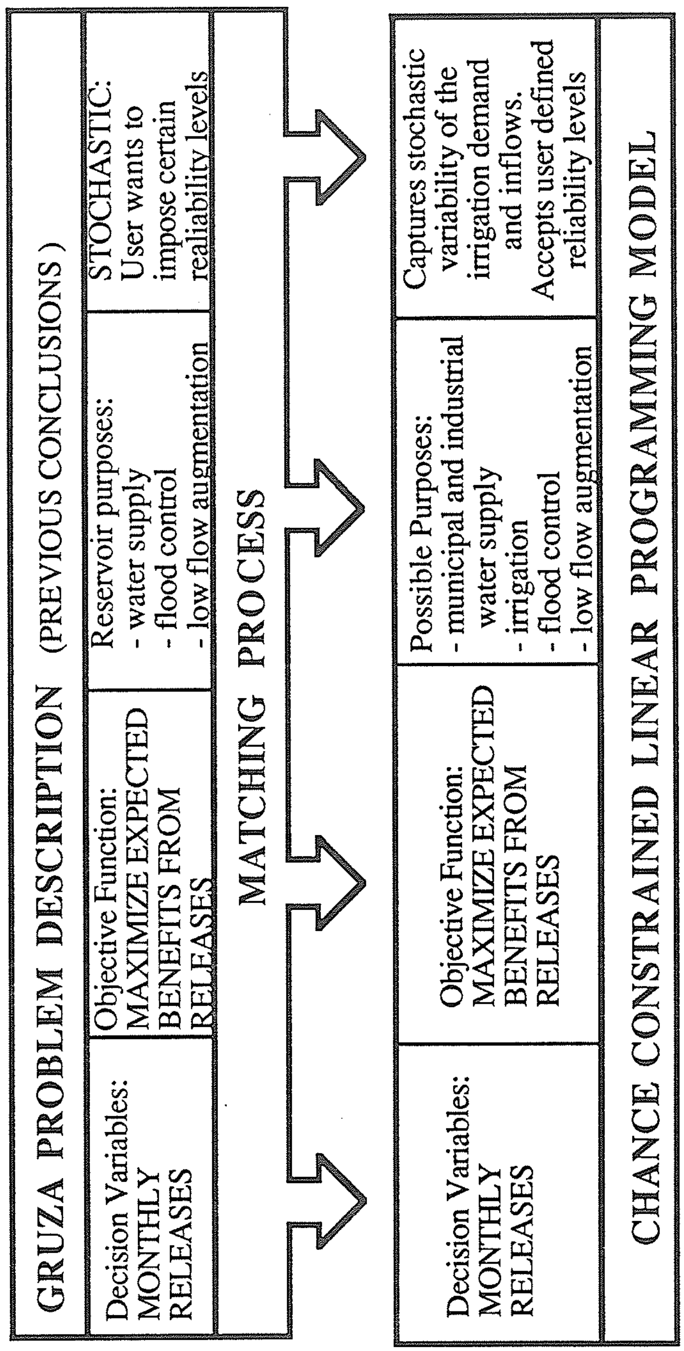

Figure 4.10. Reservoir problem characteristics as they match CCCP model characteristics

should be provided by a decision-maker or a decision-making body. Therefore, the first run was performed under the conservative assumption of very high required reliability levels, i.e., both α and β are set at 98% (see Table 4.3).

Table 4.3. Gruza Reservoir Data and Results

Month	Evaporation rate	Minimal release	Maximal release	Solution No. 1 $\alpha=\beta=0.98$ Release	Solution No. 2 $\alpha=\beta=0.925$ Release
[-]	[mm]	[$10^6 m^3$]	[$10^6 m^3$]	[$10^6 m^3$]	[$10^6 m^3$]
Oct.	65.7	0.54	8.04	1.98	0.54
Nov.	28.5	0.52	7.78	0.52	0.52
Dec.	20.8	0.54	8.04	0.54	0.54
Jan.	19.2	0.54	8.04	0.54	0.54
Feb.	19.7	0.48	7.26	0.48	0.48
Mar.	50.0	0.54	8.04	0.54	0.54
Apr.	65.7	0.52	7.78	5.39	0.52
May	96.4	0.54	8.04	5.60	3.88
Jun.	110.4	0.52	7.78	0.52	0.52
Jul.	119.0	0.54	8.04	1.02	7.52
Aug.	113.5	0.54	8.04	0.93	8.04
Sep.	90.3	0.52	7.78	0.52	0.52

The corresponding optimal release policy suggested that an additional $18.58 \times 10^6 m^3$ can be allocated annually to the downstream users. The analysis of within-year distribution of releases revealed that although higher benefit coefficients were assigned to releases during summer months (June, July, and August), most of the water was released during the spring months, April and May (41% of the total annual release during spring and 13% during summer). A careful examination of the flow duration plots for these two months reveals the reasons for these seemingly inconsistent results. The very high flows during these two months correspond to 98% flood control reliability (2% probability of exceedence on the flow duration plots), and cause flood control constraints to be binding at the optimum. Consequently, water was released from the reservoir during the spring months to ensure safe operation. However, high-valued releases during summer months were kept close to minimum allowable flows.

In the next iteration, the required reliability levels were relaxed, as suggested by REZES, to 92.5% and the model was run again. The new optimal release policy suggested that $24.16 \times 10^6 m^3$ may be released annually to the downstream users. This amount represents a 30% increase in water allocated to downstream users when compared to the results of the first run, or in total $5.58 \times 10^6 m^3$ more. This increase in supply was achieved at a cost of 5.5% in reliability levels. The within-year distribution of releases (Table 4.3) shows that most of the water (33% of the total annual release) is now released during the summer months, rather than during spring (18%). In addition, the month-to-month comparison of the first and second runs shows a significant change in released amounts even for same months, e.g., the suggested release in August has risen from 0.93 to $8.04 \times 10^6 m^3$. This change was not able to be directly explained by the model results. Examination of the flow duration plots for the inflows during the two spring months revealed the cause. The flows during April and May that correspond to 92.5% flood control reliability (7.5% probability of exceedence on the probability plots), are considerably lower than those used for the 98% reliability in the first run. Consequently, the flood control constraints did not have to force release of water in these two months.

The unexplained and abrupt changes in suggested release policy strengthened the need for a robust procedure, which may more closely explain the interaction of the two constraints and the objective function. That procedure should not be rigid and static, with respect to the strict satisfaction of the constraints, as assumed by the CCP procedure in which all constraints are considered inviolate at their fixed a priori defined levels (set up by in advance chosen reliability levels). In addition, each of the two above sets of results identifies one optimal release policy for the precisely defined input provided by the user. It does not, however, account for the uncertainty in the input parameters and functional relationships that are considered precise, reliable, and not subject to change. In practice, especially for planning purposes, users need a range of solutions which are not critically sensitive to changes in model parameters that are imprecise and hard to identify a priori. Carefully planned and performed sensitivity analysis can be used to provide the user with these important insights. The disadvantage of the classical sensitivity analysis for this purpose, is that in a highly constrained multi-dimensional feasible space (as it is in the case of CCP with high reliability levels) the analysis may not be very efficient. The uneven coverage of the feasible space may be another reason why sensitivity analysis should be guided somehow and embedded into the model, which will then allow for uncertainty and imprecision to be directly taken into account. At the same time sensitivity analysis should generate widely different solutions (in terms of the set of selected decision variables, i.e., releases) to facilitate their evaluation and elaboration. *Brill* [1979] suggested that the tailoring of available algorithms should provide this information for use in planning.

The previous discussion of the CCP model results and input parameters raises a question of adequately capturing reality in the optimization process and in rational decision making. It is argued that an unambiguous extremum on benefits requires reliable economic information which can be difficult to obtain in reality. Even if it can be obtained, the satisfactory attainment level for the objective function may not be expressed as an absolute minimum level, e.g., below which the operation of the reservoir is not economical. Because of the imprecision embedded in the objective function, some violations of the "crisp" minimum levels may be allowable. Even a range of acceptable levels may be specified for the objective and used in the analysis. Similarly, the constraints that are posed may have the same feature of uncertainty. Therefore, they need to be flexible and allow for some violations rather than being strictly inviolable. In summary, this discussion displays a separation between optimizing and the process of seeking solutions which are acceptable. *Brown* [1989] calls this process "satisficing". He contrasts optimizing, which is a procedure based upon strong mathematical foundations and allows precise statements to be made in the objective function, with "satisficing", which is then "an expectation with formal trappings which admits of imprecision in the objectives and constraints and robustness in the solution".

The following chapters introduce fuzzy set theory and a fuzzy approach to rational decision making. It will be shown that "satisficing" forms a framework for using fuzzy linear programming in reservoir analysis. A non-linear chance-constrained reservoir-operation model, which is based on the principles of satisficing and uses fuzzy set theory, is then developed and described. The model is built on the chance-constrained model developed by *Simonovic* [1979] which is tailored to account for subjective and imprecise information by using fuzzy methods. The new model exemplifies how fuzzy methods may be used to augment and improve a purely stochastic procedure. The discussion will address two common misconceptions about the use of fuzzy sets: (i) that fuzzy models are really statistical ones in disguise; and (ii) that fuzzy models are always proposed to replace stochastic ones.

CHAPTER 5.

FUZZY SETS, DECISION MAKING AND FUZZY MODELLING

This chapter reviews the theory of fuzzy sets and principles necessary for the understanding and development of a fuzzy-set-based decision-making model. These theoretical principles provide a mathematical framework for studying imprecise conceptual phenomena in modelling and decision making.

5.1. REVIEW OF BASIC FUZZY SET THEORY AND PRINCIPLES

This section is devoted to the description of basic fuzzy set theory by means of: (i) basic concepts and definitions; (ii) basic model of a decision making process in a fuzzy environment; and (iii) fuzzy linear programming. First, basic fuzzy set theory will be presented as a generalization of ordinary set theory, i.e., the theory of collections of things. Second, fuzzy decision modelling is defined and presented in terms of membership functions of the objective function and the constraints. Finally, fuzzy decision modelling principles, applied to fuzzy linear programming, are presented in more detail. Only the notions and definitions necessary for the development and understanding of the CCP reservoir operation model will be presented.

5.1.1. Some Basic Concepts and Definitions

The following definitions are adopted and/or compiled from the, now classical, paper by *Zadeh* [1965] or from the works by *Zimmermann* [1976, 1983, 1985, 1987].

[Definition 5.1]

A classical (crisp) set is a collection of elements or objects x in X, which can be finite or infinite. Each single element can either belong to or not belong to the set A, A$\in$X. Membership in a classical set A of X is often viewed as a characteristic function μ_A (binary function with two possible values, 0 or 1) such that:

$$\mu_A(x) = \begin{cases} 1, x \in A \\ 0, x \notin A \end{cases} \tag{5.1}$$

[Example 1]

A="Real numbers between 8 and 12":

$$\mu_A(x) = \begin{cases} 1, & x \in (8,\ 12) \\ 0, & x \le 8, x \ge 12 \end{cases} \tag{5.2}$$

Graphical representation of the characteristic function of A is given in Figure 5.1.

[Definition 5.2]

Fuzzy set: if X is a collection of objects denoted generically by x, then a fuzzy set A in X is a set of ordered pairs:

$$A = \{x,\ \mu_A(x)\}, x \in X \tag{5.3}$$

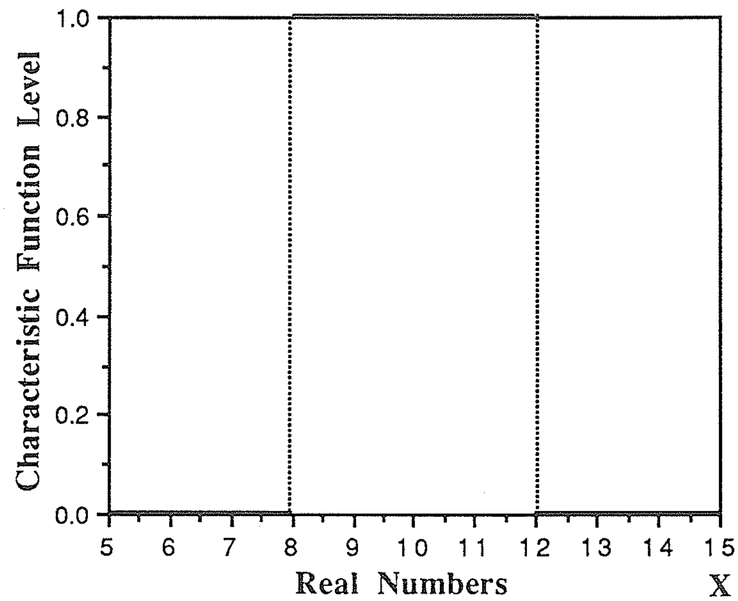

Figure 5.1. Characteristic function of the set A

where the first component of the pair refers to the element of X and the second deals with the corresponding grade of membership.

[Definition 5.3]

Membership function represents the grade of membership of x in the fuzzy set A, and its values are allowed to be in the real interval [0,1]. The closer the value of $\mu_A(x)$ is to 1, the more x belongs to A. Because fuzzy sets are represented by their respective membership functions, in this work these two terms are considered equivalent and are referred to interchangeably.

[Example 2]

A="Real numbers close to 10", where the explanation represents an example of linguistic hedges used with fuzzy sets (e.g., approximately, more or less equal, etc.):

$$\mu_A(x) = \frac{1}{1 + (x\text{-}10)^2} \tag{5.4}$$

Graphical representation of the fuzzy set A (or the membership function of A) is given in Figure 5.2.

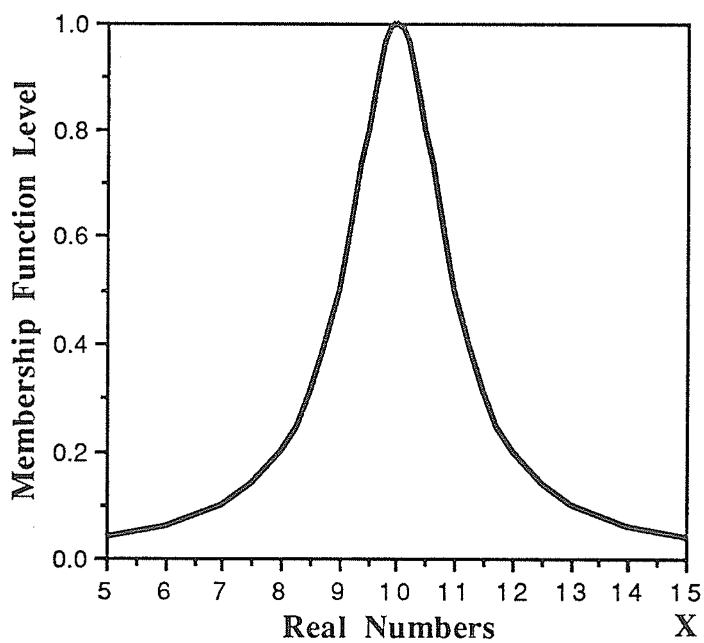

Figure 5.2. Membership function of the fuzzy set A

[Definition 5.4]

Support of a fuzzy set is an ordinary set S(A) such that x belongs to S(A) if $\mu_A>0$.

[Definition 5.5]

Normality of fuzzy sets: if Max $\mu_A(x)=1$, the fuzzy set **A** is called normal.

[Definition 5.6]

Equality of two fuzzy sets: two fuzzy sets, **A** and **B**, are equal if:

$$\mu_A(x) = \mu_B(x),\ \forall x \in \mathbf{X} \tag{5.5}$$

Basic operations on fuzzy sets are the result of an immediate generalization of the corresponding operations in classical set theory. Thus, we will start from the conventional Venn diagrams for depicting basic operations on ordinary sets. Figure 5.3 shows how the elements of two sets may be lumped together, i.e., the union operation (A∪B), or how we could examine the elements held in common by two sets, taking their intersection (A∩B). Finally, the elements not belonging to a set may be examined by taking its complement. It can be easily seen that the intersection of a set and its complement is an empty set:

$$\mathrm{A} \cap \overline{\mathrm{A}} = \varnothing \tag{5.6}$$

and that the union of a set and its complement results in the complete universe of discourse **X**:

$$\mathrm{A} \cup \overline{\mathrm{A}} = \mathbf{X} \tag{5.7}$$

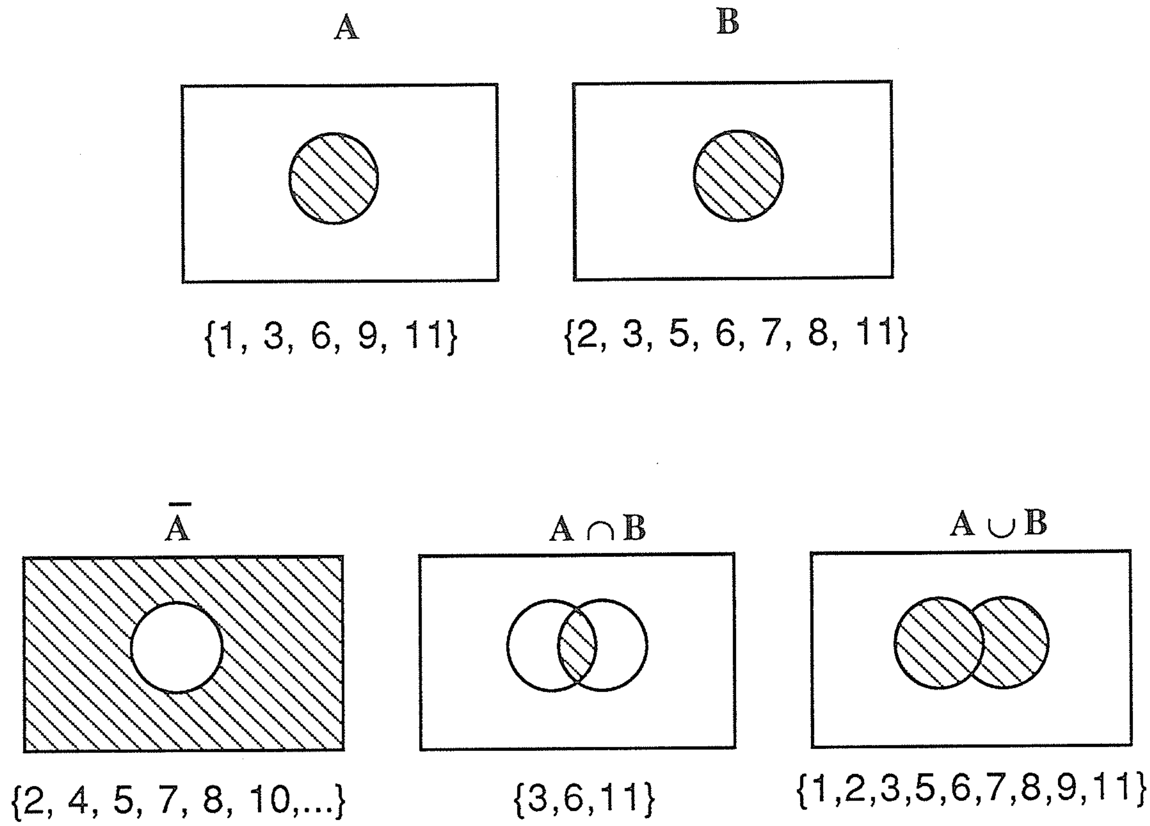

Figure 5.3. Venn diagrams of basic operations on ordinary sets

[Definition 5.6]

Union of fuzzy sets: the membership function of A∪B is defined as the maximum of the membership functions of A and B. This operation was extended from classical set theory by the following formula proposed by *Zadeh* [1965]:

$$\forall x \in X, \quad \mu_{A\cup B}(x) = \max\{\mu_A(x),\, \mu_B(x)\} \tag{5.8}$$

[Definition 5.7]

Intersection of fuzzy sets: the membership function of A∩B is defined as the minimum of the membership functions of A and B. This operation is expressed by the following formula:

$$\forall x \in \mathrm{X}, \quad \mu_{\mathrm{A} \cap \mathrm{B}}(x) = \min \{\mu_{\mathrm{A}}(x), \mu_{\mathrm{B}}(x)\} \tag{5.9}$$

[Definition 5.8]

Complement of a fuzzy set: The complement $\overline{\mathrm{A}}$ of A is defined by the membership function:

$$\forall x \in \mathrm{X}, \ \mu_{\overline{\mathrm{A}}}(x) = 1 - \mu_{\mathrm{A}}(x) \tag{5.10}$$

There is no exact analogy for these operators to the Venn diagrams used to depict traditional set union and intersection. Figure 5.4 shows a fuzzy set representation of these operations.

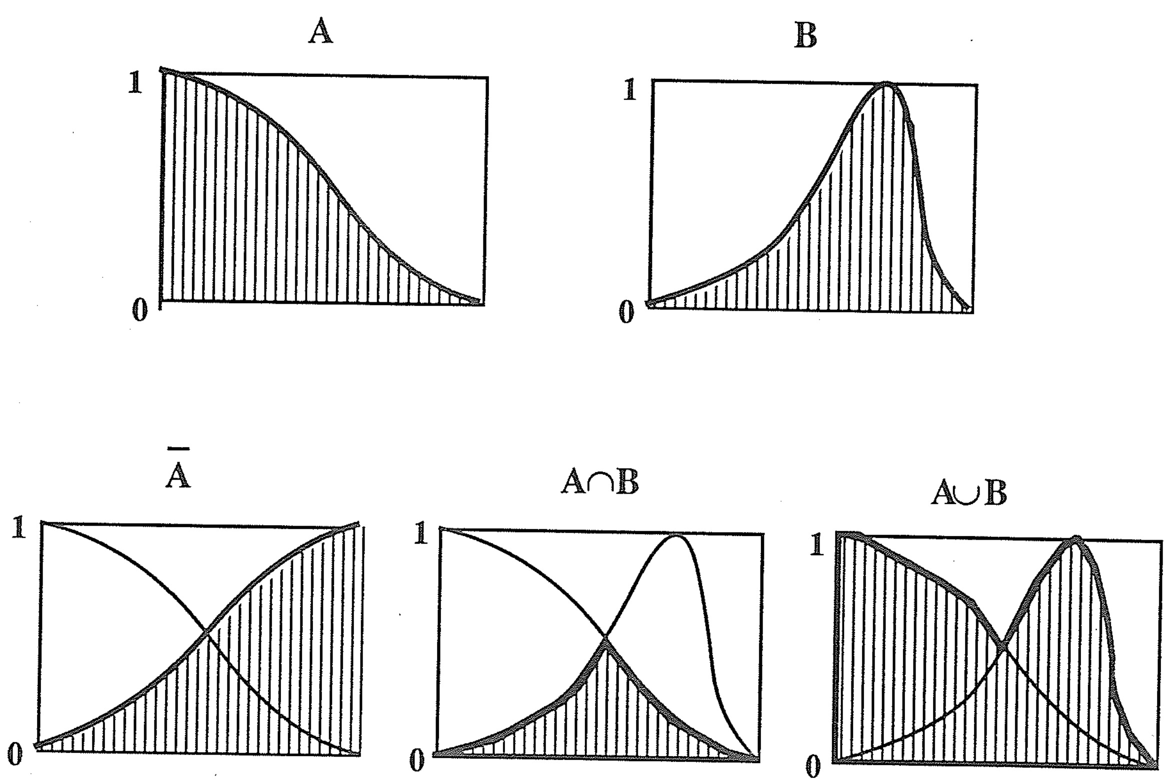

Figure 5.4. Representation of fuzzy set operations

The above formulas for operations on fuzzy sets, preserve almost all properties of operations found in traditional set theory. There are, however, two important differences. Figure 5.5 shows that the intersection of a fuzzy set and its complement is no longer an empty set:

$$A \cap \overline{A} \neq \varnothing \tag{5.11}$$

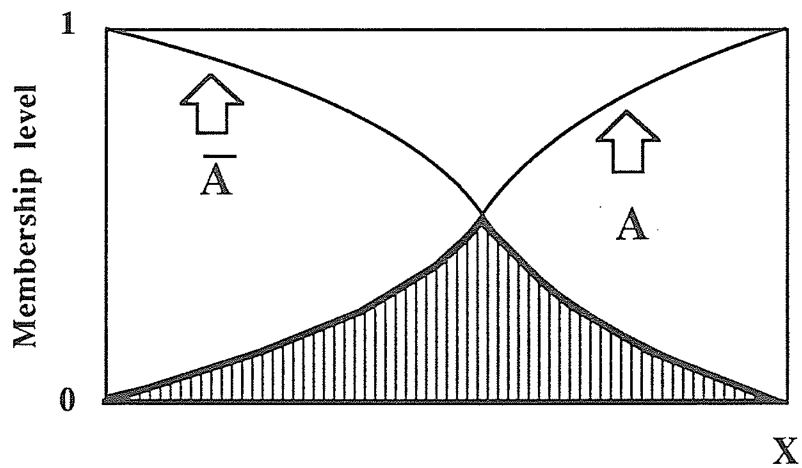

Figure 5.5. Intersection of a fuzzy set and its complement

and that the union of a fuzzy set and its complement does not result in complete universe of discourse X:

$$A \cup \overline{A} \neq X \tag{5.12}$$

These differences are the direct consequence of a lack of sharp boundaries in fuzzy sets.

