THE UNIVERSITY OF MANITOBA

IDENTIFICATION OF AN OPTIMAL OPERATING POLICY FOR A MULTIPURPOSE RESERVOIR

by

YUJUIN YANG

A Thesis
Submitted to Faculty of Graduate Studies
in Partial fulfillment of the Requirement for the Degree of
Master of Science

DEPARTMENT OF CIVIL ENGINEERING

Winnipeg, Manitoba
June 1991

ISBN 0-315-77015-5

IDENTIFICATION OF AN OPTIMAL OPERATING

POLICY FOR A MULTIPURPOSE RESERVOIR

BY

YUJUIN YANG

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

MASTER OF SCIENCE

ACKNOWLEDGMENT

The author would like to express his sincere gratitude to Dr. D. H. Burn for his invaluable advice and guidance during the research related to this thesis and the preparation of this thesis.

The author is also grateful to Dr. B. J. Lence of Civil Engineering Department of University of Manitoba for her advice during the research related to this thesis, Mr. M. Saxton and Mr. W. Brown of Manitoba Hydro, Mr. B. Webb of Water Resources Branch for providing the data employed in this thesis.

The author was supported in this program by a graduate student grant from Manitoba Hydro.

ABSTRACT

A methodology used for identifying the optimal operating policy has been presented. The technique used to develop this methodology incorporates the optimization, simulation, and multiobjective selection techniques. The optimization technique is invoked in generating optimal policies, the simulation technique is invoked in evaluating policies, and the multiobjective selection technique is invoked in selecting the most suitable policy.

This methodology has been applied to a real-world reservoir system. The utility of the methodology has been demonstrated. The generated optimal policies are evaluated under various hydrological conditions and assumptions of forecasting accuracy. The final results show that the policy derived from this procedure is quite reasonable.

TABLE OF CONTENTS

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Statement of the Problem

Natural river flow has a seasonality and stochasticity in both its occurrence and magnitude. Flow may be very small, corresponding to dry conditions, or very large resulting in flooding. Flow may occur in the time period in which there is no significant demand and may not occur in the time period in which many demands exist. In other words, the availability of water and demands for water may not be identical.

To alleviate these problems, a storage reservoir is necessary. A reservoir alters the natural flow regime and stores some of the water, and then releases water from storage in a controlled manner. Flood waters can be released over a longer time period and thus at a smaller flow rate so that downstream flooding can be avoided or reduced. Surplus water from a wet period can be stored and released in a dry period to alleviate the impacts of water shortage. In addition, the water level can be raised or lowered to alter generation of hydro-electric power. In short, a reservoir is a manner of controlling and altering the spatial and temporal distribution of natural flow in order to protect the downstream regime from flooding and more closely match the availability of water to the demands for water. As a result, a reservoir improves the efficiency of using natural water.

Water resources engineers usually face two types of problems associated with reservoirs: reservoir sizing and reservoir operation. The former deals with the determination of the capacity a planned reservoir should have, considering certain or uncertain water demands and water availability. A series of parameters such as the height of the dam, the flooded area, the discharge capacity and associated spillway structure, and the storage capacity (including dead storage, flood control pool, and conservation storage), should be chosen. The latter problem addresses the manner of operating an existing reservoir. This is the issue which is discussed in this thesis.

Reservoir system operation, in comparison with some other kind of systems operation, is generally more complex in terms of its multiple purposes, competitive demands, and seasonal and stochastic operating conditions. As mentioned above, a reservoir could be built for multiple purposes including water supply, power generation, water quality control, etc.. These purposes are often conflicting. Storage level in the reservoir versus release from the reservoir is a good example of this conflict. For generating more energy (or for some other reason), one often wishes to store more water in the reservoir to raise the water levels. However, it may not be possible to maintain such water levels if downstream users (i.e., cities, factories, farmers,etc.) request increased releases, which will lower the storage level. A conflict also exists in the temporal re-distribution of water. If a predicted dry season is coming, the reservoir operator may reduce the current water supply and save water for more important demands in the coming dry season.

Stochasticity of a reservoir system is another factor adding to the difficulty of making operating decisions. Inflow is a random variable which implies that forecasting techniques will often have to be incorporated into the decision procedure. A reservoir's purpose is to best satisfy various demands over a longer time frame and on a stochastic basis through re-regulating or re-distributing natural water supply. The problem is to determine how this can best be done or in other words what are the optimal operating policies for the reservoir that will lead to the greatest satisfaction of the goals of reservoir operation?

To answer this question, optimization theory and techniques are the most powerful and effective tools. Since they were introduced into the water resources field, various optimal management problems have been solved. For example, optimization models have been used to solve the management problems of a single reservoir with only downstream demands, a single reservoir with both downstream demands and reservoir water level goals (for recreation, fishery, power generation, etc.), or a multi-reservoir system (either in parallel or in series) of multipurpose reservoirs.

Optimization, as can be inferred from the name, is aimed at identifying the optimal solution to a problem. Optimization can determine (i) if an optimal solution exists and (ii) if such a solution does exist, how to find it. The ways of seeking optimal solution(s) depend on the characteristics of the problem to be solved, the limits imposed on the solution, and the computational burden. It is the second problem that is addressed in this work.

The focus of this study is seasonal operating policies of a multipurpose reservoir. Generally, an operating policy refers to either a set of release guidelines or a set of storage level guidelines. A release operating policy explicitly addresses water supply purposes while a storage level operating policy can reflect flood control and reservoir recreation purposes. This work deals with the development of a storage level policy.

Seasonal operating policies provide the guideline for real time operation. From this point of view, seasonal policies are the principle of the reservoir's operation while real time rules elaborate and implement the principle. There are many possible seasonal operating policies for a given season. An example is keeping the reservoir either empty or full all of the time. The former makes the reservoir useless from the point of view of water supply while the latter places the reservoir at high risk. Neither of these policies is desirable. Between the limits of empty and full, there must be a level which ensures that the reservoir will be able to provide as much water as possible to its users while providing adequate flood protection. This policy can be referred to as the optimal policy. Generally speaking, the optimal policy makes it possible for a multipurpose reservoir to have the greatest operating efficiency.

The purpose of the work described in this thesis is to develop a methodology for identifying optimal seasonal operating policies for a multipurpose reservoir. After this, a real world reservoir, the Shellmouth Reservoir, which has the functions of flood protection, water supply, and reservoir recreation, is used as an application of the methodology developed.

1.2 The Scope of the Investigation

This investigation will focus on the development of a methodology for seasonal operating policies, using Linear Programming techniques, and the application of this methodology to a case study reservoir system. The treatment of stochastic water availability in this work is different from the manner extensively employed in previous applications. The derived operating policies from different optimization models are then evaluated by simulation models and ranked according to evaluating results.

Chapter 2 gives a literature review of related research. Some of the most popular optimization models are reviewed, in terms of their capability of incorporating the linear/non-linear problems, stochasticity, and inherent computational burden.

Chapter 3 presents the development of models produced in this research. This chapter discusses the general modelling framework developed for identifying seasonal reservoir operating policies.

Chapter 4 is the application of the developed methodology to the Shellmouth Reservoir in Southwest Manitoba. Details of the Shellmouth's problems are presented and threshold values for the constraints are determined. Three optimization models are discussed separately. With the use of realistic data, optimal operating policies are derived.

Chapter 5 discusses the criteria used to evaluate the reservoir operating policies developed. Two simulation models are presented as the tools of evaluation. The operation decision incorporated in the simulation models, the purpose of using such models, the structure of the models, the simulation input arrangement, and the results of the evaluation are also presented. Some observations about the simulation results are made.

Chapter 6 presents a two-step screening procedure for multiobjective selection purpose, according to simulation results. A variation of the Compromise Programming model is developed and used. A preferred policy is finally selected using this model.

Chapter 7 presents conclusions and identifies areas for further research.

Chapter 2. Literature Review

Due to the level of importance of water resources in both economic development and environmental protection, water resources engineering systems have attracted considerable attention. Identifying techniques to design and operate a reservoir, especially a multipurpose reservoir, becomes a very interesting task. Many traditional management techniques failed to demonstrate their usefulness for this purpose. In the late 1950's, the principle and techniques of optimization were introduced into the water resources field. Since then, optimization techniques have been extensively used in planning and management of water resources systems. Hundreds of research projects have been done and this number is still increasing. The most attractive advantage of optimization techniques that fascinates professional workers is that they allow the determination of the optimal performance value that a system could have, under various constraints. So far, there are three basic kinds of optimization techniques being introduced and used in the field of water resources systems analysis: (1) linear programming; (2) dynamic programming; and (3) non-linear programming. In terms of the popularity, linear and dynamic programming are much more prevalent than non-linear programming. In this chapter, only the first two programming techniques are reviewed. Since the case study deals with a linear problem and therefore the development of the methodology will only focus on linear optimization.