5.1.2. Modelling of a Decision-Making Process in a Fuzzy Environment

In Chapter 3, conventional (non-fuzzy) modelling of a decision making process in reservoir management and operations was analyzed through the mathematical description of a system in terms of:

(i) decision variables;

(ii) objective functions; and

(iii) constraints.

The optimal decision is defined then as the value of the vector of decision variables giving the best system performance.

As is the case with operations on fuzzy sets, modelling of a decision-making process in a fuzzy environment is developed as an extension of its traditional analogue. A fuzzy decision-making model considers a situation in which the objective function as well as the constraint(s) are fuzzy. According to *Bellman and Zadeh* [1970] and *Zimmermann* [1976], since the objective function should be optimized and, at the same time, the constraint set satisfied, a decision in a fuzzy environment is defined by analogy to a non-fuzzy environment as the selection of decision variable values which simultaneously satisfy the objective function and constraints. According to this definition and assuming that the intersection operator corresponds to the logical "and", the decision in a fuzzy environment can therefore be viewed as the intersection of fuzzy constraints and a fuzzy objective function. Figure 5.6 shows how two fuzzy sets, corresponding to an objective function and a constraint, are combined to get a fuzzy set representing a fuzzy decision (shaded area). A range of x in the shaded area refers to those values of x acceptable from the point of view of the constraint as well as the objective function. The membership levels of the decisions in the shaded area may be viewed as support levels or satisfaction levels for the corresponding decisions. A mathematical formulation of the decision may be expressed in terms of membership functions:

$$\mu_D(x) = \min \{\mu_G(x), \mu_C(x)\} \tag{5.13}$$

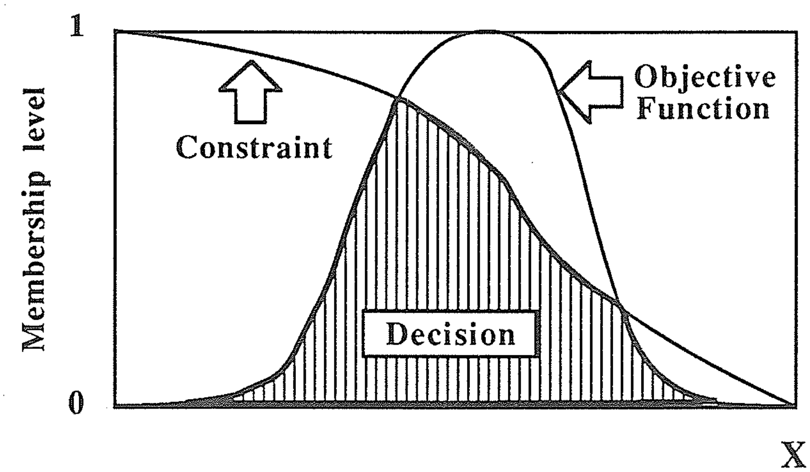

Figure 5.6. Modelling of decision making in fuzzy environment

where $\mu_D(x)$, $\mu_G(x)$, and $\mu_C(x)$ are the membership functions of the decision, objective function, and constraint respectively. It should be pointed out that if the DM needs a crisp, rather than a fuzzy decision, the solution with the highest degree of membership in the fuzzy set decision may be considered as the "optimal".

The above definition of modelling of a decision-making process in a fuzzy environment introduces a different approach to treating the relationship between objective functions and constraints. According to the fuzzy definition, there is no longer a difference between the objective function and constraints (their membership functions), i.e., the relationship between them is fully symmetric. Figure 5.6 explains this relationship in the membership space. The membership function of the objective is a bell-shaped function that reaches maximum value for some aspiration level of **X**. The membership function of the constraint is an inverse S-shaped function which embraces values of **X** within defined tolerance limits. The acceptable decision space is then the intersection of the two fuzzy sets. Exactly the same answer would have been attained if the membership function of the objective was defined as an inverse S-shaped function and the membership function of the constraint as a bell-shaped function. In other words, the treatment of the two membership functions is the same in the fuzzy decision-making process.

5.1.3. Fuzzy Linear Programming

The conceptual formulation of the fuzzy linear programming proposed by *Tanaka et al.* [1974], and developed by *Zimmermann* [1976,1983,1985,1987] will be briefly reviewed next. 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:

$$\text{Minimize } z = \mathbf{c}^{T} \cdot \mathbf{x} \tag{5.14}$$

$$\mathbf{A} \cdot \mathbf{x} \geq \mathbf{b} \tag{5.15}$$

$$\mathbf{x} \geq 0 \tag{5.16}$$

where X is a given space of alternatives ($\mathbf{x} \in X \equiv \mathbb{R}^n$); $\mathbf{c} \in \mathbb{R}^n$; $\mathbf{b} \in \mathbb{R}^m$; A, the coefficient matrix such that $A \in \mathbb{R}^{m \cdot n}$; $\mathbb{R}^k$, k-dimensional real space; n, number of decision variables; and m, 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, i.e., the intersection of the two or more constraints and the objective function.

If we assume 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. To do that, the objective function might have to be written as a maximizing goal in order to consider z as a lower bound. The objective function and constraints may be represented, then, by fuzzy sets with their corresponding membership functions. The problem is now fully symmetric with respect to objective function and constraints:

$$\mathbf{c}^T \cdot \mathbf{x} \mathrel{\tilde{\geq}} z \tag{5.17}$$

$$A \cdot \mathbf{x} \mathrel{\tilde{\geq}} \mathbf{b} \tag{5.18}$$

$$\mathbf{x} \geq 0 \tag{5.19}$$

where $\tilde{\geq}$ denotes the fuzzy version of $\geq$ relation and has the linguistic interpretation "essentially greater than or equal". Using the symmetry feature the objective (5.17) and constraints (5.18) can be represented together as:

$$\mathbf{B}\cdot\mathrm{x} \tilde{\geq} \mathbf{d} \tag{5.20}$$

where

$$\mathbf{B}\in\mathbf{R}^{n\cdot(m+1)},\ \mathbf{B}=\begin{bmatrix} \mathrm{c} \\ \mathrm{A} \end{bmatrix},\ \mathbf{d}\in\mathbf{R}^{m+1},\ \text{and}\ \mathbf{d}=\begin{bmatrix} z \\ \mathbf{b} \end{bmatrix}$$

Each of the $m+1$ rows of (5.20) are now represented by a fuzzy set S_i in the E_i, and a function h:X->E. Objects $E_1,\ldots,E_{m+1}$ are real lines which correspond to the items related to the objective and constraints. A fuzzy decision $D\in X$ is then defined as the intersection of the inverse images of $S_1,\ldots,S_{m+1}$ with respect to $h_1,\ldots,h_{m+1}$, i.e.,

$$\mathrm{D}=\bigcap_{i=1}^{m+1} \mathrm{h}_i^{-1}(\mathrm{S}_i) \tag{5.21}$$

and correspondingly, its membership function is:

$$\mu_{\mathrm{D}}(\mathrm{x}) = \mathrm{Min}\ \mu_{\mathrm{S}_i}(\mathrm{h}_i),\ \ \mathrm{x}\in\mathrm{X},\ i = 1,2,\ldots,\ m+1 \tag{5.22}$$

where μ_D is the membership function of the fuzzy (decision) set $\mathbf{D}$; μ_{S_i} is the membership function of the fuzzy set S_i corresponding to the i-th constraint.

This is the function of the set of decisions x that satisfy relation (5.20). In order to derive one executable decision it is appropriate to consider it as a solution with the highest degree of membership in the fuzzy set decision space $\mathbb{D}$. The optimization problem can be formulated as choosing an alternative $x^* \in \mathbb{D}$ such that:

$$\mu_{\mathrm{D}}(\mathrm{x}^*) = \mathrm{Max}\ \mu_{\mathrm{D}}(\mathrm{x}), \quad \mathrm{x} \in \mathbb{D} \tag{5.23}$$

At this point it should be noted that linear programming formulation requires that all membership functions of the fuzzy goal and fuzzy constraints are given in linear form. This requirement gives the following:

$$\mu_{\mathrm{S}_i}(e_i) = \mathrm{Max}\ \{\mathrm{Min}\,[\sigma_i(e_i),\ 1],\ 0\}, \quad e_i \in \mathrm{E}_i \tag{5.24}$$

where $\sigma_i(e_i)$, i=1,2,...,m+1, are linear functions. An example of the membership function of a fuzzy constraint is given in Figure 5.7.

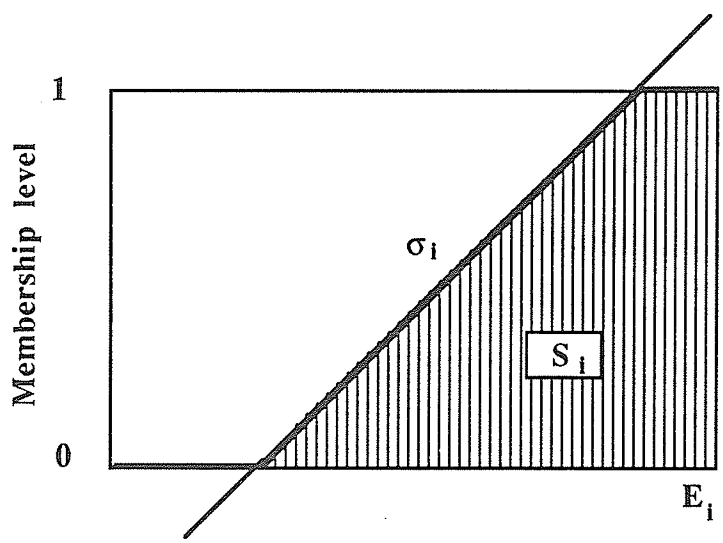

Figure 5.7. A fuzzy constraint membership function

Accordingly, the membership function of the fuzzy decision is represented by:

$$\mu_D(x) = \text{Max}\ [\ \{\text{Min}\ [\sigma_i(h_i(x))],\ 1\},\ 0],\quad i = 1,2,\ldots,m+1 \qquad (5.25)$$

The simplest form of the linear membership function, stated generally in (5.24), for the fuzzy constraints and fuzzy objective function (5.20) may be stated in the following form:

$$\mu_i((\mathbf{B}\cdot\mathbf{x})_i) = \begin{cases} 1, & \text{for } (\mathbf{B}\cdot\mathbf{x})_i \geq d_i \\ \dfrac{1-(\mathbf{B}\cdot\mathbf{x})_i - d_i}{p_i}, & \text{for } d_i > (\mathbf{B}\cdot\mathbf{x})_i > d_i - p_i \\ 0, & \text{for } (\mathbf{B}\cdot\mathbf{x})_i \leq d_i - p_i \end{cases} \qquad (5.26)$$

where d_i is i-th element of the column vector $\mathbf{d}$ given in (5.20); and p_i's are subjectively chosen tolerance levels of admissible violation of the i-th constraints,

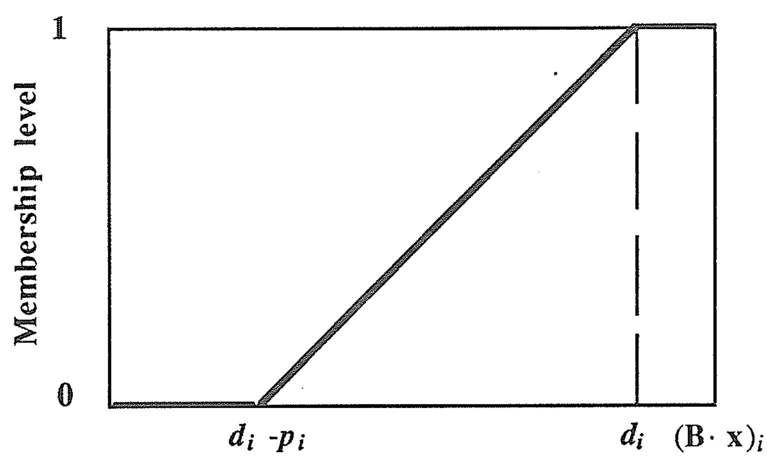

Figure 5.8. Fuzzy "greater than" constraint membership function

and $(\mathbf{B}\cdot\mathbf{x})_i$ is the i-th row of the linear system from (5.20),i.e., the left-hand side of the i-th constraint. Figure 5.8 shows a fuzzy set representing the i-th constraint.

Substituting (5.26) into (5.22) and then (5.23) yields following:

$$\text{Max}\left\{\text{Min}\left[1+\frac{(\mathbf{B}\cdot\mathbf{x})_i-d_i}{p_i}\right]\right\} \tag{5.27}$$

This problem is usually called the Maximin (or MAX-MIN) problem [*Wagner*, 1969]. It can be reformulated into the classical LP problem by introducing a new variable λ. This LP equivalent has just one more variable and two more constraints than the original problem given by (5.14), (5.15) and (5.16):

$$\text{Maximize } \lambda \tag{5.28}$$

$$\lambda p_i - (\mathbf{B}\cdot\mathbf{x})_i \leq p_i - d_i, \quad i = 1,2,\ldots,m+1 \tag{5.29}$$

$$\lambda \leq 1 \tag{5.30}$$

$$\lambda \geq 0, \ \mathbf{x} \geq \mathbf{0} \tag{5.31}$$

If (λ^*,x^*) is the optimal solution to the problem represented by (5.28), (5.29), (5.30), and (5.31), such x^* is the optimal solution to (5.23), as well as to (5.27).

In practice, it is very rare that the objective function is initially expressed in fuzzy terms, as it was in (5.17). Usually, a DM wants the objective function maximized or minimized, subject to the set of constraints, where some of them are well-defined and some are fuzzy. Accordingly, the roles of objective function and fuzzy constraints are different and the introduced symmetric approach is not applicable. In order to make the problem symmetric again, the following transformation procedure was proposed by *Zimmermann* [1985], to normalize the membership function of the original objective function:

$$\mu_G(x) = \begin{cases} 1, & \text{for } \mathbf{c}^T \cdot \mathbf{x} \le f_1 \\ \dfrac{f_0 - \mathbf{c}^T \cdot \mathbf{x}}{f_0 - f_1}, & \text{for } f_0 > \mathbf{c}^T \cdot \mathbf{x} > f_1 \\ 0, & \text{for } \mathbf{c}^T \cdot \mathbf{x} \ge f_0 \end{cases} \tag{5.32}$$

where μ_G is the membership function of the fuzzified objective function $f(x)$, f_0 is the optimal solution of the standard LP problem without any allowed violation of the original constraints (5.15), and f_1 is the optimal solution of the relaxed standard LP problem with introduced relaxation terms p_i's on the constraints (5.15):

$$f_1 = \text{Minimize } f(x)$$

$$(\mathrm{A} \cdot \mathrm{x})_i \ge b_i - p_i, \; i = 1, 2, \ldots, m \tag{5.33}$$

$$\mathrm{x} \ge 0$$

A membership function of the objective function is represented graphically in Figure 5.9.

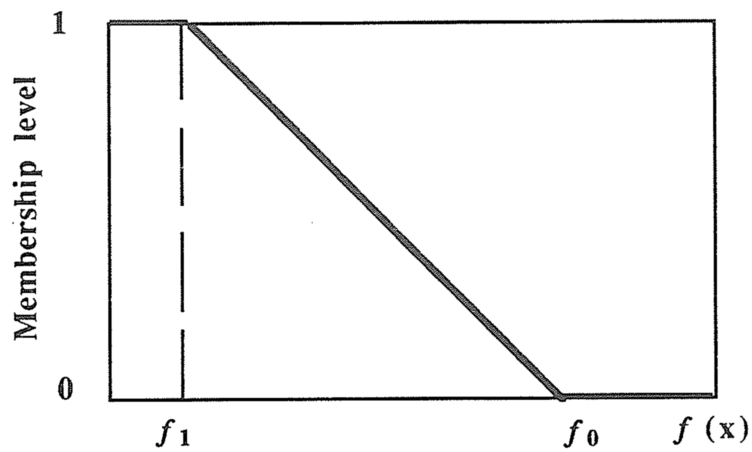

Figure 5.9. Objective function fuzzy set (membership function)

Due to the transformation, the problem is symmetric with respect to the objective function and constraints. Its equivalent LP formulation may be obtained again by introducing a new variable λ:

$$\text{Maximize } \lambda \tag{5.34}$$

$$\lambda(f_0 - f_1) + \mathbf{c}^T \cdot \mathbf{x} \le f_0 \tag{5.35}$$

$$\lambda p_i - (\mathrm{A} \cdot \mathbf{x})_i \le p_i - d_i, \quad i = 1,2,\ldots,m \tag{5.36}$$

$$\lambda \le 1 \tag{5.37}$$

$$\lambda \ge 0, \mathbf{x} \ge \mathbf{0} \tag{5.38}$$

Finally, if the problem contains some non-fuzzy constraints the constraint set may be extended to incorporate them. Simply, a set of k constraints are added to the problem formulation yielding the solution f_0, f_1, as well as the problem formulation (5.34)-(5.38):

$$(\mathbf{G}\cdot\mathbf{x})_i \leq g_i, \quad i = m+1,\ldots,m+k \tag{5.39}$$

where $(\mathbf{G}\cdot\mathbf{x})_i$ is the left-hand side of the i-th non-fuzzy constraint, and g_i is the right-hand side of the same constraint.

The fuzzy linear programming technique will be demonstrated using a simple water quality management example formulated as an LP by *Loucks et al.* [1981, pp. 46].

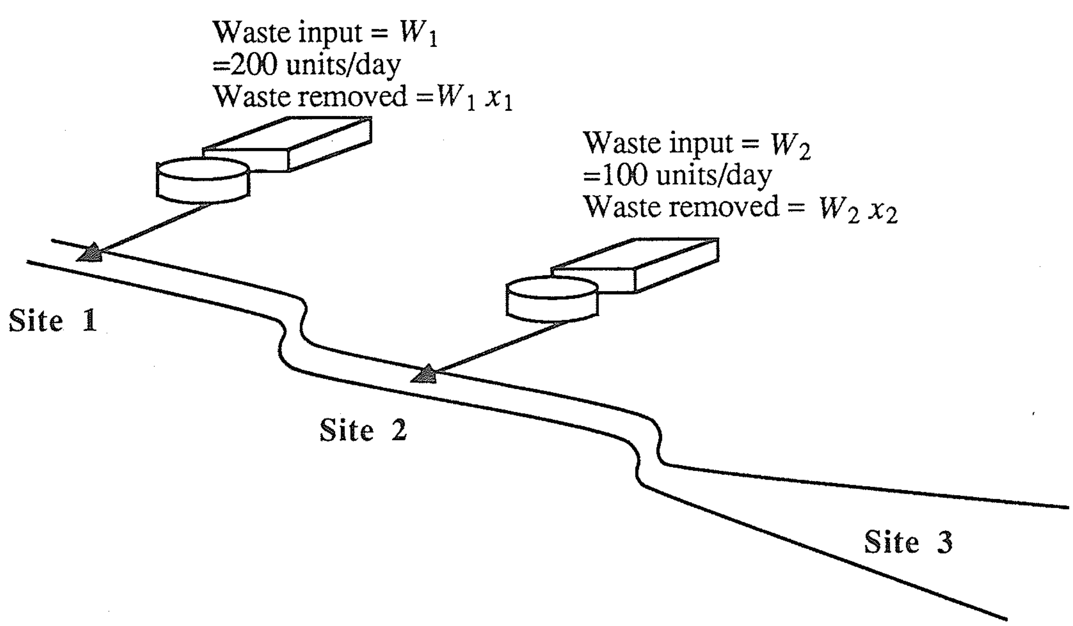

Figure 5.10. Water quality management problem (after *Loucks et al.* [1981])

A stream (Figure 5.10) receives waste from sources located at sites 1 and 2. Q_i represents the desired water quality concentration (index) and q_i represents the existing quality at the sites without any waste treatment. The problem is to find the level of wastewater treatment at sites 1 and 2 required to achieve the desired concentrations at sites 2 and 3 at a minimum cost. The transfer coefficient a_{ij} measures the improvement in the water quality concentration at site j per unit of waste removed at site i, and W_i represents the waste input at site i. The variable x_i is the fraction of waste removed at site i, and the coefficient c_i is the cost of treatment per unit of x_i.

The formulated LP model for this problem is:

$$\text{Minimize } z = c_1x_1 + c_2x_2 \tag{5.40}$$

$$q_2 + a_{12}W_1x_1 \geq Q_2 \tag{5.41}$$

$$q_3 + a_{13}W_1x_1 + a_{23}W_2x_2 \geq Q_3 \tag{5.42}$$

$$x_1, x_2 \geq 0.30 \tag{5.43}$$

$$x_1, x_2 \leq 0.95 \tag{5.44}$$

The bounds on x_i (5.43) and (5.44) represent the operating limits of the waste removal technology.

We now assume that data take the following values: c_1=10, c_2=6, q_2=3, q_3=2, a_{12}=0.025, a_{13}=0.010, a_{23}=0.025, W_1=200, W_2=100, Q_2=7, and Q_3=6. The optimal solution to this LP is x_1^*=0.8125, x_2^*=0.95, and z^*=13.825.

Suppose that desired water quality concentrations are not known precisely and that they are given as shown in Figure 5.11a and Figure 5.11b. Note that the size of the terms p_1=3 and p_2=1 give an indication of how imprecise our understanding of the lower limits on water quality is.

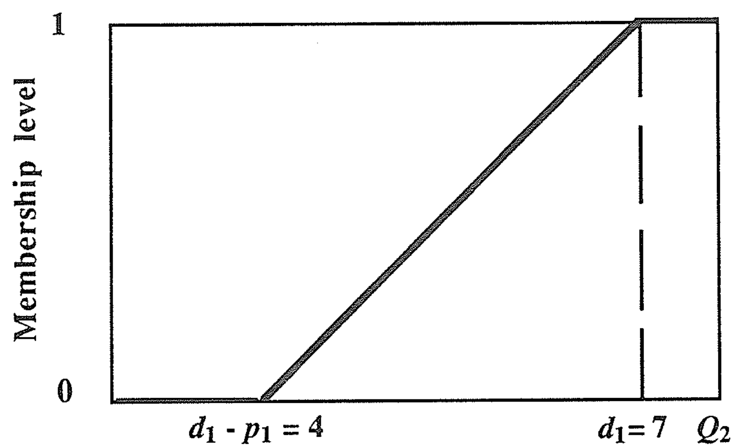

Figure 5.11a. Water quality constraint as a fuzzy set (site 2)

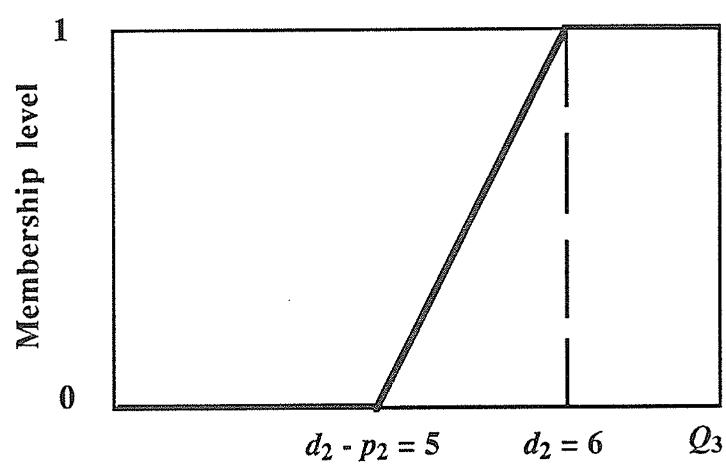

Figure 5.11b. Water quality constraint as a fuzzy set (site 3)

If we solve the given problem for f_0, i.e., using the most restrictive constraint values, the objective function yields z=13.825. If we then solve the given problem for f_1, i.e, for the relaxed (softened) constraints, the objective function yields z=7.8. Finally, if we solve the given problem for λ (Eq. 5.34-5.39), the final solution yields: λ=0.58, x_1^*=0.72, and x_2^*=0.53. If the values are substituted back into the original objective function, the value of the objective function is z=10.38.

In summary, the differences between the "crisp" model (5.40)-(5.43) and the fuzzy LP model (5.34)-(5.39) are as follows: the use of fuzzy LP admits imprecision in the constraints while the "crisp" model needs totally precise input data, i.e, the fuzzy procedure and solution may embrace the understanding of uncertain data and constraints in a more realistic manner; the solution of the "crisp" model is obtained by solving an LP problem once while the fuzzy solution is obtained by running the LP solver three times. It can be observed, however, that the solution obtained by using fuzzy LP is another "crisp" solution. The only additional information for a DM is that support (satisfaction) for this solution attains its maximum at 0.58. The apparent deficiency of the fuzzy model in terms of providing just another crisp answer, will be discussed in more detail in the following chapter and an improved methodology will be presented.

5.2. MEMBERSHIP FUNCTION ESTIMATION

The membership function is a subjective category that depends on the expert's or decision-maker's individual perception of degrees of membership. It is, therefore, obvious that membership functions are context-dependent and should be carefully analyzed for each particular application. The question of how to obtain, or at least estimate, these degrees of membership has received some attention in the literature and is described in the following sections.

5.2.1. Introduction

In general, three approaches to the membership function estimation have been followed. The first technique is simply to ask assessors to draw their membership functions, 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 main idea is to fit the empirical data set, consisting of pairs of elements of the universe of discourse and the relative grades of membership, to the analytical form of the membership function (linear, exponential, etc.). It is, however, seldom possible to get trustworthy membership functions by asking assessors to state them directly.

The second approach is based on statistical data manipulation. The approach uses a population of assessors, each of which can respond to certain questions, with respect to membership of an element in a set, with a Boolean "yes" or "no" answer. The grade of membership is taken to be the proportion of the population replying "yes" to the question [*Freeling*, 1980; *Bharathi and Sarma*, 1985]. The statistical approach makes it possible to obtain a confidence interval to the grade of membership for each element of interest. Although applicable for certain types of problems that involve group decision making, this approach is not particularly useful for individual decision modelling.

The third approach uses a basic scaling method for priorities proposed by *Saaty* [1977] or its variation [*Pedrycz*, 1989 pp. 51-53]. Its characteristics, discussed in the following section, make it the most convenient approach for the problem of determining risk levels in CCP reservoir operation modelling.

5.2.2. Saaty's Method

Saaty [1977] and *Chu et al.*, [1979] have shown that the problem of determining the degree of belonging of each member to a fuzzy set can be reduced to a matrix eigenvalue problem. To illustrate the nature of the approach, as used in this work, we use a simple chance constraint:

$$P(X \leq x) \leq \alpha \tag{5.45}$$

where P denotes probability, X is a random variable, x is a value of the random variable, and α is the fraction of time the constraint may be violated at most. Often a complement of a risk level is referred to as a reliability level ($1-\alpha$).

Let us assume that the economic consequence of violating the constraint, associated with the risk level α, is not known. The risk, in absence of economic data, should then be assessed by the DM. First, the DM compares every two discrete risk levels giving qualitative preference judgments rather than numerical values. Table 5.1 shows the nine-level qualitative scale used for pairwise comparisons of risk (reliability) levels.

Let **w** be the vector whose elements $w_i>0$, $i=1,2,...,n$, are the unknown degrees (weights) of belonging of each of n different probability levels to a set of "acceptable risk levels".

Table 5.1. Qualitative scale for pairwise comparisons

Level	Definition	Explanation
1)	Equal importance	Two risk levels are equally significant
2)	Intermediate*	
3)	Weak importance of one over another	Experience and judgment slightly favour one risk level over another
4)	Intermediate*	
5)	Essential or strong importance	Experience and judgment strongly favour one risk level over another
6)	Intermediate*	
7)	Very strong or demonstrated importance	A risk level is strongly favoured; its dominance is demonstrated in practice
8)	Intermediate*	
9)	Absolute importance	The evidence favouring one risk level over another is unquestionable

Note:* is used when a compromise among two choices is needed

Now, the pairwise comparisons may be represented by a matrix A of relative weights with elements:

$$a_{ij} = \frac{w_i}{w_j}, \quad \forall i,j : i=1,2,...,n, \quad j=1,2,...,n \tag{5.46}$$

To illustrate the idea employed by the method, let us assume first that a_{ij} values are precisely known, e.g., as a result of a precise physical measurement. Therefore, the matrix A, called a pairwise comparison reciprocal matrix, has positive entries everywhere and satisfies the reciprocal property expressed as:

$$a_{ji} = \frac{1}{a_{ij}} \tag{5.47}$$

Multiplying the matrix by the vector $\mathbf{w}=(w_1,\ldots,w_n)^T$, we have

$$\mathbf{A}\mathbf{w} = n\,\mathbf{w} \tag{5.48}$$

or

$$(\mathbf{A}-n\,\mathbf{I})\mathbf{w}=0 \tag{5.49}$$

where $\mathbf{I}$ is the identity matrix of order n by n. This is a system of homogeneous linear equations which has a non-trivial solution for the vector $\mathbf{w}$ if the determinant of $(\mathbf{A}-n\mathbf{I})$ vanishes. Furthermore, n is the only nonzero eigenvalue of A for this perfectly consistent case [*Saaty*, 1977].

Saaty [1977] has shown that in a matrix, small perturbations in its elements imply small perturbations in the eigenvalues. In the general case of membership determination, a_{ij} ratios are not known and should be estimated from a scale. The DM's subjectivity in estimating them causes inconsistency of the matrix A, i.e., the relationship

$$a_{jk}=\frac{a_{ik}}{a_{ij}} \tag{5.50}$$

is not preserved any more. Even the property in Eq. (5.47) may not be maintained. To improve the consistency in the numerical scaling of the judgment, care should be taken to ensure that whatever value a_{ij} is assigned using comparison, the reciprocal value is assigned to a_{ji}. In the next step, Eq. (5.48) becomes

$$A'w' = \lambda_{max} w' \tag{5.51}$$

where w' is the n-dimensional eigenvector associated with the largest eigenvalue λ_{max} of the perturbated comparison matrix A'. At the same time this vector represents the desired vector of weights (after proper scaling). Carrying the analysis one step further, it can be shown that the largest eigenvalue of the matrix A' satisfies

$$\lambda_{max} \geq n \tag{5.52}$$

where equality holds for perfectly consistent cases only.

For the evaluation of matrix consistency a simple measure, the consistency index (*CI*), has been defined by *Saaty* [1977] as:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{5.53}$$

It is obvious that the closer the *CI* is to zero, the better is the consistency of the matrix of comparison.

For establishing the reasonable upper limit on the *CI*, a sample of 500 matrices of different sizes have been randomly generated [*Saaty and Vargas*, 1980, pp.24]. Their consistency is presumed to be very poor as the entries have been chosen randomly from a numerical scale. A scale with the upper bound value of 9 and the lower bound value of 1/9, to comply with Eq.(5.47), was used. The average consistency index values, which depend on the size of the generated random matrix, are shown in Table 5.2.

Table 5.2. Average consistencies of randomly generated matrices (after *Saaty* [1977])

Matrix size	Average consistency
1	0.00
2	0.00
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

The average consistency index values presented in Table 5.2 show the worst consistency scenario for the particular matrix size because all the entries a_{ij} of the matrices used in the calculation are randomly generated. It can be observed that the value of the index increases with the size of the matrix. This trend occurs due to the relatively higher increase in the largest eigenvalue λ_{max} compared to the increase in matrix size, n.The explanation follows directly from Eq. 5.53.

It is suggested by *Saaty* [1977] that a ratio of a CI and the average random consistency index (from Table 5.2) for the same size matrix, should be around 10 percent or less, to be acceptable. This descriptive measure is called the consistency ratio (CR), and its interpretation is analogous to descriptive measures of association between independent and dependent variables X and Y in regression models. Similarly to the coefficient of determination, r^2 (which measures the strength of the linear relationship between X and Y [*Neter et al.*, 1989]), the limiting values of CR are between 0 and 1. The only difference is in the interpretation of CR. The closer CR is to zero, the greater is said to be the degree of consistency of the matrix $\mathbf{A}'$.

Because of the subjective nature of the manager's attitude toward the acceptable risk levels in (5.45), information provided by the manager is not actually verifiable. Therefore, the consistency measures are descriptive and should serve mainly to highlight anomalous data for the managers' reconsideration. However, some work on selecting a numerical scale for a_{ij}', for which assessor's information is actually or conceptually verifiable from other sources, has been done [*Saaty*, 1980, pp. 53-64]. Different scales were investigated and it was found that a scale with the upper bound value of 9 provides sufficient flexibility to differentiate between two elements. These findings are used here for adopting a scale for estimating the membership functions of chance constraints and the objective function for reservoir planning optimization.

The use of Saaty's eigenvector method in the so-called Analytic Hierarchy Process [*Saaty*, 1980] for multiobjective optimization in water resources planning and management has been documented by *Palmer and Lund*[1985]. They used the method for a discrete case to create the "importance (or weight) of an alternative with respect to an objective". The following simplified example will illustrate Saaty's method applied to a verifiable problem of estimating weights. Assume that we have 4 objects. If we measure their weights we can easily construct a pairwise comparison matrix (4 by 4) which satisfies Eq. (5.46) and (5.47). We now assume that actual weights take the following values: W_1=3, W_2=2, W_3=1, W_4=5 (or if we normalize them: w_1=0.2727, w_2=0.1818, w_3=0.0909, w_4=0.4545). A pairwise comparison matrix constructed by using the data is:

$$A=\begin{bmatrix} a_{11} a_{12} a_{13} a_{14} \\ a_{21} a_{22} a_{23} a_{24} \\ a_{31} a_{32} a_{33} a_{34} \\ a_{41} a_{42} a_{43} a_{44} \end{bmatrix} = \begin{bmatrix} 1 & \frac{3}{2} & 3 & \frac{3}{5} \\ \frac{2}{3} & 1 & 2 & \frac{2}{5} \\ \frac{1}{3} & \frac{1}{2} & 1 & \frac{1}{5} \\ \frac{5}{3} & \frac{5}{2} & 5 & 1 \end{bmatrix}$$

Solving the system of equations (5.49) we get w_1=0.6, w_2=0.4, w_3=0.2, w_4=1.0 and $\lambda_{max}=n=4$. If we then normalize the solution it yields exactly the same values as obtained by the physical measurement. This is an example of an perfectly consistent case.

If however, the actual measurements are not available and we have to assess relative weights of the four objects, then Saaty's method may be applied as follows. First, we compare four objects in pairs by picking them up one at time to get an idea of the range of their weight intensities; then we compare all the objects with each other by picking them up. Suppose that the matrix of pairwise comparisons is

$$A' = \begin{bmatrix} 1 & 2 & 3 & \frac{1}{2} \\ \frac{1}{2} & 1 & 2 & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{2} & 1 & \frac{1}{5} \\ 2 & 3 & 5 & 1 \end{bmatrix}$$

Solving the system of equations (5.51) we get an eigenvector w=(w_1=0.563, w_2=0.325, w_3=0.183, w_4=1.0) and λ_{max}=4.0145 (or normalized w_1=0.2719, w_2=0.1570, w_3=0.0880, w_4=0.4829) which is close to actual values. For this case CI=0.0048. The consistency ratio for this case was calculated as a ratio of CI and the average random consistency index for the matrix of size 4, i.e., the average random consistency index is 0.90. The calculated CR=0.0054<0.1 shows that the ratio is smaller than 10% and therefore, the assessment was consistent.

CHAPTER 6.

RISK LEVEL SELECTION IN CHANCE-CONSTRAINED RESERVOIR OPERATION MODELLING: A FUZZY SET APPROACH

It was shown by example (Chapter 4) that even with using the ES technology some problems, associated with the use of models, still exist. Fuzzy set theory was introduced as a possible way to treat the non-random uncertainty. This chapter demonstrates how fuzzy set theory may be used to represent the imprecision inherent in probabilities and utilities used in a decision-making process and thereby overcome some of these problems. Chance constraints and the objective function of the chance-constrained programming (CCP) reservoir operation problem have been identified as potential components which might benefit from being expressed in a fuzzy manner. To achieve these improvements, special numerical procedures have been developed in this work. These procedures, for the most part, require knowledge of basic fuzzy set theory.

An original approach to the formulation of a multi-purpose reservoir long-term operation planning problem is presented next. This approach, based on fuzzy sets, incorporates the estimation of fuzzy membership functions for constraints and the objective function, as well as formulation of a solution algorithm for deriving an optimal decision. Finally, an application of the model to the Gruza reservoir case study (Yugoslavia) is presented as an example.

6.1. RISK LEVEL SELECTION IN CHANCE-CONSTRAINED RESERVOIR OPERATION MODELLING

The problem of how to choose appropriate risk levels is as old as the CCP approach to water resources optimization. Two different methods have been used for incorporating the selection of risk levels into the CCP solution process. The first one, a reliability programming approach, as proposed by *Sengupta* [1972], and applied by *Simonovic and Marino* [1981], explicitly considers a trade-off between the benefits and the cost of risk. The approach may be useful for situations where existing economic data are available for the development of so-called risk-loss functions. The second method, which uses a multiple-objective programming approach, was introduced by *Rakes and Reeves* [1985]. A similar method has been applied to reservoir design and operation by *Uan-On and Helweg* [1988]. The multiobjective methods provide the DM with trade-off curves between system reliability levels and economic benefits.

Lack of economic data and the fact that establishment of acceptable risk levels involves a human factor, with all its vagueness of perception, subjectivity, and attitudes, may not permit a proper application of either of the above approaches. With that situation in mind, a new approach is proposed and applied in this work. This approach is based on fuzzy set theory. It holds promise as a bridge for part of the gap, caused by imprecision that is not statistical or random in nature, between real systems and their modelling.

Situations where the concept of so-called "classical" probability, alone, is not adequate to describe real-world problems, regularly occur in water engineering practice. When questions arise about exactness of concepts, correctness of statements and judgments, degrees of credibility, etc, the probability framework, alone, is not appropriate for representing reality. Yet, to account for hydrologic uncertainty, a formal model used to estimate reservoir size and select its operating policy must incorporate the stochastic nature of inflows and demands. Therefore, a joint stochastic and fuzzy-set approach may be appropriate for credible reservoir design and operation modelling. The key concept of fuzzy set theory is the membership function which numerically represents the degree to which an element belongs to a set. The following work concentrates on the estimation of the membership functions and development of the solution procedure to arrive at the desirable reservoir operating policy. Although the following methodology can be applied to different CCP formulations, the one developed by *Curry et al.*, [1973] and later modified by *Simonovic* [1979], is employed to demonstrate the process of selecting risk levels.

6.1.1. Chance-Constrained Reservoir Operation Planning Model

The model is derived from consideration of the storage balance equation with the reservoir release as the decision variable. The storage balance equation reflects the conservation of water in the reservoir (Figure 6.1):

$$S_t = S_{t-1} + \tilde{q}_t - d_t - r_t - l_t \quad \forall t,\ t = 1,2,\ldots,T \tag{6.1}$$

where S_t is the volume of water stored in the reservoir at time t, $\tilde{q}_t$ is the stochastic inflow into the reservoir during the time interval $(t\text{-}1,t)$, d_t represents deterministic extractions directly from the reservoir, r_t represents additional downstream release in the time interval, and l_t denotes losses from the reservoir in the time interval.

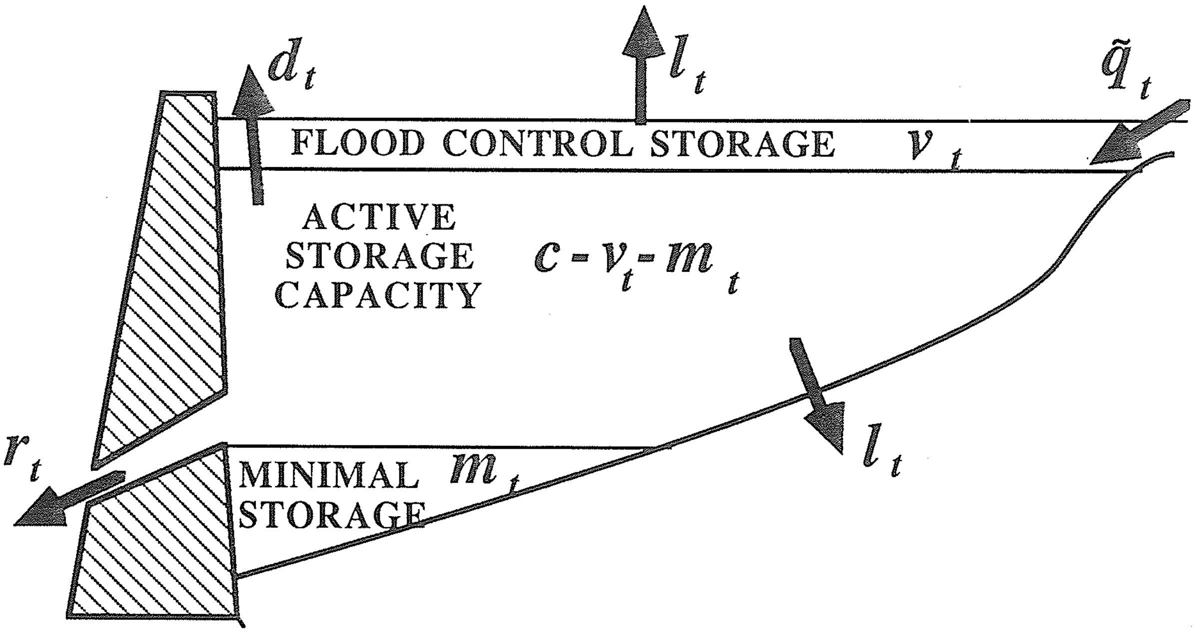

Figure 6.1. Schematic representation of a reservoir (after *Simonovic*[1979])

Let the objective function be

$$\max_{\{r\}} f(r) \tag{6.2}$$

where $r=(r_1,...,r_T)^T$ is the vector of releases within the planning horizon, $1 \le t \le T$. The function f is a suitably defined function incorporating benefits and costs of releasing water from the reservoir. The chance constraints expressing the accepted risk levels, with regard to reaching storage targets, are as follows:

$$P\,(S_t \ge c - v_t\,) \le \alpha \tag{6.3}$$

$$P\,(S_t \leq m_t\,) \leq \beta \tag{6.4}$$

in which c is the reservoir capacity, v_t represents reservoir storage for flood routing, m_t denotes minimal reservoir volume, and α and β are the risk levels ($0<\alpha,\ \beta<1$). The constraint set is completed by specifying bounds on the downstream releases

$$r_{min} \leq r_t \leq r_{max} \quad \forall t \tag{6.5}$$

where r_{min}, and r_{max}, respectively, are the minimum and maximum allowable release levels. The detailed description of the model (6.1)-(6.5) and the development of the deterministic equivalent of the stochastic LP reservoir problem, following *Simonovic* [1979], is given in Appendix A.

This model is a long-term planning model which provides a preliminary monthly schedule of releases within a planning horizon of one year. The identified "crisp" set of releases is based on the previous realizations of random streamflows and serves as a general guideline, for resource allocation and strategic planning, by the model user. The actual realizations of random inflows and storages should be taken into account to revise the planning solutions. This revision is done by means of sequential use of an optimization model (usually one different from the long-term planning model), in a mid-term or real-time manner, i.e., using forecasted information. The reliability levels and the objective function coefficients which are necessary for the analysis must be provided, a priori, by a DM. This is a disadvantage of the model because these estimates are unreliable and hard to obtain unless a range of values is considered. In addition, the chance-constrained approach does not evaluate, the sometimes difficult to quantify, effect of constraint violation.

As noted above, in practice, it is very hard to fix the risk levels or to define them precisely, for a particular problem. In addition, the objective function form and/or its coefficients may be ambiguous in the absence of an explicit rationale, e.g., *Bogardi et al.* [1983] found it difficult to express a non-economic environmental objective in economic terms. Having this in mind, research has been performed to arrive at: (a) a general approach for developing a fuzzy membership function for chance constraints; and (b) an approach for choosing objective function coefficients and determining membership levels of an imprecise objective function. In both of the approaches, the DM's input is essential for estimation of the membership functions.

6.2. ESTIMATION OF MEMBERSHIP FUNCTIONS FOR CONSTRAINTS

The procedure is based on the use of a DM or a group of DMs as assessors. The assessors are presented with a questionnaire which requires no numerical input about imprecise problem elements. They are asked, instead, to make pairwise comparisons between the imprecise elements, i.e., risk levels. The comparisons may be performed using a scale similar to one in Table 5.1. After associating numerical values from the scale 1-9 with the nine qualitative levels of comparison identified by assessors, the remaining entries in the matrix A are obtained by taking their respective reciprocal values. The approach is basically qualitative and may be applied in an iterative manner if consistency is to be preserved.

The estimation of a membership function, using this approach, was implemented for the chance constraints (6.3) and (6.4). The Gruza reservoir CCP problem, which will be presented in detail later in the chapter, served as the example. Using known trends in past operations of the reservoir in the past and its potential future use, a DM body assesses the acceptable risk of violating reservoir minimal and flood storage. A reasonable range for pairwise comparisons of risk levels and use in CCP is chosen to be between 0.5 and 0.0 (corresponding reliability levels are between 0.5 and 1.0). Ten discrete risk levels α_i and β_i, i=1,2,...,10, from within this range were analyzed and compared by assessors. The matrix A is formed using the scale from Table 5.1. The system of equations (5.49) is solved, giving the real eigenvector w, i.e., the membership function of the constraint (5.45).

The effect of the scale upper bound on the membership function of reliability levels (1-α_i), and the effect on their degree of belonging (membership level) to a set of "acceptable reliability levels" is shown in Figure 6.2. It was observed that more conservative membership levels were obtained for higher upper bound values of the numerical scale. It is likely that the nature of entries in the matrix A, most particularly reciprocity of a_{ij} and a_{ji}, causes this effect.

For the five membership functions, which correspond to the five upper bound values of the numerical scale, differences in membership levels diminish as the value of reliability levels approaches 1.0 (risk levels approach 0). It was also observed that no matter which upper bound value is used the same preference relationship is maintained between successive reliability levels.

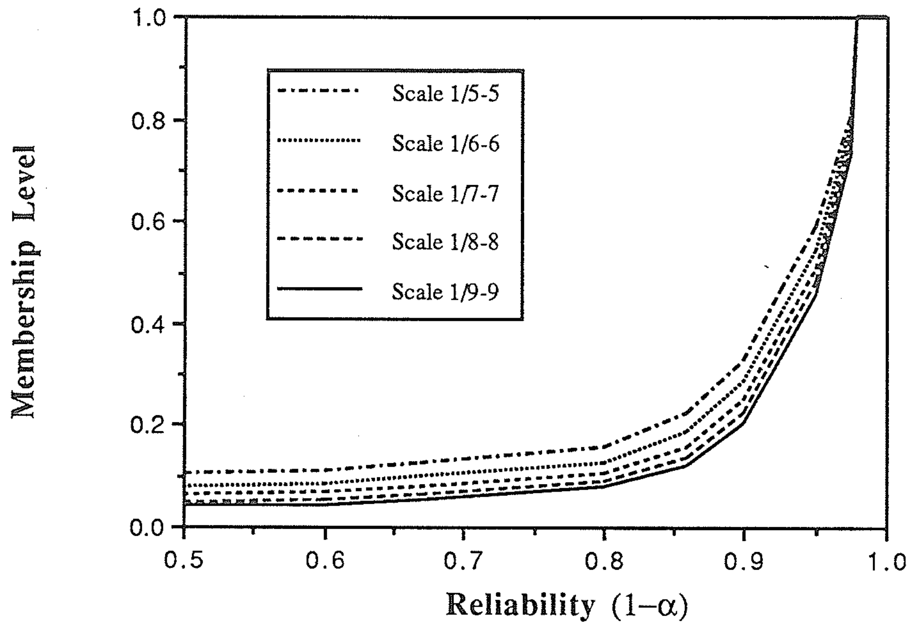

Figure 6.2. Effects of different scales on the membership function of a constraint

The target value for the chance constraint is in the region of high reliability values, with membership levels close to or equal to 1.0, i.e., high reliability levels are more desirable. As the assessor's input is not actually verifiable, the selection of the most appropriate numerical scale was based on the recommendation by *Saaty*, [1977]. Thus for this reservoir operations planning, membership functions are obtained using the 1/9-9 scale.