2.1. Linear Programming (LP)

Linear programming techniques address linear systems. In a linear model, both objective function and constraints are linear. In dealing with this kind of problem, LP is advantageous in terms of the following aspects: (1) straightforward concept; (2) the solution algorithm is well established and a multitude of computer codes exist to solve the algorithm; and (3) the technique is well documented.

A typical LP model has the form of

$$\min_{X} Z = C^T X \tag{2.1}$$

subject to

$$AX \geq b \tag{2.2}$$

$$X \geq 0 \tag{2.3}$$

in which

C is an n-dimensional vector of objective function coefficients;

X is an n-dimensional vector of decision variables;

b is an m-dimensional vector of right-hand sides;

A is an [m x n] matrix of constraint coefficients; and

T is the transpose operation.

LP can be very effective for planning and management problems, as long as the linearity requirement is satisfied. ReVelle and Gundelach (1975) used an LP model to determine the size of a reservoir. The system had only one reservoir and the objective function was to minimize the capacity of the reservoir while meeting all of the demands. Dagli and Miles (1980) demonstrated how LP could be used for a hydro-power generation problem of a multireservoir system (in series). The non-linear elevation-storage curve was piecewise linearized.

2.2 Dynamic Programming (DP)

2.2.1 Dynamic Programming Technique

Dynamic programming is another popular optimization technique used in water resources systems analysis. Unlike the LP technique, DP divides a problem into several stages, and solves it stage by stage. Therefore, it does not need to solve simultaneous functions regarding stages as an LP model does. DP is able to solve both linear and non-linear problems.

A typical recurrence relation of the DP procedure is

$$f_n(x_n) = \max_{d_n} [\, r_n(x_n, d_n) + f_{n-1}(x_{n-1})] \tag{2.4}$$

$$f_1(x_1) = \max_{d_1} [\, r_1(x_1, d_1) + f_0(x_0)] \tag{2.5}$$

in which

x is the state variable;

d is the decision variable;

r is the return function;

and n is the stage.

A DP problem can be solved using forward or backward recurrence procedure. Yeh (1985) indicated that backward recurrence was essential in stochastic DP problems since each stage depends on the former stage while forward recurrence was advantageous for a deterministic problem since it had to be solved several times in different planning horizons.

DP has the ability of handling not only linear but also non-linear problems. Most kinds of problems arising in water resources systems can be solved by it.

Collins (1977) reported his work using a monthly deterministic DP model to find the least cost withdrawal and release patterns for a multiple reservoir system; Marino and Loaiciga (1985) applied a dynamic programming model to a hydro-power plant monthly operation problem. Some examples of DP models will be introduced later.

2.2.2 Improvement in Computational Burden

Decomposing the decision space is a key feature of DP and it reduces a complex problem into a series of simpler sub-problems. However, it also quickly increases the requirement on computer capacity and computation time, or in other words, curses heavy dimensionality burden. To overcome this shortcoming, several improvements have been suggested. One of these improvements is called incremental DP (IDP). IDP starts with an initial feasible solution and then checks the neighbor states of the initial points. If any of the neighbor points give a better value of the objective function, the initial point is replaced by this new one. New neighbors are then examined again. This process is executed until a convergent optimal solution is found.

A generalization of IDP is called Discrete Differential DP (DDDP). Nopmongcol and Askew (1976) indicated that IDP and DDDP were essentially the same. "The confusion between these terms is most unfortunate". In their paper, the terms IDP and DDDP were used interchangeably.

Since IDP and DDDP search for the optimal solution from a part of the solution space, instead of from the whole solution space, as traditional DP does, the choice of the initial point could be significant. Convergence to the global optimum is not guaranteed. Furthermore, the increments of the variables are also important not only for finding the optimal solution, but for guaranteeing convergency of the solution algorithm. Hall et al. (1969) suggested two ways for defining the increments of the variables. One way is to keep the increments small but constant throughout the whole iteration process; another is to make the increments a function of the iteration. Generally, increments become finer and finer as the iterations proceed. In an application, Paudyal et al. (1990) reported their work of selecting the optimal hydropower system configuration using IDP and Stochastic DP, SDP. The IDP was invoked to optimize the monthly power generation of each potential configuration, and then the SDP was applied to the three best configurations derived by IDP to optimize annual power generation.

Another method designed to alleviate the curse of dimensionality is called Incremental DP with Successive Approximations (IDPSA). The basic idea is to first discretize the multidimensional problem into several one-dimensional subproblems, and then these subproblems are converged toward the optimal solution of the original problem.

Karamouz and Houck (1987) compared monthly reservoir operating rules generated by stochastic DP and deterministic DP respectively. They found that DDP was better than SDP in 9 of 12 cases, in terms of the efficiency of the derived rules, the consistency of the rules, and the effect and adequacy of the number of characteristic inflows and the number of characteristic storages.

Besides the methods reviewed above, some other similar efforts also exist. Wasimi and Kitamidis (1983) developed a methodology called Linear Quadratic Gausian Programming (LQG). Georgakakos and Marks (1987) extended LQG and called it extended LQG. Both LQG and the extended LQG employed a set of linear differential equations and a quadratic penalty objective function.

Other progressive methods include the Progressive Optimal Algorithm (Marino et al. 1985; Lucas et al. 1985), the Progressive Optimality (Zessler and Shamir, 1989), and the Discrete Maximum Principle (Papageorgion 1985).

2.3 Stochastic Considerations

Water resources problems are complex due to the uncertainty of flows. Several methods have been developed to deal with the uncertainty or stochasticity that is a distinct characteristic of water resources problem. Some of the main methods are reviewed, namely deterministic programming, chance-constrained programming, stochastic programming, and reliability programming.

2.3.1 Deterministic Programming.

In a deterministic model, a set of inflow sample based on historical or other data is chosen as a representative of the possible future conditions. Once this sample data is input, the model generates the output associated with this certain (known) sample.

Windsor (1981) developed a methodology using deterministic mixed integer programming for the planning and design of flood control systems. Turgeon (1987) reported on an application of a monthly deterministic LP model for selecting the sites at which reservoirs and hydro-power plants should be built. Goulter and Castensson(1988) utilized a deterministic goal programming model of the Sommen Reservoir to alleviate the competition between downstream water supply and lake boating and fishing.

2.3.2 Chance-Constrained Programming (CCP)

Chance-Constrained Programming reflects the probability conditions on constraints. Typically, the probability of satisfying a constraint (e.g., in supplying promised water, or in protecting against flooding, etc.) is required to be greater than a threshold value:

$$P\{AX \geq B_0\} \geq \partial \qquad (2.6)$$

in which

∂ is a probability vector;

B_0 is a vector of known threshold values;

other terms are as previously defined.

As long as the distribution function (DF) of X is available, and ∂ vector is known, the constraint can be converted to

$$X \geq F^{-1}{}_0(\partial)$$

in which $F^{-1}{}_0$ is the inverse of F(X) at $X = B_0$.

Since the right hand side is a constant value now, the constraint is deterministic. By converting probabilistic constraints to deterministic ones, CCP converts a stochastic-type model to a deterministic-type one, and then solves this deterministic equivalent.

ReVelle et al. (1969) employed a CCP model to a reservoir sizing problem when they demonstrated Linear Decision Rules (LDR), which is discussed in Section 2.3.3. In this straightforward example, release and storage were simply bounded by upper and lower bounds with certain probability. This was the first time that the CCP model appeared in water system optimization. Following this application, many other researchers used this technique extensively. Eised (1972) applied a CCP model to derive the optimal policy for an irrigation reservoir; Curry et al. (1973) extended the work of ReVelle et al. by omitting the LDR from the model. They showed the advantages of doing so were the ability to include the release in the objective function and to adequately account for stochastic inflow. Askew (1974) introduced chance-constraints (C-C) into a DP model. The objective function maximized the net benefit of pursuing the target release. C-C were set to control the probability of system failure. He illustrated that CCP could be well combined with the DP technique. Takeuchi (1986) invoked a CCP model to solve a real-time reservoir operating problem. The chance constraints were set on the probability of the reservoir becoming empty. Changchit et al. (1989) combined CCP with Goal Programming to operate a multiple reservoir system.