Rather than relying on the CI index and on Saaty's experiment with randomly generated entries for comparison matrices, the following procedure was designed and implemented to investigate the soundness of the CI measure. Many samples, each of them consisting of 100 matrices, were generated from the original pairwise comparison matrices obtained from the assessors. The samples were generated by introducing a random noise into each of the comparison matrices:

$$A_{\varepsilon}^{(j)} = A + \varepsilon_j \tag{6.6}$$

Where $A_{\varepsilon}^{(j)}$ denotes j-th matrix generated from the original matrix A, j=1,...,100; and ε_j is the random noise matrix generated using the j-th seed value. The matrix $A_{\varepsilon}^{(j)}$ is obtained when all entries of the matrix A (except $a_{ij}=1$, i=1,2,...,10, j=1,2,...,10) are disturbed using generated noise values. The disturbed matrices $A_{\varepsilon}^{(j)}$ were used to calculate the maximal eigenvalue, *CI* index, and CR for each of them. For each sample of 100 values of *CR*s, generated from an original matrix A, a frequency distribution was constructed. Figure 6.3 shows the frequency distribution of the consistency ratio obtained by disturbing what was originally considered a consistent matrix with CI=0.026 and CR=0.017<0.10 (calculated for a matrix of order n=10). It is clear, from Figure 6.3, that the original value of the consistency ratio (dotted line) is in the acceptable region of 10% (shaded area) and that there is not much room for improving the consistency of the original pairwise comparison matrix (as all generated CRs are greater than the original).

However, Figure 6.4 shows that an originally inconsistent matrix (CI=0.405, CR=0.272>0.10) can improve its consistency even with the introduction of a random noise. Figure 6.4 clearly indicates that this pairwise comparison matrix should be given back to the assessor for reconsideration.

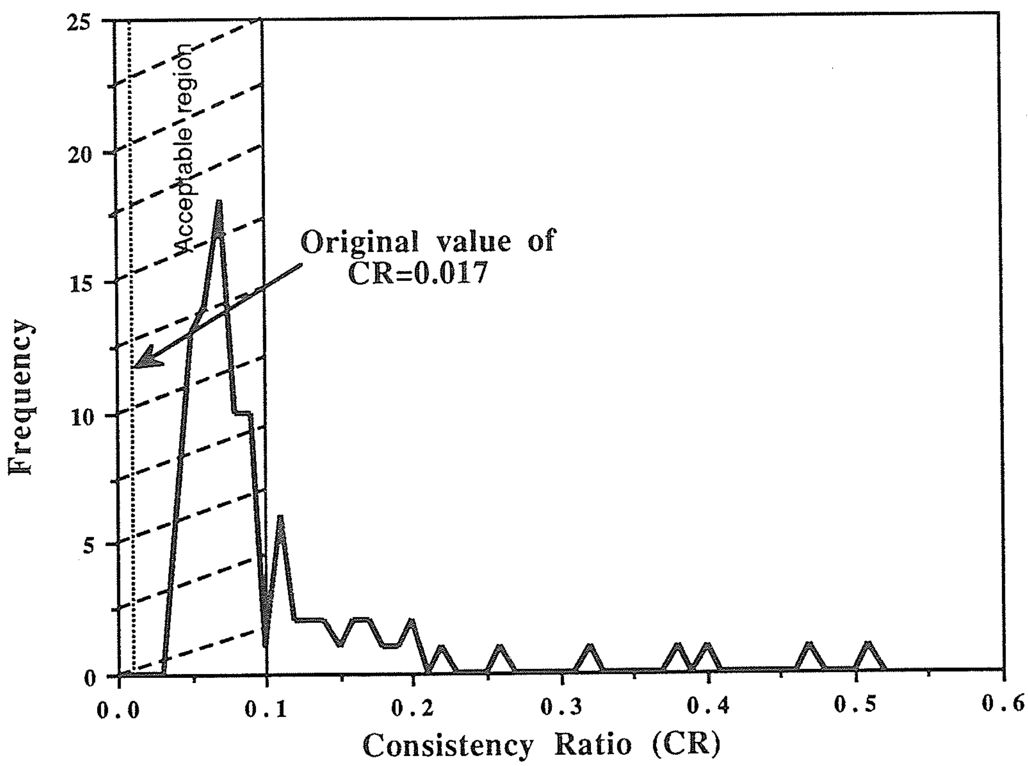

Figure 6.3 Frequency distribution of CR for disturbed consistent matrix

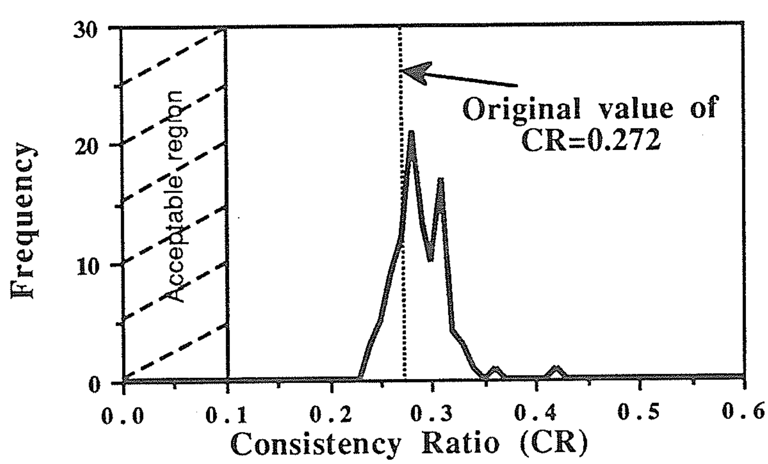

Figure 6.4. Frequency distribution of CR for disturbed inconsistent matrix

6.3. MEMBERSHIP FUNCTION ESTIMATION FOR THE OBJECTIVE FUNCTION

Depending on the purposes of the reservoir, different economic or social utility objectives may be quantified and integrated into a single indicator. This indicator, an objective function, describes how the reservoir should be operated. A common procedure for multi-purpose, multi-objective study is to use the weighting method, where weights reflecting priorities are assigned to each objective [*Bras et al.*, 1983]. These weights are often called objective function coefficients. If a realistic evaluation of economics or utility is not possible, a different approach to determining objective function coefficients may be required.

In this work, the DM's assessment of the importance of the reservoir monthly release r_t is used for deriving the coefficients of the objective function $f(\mathbf{r})$. Similarly, as in the case of the chance constraint, no absolute values of the net benefits or costs, associated with the monthly release, are used. A planning horizon of a year was used in the example (T=12 months). Following the scaling method for priorities, a group of twelve objective function coefficients associated with reservoir monthly releases has been sorted into four clusters. Each cluster is related to the coefficients associated with releases during three months of similar importance. Clustering (in this problem) makes possible, efficient pairwise comparisons and greater consistency of the comparison matrix A. Comparisons are performed using a qualitative scale similar to one presented in Table 5.1. Instead of comparing two risk levels, as in the case of chance constraints, two clusters, containing different objective function coefficients, are compared.

Elements of the resulting vector $\mathbf{w}'=\mathbf{c}(c_1,c_2,c_3,c_4)^T$ represent objective function coefficients associated with each cluster. They are then normalized to give:

$$\sum_{i=1}^{4} c_i = 4 \tag{6.7}$$

If further differentiation among the coefficients in a cluster is needed, the relative priorities of releasing water during the individual months in each cluster may be compared. Figure 6.5 shows clustered months and the objective function coefficient values associated with reservoir releases for the Gruza reservoir. The cluster consisting of summer months (June, July, and August) was given the highest priority by the assessors, followed by the cluster of late spring and early autumn months (May, September, and October), and the cluster of early spring and early winter months (March, April, and November). The lowest priority was given to releases during winter months (January, February, and December).

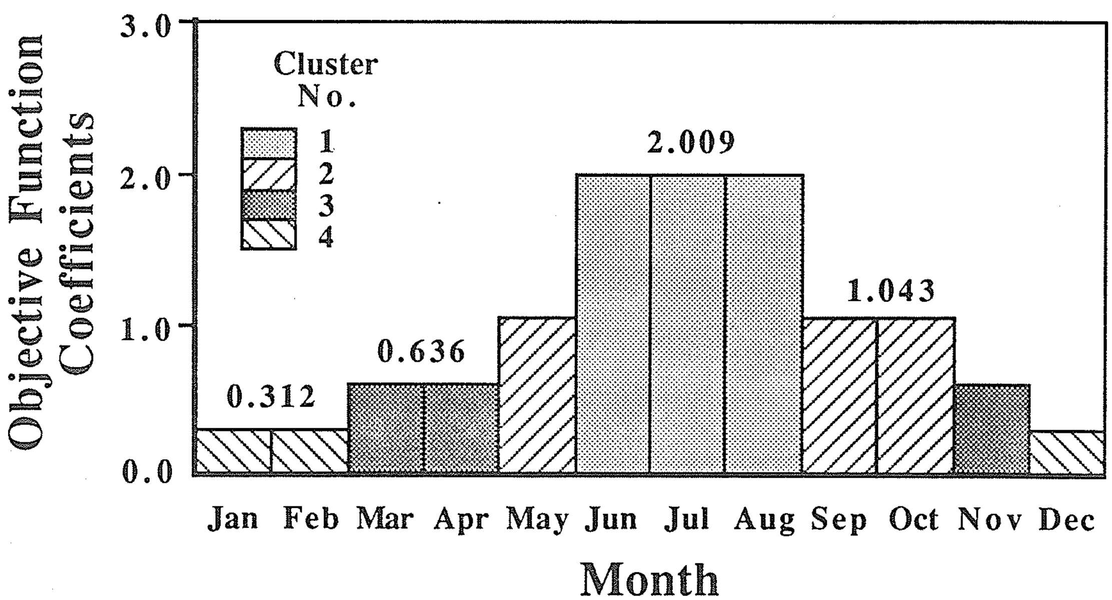

Figure 6.5. Objective function coefficients obtained using Saaty's procedure

The target value (maximum membership level) for the objective function is established as the value obtained by solving the CCP problem (6.1)-(6.5) for risk levels α and β, both,set to 0.5. That value is the level for which the membership function of the constraint attains its minimum (Figure 6.2). Accordingly, it is assumed that the minimum membership level of the objective function is reached when no risk is imposed on the system (note that this solution is theoretically and computationally infeasible). Intermediate membership levels for the objective function are calculated as:

$$\mu\{f_{\alpha,\beta}(\mathbf{r})\} = \frac{f_{\alpha,\beta}}{f_{.5,.5}} \tag{6.8}$$

where $\mu\{f_{\alpha,\beta}(\mathbf{r})\}$ is the membership function level for the objective function $f_{\alpha,\beta}(\mathbf{r})$, $f_{\alpha,\beta}$ is the objective function value for the risk levels α, β from within the interval (0,0.5), and $f_{.5,.5}$ is the objective function for α=0.5 and β=0.5.

6.4. SOLUTION PROCEDURES FOR RISK LEVEL SELECTION

In the introduction to fuzzy LP decision making, it was pointed out that such a formulation requires all membership functions to be given in linear form. The solution to the problem is obtained by solving three standard LP problems giving f_0, f_1, and λ respectively. However, membership functions of the constraints and the objective function for the CCP reservoir operation problem are non-linear (given in a piecewise linear form). Therefore, a non-linear procedure is proposed for solving the problem of the risk level selection.

It was previously shown that the solution of a problem, which is specified using membership functions, is defined as the selection of risk levels and corresponding statement of reservoir release policy, which simultaneously satisfy the objective function and constraints. The solution to the problem represented by Eq.(6.1)-(6.5) and (6.8) can therefore be viewed as the intersection of the single fuzzy set representing constraints and the fuzzy set representing the objective function. Both the objective function and constraints are given in the form of fuzzy inequalities. The intersecting fuzzy set identifies a range of solutions among which one may be selected, if necessary, as a "crisp" solution. The "crisp" solution to fuzzy LP problems (see Eq. 5.27) is obtained by identifying the maximum of the minimum supports (membership function values) among the fuzzy inequalities. The mathematical expression in Eq. 5.27 can be interpreted as an attempt to arrive at a solution which has the "greatest satisfaction" (maximum membership function value overall) under the "worst possible scenario" (minimum membership function values). The logic will suit the viewpoint of a DM who wishes to identify the best decision but takes a more conservative (risk-averse) outlook within his/her decision environment. That is, the minimum operator represents a conservative way of simultaneously satisfying the constraints and the objective function.

However, under the assumption that: (a) the above deductive model, i.e., MAX-MIN approach, correctly represents the decision making process involved in reservoir operation planning; (b) a range of solutions that satisfy minimum requirements is needed ; (c) a "crisp" solution should be identified as the best in the set; the following procedure was developed. Firstly, a single membership function of the fuzzy set which corresponds to the two chance constraints is obtained as the intersection of the two related fuzzy sets. The resulting fuzzy set, represented by the shaded area in Figure 6.6, is obtained using the minimization operator (5.13). It can be observed that more conservative values of the membership functions $\mu\{\alpha\}$ and $\mu\{\beta\}$at any point determine the resulting fuzzy set. Therefore, the conservative attitude is a driving force of the algorithm.

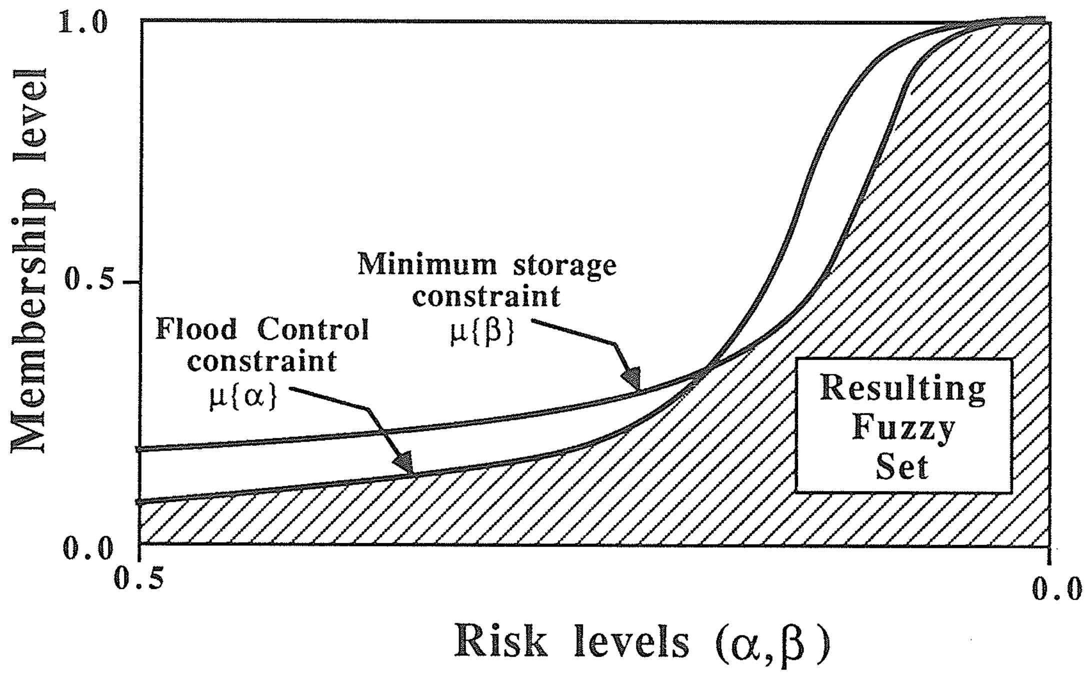

Figure 6.6. Chance constraints fuzzy set

The intersection of the resulting chance constraints fuzzy set and the objective function fuzzy set is obtained next. The shaded intersection zone in Figure 6.7 represents the solution fuzzy set for the reservoir problem, as defined above. The tails of the zone should be excluded from solution consideration because of the low membership levels. The intersection point of the two functions distinguishes the decision with the maximum membership (support) value among other acceptable decisions. Risk levels $\alpha = a$, and $\beta = b$ in Figure 6.7, which correspond to the maximum membership level, are the "optimal crisp" risk levels (corresponding reliability levels are $1-\alpha = 1-a$ and $1-\beta = 1-b$ respectively).

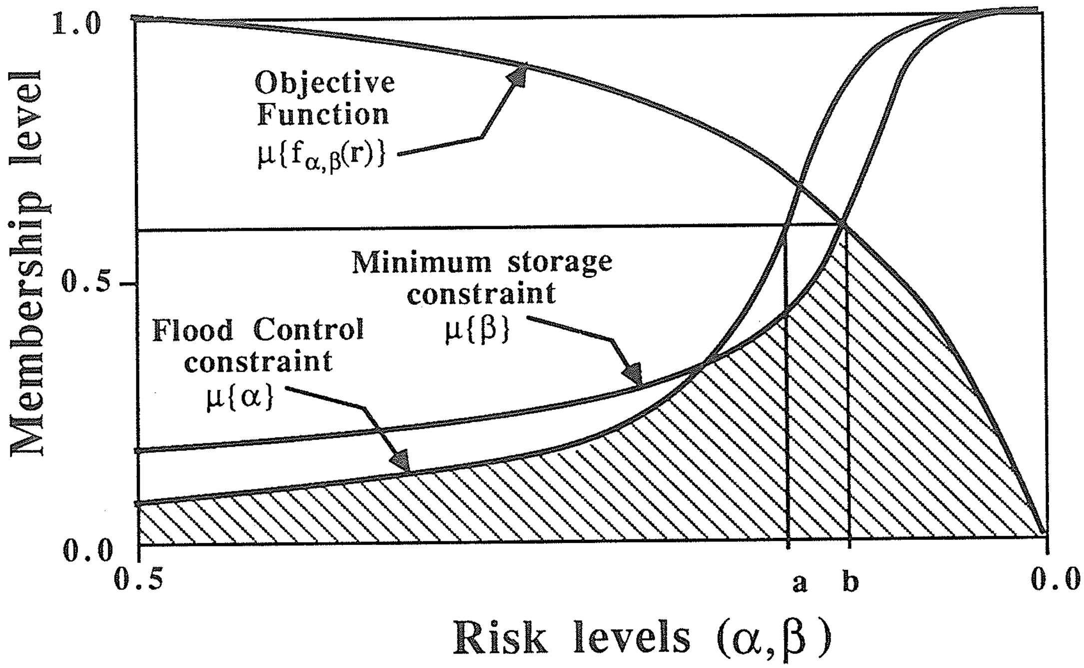

Figure 6.7. "Optimal" (crisp) risk levels solution

A simple search routine was developed to find the intersection point, i.e., the "crisp" solution, as well as a range of solutions to the reservoir problem formulated in terms of chance constraints. The flowchart of the algorithm is given in Figure 6.8. The procedure is as follows:

1. Define the search step $\Delta\mu$ and acceptable search accuracy ε_μ in terms of membership levels $\mu \in [0,1]$ of the solution.

2. Start from solving the CCP problem (6.1)-(6.5) for both α and β equal to 0.5 and obtain $f_{.5,.5}$. Then associate the membership level of 1.0 with

$\mu\{f_{.5,.5}(r)\}$ and find the minimal membership level for the two constraints $\mu\{\alpha=0.5,\beta=0.5\}$ by comparing membership levels that are read for $\alpha=0.5$ and $\beta=0.5$ from their membership functions respectively.

3. Increase the membership level of the constraints using the search step $\Delta\mu$ and read α and β from the two membership functions of the constraints.

4. Solve the CCP problem for new values of α and β and compare obtained $\mu\{f_{\alpha,\beta}(r)\}$ to $\mu\{\alpha,\beta\}$.

5. If $\mu\{f_{\alpha,\beta}(r)\}$ is still greater than $\mu\{\alpha,\beta\}$, go back to step 3. If the opposite is true or the solution is infeasible, decrease the membership level by one search step $\Delta\mu$, change the search step to $\Delta\mu/2$, and go back to step 3. The procedure is continued until $\mu\{f_{\alpha,\beta}(r)\}$ is equal to $\mu\{\alpha,\beta\}$, or they differ less than the given search accuracy.

The model formulated through these five steps is analogous to the fuzzy LP model given by (5.34)-(5.39). However, this model may not give a preferred solution to every DM. In situations where more than one DM is involved in the decision-making process, the conservative MAX-MIN procedure may not be appropriate. A DM body may accept a less conservative approach to combining the constraints and the objective function which can provide greater trade-offs among fuzzy inequalities. This can be achieved by maximizing the total support (satisfaction) for all fuzzy inequalities individually.

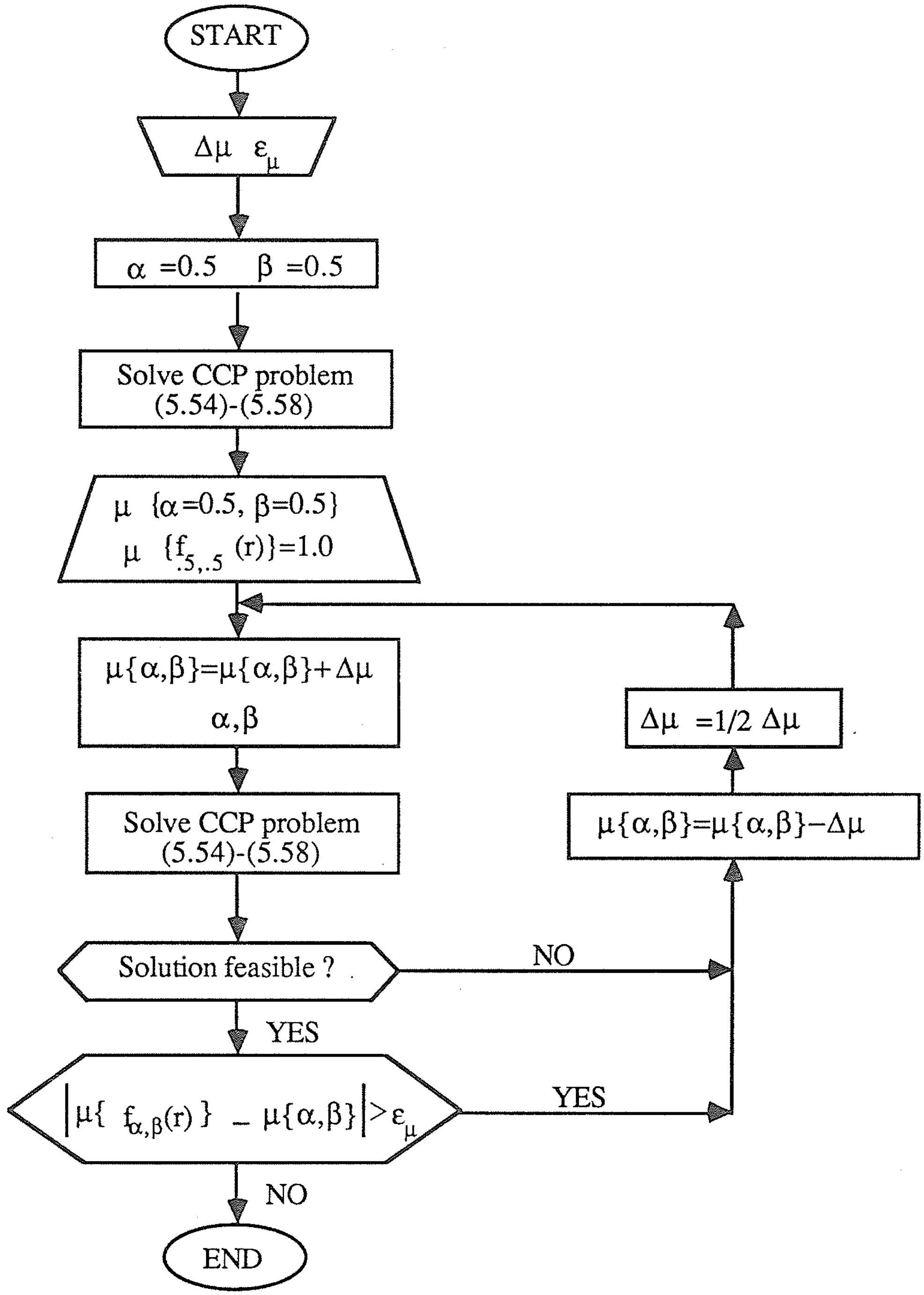

Figure 6.8. Flowchart of the risk level selection algorithm

The mathematical model given by (5.34)-(5.39) may be expressed then as:

$$\text{Maximize} \sum_{i}^{m+1} \lambda_i \tag{6.9}$$

$$\lambda_1(f_0-f_1) + \mathbf{c}^T \cdot \mathbf{x} \leq f_0 \tag{6.10}$$

$$\lambda_i p_i - (\mathbf{A} \cdot \mathbf{x})_i \leq p_i - d_i, \quad i=2,\ldots,m+1 \tag{6.11}$$

$$\lambda_i \leq 1 \tag{6.12}$$

$$\lambda_i \geq 0, \ \mathbf{x} \geq \mathbf{0} \tag{6.13}$$

For this particular case of the CCP model the objective function will be:

$$\text{Maximize } \mu\{f_{\alpha,\beta}(\mathrm{r})\} + \mu\{\alpha\} + \mu\{\beta\} \tag{6.14}$$

The symmetry feature of the objective function and constraints is still preserved with this model. Support levels (λ_i) in this model are defined for each of the fuzzy inequalities as opposed to a combined support for all inequalities (minimum λ). These support levels are not necessarily equal at the "optimum" (crisp solution) as was the case with the MAX-MIN formulation of the same problem. This change gives additional flexibility to the fuzzy programming model. However, there is a trade-off between a more flexible model and the attained level of support for each of the fuzzy inequalities. Using this model, some of the inequalities may result in lower support (satisfaction) levels than those produced by the MAX-MIN model.