2.3.3 Linear Decision Rules (LDR)

ReVelle et al. (1969) introduced a special technique called Linear Decision Rules (LDR) into an LP model. Since then, LDR has been frequently cited, discussed, and verified (ReVelle et al., 1970, Loucks, 1970, Loucks and Dorfman, 1975, Joeres et al., 1981, and Stedinger, 1984).

The original LDR has the simple form of

$$X_t = S_t + b_t \qquad (2.7)$$

in which

X_t is the release in period t;

S_t is the ending storage in the same period; and

b_t is a decision constant.

This formula denotes the release as a linear function of storage. Loucks (1970) commented that LDRs led to an easy to solve model because of the simplistic nature of the formulation and the objective function. Generally, a model with LDR leads to conservative results. Recognizing this, Loucks defined a new rule in which the release is a linear function of beginning storage, decision constant, and inflow. He also indicated that introducing the inflow term reduced the conservative nature of the results. Because of the introduction of the inflow term, release is no longer a commitment at the beginning of the time period, but rather a decision at the end of the period. Loucks and Dorfman (1975) compared the required capacity of a reservoir resulting from a model using the original LDR with that resulting from a simulation model, and they also found that the former was overestimated, i.e., original LDRs yielded conservative results. Houck (1979) developed a multiple LDR in order to improve the estimation of reservoir capacity. His multiple LDR has the same form as ReVelle's s-type (which only has a storage term) and Loucks' sq-type (which has both storage and inflow terms) LDR, but each term is associated with a certain interval of inflow. Houck et al. (1981) demonstrated that multi-LDR models are less conservative than single LDR models. However, Stedinger (1984) commented, after examining the performance of LDR models for preliminary design and reservoir operation, that "s-type LDRs substantially overestimate required capacities if an efficient operating policy is used to operate the reservoir system. In some cases and for some problem formulations, simple sq-type LDR screening models may provide satisfactory results". Another factor influencing the conservative nature of the models with LDR is the consideration of proceeding streamflow (Loucks and Dorfman, 1975; Houck, 1979; Houck et al., 1981; and Joeres et al., 1981). Houck (1979) stated that the cause of the conservative nature of the LDR model is that only an unconditional CDF was used instead of conditional CDF. He said that using conditional CDF was a remedy to the conservative nature of the results.

2.3.4 Reliability Programming (RP)

CCP fixes the probability of stochastic constraints prior to solving the model. This is a restriction because it limits the solution space. On the other hand, sometimes people may hope to know the "best choice" of the given probability. In order to address this question, models are developed in such a way that the probability is a decision variable and therefore incorporated into the objective function. Reliability Programming (RP) is an application of this idea. Its form is:

$$\text{Max } f(X,\partial) \tag{2.8}$$

subject to

$$A^T X \geq P(\partial) \tag{2.9}$$

$$X \geq 0 \tag{2.10}$$

in which X, ∂, A are the control variable, decision variable, and parameter vectors, respectively.

Colorni and Fronza (1976) initiated the application of RP to the reservoir management problem. In their model, the objective was to maximize the benefit from releasing water. Risk is accounted for by choosing different probability values which constrain the degree of satisfying the contracted release. Simonovic and Marino (1980) presented a RP model for a similar case. The objective function maximized the benefit from release minus the risk losses associated with probabilities on the constraints of storage. A two-stage solution algorithm was used to solve the problem. First, a search for the probability values was conducted. Then, with the selected values, the resulting problem was solved as a CCP. Noticing that the loss function is a key factor in applying RP, Simonovic and Marino (1981) presented a methodology for building loss functions associated with several kinds of system failures. Marino and Mohammudi (1983) developed a new RP model based on C-C LP and DP. The probabilities were discretized from the lower bound to the upper bound. With given levels of incremental probability values, the C-C LP model was solved. The probability values were then changed and the C-C LP model was solved again. Finally, the best solution was derived by using a DP algorithm. This method avoided the risk losses functions greatly increased the size and complexity of the model.

2.3.5 Stochastic Dynamic Programming (SDP)

Stochastic dynamic programming is another popular method of handling the stochasticity of inflow. While C-C programming is more common in LP models, Stochastic Programming is more common in DP models. In a stochastic model, usually a Markov probability transition matrix is invoked which describes the time series process of the inflows and then the expected values of random variables are dealt with.

A typical discretized stochastic dynamic programming model has the following form (Yeh, 1985):

$$f_t\,(S_t, I_{t+1}) = \max_{R_t} \{ \sum_{I_t=0}^{I_t,\max} P[I_t / I_{t+1}]*[B(R_t)+f_{t-1}(S_{t-1}, I_{t-1})]\} \qquad (2.11)$$

$$f_1\,(S_1, I_2) = \max_{R_1} \{ \sum_{I_1=0}^{I_1,\max} P[I_1 / I_2]*[B(R_1)\} \qquad (2.12)$$

in which

$f_t\ (S_t, I_{t+1})$	expresses return from the optimal operation of the system which has t time periods to the end of the planning period;
S_t	is storage at the beginning of time period;
I_t	is inflow during time period t;
B	is the return obtained consequent to releasing a quantity of water "R_t" during time period t. B can also be a function of the storage as in the case of hydropower connecting productions.
$P[I_t / I_{t+1}]$	transition probabilities connecting inflow I_t in the tth time period with inflow I_{t+1} in time period t + 1;
t	time period index.

Trezos and Yeh (1987) applied SDP to solve a real-time hydropower operation problem. The objective was to maximize the expected value of deliverable on-peak energy or total benefit from hydropower operation. To avoid uncontrollable computational burden, the authors used an algorithm similar to DDP. Tai and Goulter (1987) applied a similar model for a monthly operating policy. Stedinger et al. (1984) suggested the use of the expected value of the state variable (inflow) in the objective function instead of using predicted ones. The purpose of doing this was, as they stated, to reduce the dimensionality problem. Huang et al. (1991) tested SDP models with different stochastic considerations: using forecasted and observed inflow data and coping with a conditional and an unconditional distribution function. When forecasted inflow is used, the decision variable is the final storage state, otherwise, it is the release. They concluded that using observed inflow has more efficient than using forecasted flow.

2.4 Comments on Various Optimization Models

2.4.1 LP Models

For linear problem formulations, LP models have the advantage of a smaller computational burden than DP models. This advantage is significant in dealing with large scale problems such as multiple reservoirs or multiple purpose systems, as we are facing more and more today. By means of chance-constraints or reliability-constraints, LP is able to easily incorporate the stochasticity.

2.4.2 DP Models

The greatest advantage of the DP technique is its capability of handling both linear and non-linear problems, as long as the problem is stage discretizable. Stochasticity can be incorporated into DP models, but it usually increases the computational burden.

2.4.3 Deterministic Models

Deterministic models have several computational advantages over stochastic models, because they simplify the system. However, such models can introduce bias because the hydrologic pattern of the future may differ from that of the past which has been used as the input of the optimization models (Huang et al., 1991; Loucks et al., 1981).

2.4.4 CCP Models

CCP incorporates the stochastic nature of the inflows explicitly but has the same advantage as a deterministic solution algorithm. Unlike Reliability Programming, it alleviates the burden of developing loss functions. These are the major merits which have made CCP so attractive. However, Hogan et al. (1981) warned that CCP is seriously limited because it neither penalizes explicitly the constraint violations nor provides recourse action to correct the realized constraint violation as a penalty, and should not be regarded as a substitute for stochastic programming with recourse.

2.4.5 RP Models

The RP technique deviates from the fixed probabilities which could be considered as extra constraints and searches for optimal solutions in a larger solution space in comparison with CCP.

The loss function is a key component in an RP model. In some cases, the building of this function could be difficult. On the other hand, Strycharczyk and Stedinger (1987) have commented that the RP approach still could not capture all reservoir operating issues in its loss functions, and reliabilities of minimum and maximum storage target did not directly relate to the frequency with which minimum and maximum release bounds would be violated. The RP method, without employing LDR, was very conservative in identifying the capacity of a reservoir.

2.4.6 SDP Models

SDP lets a DP model incorporate stochasticity explicitly, but it also increases the dimensional burden that a DP has. Therefore, its use in practice is greatly limited.

As mentioned in the beginning of this chapter, the case study reservoir system used in this research is formulated as a linear problem. To address a linear problem, various LP models could be very effective. To lighten the computational burden, deterministic type models have advantages over stochastic type models. Considering these reasons, this work focuses on deterministic LP models. But, as will be discussed in chapter 4, the handling of stochasticity will differ from the traditional methods.

Chapter 3 Development of Modelling Approach

The focus of this work is the development of a procedure which will be used in identifying optimal operating policies for a multipurpose reservoir. It should be indicated that the optimal operating policy for a reservoir varies with hydrologic conditions and hydrologically dependent demands, i.e., the policy is conditional. On the other hand, since these hydrological variables are not able to be perfectly forecasted, and they will not precisely re-appear, a "perfectly accurate" policy which is derived based on a specific year's conditions is of limited use. What is required is a policy which will be specific to a certain category of hydrological conditions. In this work, hydrological conditions are classified into three classes: wet, average, and dry. For each of them, a corresponding policy is developed or in other words, a conditional policy is obtained.

The procedure includes three steps, as shown in Figure 3.1:

1. Optimal Policy Generation. Optimization models are formulated and solved. Different models emphasize different aspects of the reservoir management problem. Since it is not able to foresee the relative advantages and disadvantages of the model formulations before they are actually solved and the resulted operating policies are subsequently evaluated, we generate the models first, then evaluate the policies, and finally select one policy for implementation.

2. Optimal Policy Evaluation. The measure of a policy is whether or not it allows the reservoir to perform well. The performance of a reservoir, when following a given operating policy, can be determined by simulation models. The generated optimal policies identified in the first step are therefore evaluated in this step. The criteria of evaluation are risk, resilience, and vulnerability of the reservoir system.

Risk is a measure of the probability that a reservoir system is in a failure state. Here we

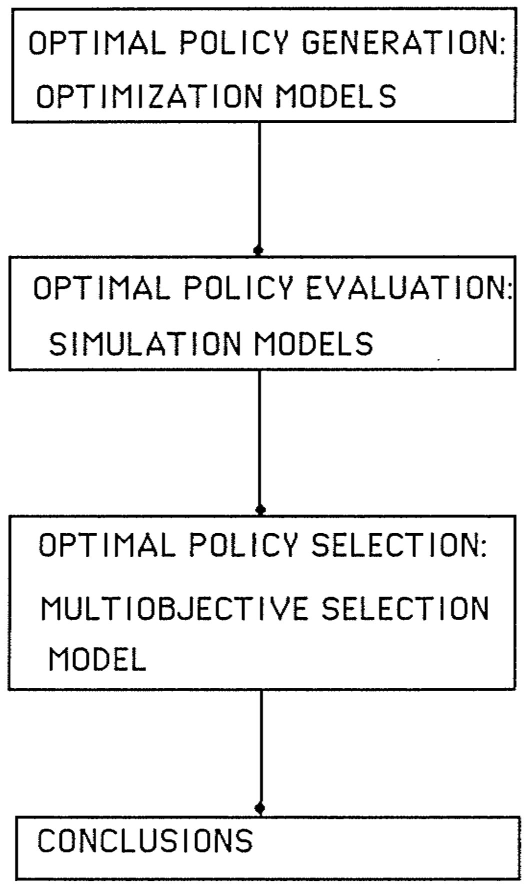


Fig. 3.1 The Procedure of the Methodology

a failure is defined as a state when the reservoir does not meet one or more of its goals (such as contracted water supply or preferred storage level). This index will be a description of how frequently a reservoir will not perform successfully. Resilience measures the ability of a reservoir system to recover from a failure. Since it is not expect that the reservoir always is in a satisfactory state, it is hoped that it is able to recover from the failures easily. Vulnerability describes the severity of the consequences of a failure. With these three indices, it is possible to characterize the reservoir performance in terms of the frequency, duration, and severity of failures.

3. Optimal Policy Selection. Generally, none of the policies is expected to dominate all other policies in terms of all of the objectives. For identifying the most suitable policy among non-dominated options for a given reservoir, multiobjective selection techniques are invoked. Two of the techniques commonly used for discrete problems of this type are the Electre technique and Compromise Programming.

The Electre technique is recursive. With the given judgement criteria, a set of non-dominated options, or so called "cores", are screened out. Then, given more refined criteria, a smaller group of cores are generated from the previous cores. This procedure is continued until the best option is screened out.

The Compromise Programming technique is a one-step ranking procedure. Instead of only screening out the best single option, it ranks all of the options according to a given evaluation measure. The evaluation measure is a function of the values of the various model objectives. It reflects the deviation from the ideal status of each objective. There are two parameters included in the evaluation measure. One is a weight which reflects the importance of a given objective while the other is an exponent which reflects the importance of the degree of deviation from the ideal status. In this work, a variation of the Compromise Programming technique is used.

3.1 Optimization Modelling

Generally, in a given solution space (limited by constraints), if there are a finite number of feasible solutions to a given objective function, (i.e., solutions which do not violate any constraints), one or more solutions can be found among the options at which the objective function will obtain its optimal value. In many cases, these are the solutions to the problem at hand that must be identified. The techniques and procedures for searching for these solutions are collectively termed optimization.

Typically, an optimization model has the form of

$$\text{Max } F(\mathbf{X}) \tag{3.1}$$

Subject to

$$\mathbf{A}^T\mathbf{X} \geq \mathbf{B} \tag{3.2}$$

$$\mathbf{X} \geq 0 \tag{3.3}$$

where

F(**X**) is the objective function;

X is the control variable vector;

A is a parameter matrix; and

B is a parameter vector.

The formulae (3.2) and (3.3) are constraints.

The reservoir management problem can be formulated as an optimization model. The essential goal of the operation of a multipurpose reservoir is to satisfy as many of the users' demands as possible, while ensuring reservoir (dam) safety and meeting other limits such as engineering, societal, and environmental considerations, that may be of concern. If the satisfaction of users' demands is formulated as the objective function, and reservoir safety and other limits on reservoir operation are incorporated into the constraints, then the optimization model can be used to determine an operating policy to approach this essential goal. The solution of the optimization model is an optimal policy.

The reservoir operating problem has two decision variables, the storage level and the release. Generally, either of these can be chosen as the primary decision variable. If the release is the primary decision variable, the policy is a release trace; if storage level is the primary decision variable, the policy is a trace of the storage levels. Conventionally, reservoir operators choose the storage level as the decision variable because it makes it easier to ensure the dam's safety. In the remainder of this thesis, an operating policy will automatically mean the trace of storage levels unless indicated otherwise.

In this work, optimization models are developed to generate optimal reservoir operating policies. In an optimization model, goals are formulated as the objective function, while constraints, which express the limitation on solving the objective function, define the feasible solution space. By emphasizing different purposes, different objective functions or constraint sets can be built, which would then give rise to different optimization models. The solutions resulting from the models will reflect the different concerns built into the models and will be oriented towards those concerns.

In this thesis, two types of optimization models are developed. The first type of model, the Maximize Release Model (MAXR), emphasizes downstream water supply demands, while the second type of model, the Minimize Storage and Release Deviation Model (MINSR), is a Goal Programming model and places greater emphasis on meeting reservoir storage level targets. The general form of the MAXR model is

$$\text{Max } \Sigma_{i,j} \text{ release}$$

Subject to

maintain dam safety

eliminate flooding

meet releases demands

maintain storage level higher than dead storage level

while the general form of MINSR model is

$$\text{Min } \Sigma_n \Sigma_{i,j} \text{ deviation from storage and release goals}$$

Subject to

same as above

definitions of storage and release deviations

in which

i and j denote the month and year; and

n is the number of goals.

The details of these models will be discussed in Chapter 4.

3.2 Simulation Evaluation

For selecting the most suitable policy generated by the different models, it is needed to evaluate them according to relevant criteria. For this purpose, simulation is the technique which is most frequently invoked because it is the best way to display the performance of a system in detail under various operating conditions. In this work, two simulation models were developed. One is a monthly model which examines the reservoir's monthly performance, following a particular operating policy, in terms of risk, resiliency, and vulnerability. The other one is a daily model which examines the details of a policy's flood protection function.