For example, one of the reliability levels may be sacrificed for an increase in the other reliability level and the objective function.

In reservoir operation planning decision-makers tend to be sensitive to the issue of reliability. It is, therefore, unlikely that the above model may be used for practical problems. If a distinction in treatment of the original objective function and treatment of reliability constraints should be made, a compromise between MAX-MIN and a risk-inclined solution procedure may be adopted. The idea is to use a minimum operator for combining the reliability constraints and then to maximize the sum of supports for the objective function and constraints, i.e.

$$\text{Maximize } \mu\{f_{\alpha,\beta}(\mathbf{r})\} + \mu\{\alpha, \beta\} \tag{6.15}$$

where $\mu\{f_{\alpha,\beta}(\mathbf{r})\}$ and $\mu\{\alpha, \beta\}$ are previously defined membership functions. This model and the MAX-MIN model will be used, and their results analyzed, in the Gruza reservoir case study.

6.5. MODEL IMPLEMENTATION AND RESULTS

The developed modelling approach has been applied to the Gruza reservoir in Yugoslavia. The long-term planning objective for the Gruza reservoir concerns conservation storage for water supply of the city of Kragujevac, flood and sediment deposition control, and the low flow augmentation downstream from the reservoir [*Jaroslav Cerni Institute*, 1976]. A realistic economic and social utility evaluation was not available for the reservoir objectives. This is a consequence of the specific characteristics of the economy in this developing country. According to the mentioned reservoir purposes, the storage capacity of the Gruza reservoir of 64.6×10^6 m^3 is divided into three zones:

(i) the dead storage zone of 8.5×10^6 m^3 (258 m.a.s.l.);

(ii) the active storage zone of 48.4×10^6 m^3 (269.25 m.a.s.l.); and

(iii) the flood control zone of 7.7×10^6 m^3 (270 m.a.s.l.).

The reservoir must provide a firm water supply in the amount of $Q=0.816$ m^3/s for municipal water supply, and an additional $Q=0.20$ m^3/s for instream release throughout a year. The reservoir started operation in 1983. Since then feasibility of improved utilization and potential water supply to rural areas has become apparent. Figure 6.9 shows that high storage levels were maintained in the reservoir during the period 1985-1988 despite measured inflows below the long-term average for 52 years. Therefore, utilization of excess water seems even more appropriate.

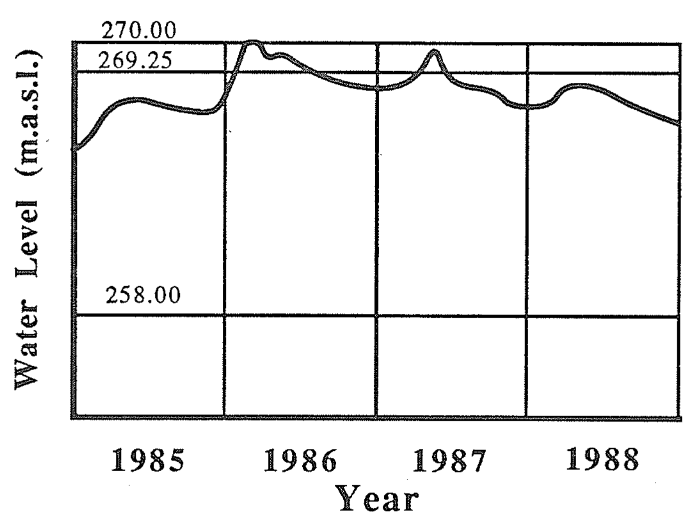

Figure 6.9. Gruza reservoir water levels during the period 1985-1988

Using available streamflow observations of the Gruza basin, monthly inflow distributions were derived for use by the model. Attempts were made to fit each month's inflows to a normal, log-normal, Pearson type III, or log-Pearson type III distribution. Using both the Chi-square and Kolmogorov-Smirnov goodness of fit tests, a log-normal distribution has been selected as the most suitable. Upon fitting each month's inflows to a log-normal distribution, the monthly marginal probability distributions are completely described by their respective means and variances. The detailed input data and results of the streamflow statistical analysis are presented in Appendix B.

For the testing of the fuzzy set approach developed in this work, a group of professors and graduate students of the Civil Engineering Department at the University of Manitoba served as a "decision-making body". They were presented with the information on reservoir characteristics, purposes, past performance, and considerations about improved use. The attitude toward operating the reservoir in the past was illustrated by the reservoir levels, inflows, and releases during the period 1985-1988. Using the scale from Table 5.1, a questionnaire presented to the "decision-makers" asked them to rank the relative importance of ten discrete risk levels. The judgment was based on the past management decisions, their personal judgment, and knowledge about the reservoir system as provided in the questionnaire. In addition to this, they were asked to give a point estimate of the risk levels, as required for the classical approach to the selection of risk levels in chance-constrained reservoir operation modelling. A sample of the questionnaire is given in Appendix C. A matrix of comparisons was established from the questionnaire and an appropriate set of weights, and *CI* were calculated for each experiment.

The consistency measures used in the context of the Gruza reservoir problem served to highlight anomalous data supplied by the assessors. The results in Table 6.1 demonstrate that the consistency ratio values, for most of the comparison matrices, stayed within the acceptable limits ($0<CR\leq 0.1$). Those assessors whose matrices show larger inconsistency than allowed, were asked to reconsider and adjust their priority estimations among different risk levels.

Table 6.1 Largest eigenvalue, consistency index, and consistency ratio for membership functions of the two chance constraints

Assessor No.	Constraint type	λ_{max}	*CI*	*CR*
1	α	10.417	0.046	0.031
1	β	10.387	0.043	0.029
2	α	11.019	0.113	0.076
2	β	11.314	0.146	0.098
3	α	11.487	0.165	0.111*
3	β	11.113	0.124	0.083
4	α	10.232	0.026	0.017
4	β	11.152	0.128	0.086
5	α	11.328	0.148	0.099
5	β	12.445	0.272	0.182*
6	α	11.022	0.114	0.076
6	β	12.657	0.295	0.198*

* these comparison matrices were considered inconsistent and were submitted to assessors for reconsideration

The results, of the MAX-MIN methodology applied to selecting risk levels in CCP, were compared to the point estimates of the acceptable risk levels elicited from the assessors. Table 6.2 shows how the obtained results compare to the point estimates. For example, the results for assessor No. 2 show the inconsistency in his a priori estimates of the acceptable risk when compared to his priorities as set up by pairwise comparison. The assessor was ready to accept flood control reliability of 75% when asked about acceptable levels. However, the fuzzy set procedure, using the data provided by pairwise comparison, showed that a higher reliability level is required.

Table 6.2. A priori risk estimates and risk levels obtained using the proposed fuzzy set approach

Assessor No.	**Risk point estimates** α, β	**Risk levels calculated** α, β
1	0.100, 0.150	0.063, 0.082
2	0.250, 0.050	0.059, 0.061
3	0.020, 0.100	0.060, 0.059
4	0.150, 0.000	0.155, 0.049
5	0.050, 0.010	0.057, 0.068
6	0.100, 0.000	0.065, 0.053

Another example shows that a risk-free solution (β=0.0), required by assessors No.4 and No.6, was not workable. More realistic solutions, i.e., β=0.049 and β=0.053 respectively, were obtained using the fuzzy set approach. Considering that assessors supplied only qualitative input to the model the agreement between the obtained results and a priori fixed risk levels is very good.

The detailed results from an iterative search procedure run are shown in Table 6.3 and Table 6.4. Membership levels for both the objective function and constraints (assessor No. 4), as well as the change in risk levels throughout eleven iterations of the MAX-MIN procedure, are presented in Table 6.3. The results demonstrate how the significant changes in the risk level α did not allow the search to be terminated before the required level of accuracy was achieved although the change in the risk level β had diminished in the last three iterations. The column with the additive objective function ($z=\mu\{f_{\alpha,\beta}(r)\} + \mu\{\alpha,\beta\}$) shows that the additive model, i.e., the less conservative model, achieved the maximum satisfaction level (1.078) earlier than the MAX-MIN procedure, and at risk levels higher than those obtained by the MAX-MIN procedure. This table also demonstrates how each of the models treats a trade-off between reliability levels and the objective function. The MAX-MIN procedure is always driven by the lower membership level of $\mu\{f_{\alpha,\beta}(r)\}$ or $\mu\{\alpha,\beta\}$, while the additive model is driven by the average value of the two. Table 6.4 reports on how the reservoir policy, recommended by the CCP model, changes during the last several iterations. Again, a comparison between the results in iteration 6 (the "crisp" solution of the additive model) and iteration 11 (the "crisp" solution of the MAX-MIN model) shows the impact of the different procedures, e.g., the total annual release decreases from 25.54×10^6 to 24.45×10^6 m^3 if the more conservative procedure is used. However, the impact, especially in August and October, on within-year release distribution is more pronounced. As shown in Chapter 4 these releases are most sensitive to a change in reliability levels.

Finally, these two tables demonstrate how the model presents the user with a range of near-optimal solutions from which to choose. In the example MAX-MIN solution (Table 6.4), release policies from the iterations 6,8,9, and 10, for which the risk levels are not very different, may be considered as near-optimal solutions. Direct presentation of solutions to the user is an obvious benefit of the method if the user has other reasons to prefer the solution with a lower membership level but still close to the identified intersecting solution (iteration 11). These two tables also

Table 6.3. Risk and membership levels throughout the iterative search procedure run

Iteration No.	Membership levels $\mu\{f_{\alpha,\beta}(r)\}, \mu\{\alpha,\beta\}$	$\mu\{f_{\alpha,\beta}(r)\}$ $+\mu\{\alpha,\beta\}$	Risk levels α, β
1	1.000, 0.037	1.037	0.500, 0.500
2	0.771, 0.100	0.871	0.500, 0.196
3	0.654, 0.200	0.854	0.500, 0.117
4	0.603, 0.300	0.903	0.500, 0.089
5	0.588, 0.400	0.988	0.415, 0.071
6	0.578, 0.500	1.078	0.180, 0.054
7	infeasible	-	0.098, 0.039
8	0.495, 0.550	1.045	0.140, 0.046
9	0.537, 0.525	1.062	0.160, 0.050
10	0.517, 0.537	1.054	0.150, 0.048
11	0.527, 0.531	1.058	0.155, 0.049

explain the relationship between grades of membership and physical variables (release).

Table 6.4. Annual release policies for the first and last five iterations of an iterative search procedure run

Month	Min. Allow. Release	Max. Allow. Release	Iteration No.[1]					
			1	6	8	9	10	11
	$[10^6m^3]$	$[10^6m^3]$	$[10^6m^3]$					
October	0.54	8.04	0.54	6.65	8.03	7.37	7.69	7.53
November	0.52	7.78	0.52	0.52	0.52	0.52	0.52	0.52
December	0.54	8.04	0.54	0.54	0.54	0.54	0.54	0.54
January	0.54	8.04	0.54	0.54	0.54	0.54	0.54	0.54
February	0.48	7.26	0.48	0.48	0.48	0.48	0.48	0.48
March	0.54	8.04	0.54	0.54	0.54	0.54	0.54	0.54
April	0.52	7.78	0.52	0.52	0.52	0.52	0.52	0.52
May	0.54	8.04	8.04	5.04	5.21	5.13	5.17	5.15
June	0.52	7.78	7.78	1.60	1.62	1.61	1.62	1.61
July	0.54	8.04	8.04	0.90	0.99	0.94	0.96	0.95
August	0.54	8.04	8.04	7.69	4.29	5.99	5.17	5.58
September	0.52	7.78	1.60	0.52	0.52	0.52	0.52	0.52

[1]Note: Results from iterations 2-5 and 7 are omitted in the presentation because of high risk levels while iteration 7 rendered an infeasible solution.

The fuzzy set approach for handling imprecision can reduce the requirement for precise numerical inputs in decision modelling. The imprecision in the input is modelled using fuzzy set theory, which is then used to calculate the imprecision implied in the results. But so far, the DM is presented only with the results which were reduced to numbers. For example, the release of 5.15×10^6 m^3, with the membership degree of 0.53 calculated for May, is of no immediate use to a DM. If however, reservoir monthly releases are plotted against membership levels for each iteration of the search procedure, then the information available from the fuzzy analysis may be seen and stated more clearly. Figure 6.10 shows a membership function of the release for the month of May.

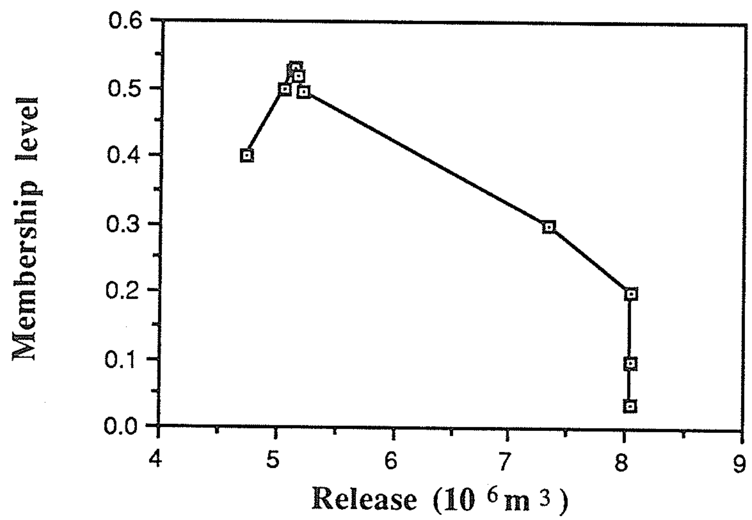

Figure 6.10. Fuzzy set representing recommended reservoir release in May

Clearly, some form of hedged advice may be given from observing this fuzzy set. The recommended release in May can be characterized as "approximately $5x10^6$ m^3".

Careful analysis of Figure 6.10 reveals that a risk-averse attitude toward operating the reservoir is represented by the rising limb of the membership function as the release is decreased from $8x10^6$ m^3 to around $5x10^6$ m^3. In this part of the function membership levels of the fuzzy set constraints dominate over membership levels of the fuzzy set objective function ($\mu\{\alpha,\beta\} > \mu\{f_{\alpha,\beta}(r)\}$). This information may be used in situations which dictate risk-averse actions. On the other hand, the falling limb of the fuzzy set membership function to the left of the $5x10^6$ m^3 in Figure 6.10, represents releases for the risk-inclined operation. It should be noted that the rising limb is not completed because the procedure had ended the search for the "optimum" before lower membership levels were investigated. Furthermore, this example reveals the dominance of the minimal storage constraint over the flood control constraint because the increase in membership values causes reduction in release values.

An opposite example, for the dominance of the flood control constraint is given in Figure 6.11.

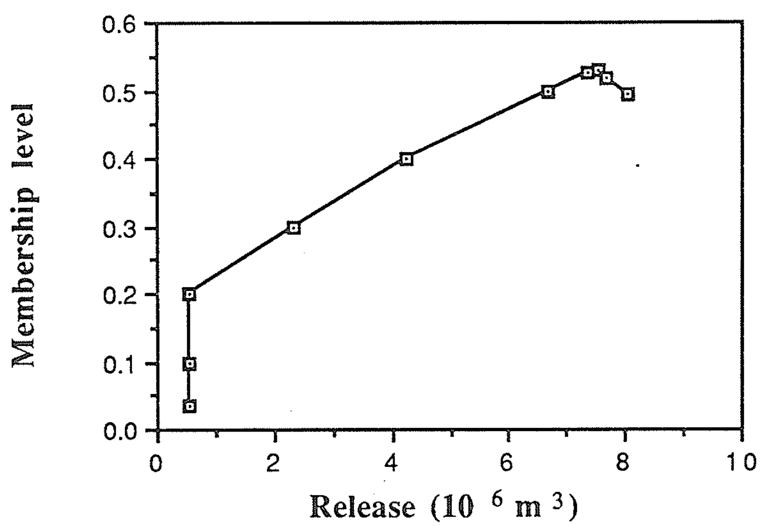

Figure 6.11. Fuzzy set representing recommended reservoir release in October

The rising limb of the release membership function for the month of October from $0.5x10^6$ m^3 to $7x10^6$ m^3 represents the risk-inclined decisions. Conversely, the risk-averse decisions are represented by the falling limb to the right of $7x10^6$ m^3. Again, some form of hedged advice may be given from observing this fuzzy set. The recommended release in October can be characterized as "approximately $7x10^6$ m^3".

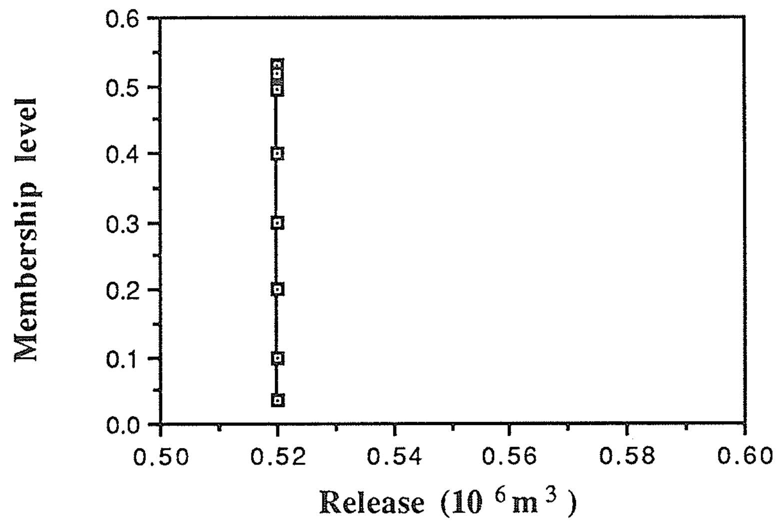

Figure 6.12. Fuzzy set representing recommended reservoir release in January

Finally, Figure 6.12 shows a special case of a membership function for a release during one of the winter months. This was one of the months from the cluster with the lowest release priority in Figure 6.5. In addition, the quantity of accumulated water was below the flood control pool in this month, so the flood control constraint was not binding. Thus, the recommended release stayed at the minimal allowable level for all membership degrees.

Special attention should be directed to the sensitivity of the "crisp" results to the upper bound value of the scale used for pairwise comparison of the risk levels and clustered months. Table 6.5 shows the difference in the membership levels and risk levels obtained by using three different upper bound values of the scale. It may be observed that similar risk values were obtained for α. β values varied slightly. The overall similarity does, however, demonstrate the robustness of the procedure with respect to the selection of the upper bound value of the scale.

Table 6.5. The effect of the scale on selected risk levels

Scale	1-5	1-7	1-9
$\mu\{f_{\alpha,\beta}(r)\}$	0.625	0.567	0.527
$\mu\{\alpha,\beta\}$	0.637	0.575	0.531
α	0.050	0.049	0.049
β	0.198	0.171	0.155

A similar conclusion may be drawn from Table 6.6 which shows the difference in release policies with respect to variation in the same parameter. The difference between the annual release schedules obtained using the scales 1-5 and 1-9 is 7.4%, while the difference drops to 2.9% when the scales 1-7 and 1-9 are compared. Again, the impact of the upper bound value of the scale on the within-year distribution of releases is most significant for the month of August. It should be noted that the similar general conclusions will hold for each set of near-optimal solutions provided along with the "crisp" solution.

Table 6.6. The effect of the scale on release schedule

	Release $10^6 m^3$		
Month	Scale 1-5	Scale 1-7	Scale 1-9
Oct	7.30	7.46	7.53
Nov	0.52	0.52	0.52
Dec	0.54	0.54	0.54
Jan	0.54	0.54	0.54
Feb	0.48	0.48	0.48
Mar	0.54	0.54	0.54
Apr	0.52	0.52	0.52
May	5.12	5.14	5.15
Jun	1.61	1.61	1.61
Jul	0.94	0.95	0.95
Aug	7.66	6.37	5.58
Sep	0.52	0.52	0.52

6.6. SUMMARY OF FINDINGS

An attempt has been made to discuss the characteristics of an optimization model, i.e., chance-constrained (CCP); and a model based on principles of "satisficing", i.e,.fuzzy chance-constrained (FCCP). The best comparison may be obtained if characteristics of the two models are contrasted on a one-to-one basis. The following is a summary of findings:

Common Characteristics:

Both models are long-term reservoir planning models, i.e., both provide a monthly schedule(s) for releases within a one-year planning horizon. Both models are consistent in terms of how they use input information to provide a solution(s): CCP uses "crisp" data and renders a "crisp" solution; FCCP uses imprecise information and arrives at a range of near-optimal solutions from which one may be selected if necessary. The preliminary set of releases, of both models, is based on the previous realizations of random streamflows, i.e., both models are stochastic in nature.

Model use:

The release set identified by both models serves as a general guideline for resource allocation and strategic planning on the part of the water authority. In practice, the actual realizations of random inflows, storage states, as well as unexpected shifts in decision-making attitudes, should be taken into account to revise the planning solutions. This is done by means of the sequential use of an optimization model (usually one different from a long-term planning model), in a mid-term or real-time manner (i.e., using forecasted information).

Differences:

1) CCP - Reliability levels are provided by a DM or an analyst without an explicit rationale for assessing the consistency of DM's input (e.g., why certain reliability levels vs. others).

FCCP - Reliability levels are decision variables. Only the relative importance of different reliability levels are needed from a DM. The information necessary to do the analysis is also extracted qualitatively. A consistency measure is available to evaluate the consistency of the DM's input and thereby ensure a reasonable solution.

2) CCP - Objective function coefficients (i.e., value of released water), which are necessary for the analysis must be provided a priori. *Brill* [1979] identifies empirical shortcomings in estimating benefits and costs. He suggests that "in going from quantitative descriptions to benefits and costs, more judgmental and subjective elements enter the analysis", so they should be dealt with qualitatively. These "crisp" benefits/costs estimates are hard to obtain and unreliable. In addition, optimization results tend to be highly sensitive with respect to changes in objective function coefficients.

FCCP - Objective function coefficients are obtained using information on the relative importance of releasing water in one particular month vs. other months. The preference scale (weights) is constructed from information obtained qualitatively. Again, the consistency index is available for evaluating the consistency of the DM's responses.

3) CCP - Feasible space is highly constrained even for lower values of reliability levels. The specified constraints are inflexible.

FCCP - Presents and treats the relaxed (softened) objective function and constraints as fuzzy inequalities. The model explores a broader feasible region than the original CCP model. In terms of multi-objective analysis, it is hypothesized that with relaxing the original feasible space the model explores the interior region of the non-inferior set without determining the complete "crisply" defined inferior set. That interior search is not achieved in the same manner as in a classical multi-objective analysis, i.e., by carrying out a parametric analysis of objectives expressed as constraints. It is done in a more directed way using a qualitatively provided preference structure. The flexible specification of the limits requires no absolute boundaries, but uses tolerance levels ("satisficing" vs. optimizing) to explore those regions of interior space which are denser with respect to preference information provided. In this manner, the algorithm explicitly takes into account fuzziness, vagueness, and imprecision.

4) CCP - Does not directly evaluate the effect of constraint violation - an effect that is sometimes difficult to quantify.