An operating policy is a guideline for reservoir operation. The simulation models display the results when the reservoir is under this guideline. If the policy cannot be exactly executed in some time periods (this happens when the hydrologic conditions are too different from those under which the policy was derived), or if the policy is not reasonable, the reservoir should be operated by certain contingent rules. These rules should be reflected in the simulation process. The specific rules used herein can be summarized as:

1. the basic water demands (municipal and industrial demands, irrigation) should be met if possible; and
2. during summer, the storage target for recreation has a higher priority than the cooling water withdrawal and water quality control demands.

3.3 Multiobjective Selection

Usually one optimal policy is not able to dominate all others in all concerned objectives. In one objective, some policies may have advantages over others; but in other objectives, the situation may be reversed. In such a situation, the multiple objective decision techniques are necessary. The general concept of any multiobjective selection method is to mix or combine non-dominated objectives into one parameter and then select the policies which have the best parameter value. In this work, the objectives are water supply, flooding control, and storage targets. All the deviations of each objectives are expressed in terms of the magnitude and the number of the occurrences of them. A method called "Discrete Compromise Programming", which will be described in detail in Chapter 6, is developed for multiobjective selection. The main idea of this method is to discretize the deviations into several classes, use conventional Compromise Programming for each of the classes, and finally summarize the results of each classes together. The deviations located in each class give the magnitude and distribution of the deviations.

Chapter 4. Application - Shellmouth Reservoir's Study

4.1. The Shellmouth Reservoir

The Shellmouth reservoir is located in Southwest Manitoba, 18 km north of the Russell, Manitoba (see Figure 4.1). The Assiniboine River and the Shell River flow into Reservoir. Its drainage area is 17,801 km^2; its full supply level is 429.42 m, and its storage at this level is 477.36 x 10^6 m^3, conduit invert elevation is 417.32 m, with corresponding storage (dead storage) of 12.33 x 10^6 m^3. The maximum capacity of gate-controlled outlet is 198.1 m^3/s. The reservoir is about 1.28 km wide and 56.5 km long and at its full supply level, the flood area is 61.5 km^2. Downstream channel capacity in the vicinity of the Shellmouth Dam is 42.45 - 50.94 m^3/s.

The Shellmouth Dam, built in 1969 - 1971, was initially designed for flood control. After it was built, some water usage purposes were added. Now the reservoir is required to satisfy following demands:

a. municipal water supply for the Cities of Portage La Prairie and Brandon, Manitoba;
b. irrigation and farm water supply for users downstream of the reservoir on the Assiniboine River;
c. dilution of the waste effluent from the Cities of Portage La Prairie, Brandon, and Winnipeg, Manitoba;
d. dilution of the heated effluent and wastewater effluent from Manitoba Hydro's thermal generating plant located in Brandon, Manitoba;
e. Maintenance of a sport fishery in the Shellmouth reservoir and in the downstream reaches of the Assiniboine River;
f. dilution of industrial waste effluent from various facilities;
g. water supply source for industrial processes and food processing at various locations; and
h. recreation.

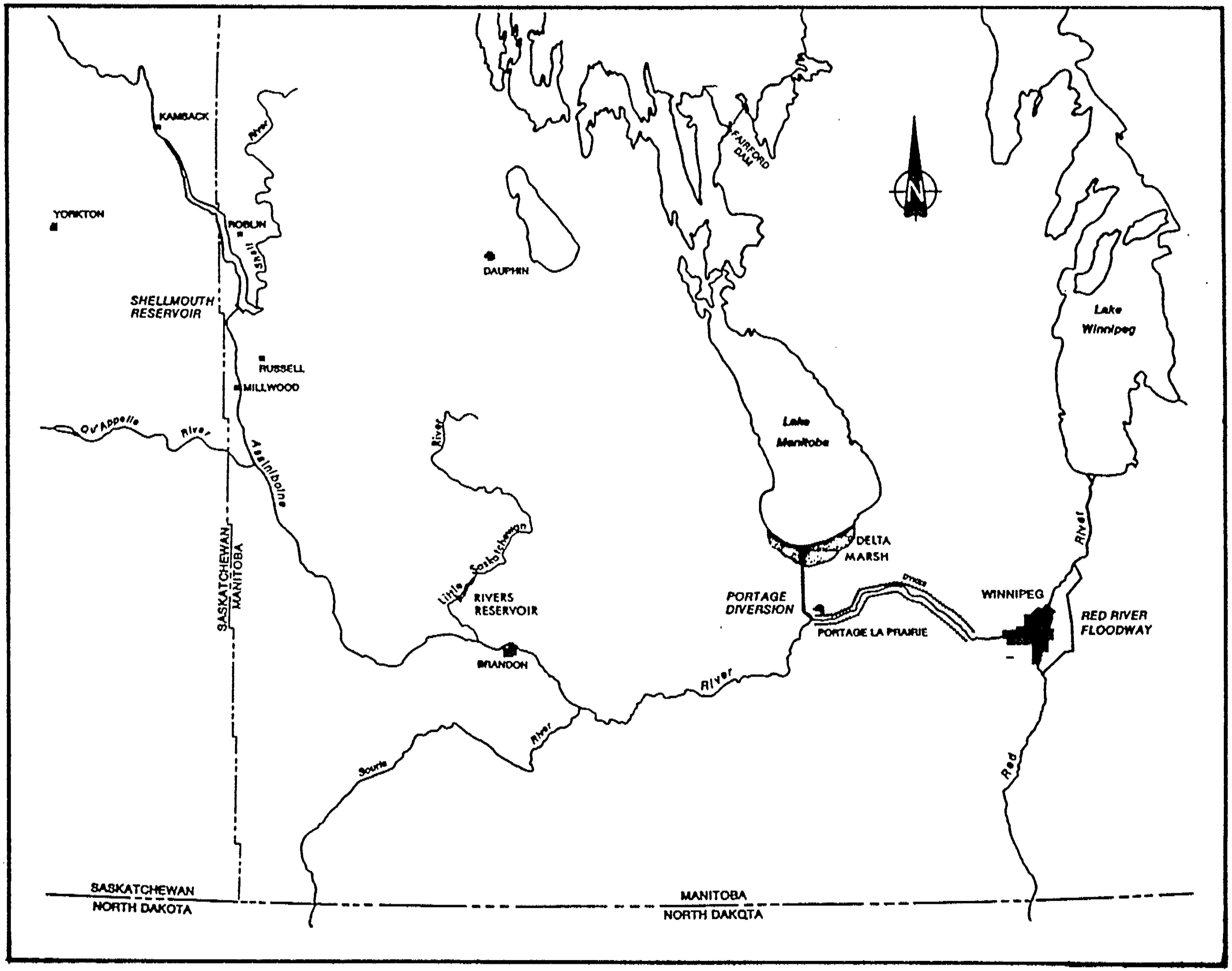


Fig. 4.1 Location map

Usually, these demands cannot be entirely satisfied at same time. For example, during summer, reservoir manager hopes to have a higher storage level for lake recreation purposes, while downstream users (eg., farmers) want more water for their purposes too; during dry years, thermal power generation plant at Brandon operates more since other hydro-electrical plants may have less water to work. That produces more thermal sewage eject and need more fresh water released from reservoir to dilute it. This increases the water supply load of the reservoir. The purpose of the optimization models developed in this thesis is to identify an optimal policy which enables the Shellmouth Reservoir to best fulfil its varied and conflicting tasks.

4.2. Mathematical Formulation

Two linear programming models, as essentially discussed in Chapter 3, are developed for Shellmouth reservoir's case. But before presenting detail discussions of the models, some of the basic and common constraints are discussed and formulated first.

A reservoir releases water from its effective pool (active pool plus flooding control pool) as shown in Figure 4.2. The active pool is above the dead pool which is usually under the elevation of outlet. At any level lower than this elevation no water can be released unless it is pumped. The flooding control pool can be up to either top elevation of dam or the bottom elevation of spillway. Water levels higher than this upbound result in a great risk collapsing the dam. Denoting these lower and upper bounds on storage level by SL_{min} and SL_{max} respectively, results in

$$SL_{min} \le SL \le SL_{max} \qquad (4.1')$$

or

$$S_{min} \le S \le S_{max} \qquad (4.1)$$

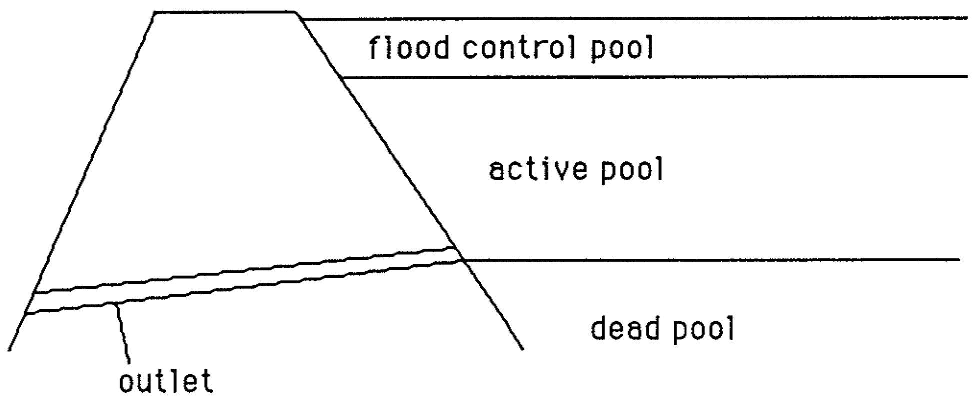


Fig. 4.2 Operating Zones of A Reservoir

where

SL is storage level at any time;

S is the expression of SL in storage volume; and

S_{min} and S_{max} are the translated expressions in storage volume of SL_{min} and SL_{max}, respectively.

To avoid flooding in the downstream vicinity of the dam, the release from reservoir should not be greater than the full channel discharge capacity, otherwise flood occurs. This limit could be taken as the upper bound of release, denoted by R_{max}. On the other hand, for some environmental reasons a minimum release should be kept in the channel all the time. Denoting this minimum value as R_{min}, results in

$$R_{min} \leq R \leq R_{max} \qquad (4.2)$$

where R is the release from reservoir.

Another constraint always being imposed to a management problem is

$$S_{ini} = S_{end} \qquad (4.3)$$

where S_{ini} is the starting storage of the whole operating period while S_{end} is the ending storage of that period. Setting this constraint protects the reservoir from emptying at the end of the operating period. If there is no such limit, the water storage in the reservoir could be totally exhausted at the end of this operation period because all of the water could be used for the demands in that period.

A basic relation which should be obeyed if one is dealing with a reservoir system problem is the continuity function

$$S_{j,i+1} = S_{j,i} + I_{j,i} - Ev_{j,i} - R_{j,i} \qquad (4.4)$$

where

$S_{j,i+1}$ is the ending storage of time period i in year j;

$S_{j,i}$ is the initial storage of time period i in year j; and

$I_{j,i}$, $Ev_{j,i}$, and $R_{j,i}$ are inflow, evaporation, and release during time period i in year j, respectively.

The decision variable S could be single or double dimensional variable. If S is a one dimensional variable, i.e., if the storage is only allowed to change from month to month, but the storage for each month is fixed from year to year, the obtained policy will be suitable for all kind of years (or all kinds of hydrological conditions). In such cases the storage levels identical over years is a very restrictive constraint, and consequently such a policy might not exist. Moreover, if such a policy does exist, it is of limited utility since the hydrological conditions could vary greatly from those used to devise the policy. In other words, this policy is too general to be useful.

If S is a two dimensional variable, i.e., if S is allowed to change from month to month and from year to year, then what is obtained is a group of policies which have a specific policy for each year of record accounted for in the models. Because these hydrological conditions will never repeat again, there is no specific policy for a coming new year since the new conditions are different from past results. In this case, the resulting policy is too specific.

The goal in such analyses is the policy which is neither too specialized nor too generalized. A compromise is to classify each year (hydrological conditions) into one of several kinds of hydrological conditions and to seek policies for each of these kinds.

In this work, all historic records are classified into three kinds, namely wet, average, and dry, mainly according to the inflows during April through August. For the resulting operation policies, storage for all years which are "wet" would be same, and say the same thing for average years, so on. Therefore, there are some additional constraints:

$$S_{j,i} = S_{k,i} \qquad j,k \text{ are wet years;} \qquad (4.5)$$

$$S_{l,i} = S_{n,i} \qquad l,n \text{ are average years} \qquad (4.6)$$

$$S_{m,i} = S_{g,i} \qquad m,g \text{ are dry years} \qquad (4.7)$$

Besides constraint Equations 4.1 - 4.7, there are others varying in different models. They will be formulated later.

Next, three optimization models are developed. One is called Maximize Release model, or MAXR model, the rest are called Minimize Deviations of Storage and Release model version A, or MINSRA model, and Minimize Deviations of Storage and Release model version B, or MINSRB model. All of them are linear and deterministic type.

Model 1: Maximum Release Model (MAXR)

In the MAXR model, the main objective is to satisfy downstream demands while maintaining dam safety and eliminating flooding. No direct consideration on summer storage targets is expressed in the model.

Based on a simple assumption that more release results in higher downstream benefits providing no flood occurs, it can be rationally expect that the release should be as large as possible. Thus the objective function is

$$\text{Max} \sum R_{j,i} \qquad (4.8)$$

The variables are as defined before.

To take account of the demands and tributaries along the Assiniboine River after the

Shellmouth Dam, the whole channel from Shellmouth to City of Winnipeg is divided into three reaches in this work. The first reach is from the Shellmouth Dam to Brandon, the second is from Brandon to Portage La Prairies, and the last is from Portage La Prairies to the City of Winnipeg. All water supply demands and tributary inflows are summarized respectively in three reaches and abstracted into three representative points as shown in Figure 4.3

It is assumed that tributaries in each reach come into main channel at the endpoint of each reach so that they only contribute to the water supply of succeeding reach.

Denoting

TRI1, TRI2 and TRI3 as the flow volumes of the tributaries of reach 1, reach 2, and reach 3, respectively;

WM1, WM2, and WM3 as the municipal and industrial demands of reach 1, 2, and 3, respectively;

WI1,WI2, and WI3 as the irrigation demands of reach 1, 2, and 3, respectively;

WQ1 as the net cooling water withdrawal at Brandan, subtracting the contribution from runoff;

WQ3 as the demand of water quality control for City of Winnipeg;

R1, R2, and R3 as the releases for reach 1, 2, and 3, respectively; and

R as the total release from the reservoir.

The first set of constraints are:

$$R1_{j,i} \geq WM1_i + WI1_i + WQ1_{j,i} \qquad (4.9)$$

$$R2_{j,i} \geq WM2_i + WI2_i - TRI1_{j,i} \qquad (4.10)$$

$$R3_{j,i} \geq WQ3_i - TRI2_{j,i} \qquad (4.11)$$

$$R_{j,i} = R1_{j,i} + R2_{j,i} + R3_{j,i} \qquad (4.12)$$

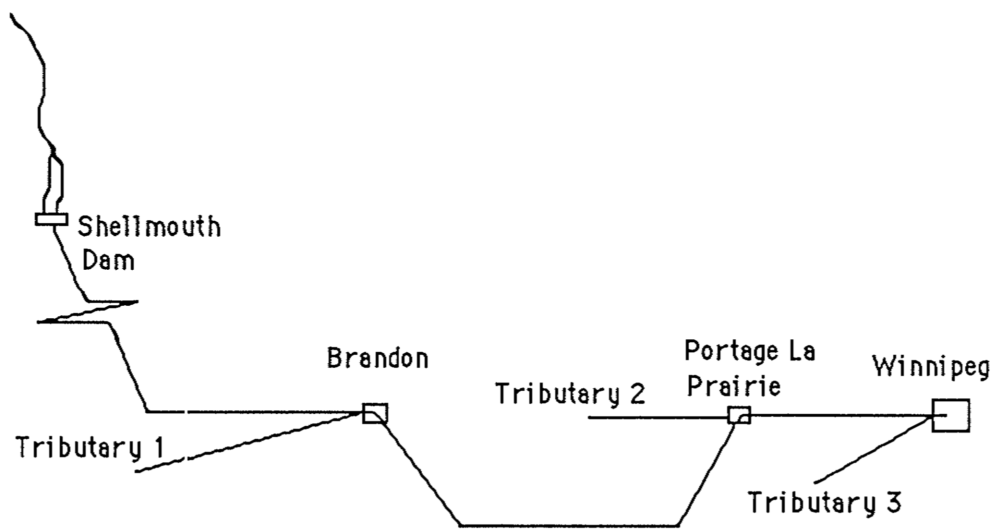


Figure 4.3 Division of Assinibone River

The cooling water withdrawal of the thermal power plant at Brandon is a special demand. Certainly TRI1 can be used for this purpose, and since the cooling system of the thermal power plant ejects all withdrawn water after it is used, it is reasonable to assume that from the point of view of second reaches' demands, the plant (almost) does not consume the water quantity. Therefore, the water coming from tributaries of reach 1 that is available for reach 2 is still TRI1. Since each tributary flow is only available for a succeeding reach's demands, TRI1 and TRI2 only appear in the formula of R2 and R3 respectively and TRI3 does not appear. Obviously this leads to a conservative result. But since demands along the Assiniboine River aggregated mainly in 1st and 2nd reach, the effects of this conservative assumption should not be significant. The rest of constraints include those defined by Equations (4.1) through (4.7).