FCCP - The membership functions obtained using qualitative data from assessors represent measures which implicitly consider the effect of both the frequency and the extent of constraint violation.

Finally, the choice of the fuzzy procedure, i.e., MAX-MIN or additive, should be carefully analyzed in each situation. The solutions identified by both procedures should be presented to the DM or DM body, which will eventually select the best compromise between high reliability levels and potential benefits to be gained by releasing water from the reservoir.

CHAPTER 7.

SUMMARY AND CONCLUSIONS

7.1. SUMMARY

Reservoir modelling and model use, if properly performed, may result in increasing potential benefits or decreasing costs of managing water in reservoirs. However, several problems in applying formal models for reservoir sizing and short- and long-term planning have been encountered by different water authorities and agencies. The most frequently reported problems are related to the lack of communication and understanding between model users and model developers. This leads to the first contribution of the research: identifying, formalizing, and structuring reservoir modelling expertise, which by its nature resists completely formal (algorithmic) representation. By formalizing and structuring reservoir analysis knowledge in REZES (an intelligent decision-support system), reservoir analysis expertise becomes more explicit and available to different potential users. As a user friendly, educational and practical tool, REZES can bridge the gap between a potential user and a model. REZES is intended to advise users and explain and perform tasks usually reserved for an expert planner or modeller. REZES performs within the limits of the eleven incorporated models.

A second contribution of the research presented in this thesis is in combining formal (mathematical) models with "expert" knowledge (in the form of experience, judgment, etc.), that lacks formal structure. Human experts, experienced in applying formal models to practical problems, possess and use both types of knowledge in solving real-world problems. Through the deeper understanding of a reservoir model, and the understanding of the parameters influencing the solution as offered by REZES, a user may improve his/her perception of the problem. The potential benefits of combining this knowledge into one computerized tool is illustrated by the Gruza reservoir example. In the case of the Gruza reservoir, changing the reliability levels and then observing consequent changes in operating policies, may help the user to reach a conclusion about an acceptable compromise between reliability levels and expected returns from improved water allocation.

A careful selection of reservoir models included in REZES has been made to minimize the uncertainty and subjectivity involved in reservoir analysis. However, it was demonstrated through the Gruza example that even by using the expert systems technology, uncertainty and subjectivity may not be adequately treated. A need for treating both stochastic uncertainty and imprecision, that is non-random in nature, stimulated the development of a fuzzy-set-based approach to reservoir chance-constrained modelling. The two methods for selecting risk levels within a chance-constrained reservoir operation model, based on the fuzzy set approach, represent the third contribution of the thesis. Both methods incorporate imprecision directly into the model.

An application of the fuzzy model to the Gruza reservoir operation problem demonstrates the feasibility, robustness, and efficiency of both the proposed approach and its iterative search procedure. This fuzzy procedure leads to sets of results which are of practical interest and which are not critically sensitive to changes in model parameters. A group of professors and graduate students has been used to provide necessary input for estimating membership functions. Although the actual decision-maker may provide different comparison matrices than the ones which were selected by these "decision-makers", the methods of estimating membership functions and the iterative procedure are essentially the same.

To summarize, the use of the Engineering Expert Systems approach, and the development of an intelligent decision support system for reservoir modelling, is introduced as an appropriate application of emerging technologies to the single multipurpose reservoir optimization. However, not all identified problems can be solved by using this approach. It is believed that only a combination of existing ("classical" and non-classical) models, new (fuzzy) models, and new technologies will bring the full potential of benefits to water resources practice.

7.2. CONCLUSIONS

The REZES system, developed in this thesis, can be used to optimize the size or the release schedules of single multi-purpose reservoirs, given a variety of reservoir uses and assuming a deterministic or stochastic future. The major benefit of using REZES lies in its ability to perform analysis and explain the reasoning used therein, to provide recommendations, and to take actions during a consultation. The intelligent decision-support system (IDSS) capable of doing so can stimulate the participation of the people concerned with reservoir management decision making (DMs) in using the expertise and models provided by the people concerned with reservoir modelling (experts). Therefore, reservoir management can benefit from providing an opportunity for greater involvement of DMs or reservoir operators in using mathematical models. It is hoped that due to its relative ease of use REZES will encourage more reservoir operators, managers, or less skilled water resources engineers to actually use mathematical models when making release decisions.

As no general algorithm exists for reservoir analysis problems, an additional benefit in using REZES is is that it provides a selection of procedures that perform differently depending on the form of the mathematical model they employ. The differences and similarities among the eleven models, and the situations in which it is most appropriate to use each of them, may still cause some confusion with potential users. However, this situation is still preferable to having too few methods from which to choose.

The increasing demand for proper management of water quantity requires development of comprehensive water resource management models to cope with the complexity of multi-purpose, multi-reservoir systems. Even if a deterministic future with perfect flow forecasts is assumed, most of the multi-reservoir models suffer from the so-called "curse of dimensionality". The introduction of stochastic inflows into a model formulation only further aggravates the problem. REZES comprises both stochastic and deterministic mathematical models but only for single reservoir schemes. The consequences of not treating multi-reservoir systems may, however, be reduced by the careful selection of the system constraints for each of the mathematical models. For example, relationships (hydraulic, electrical, etc.) among reservoirs in a system or external connections may be represented through a set of constraints.

In the last two decades there has been an increased awareness of the need to identify, and simultaneously consider, several reservoir management objectives. Although REZES does not cover any of the classical multi-objective techniques, multiple objectives have been incorporated into the mathematical models. This incorporation was accomplished by simple addition, when a common metric was available, or by the single objective function and the imposition of constraints related to additional objectives.

The second major contribution, presented in this thesis, considers the treatment of non-random imprecision or "vagueness" in reservoir modelling. The fuzzy-set approach, applied to the risk-level-selection problem, gives worthwhile results when some functional relationships, e.g., system constraints or objective functions, cannot be quantified for the formulation of the model. In the context of chance-constrained programming (CCP) used to demonstrate the approach, the developed method combines use of the fuzzy set operations and the linear programming technique. In this work the more common "MAX-MIN" relation, stemming from the intersection of the fuzzy objective and fuzzy constraints, is questioned as to whether it is the most appropriate one for the fuzzy optimization criteria.

An alternative procedure which gives less "conservative" solutions is developed and compared to the "classical" MAX-MIN approach. The new model incorporating fuzzy sets is developed by tailoring the chance-constrained reservoir operation model developed by *Simonovic* [1979]. It should be noted, however, that certain limitations of the original CCP model still apply to the new model formulation but their impacts are reduced. One such limitation is related to the increase in variance of the convoluted inflows with the increase of the number of time steps in the time horizon.

The procedure for selecting the risk levels is general, in that it is able to handle non-linear membership functions for both fuzzy constraints and the fuzzy objective function. The procedure may also be applied to less imprecise situations where, for example, objectives, related economic and/or social utilities, and weights are known with certainty and only constraints are fuzzy. The simple search procedure, employed to render the intersection of the two fuzzy sets, is very efficient even if implemented on a PC-based micro-computer. An additional major benefit of using the procedure lies in the fact that one may view the near-optimal solutions, which the procedure provides as a form of automated sensitivity analysis. The generation of these near-optimal solutions by this sensitivity analysis directly accounts for the imprecision involved in defining constraints or an objective function.

The crucial task of estimating membership functions was performed by applying the scaling method for priorities. This method reduces the main drawback of using inconsistent DM's input in model building. It also reduces the complexity and pressure on a DM by using a linguistic approach to eliciting data rather than a numerical one. Nevertheless, the major benefit, in using the proposed method, remains in easy incorporation of qualitative, imprecise, and subjective input into a CCP model formulation.

7.3. RECOMMENDATIONS FOR FUTURE RESEARCH

In order to be well-received among practitioners, REZES needs verification in practice and some further refinements. Recommended directions for future research on interactive modelling and use of REZES in reservoir management are: expanding the limited library of formal mathematical models and augmenting the user interface to handle additional graphics, especially for handling output results. Currently, REZES is not able to distinguish between an expert user and a complete novice, i.e., explanation and help facilities are insensitive to the user's level of expertise. In some cases, more efficient use and faster consultations may be achieved when detailed help is not needed.

Remaining problems for discussion and future research are: (a) analysis of the uncertainty inherently associated with reservoir modelling expertise; and (b) treatment of the subjectivity with which different experts approach the same type of reservoir problem.

Another major area that could benefit from further research is related to the improvement of algorithms. One obvious improvement would be to make use of variable time steps in formal models. Even more radical changes to the mathematical models would be needed to allow REZES to address optimization problems of multi-reservoir systems. The large number of variables in a stochastic model makes the present techniques impractical for multi-reservoir systems.

In this thesis, the application of fuzzy sets to reservoir analysis has been carried out through an optimization long-term reservoir operation planning model. Yet, uncertainties and imprecision in inflow forecasting and in estimating outflow effects, make fuzzy sets an appealing approach to real-time reservoir operation modelling. Two research directions on this issue may be worth examining: fuzzy optimization and fuzzy reasoning. The former is related to new applications of, or even possible computational improvements to fuzzy optimization models similar to that presented in the thesis. The latter is related to research in fuzzy logic, i.e., the logic underlying approximate, rather than exact, modes of reasoning. That reasoning plays an essential role in the human ability to make rational decisions in a fuzzy environment. The research in this area may result in better management of uncertainty in IDSS and expert systems.

As for the improvement and application of the presented reservoir model, the involvement of a decision-maker must be ensured. Therefore, further improvements and implementation must be carried out in cooperation with a person actually involved in decision making.

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APPENDIX A

The following section gives the detailed description of the chance-constrained reservoir operation model [*Simonovic*, 1979] briefly introduced in Chapter 6, and the transformation of the stochastic problem into its deterministic equivalent.

We recall that the model (6.1)-(6.5) was stated in the following form:

$$S_t = S_{t-1} + \tilde{q}_t - d_t - r_t - l_t \quad \forall t, \; t = 1,2,...,T \tag{A1}$$

$$\max_{\{r\}} f(r) \tag{A2}$$

$$P\,(S_t \geq c - v_t) \leq \alpha \tag{A3}$$

$$P\,(S_t \leq m_t) \leq \beta \tag{A4}$$

$$r_{min} \leq r_t \leq r_{max} \quad \forall t \tag{A5}$$

Substituting equation (A1) into equation (A3) yields:

$$P\,(S_{t-1} + \tilde{q}_t - d_t - r_t - l_t \geq c - v_t) \leq \alpha \tag{A6}$$

Using the basic property of a probability inequality with the random variable $\tilde{q}_t$ taken to the left-hand-side of the constraint gives:

$$P\,(\,\tilde{q}_t \leq c - v_t - S_{t\,-1} + d_t + r_t + l_t\,) \geq 1 - \alpha \tag{A7}$$

The expression in equation (A7) is equivalent to:

$$F\;\,[c - v_t - S_{t\,-1} + d_t + r_t + l_t\,] \geq 1 - \alpha \tag{A8}$$

if F[·] denotes the cumulative distribution function of the convoluted inflows. In his work *Simonovic* [1979] combined random inflow and random irrigation demand into the random variable $\tilde{i}_t$. Both variables, inflow and demand, were assumed to be independent. In this thesis only one random variable is treated, i.e., random inflow. In addition to that instead of using iterative convolution method, the historical realizations of cumulative inflows were investigated and employed to estimate the distribution of the joint events (cumulative flows). Knowing the probability density function of $\tilde{q}_t$, the final form of the constraint is:

$$c - v_t - S_{t\,-1} + d_t + r_t + l_t \geq F_t^{-1}(1\text{-}\alpha\,) \tag{A9}$$

where F_t^1 denotes the inverse of the cumulative distribution function F_t.

Similarly, for constraint (A4),

$$P\,(S_{t\,-1} + \tilde{q}_t - d_t - r_t - l_t \leq m_t\,) \leq \beta \tag{A10}$$

$$P\,(\,\tilde{q}_t \leq m_t - S_{t\,-1} + d_t + r_t + l_t\,) \leq \beta \tag{A11}$$

$$F\ [\, m_t - S_{t-1} + d_t + r_t + l_t \,] \leq \beta \tag{A12}$$

$$m_t - S_{t-1} + d_t + r_t + l_t \leq F_t^{-1}(\beta) \tag{A13}$$

Finally, the deterministic equivalent of the stochastic problem (A1)-(A5) may be stated in the following form:

$$\max_{\{r\}} f(\mathrm{r}) \tag{A14}$$

$$c - v_t - S_{t-1} + d_t + r_t + l_t \geq F_t^{-1}(1-\alpha) \quad \forall t \tag{A15}$$

$$m_t - S_{t-1} + d_t + r_t + l_t \leq F_t^{-1}(\beta) \quad \forall t \tag{A16}$$

$$r_{min} \leq r_t \leq r_{max} \quad \forall t \tag{A17}$$

APPENDIX B

Mean Monthly Flows [m^3/s]
for period 1926-1975

River: Gruza
Gauging St: Tucacki Naper

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ann mean
1926	2.850	4.890	0.220	1.320	0.429	2.370	3.400	0.501	0.834	0.350	0.495	0.450	1.509
1927	2.520	0.754	3.500	2.500	1.030	1.570	0.199	0.377	0.640	2.700	1.170	0.740	1.475
1928	0.394	0.760	2.770	4.170	2.910	1.160	0.218	0.110	0.147	0.531	0.430	1.410	1.251
1929	0.815	1.550	1.780	6.350	4.210	0.976	0.497	0.706	1.430	0.740	0.340	1.160	1.713
1930	0.707	0.420	2.320	2.270	4.100	0.990	0.980	0.820	0.200	1.280	0.037	0.290	1.201
1931	0.420	0.901	4.000	1.470	2.670	0.820	0.202	0.567	0.331	1.880	2.090	0.367	1.310
1932	1.920	2.060	3.020	5.910	1.820	1.440	0.440	0.351	0.759	0.135	1.460	1.390	1.725
1933	1.470	1.480	1.700	4.330	5.530	2.190	0.620	0.710	1.700	0.372	1.940	1.320	1.947
1934	0.939	1.300	4.880	0.590	1.610	1.810	3.190	0.860	1.590	0.960	0.750	0.670	1.596
1935	2.190	4.380	1.900	3.000	2.920	0.984	0.393	0.490	2.240	1.190	1.690	1.460	1.903
1936	1.970	3.790	2.050	1.420	0.910	1.620	0.122	0.786	0.415	0.556	2.100	1.050	1.399
1937	1.720	4.450	4.820	3.150	5.230	2.360	2.730	5.190	2.200	1.140	1.960	1.430	3.032
1938	2.720	2.400	2.770	6.410	2.890	0.780	2.050	0.754	1.150	1.250	1.920	0.730	2.152
1939	1.800	0.340	2.510	4.350	2.350	0.820	1.050	0.726	0.780	0.701	2.740	1.980	1.679
1940	1.680	3.660	4.000	4.000	1.790	2.530	1.910	0.794	0.377	1.100	1.390	1.610	2.070
1941	2.070	5.290	3.110	2.040	2.220	1.720	0.169	0.168	0.400	1.440	2.160	2.040	1.902
1942	2.600	1.680	5.420	4.450	2.610	1.760	0.860	1.040	0.927	0.081	1.680	0.220	1.944
1943	0.620	2.290	0.930	2.430	0.377	2.590	0.536	0.229	1.330	0.346	0.190	0.253	1.010
1944	0.740	1.000	5.320	5.350	0.730	2.050	4.310	0.067	1.100	1.820	2.200	2.000	2.224
1945	1.880	4.020	2.560	4.910	0.841	1.710	0.362	0.693	0.142	0.672	1.070	0.603	1.622
1946	0.680	0.915	1.830	1.840	0.440	0.330	0.168	0.089	0.093	0.172	1.120	1.200	0.740
1947	0.565	2.690	4.540	0.794	0.338	0.319	0.077	0.588	0.166	0.131	1.010	0.550	0.981
1948	3.000	1.940	0.770	1.580	1.290	6.060	0.410	0.246	1.850	0.174	0.062	0.229	1.468

1949	0.432	0.564	0.860	2.490	0.611	1.320	1.380	0.291	0.233	0.233	0.706	0.531	0.804
1950	0.614	1.060	1.600	0.607	0.396	1.150	0.264	0.186	0.246	0.240	0.554	1.320	0.686
1951	0.548	1.200	2.040	2.230	1.590	0.276	0.352	0.277	0.243	0.231	0.299	0.713	0.833
1952	1.240	0.900	0.600	2.070	0.460	0.381	0.285	0.207	0.187	0.972	1.130	3.660	1.008
1953	1.610	1.850	2.750	2.310	0.400	1.050	0.938	0.400	0.396	1.070	0.345	0.352	1.123
1954	0.338	0.750	3.760	3.940	5.210	1.210	0.426	0.821	0.262	1.600	0.860	2.470	1.804
1955	3.440	3.960	0.840	6.180	1.240	1.150	0.800	7.060	1.160	2.770	1.500	4.300	2.867
1956	2.900	3.050	10.100	5.760	2.530	1.290	0.405	0.130	0.104	0.135	0.212	0.385	2.250
1957	0.702	1.970	0.731	0.773	4.500	2.390	0.665	0.848	0.960	1.230	0.550	1.860	1.432
1958	2.120	1.150	3.250	5.920	1.630	0.308	0.196	0.159	0.163	0.222	0.338	0.503	1.330
1959	0.985	0.433	0.708	0.428	0.405	2.160	1.350	0.897	0.987	0.437	1.290	0.957	0.920
1960	1.380	2.160	1.260	1.330	1.320	0.794	0.899	0.509	0.406	0.492	0.658	0.924	1.011
1961	0.951	1.115	0.746	1.000	4.000	2.010	0.905	0.521	0.560	0.467	0.718	0.932	1.160
1962	1.800	3.480	7.200	5.240	1.080	0.944	0.278	0.120	0.117	0.163	0.227	0.264	1.743
1963	1.750	5.640	1.250	1.390	0.184	0.208	0.098	0.082	0.211	0.093	0.097	0.101	0.925
1964	0.189	0.944	2.430	1.930	1.040	0.267	0.738	0.136	0.170	0.720	1.840	1.800	1.017
1965	1.370	2.640	3.350	1.660	4.510	0.810	0.227	0.047	0.053	0.033	0.085	0.153	1.245
1966	1.670	5.320	1.530	1.390	1.030	0.310	0.659	0.138	0.143	0.089	0.184	1.210	1.139
1967	1.270	1.690	3.650	2.170	3.200	1.410	0.272	0.048	0.059	0.063	0.081	0.202	1.176
1968	1.190	3.820	1.620	0.404	0.378	0.232	0.174	0.397	0.539	0.300	1.100	0.781	0.911
1969	1.240	6.680	3.130	1.770	0.692	2.360	0.678	0.364	0.876	0.186	0.276	0.536	1.566
1970	3.550	6.900	4.000	2.200	6.130	1.840	1.400	0.376	0.206	0.398	0.520	0.384	2.325
1971	0.652	1.380	5.060	3.180	0.753	0.612	0.408	0.215	0.342	0.410	0.397	0.707	1.176
1972	0.454	0.430	0.358	0.261	0.234	0.118	0.717	0.291	0.730	5.370	1.280	0.718	0.913
1973	0.760	1.490	4.160	3.730	1.080	0.480	0.615	0.176	0.183	0.163	0.188	0.715	1.145
1974	1.530	0.785	0.583	1.040	2.570	1.060	0.387	0.073	0.065	0.184	1.280	4.770	1.194
1975	1.640	0.939	3.310	0.996	2.050	2.370	0.802	2.560	0.775	1.080	1.260	0.963	1.562
1976	1.990	3.630	4.870	1.900	0.991	3.090	0.485	0.385	0.364	0.207	0.616	1.100	1.636
1977	1.920	3.510	3.430	4.870	1.230	0.578	0.457	0.311	0.247	0.272	0.420	1.230	1.540
Mean	1.471	2.354	2.806	2.765	1.936	1.368	0.811	0.671	0.611	0.761	0.943	1.109	1.467
StDv	0.848	1.722	1.888	1.805	1.586	1.015	0.885	1.187	0.566	0.915	0.708	0.972	
r1	0.382	0.540	0.110	0.405	0.204	0.143	0.271	0.221	0.421	0.215	0.364	0.414	
r2	0.315	0.041	0.160	0.002	0.141	-0.083	0.048	0.136	0.411	0.318	0.322	0.233	
r3	0.120	0.166	0.368	0.326	0.012	-0.022	0.081	0.185	0.501	0.159	0.291	0.040	
Cskw	0.564	0.921	1.267	0.599	1.007	1.947	2.291	4.216	1.289	2.912	0.579	2.045	
Cvar	0.577	0.731	0.673	0.653	0.819	0.742	1.092	1.770	0.926	1.202	0.751	0.876	

MONTHLY INFLOW DISTRIBUTIONS

This section presents graphical results of hydrologic frequency analysis of historical monthly streamflows at the Gruza dam site. Statistics derived from historical monthly streamflow observations are used to generate the required monthly distributions. Four theoretical distributions were investigated: normal, log-normal, Pearson type III, and log-Pearson type III. For each distributional assumption, the magnitude of events for various return periods is selected from the theoretical "best-fit" line according to the assumed distribution. Computer programs for analysis are taken from *Kite* [1985]. Both solutions for the method of moments and the maximum likelihood method have been investigated.

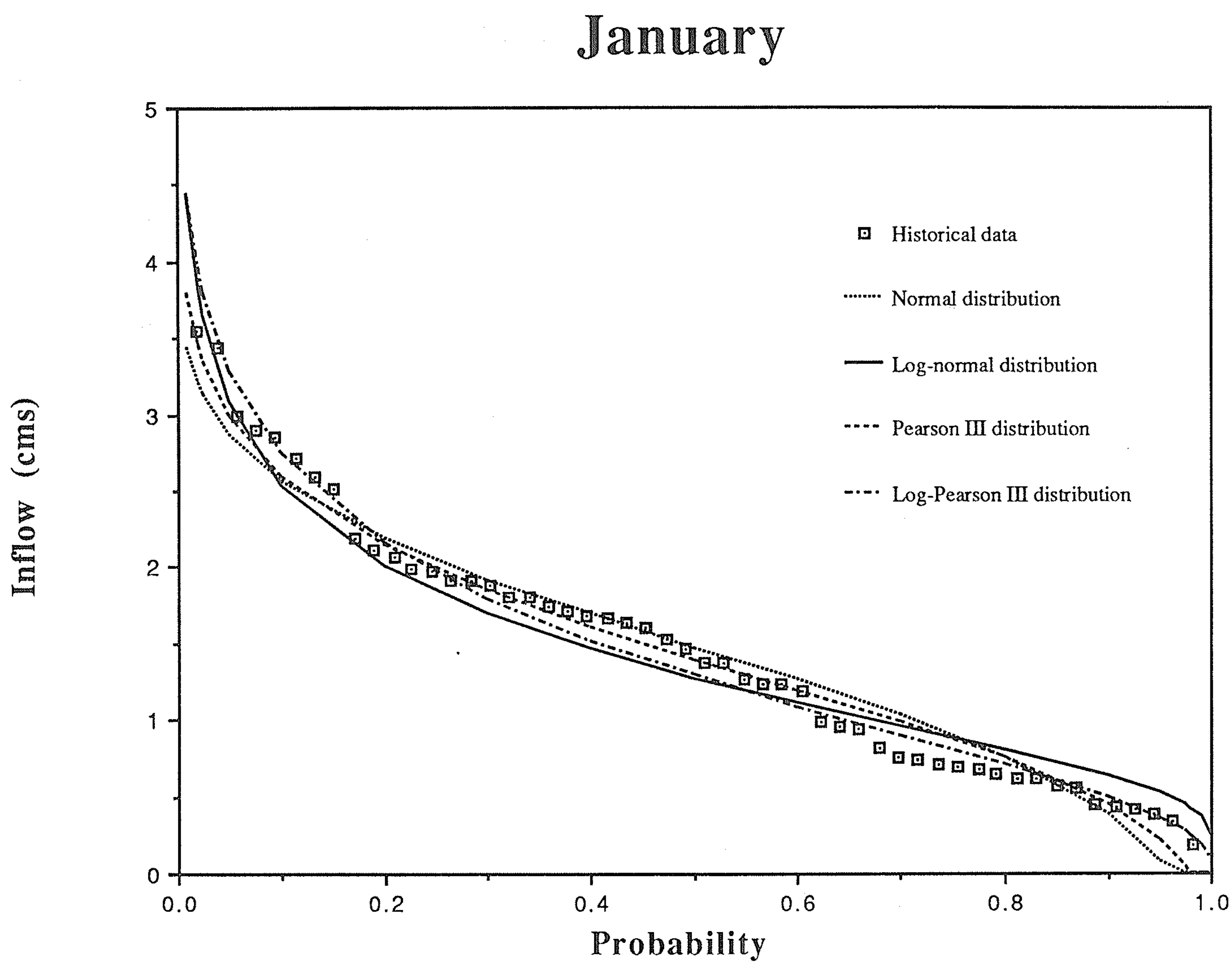


Figure B1. Flow duration plot Gruza river data (January)

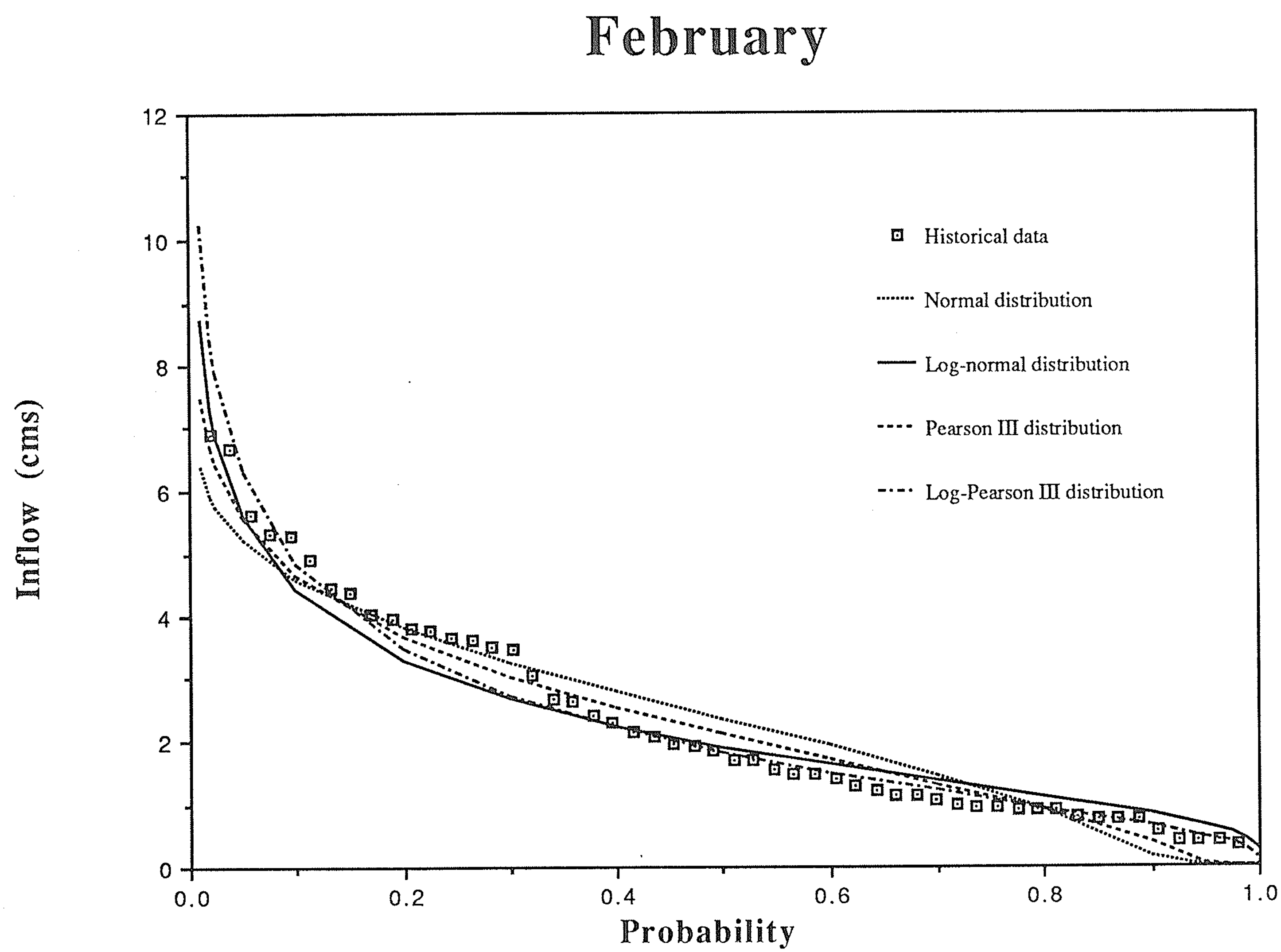


Figure B2. Flow duration plot Gruza river data (February)

March

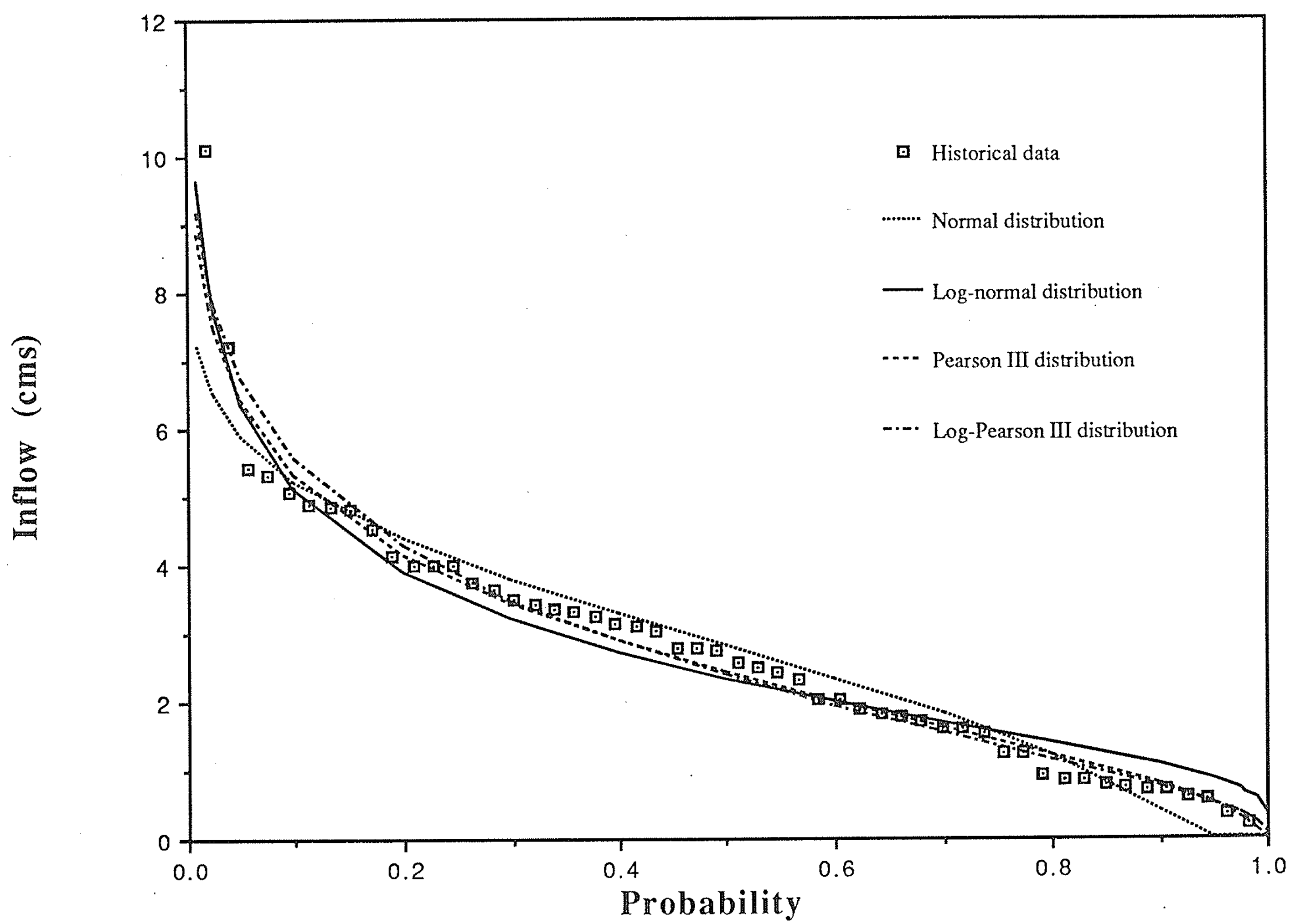


Figure B3. Flow duration plot Gruza river data (March)

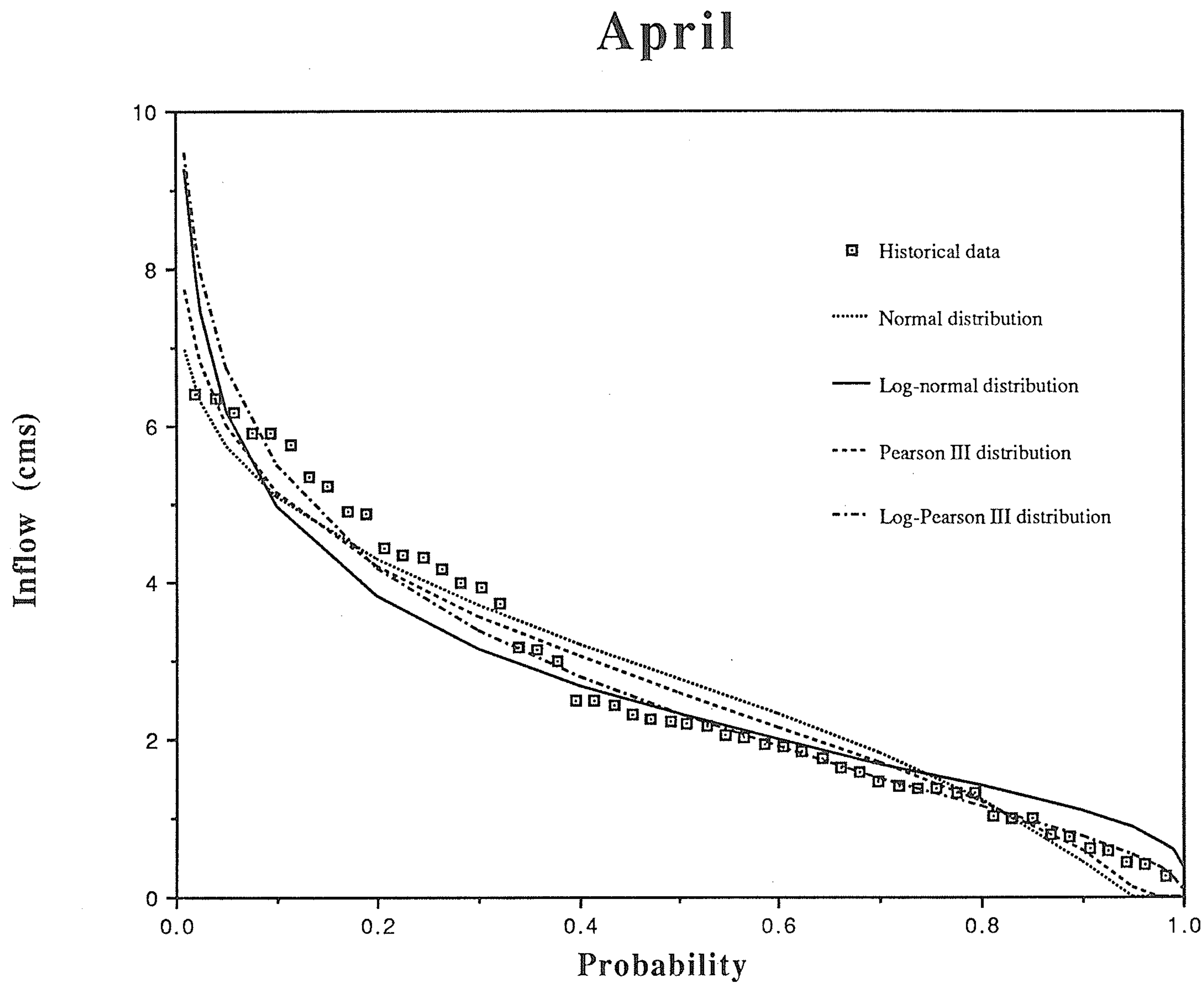


Figure B4. Flow duration plot Gruza river data (April)

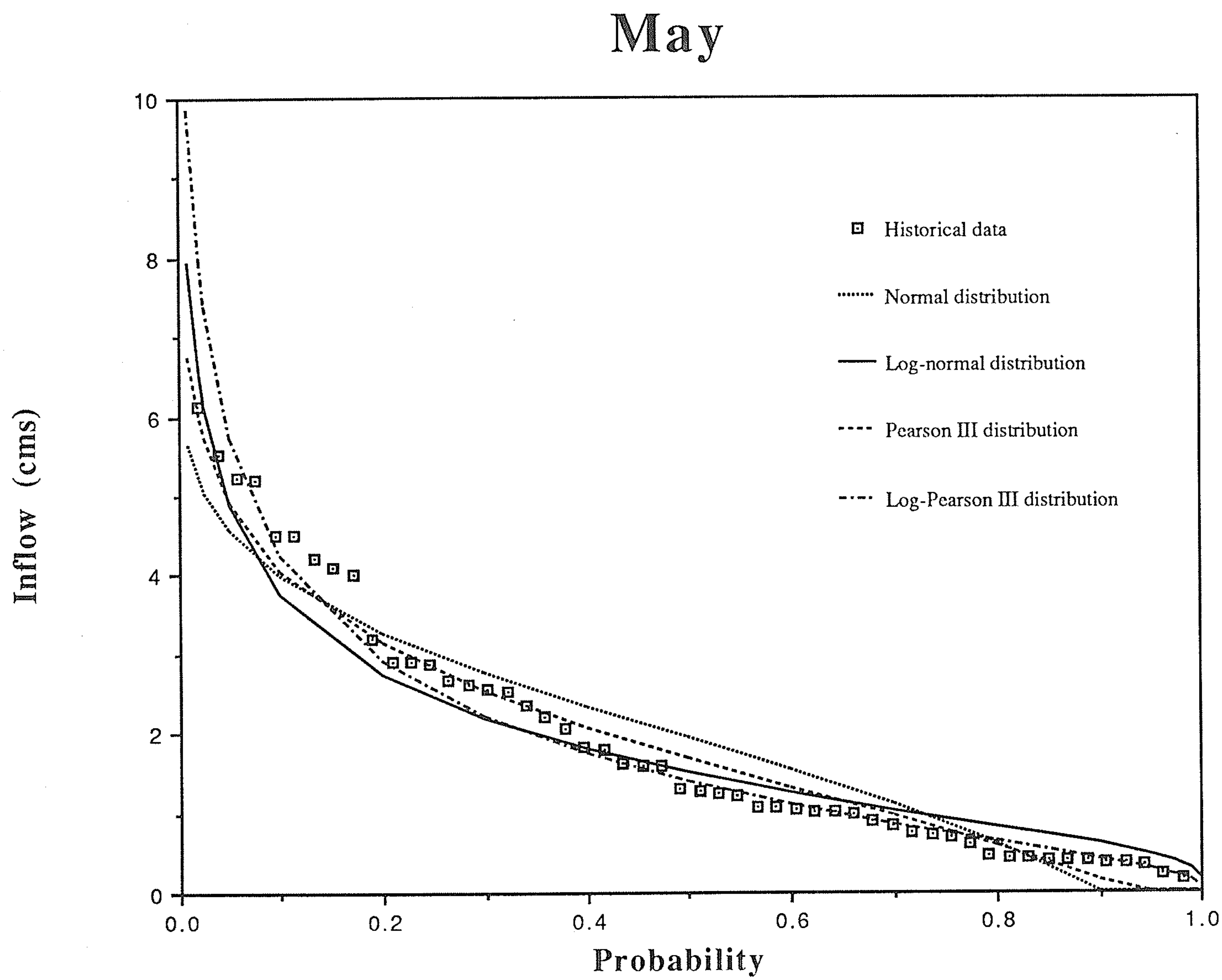


Figure B5. Flow duration plot Gruza river data (May)

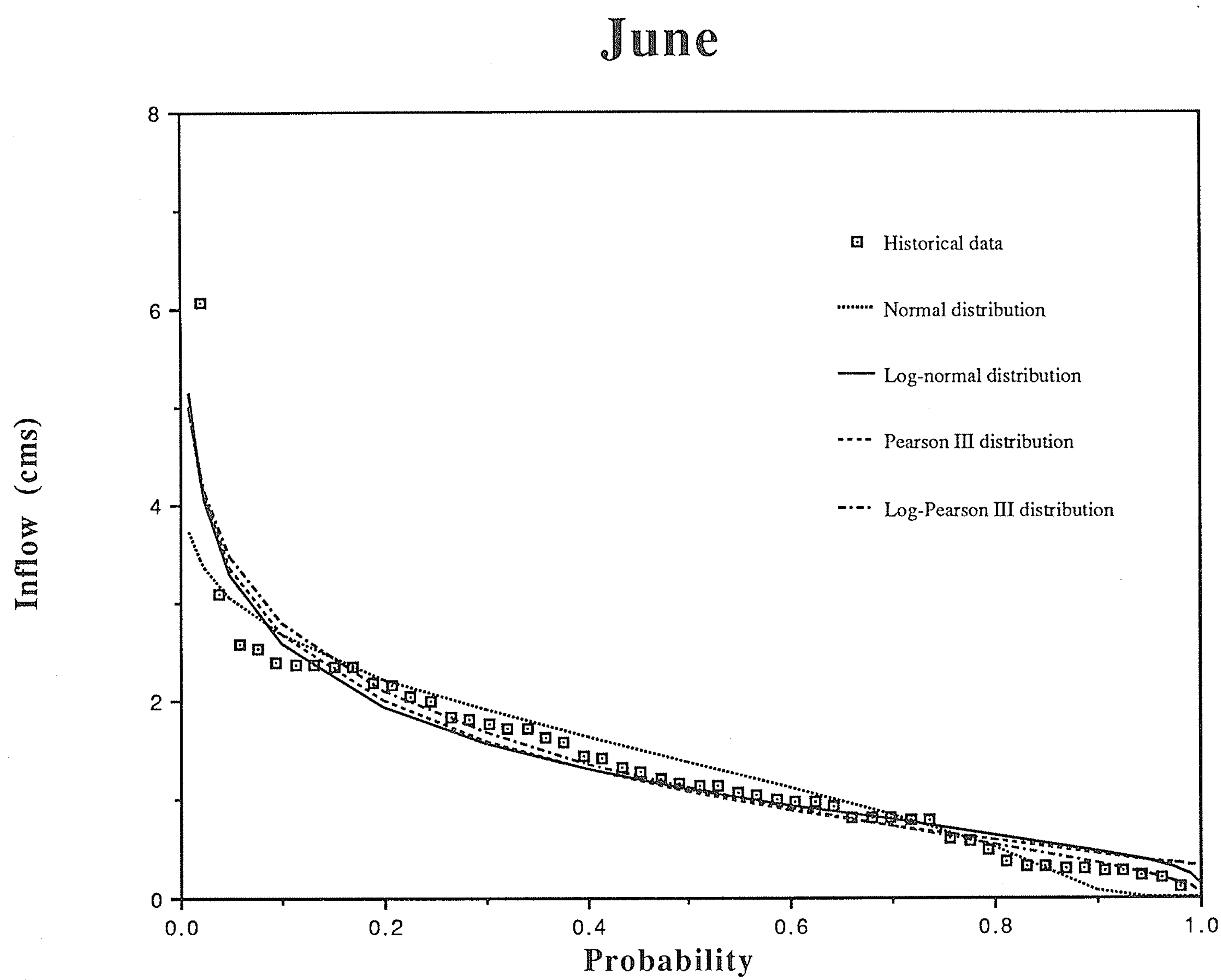


Figure B6. Flow duration plot Gruza river data (June)

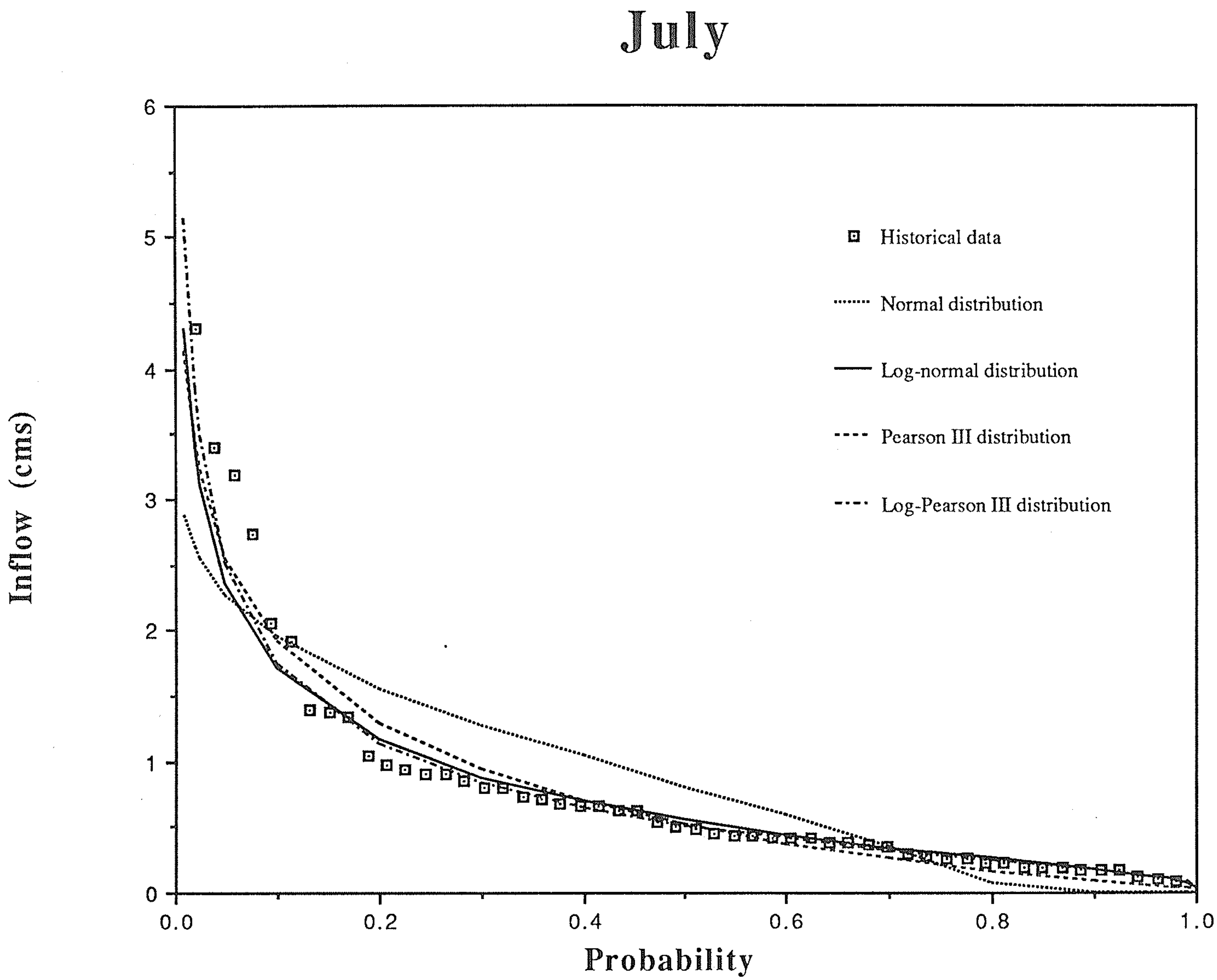


Figure B7. Flow duration plot Gruza river data (July)