The entire MAXR model is as below:

$$\text{Max} \sum R_{j,i}$$

subject to

$$R1_{j,i} \geq WM1_i + WI1_i + WQ1_{j,i}$$

$$R2_{j,i} \geq WM2_i + WI2_i - TRI1_{j,i}$$

$$R3_{j,i} \geq WQ3_i - TRI2_{j,i}$$

$$R_{j,i} = R1_{j,i} + R2_{j,i} + R3_{j,i}$$

$$S_{min} \leq S_{j,i} \leq S_{max}$$

$$R_{min} \leq R \leq R_{max}$$

$$S_{ini} = S_{end}$$

$$S_{j,i+1} = S_{j,i} + I_{j,i} - Ev_{j,i} - R_{j,i}$$

$$S_{h,i} = S_{k,i} \qquad \text{h,k are wet years;}$$

$$S_{l,i} = S_{n,i} \qquad \text{l,n are average years}$$

$$S_{m,i} = S_{g,i} \qquad \text{m,g are dry years}$$

$$R1_{j,i},\ R2_{j,i},\ R3_{j,i},\ R_{j,i}\ ,\ S_{j,i} \geq 0$$

where the storage is the ending storage of each time period.

An obvious argument is that the MAXR model "wastes water" because it does not save spared water in storage. It is not always true. Suppose the total monthly volume of downstream water demands is much smaller than that of the active pool, MAXR will waste some water because extras water beyond the demands could have been used to raise the storage level when the reservoir has more capacity to accept this water. But if two volumes are close enough, when the reservoir has stored water for downstream demands, the active pool could be mostly occupied. Therefore, it does not have much more volume for additional water. Instead, the additional water should be released to lower down the storage level for the safety of the dam since the full active pool might result in a very high storage level. In this case, there is no significant waste at all.

The MAXR model will answer the question, if all of the water supply demands must be met, what will the reservoir operating policy look like?

Model 2: Goal Programming (GP) Model : Minimize Storage and Release Deviations Model, Version A (MINSRA)

MAXR model emphasizes water supply, but water supply is not the sole purpose for the Shellmouth reservoir. The Shellmouth Reservoir should also have a storage level at a preferred high level during summer. To be successful in this task, the storage targets should be explicitly incorporated in the objective function. That means, besides the release target, there is storage level target.

For incorporating targets on decision variables, Goal Programming (GP) is effective. The basic form of a (GP) model is

$$\text{Min} \sum_t \sum_m (A_m\text{*deviations from target m})$$

subject to

Definitions of deviations;

Other constraints.

where

A_m are weight parameters;

m denotes the number of goals; and

t denotes time.

For the Shellmouth Reservoir, the preferred storage target is a range instead of one fixed value. The range is bounded by an upper level STH1 and a lower level STH2. It is hoped that the storage level could be kept in this range. The storage targets are only active in summer while the release target lasts whole year.

Define

surplus deviation from storage target (preferred range) as

$$SU_{j,i} \geq S_{j,i} - STH1 \quad (4.13)$$

$$SU_{j,i} \geq 0 \quad (4.14)$$

deficit deviation from storage target (preferred range) as

$$SL_{j,i} \geq STH2 - S_{j,i} \quad (4.15)$$

$$SL_{j,i} \geq 0 \quad (4.16)$$

where SU and SL are deficit and surplus deviations from the storage target, respectively.

When $S_{j,i}$ is higher than STH1, $SU_{j,i}$ positive while $SL_{j,i}$ is 0 (STH2 - $S_{j,i}$ is negative but, constrained by $SL_{j,i} \geq 0$, the $SL_{j,i}$ is 0), vice versa. When $S_{j,i}$ is in the preferred range, both $SU_{j,i}$ and $SL_{j,i}$ are 0.

Similarly, there are the definitions of deviations from release targets:

deficit deviations from release targets are

$$FL1_{j,i} \geq (WM1_i + WI1_i + WQ1_{j,i}) - R1_{j,i} \qquad \text{in reach 1} \qquad (4.17)$$

$$FL2_{j,i} \geq (WM2_i + WI2_i - TRI1_{j,i}) - R2_{j,i} \qquad \text{in reach 2} \qquad (4.18)$$

$$FL3_{j,i} \geq (WQ3_{j,i} - TRI2_{j,i}) - R1_{j,i} \qquad \text{in reach 3} \qquad (4.19)$$

$$FL_{j,i} = FL1_{j,i} + FL2_{j,i} + FL3_{j,i} \qquad (4.20)$$

$$FL1_{j,i},\ FL2_{j,i},\ FL3_{j,i} \geq 0 \qquad (4.21)$$

where $FL1_{j,i}$, $FL2_{j,i}$, $FL3_{j,i}$, and $FL_{j,i}$ are the deficit deviations from the release targets of reach 1, 2, 3, and entire river, respectively.

From the water supply demands (see Table 4.1), it can be observed that cooling water withdrawal is the largest demand for water from the reservoir. In comparison with it, municipal, industrial, and irrigation demands are insignificant terms. In terms of importance, municipal, industrial, and irrigation demands can be considered basic. Considering this, the entire demands are divided into two kinds: basic demands and target demands. Basic demands are those which must be met at first priority and guaranteed by constraints of

$$R_k \geq \text{basic demands}, \quad k = 1, 2, 3 \qquad (4.22)$$

where k denotes the reaches. In reach 1, the basic demands are WM and WI. The target demands are those which the reservoir may not be able to meet all the time but it is desired to meet in as many time intervals as possible. In reach 1, it is the sum of WM1 plus WI1 plus WQ1. Therefore, a new set of constraints on release in reach 1 is

Table 4.1 Water supply demands (unit: 10^3 m^3)

	M and I* reach 1	Irri.** reach 1	M and I* reach 2	Irri.** reach 2	Cool# for w/a. yrs	Cool# for dry yrs	dilution for Winnipeg
Jan.	881.35	0.0	1145.39	0.0	11156.4	14875.2	7437.6
Feb.	933.42	0.0	1123.08	0.0	14875.2	14875.2	7437.6
Mar.	933.42	0.0	1145.39	0.0	11156.4	14875.2	7437.6
Apr.	963.17	0.0	1145.39	0.0	0.0	14875.2	7437.6
May	1097.05	81.81	1249.5	3205.6	0.0	7437.6	7437.6
Jun.	1521.00	238.04	1204.9	6277.3	0.0	7437.6	7437.6
Jul.	1201.17	788.39	1160.3	6277.3	0.0	7437.6	7437.6
Aug.	1201.17	394.19	1160.3	6277.3	0.0	7437.6	7437.6
Sept.	1015.23	81.81	1190.0	3205.6	0.0	7437.6	7437.6
Oct.	933.42	0.0	1197.5	2975.0	0.0	7437.6	7437.6
Nov.	903.67	0.0	1137.95	0.0	11156.4	14875.2	7437.6
Dec.	881.35	0.0	1093.32	0.0	11156.4	14875.2	7437.6

* M and I: municipal and industrial

** Irri. : irrigation

Cool : Cooling withdrawal

$$R1_{j,i} \geq WM1_i + WI1_i \tag{4.23}$$

$$FL1_{j,i} \geq (WM1_i + WI1_i + WQ1_{j,i}) - R1_{j,i} \tag{4.24}$$

$$FL1_{j,i} \geq 0 \tag{4.25}$$

In reach 2 and 3, since the demands are much smaller than WQ1, there is no need to divide them further, i.e., the basic demands are equal to target's. So the FL2 and FL3 are redundant and can be eliminated.