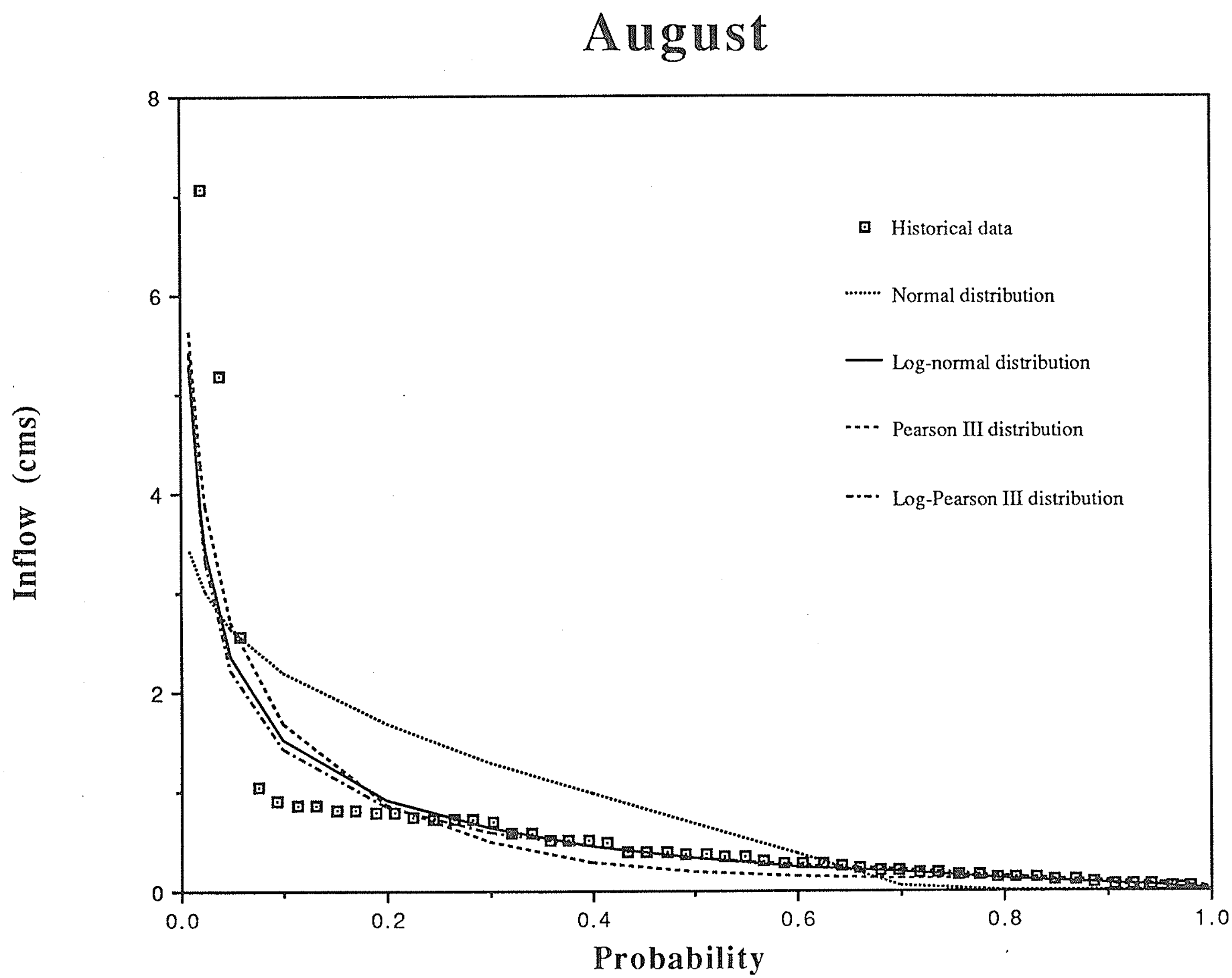


Figure B8. Flow duration plot Gruza river data (August)

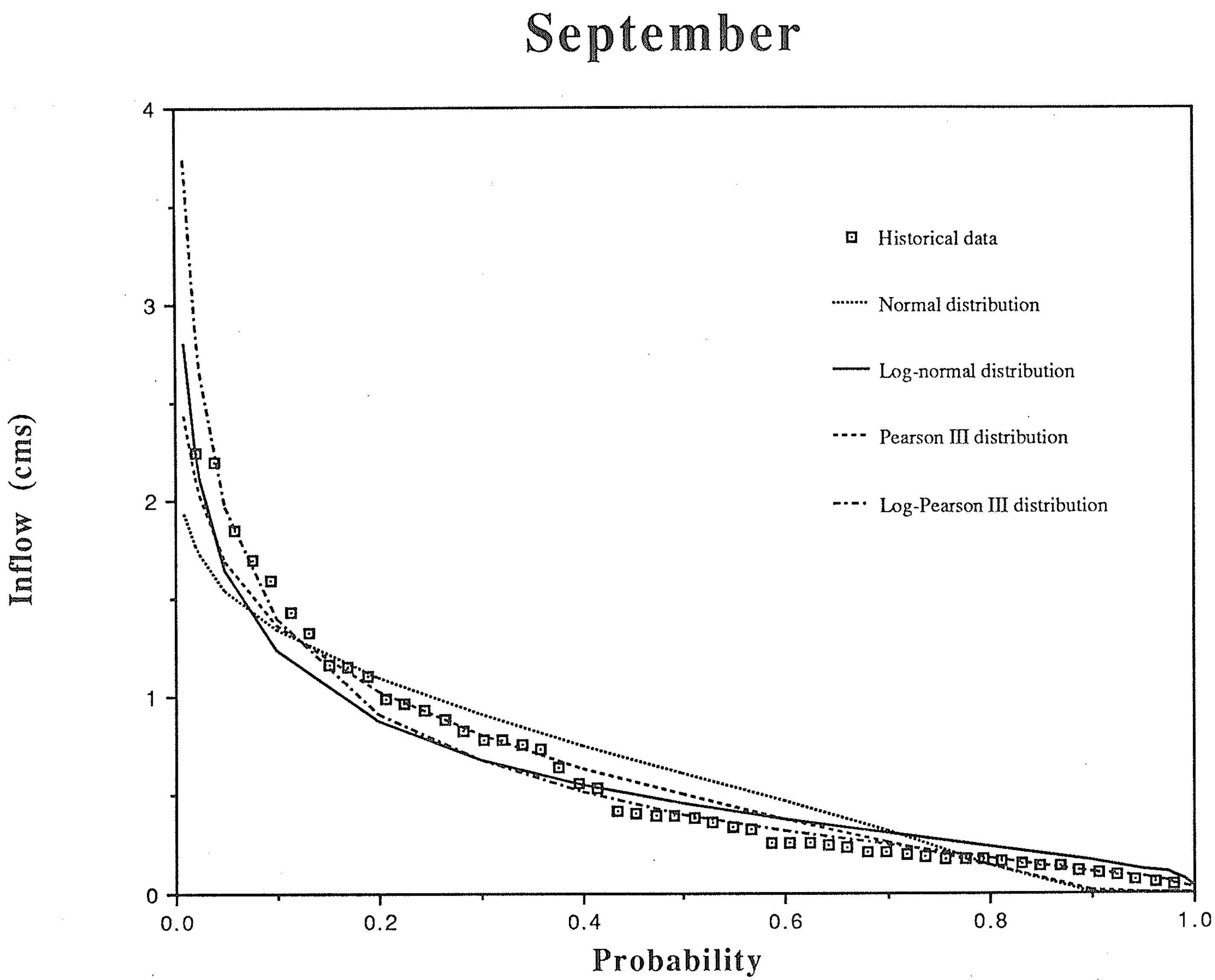


Figure B9. Flow duration plot Gruza river data (September)

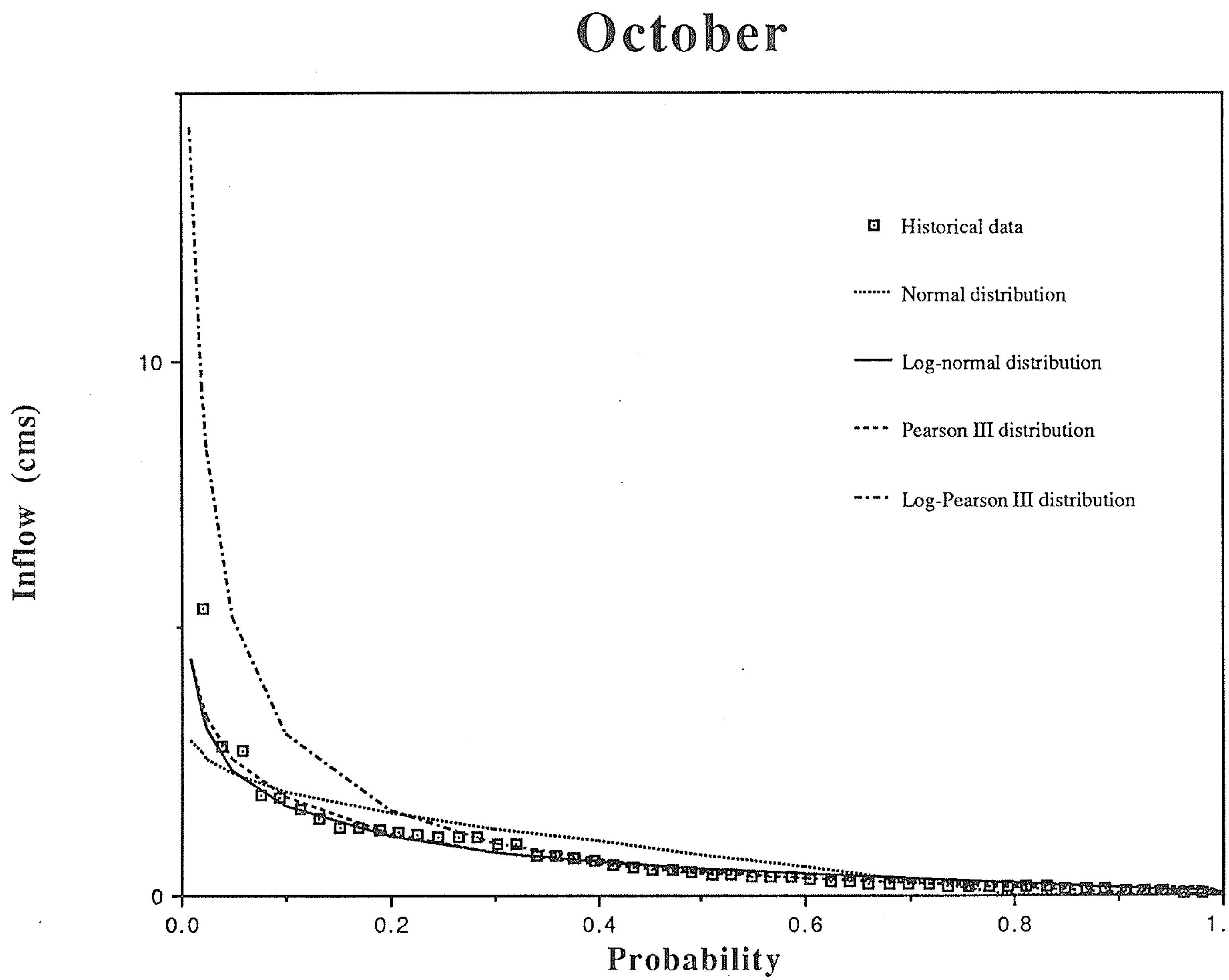


Figure B10. Flow duration plot Gruza river data (October)

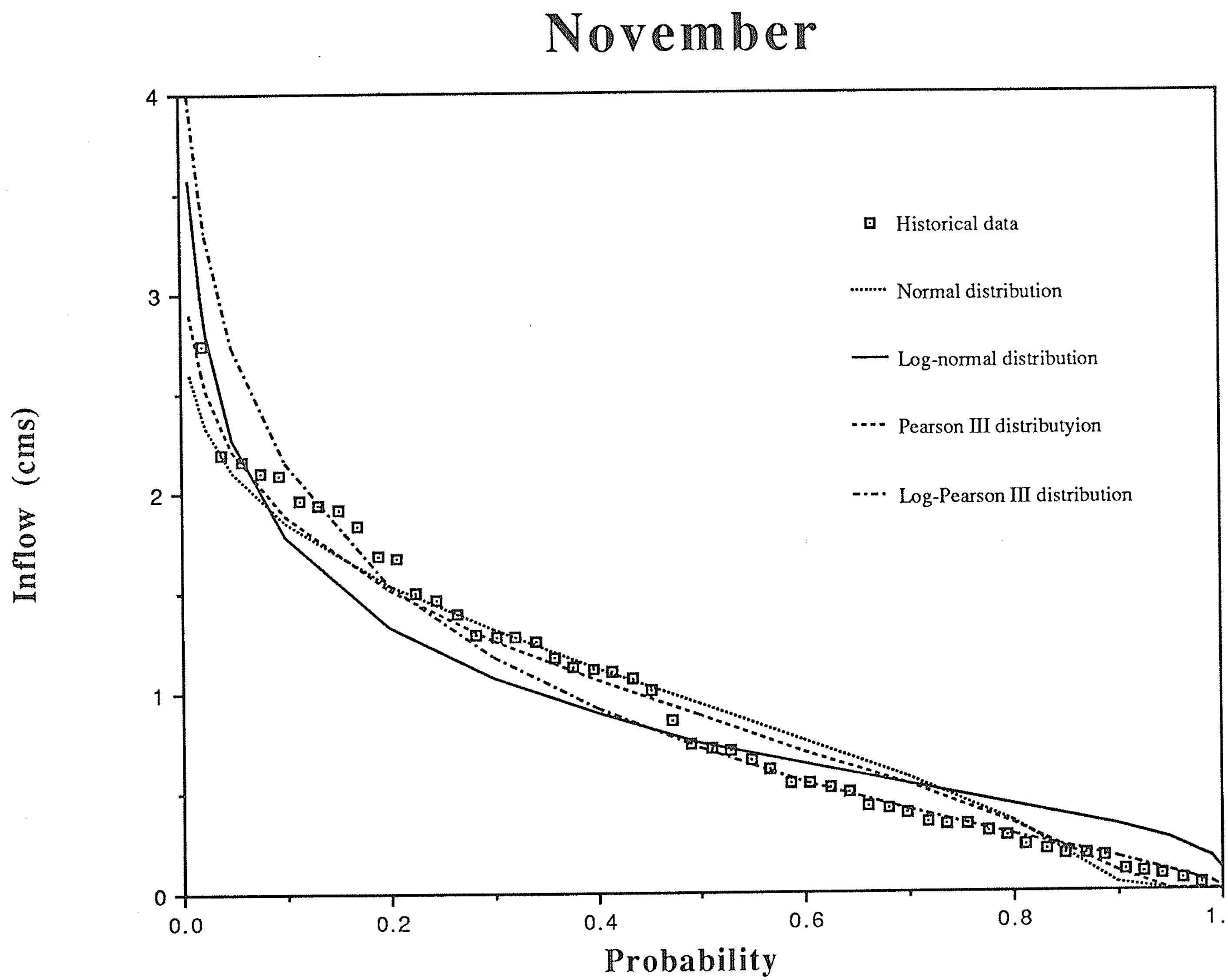


Figure B11. Flow duration plot Gruza river data (November)

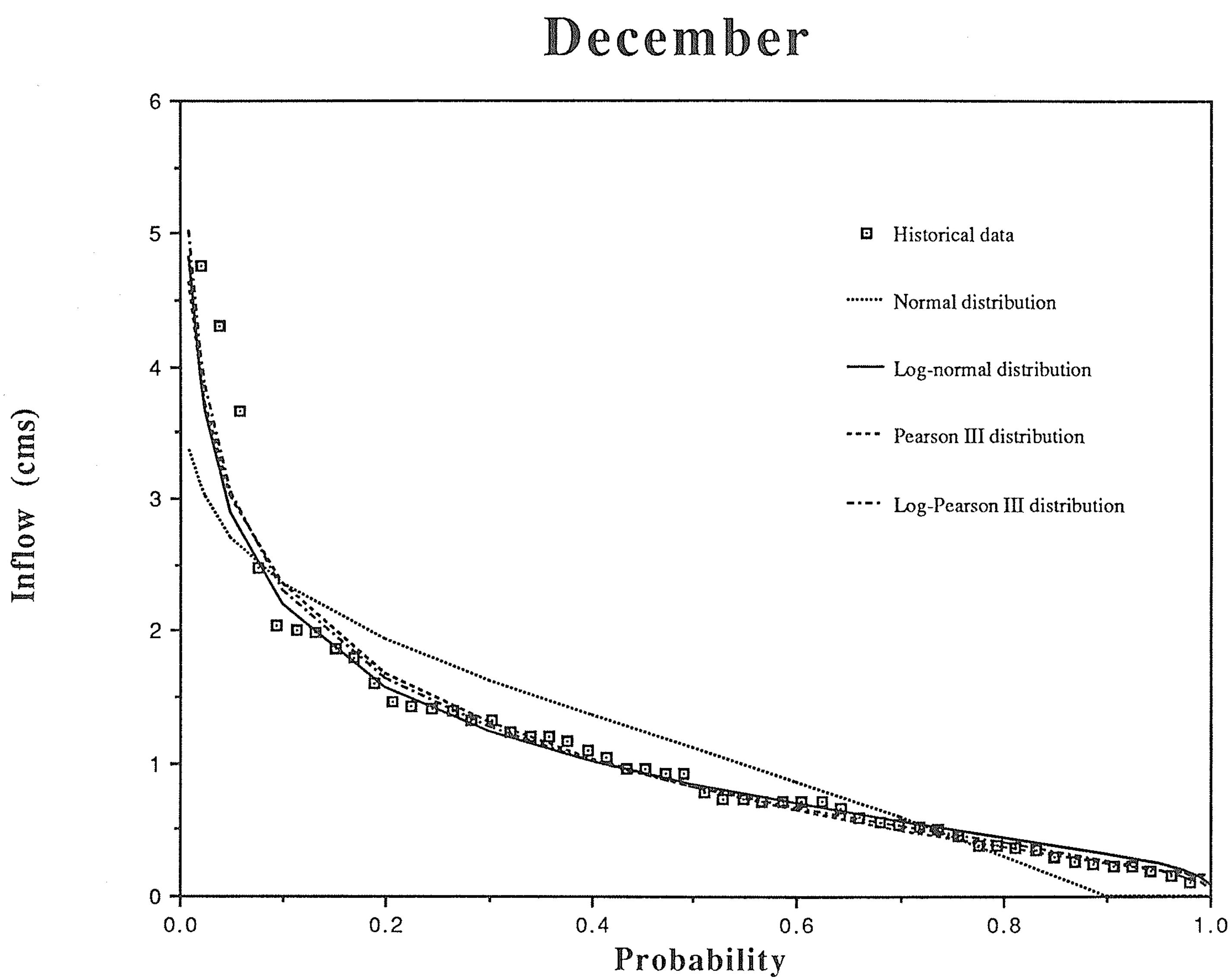


Figure B12. Flow duration plot Gruza river data (December)

TESTING THE GOODNESS OF FIT OF STREAMFLOW DATA TO PROBABILITY DISTRIBUTIONS

Two statistical tests: Chi-Square and Kolmogorov-Smirnov were used to help judging whether or not a particular distribution adequately describes the set of streamflow observations on the Gruza river. Both test were performed for 95% confidence level (α=0.05). The following table shows whether particular distribution provides a good approximation to the orginal sample or not.

Distr.	NORMAL		LOG-NOR		PEAR-3		LPEAR-3	
Test	CH2	KST	CH2	KST	CH2	KST	CH2	KST
Jan	*	*	*	*	*	*	*	*
Feb	?	*	*	*	?	*	*	*
Mar	*	*	?	*	*	*	?	*
Apr	?	*	*	*	?	*	*	*
May	?	*	*	*	*	*	?	*
Jun	*	*	*	*	?	*	*	*
Jul	?	?	*	*	?	*	*	*
Aug	?	?	*	*	?	?	*	*
Sep	*	*	*	*	?	*	*	*
Oct	?	*	*	*	*	*	*	*
Nov	?	*	*	*	?	*	*	*
Dec	*	*	*	*	*	*	*	*

* Test OK
? Test failed

APPENDIX C

QUESTIONNAIRE USED FOR THE CONSTRUCTION OF THE MEMBERSHIP FUNCTIONS

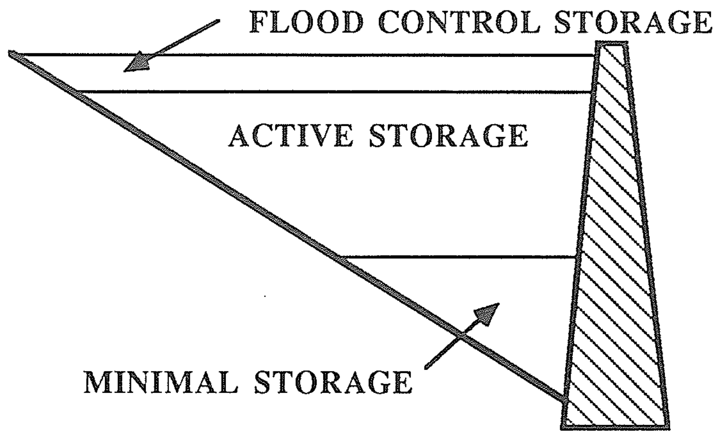
Imagine yourself as a member of a decision-making body preparing long-term planning guidelines for managing a reservoir. The following reservoir characteristics should help you in finding the most appropriate answers:

Dam type: arch (relatively safe to overtopping)

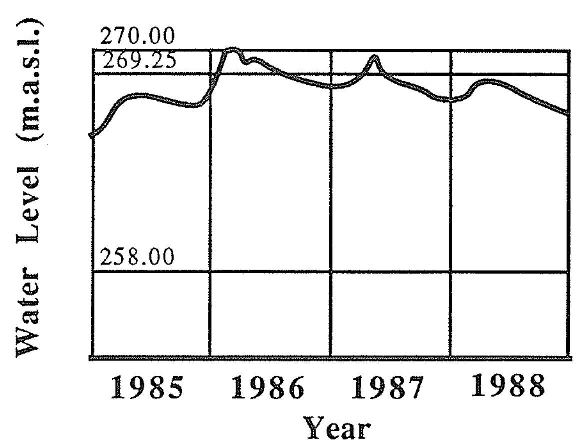
Reservoir purposes:
1) water supply (municipal and industrial),
2) flood control of the downstream area which is predominantly rural (rarely populated),
3) sediment deposition control, and
4) low flow augmentation.

The reservoir is built primarily for providing water for a large municipal settlement (the town of Kragujevac) 10 km from the reservoir site and releasing minimal contracted volume downstream from the reservoir. The obligation of the reservoir management is to provide constant amount of water each month for these purposes. The potential of supplying rural areas with drinking water prompted the question of utilizing excess water (if any).

The following three storage zones are identified in the reservoir design process:



The attitude of the managers towards operating the reservoir in the past may be illustrated by the reservoir levels during the period1985-88 (the reservoir started operation in 1983).



QUESTION No. 1

What would be the minimal required reliability levels for keeping reservoir storage below flood control and above minimum storage levels respectively, in %, i.e., what is the percentage of time that the reservoir flood control storage and minimal storage are not corrupted (e.g., X % for flood control and Y %).

Flood Storage Reliability %

Minimum Storage Reliability %

QUESTION No. 2

Using the following scale indicate the relative importance of different failure frequencies to each other (e.g., how important is the difference between having minimal reservoir storage corrupted on average once in five and once in seven years of operation). Base your decision on past management decisions (previous page) and your personal judgement and knowledge of the reservoir system.

Scale Description

a) two frequencies are equally significant

b) experience and judgement slightly favor one frequency over another

c) experience and judgement strongly favor one frequency over another

d) a frequency is strongly favored and its dominance is demonstrated in practice

e) the evidence favoring one frequency over another is of the highest possible order of affirmation

Note: When the compromise among two adjacent choices (e.g., b&c, or d&e) is needed use both letters.

The following is the proposed notation for frequencies:

A. on average 50%

B. on average 60%

C. on average 70%

D. on average 80%

E. on average 90%

F. on average 92.5%

G. on average 95%

H. on average 97.5%

I. on average 98%

J. on average 99%

Explanation of the following tables:

- It is assumed that a frequency is equally significant in comparison with itself (that is why the scale notation "a" is used for the same corresponding rows and columns).

- You are not supposed to fill a space with "X"

i) Flood storage :

	A	B	C	D	E	F	G	H	I	J
A	a	X	X	X	X	X	X	X	X	X
B		a	X	X	X	X	X	X	X	X
C			a	X	X	X	X	X	X	X
D				a	X	X	X	X	X	X
E					a	X	X	X	X	X
F						a	X	X	X	X
G							a	X	X	X
H								a	X	X
I									a	X
J										a

ii) Minimal Storage

	A	B	C	D	E	F	G	H	I	J
A	a	X	X	X	X	X	X	X	X	X
B		a	X	X	X	X	X	X	X	X
C			a	X	X	X	X	X	X	X
D				a	X	X	X	X	X	X
E					a	X	X	X	X	X
F						a	X	X	X	X
G							a	X	X	X
H								a	X	X
I									a	X
J										a

Thank you for your time