The definitions of excess flow deviations are similar. But it will not be incorporated in the model. As long as no downstream flooding occurs, releases higher than the target are acceptable.

Then the objective is simply formulated as

$$\text{Min Dev} = \text{Min } \Sigma_{j,i} (SU_{j,i} + SL_{j,i}) \text{ in summer}$$
$$+ \text{Min } \Sigma_{j,i} FL1_{j,i} \tag{4.26}$$

Combining this new objective function and definitions with the constraints described in MAXR model results in a GP model as below:

$$\text{Min Dev} = \text{Min} \sum_{j,i} (SU_{j,i} + SL_{j,i}) \text{ in summer}$$
$$+ \text{Min} \sum_{j,i} FL1_{j,i}$$

subject to

$$SU_{j,i} \geq S_{j,i} - STH1$$
$$SL_{j,i} \geq STH2 - S_{j,i}$$
$$FL1_{j,i} \geq (WM1_i + WI1_i + WQ1_{j,i}) - R1_{j,i}$$
$$R1_{j,i} \geq WM1_i + WI1_i$$
$$R2_{j,i} \geq WM2_i + WI2_i - TRI1_{j,i}$$
$$R3_{j,i} \geq WQ3_i - TRI2_{j,i}$$
$$R_{j,i} = R1_{j,i} + R2_{j,i} + R3_{j,i}$$
$$S_{min} \leq S_{j,i} \leq S_{max}$$
$$R_{min} \leq R_{j,i} \leq R_{max}$$
$$S_{ini} = S_{end}$$
$$S_{j,i+1} = S_{j,i} + I_{j,i} - Ev_{j,i} - R_{j,i}$$
$$S_{h,i} = S_{k,i}, \qquad h,k \text{ are wet years;}$$
$$S_{l,i} = S_{n,i}, \qquad l,n \text{ are average years;}$$
$$S_{m,i} = S_{g,i}, \qquad m,g \text{ are dry years}$$
$$FL1_{j,i},\ SU_{j,i},\ SL_{j,i} \geq 0$$
$$R1_{j,i},\ R2_{j,i},\ R3_{j,i},\ R_{j,i} \geq 0$$
$$S_{j,i} \geq 0$$

All of the symbols are as defined before.

GP has the advantage of considering multiple targets, and considering targets according to the priorities assigned to targets (by weights in this case). In this model, each of the variables are weighted equally. During the non-summer months, there is no storage target. Therefore the sole target is water supply, and the water supply demands in different months of the non-summer seasons are considered equal (there is no reason to think that the water supply of for example, November, is more important than that of December). During the summer months, the storage target should have higher priority in comparison with water supply. Since the magnitude of the storage variable S is generally about one order larger than that of release variable R, the objective function automatically assigns a higher weight to S so that the storage concern obtains higher priority.

Model 3: Goal Programming (GP) Model : Minimize Storage and Release Deviation Model, Version B (MINSRB)

The MINSRB model is a variation of MINSRA model. In the MINSRA model, the storage level targets are effective only in summer months; in the MINSRB model, the storage level targets are extended to whole year. The storage targets for the summer are same as in the MINSRA model; the target for all non-summer month is chosen as 200 million m^3 (423.83 m high), which is the target for March 31, the start date of the flooding season, chosen by the reservoir's operator. Since the storage targets are set equally for each hydrologic scenario, if the policies corresponding to each scenarios could be sufficiently close to the target levels, it is possible to obtain a generic policy which is suitable for all kinds of hydrologic patterns. This is the motivation for the MINSRB model.

To generate this new model, it is only necessary to prolong the effective time period of storage targets:

$$\text{Min Dev} = \text{Min}\ [\Sigma_{j,i}\ (SU_{j,i} + SL_{j,i}) + \Sigma_{j,i}\ FL1_{j,i}] \qquad (4.27)$$

and the constraints are the same as those for the MINSRA model.

4.3 Solutions of the Models

All of the three models (MAXR, MINSRA, and MINSRB) are deterministic models. The time interval of the models is month. For solving the models, two kinds of input data are needed. They are hydrologic data (inflow, evaporation) and demand data.

4.3.1 Hydrologic Data Arrangement

Monthly evaporation data

The Water Resources Branch of the Natural Resources of Manitoba provided 68 years evaporation data (1921 - 1988). The lake evaporation has been derived from two evaporation gauging stations, Yorkton and Dauphin. The average value of these two stations' records were used as the evaporation estimate.

Monthly inflow data

The inflow data are used and prepared for two purposes: identifying three kinds of hydrologic years (wet, average, and dry) for the optimization models, and arranging an input series (mainly for evaluation) for the simulation model.

There are more than 30 inflow gauging stations on the Assiniboine River and its tributaries, upperstream and downstream of the Shellmouth Dam. Table 4.2 shows all of these stations. Considering the record length, the length of the river the stations monitor, and the geographic location (a downstream station is preferred if there is more than one station on same tributary) of the stations, 18 stations were selected (these stations are marked with * in Table 4.2). The remaining stations either have too short records, only gauge a small segment of the stream, or are covered by a more downstream station.

Above the Shellmouth Dam, in addition to the tributaries contributing to the reservoir inflow, the local surface run inflow is also of significant. Comparing the total inflow value from stations MD004, MD005, and MD007 which control a very large percentage of the tributaries to the reservoir, and the inflow value of station ME001 which is immediately downstream of the Shellmouth Dam, the difference in inflow value can be obtained. This difference is attributable to local inflow. To re-generate local inflow, monthly regression

Table 4.2 The Gauging Stations Connected

	Station No.	River and Location
Above the Shellmouth Dam:		
	05MD004*	Assiniboine at Kamsack
	05MD005*	Shell near Inglis
	05MD007*	Shell near Roblin
	05MD010	Stony near Kamsack
Below the Shellmouth Dam:		
	05JM003	Qu' Appelle at Tantallon
	05JM013*	Qu' Appelle at Hyde
	05JM015*	Caterm near Spy Hill
	05LL019	Portage Diversion
	05ME001*	Assiniboine near Russell
	05ME003*	Birdtail Creek Birtle
	05ME005*	Conjuring Creek near Russell
	05ME006	Assiniboine near Miniota
	05ME008*	Minnewasta Creek near Beulah
	05ME009*	Scissor Creek near Kellde
	05MF001	Little Saska near Minnesoda
	05MF018*	Little Saska near Rivers
	05MG001*	Arrow near Arrow
	05MG003*	Gopher Creek near Virden
	05MG004*	Dak near Rivers
	05MG006*	Kenton Creek at Kenton
	05MH001	Willow at Brandon

Table 4.2 The Gauging Stations Connected (continued)

Station No.	River and Location
05MH004*	Cypress near Cypress River
05MH005	Assinoboine near Holland
05MH006*	Little Souris near Brandon
05MH007*	Epinette near Carberry
05MJ001	Assiniboine at Headingley
05MJ003	Assiniboine near Portage La Prairie
05MJ004*	Sturgeon at St. James
05MJ008	Omands near Brookside Cemetery
05MJ010	Truro near Assiniboine Golf course
05NG001*	Souris at Wawanesa
05NG003	Pipestone near Pipestone
05NG007	Plum near souris
05NG010*	Oak Creek near Stockton
05NG012	Elgin near Souris

equations are built. These equations have the form of:

$$LINFE_{ij} = a_i*INF4_{ij} + b_i*INF5_{ij} + d_i \qquad (4.28)$$

where

$LINFE_{ij}$ is estimated local inflow in year j and month i;

$INF4_{ij}$ and $INF5_{ij}$ are the inflows in year j and month i recorded by station MD004, and MD005, respectively;

a_i, b_i, and d_i are regressive parameters associated with $INF4_{ij}$, $INF5_{ij}$, and a constant, respectively;

i denotes the month; i=1,........, 12.

The derivation of the regressive parameters is presented in Appendix A. Given inflow data of station MD004 and MD005, the local inflow values are obtained.

The total inflow discharging into the Shellmouth Reservoir can be obtained by summarizing the local and recorded inflow data.

4.3.2 Users' Demands

All kinds of demands have been mentioned in Section 4.1. Essentially, they are either storage level demands or water supply demands. The former is the demand for the storage level during the summer season. The preferred storage level ranges from 426.83 - 428.35 m high. Summer is from May 01 to August 31. The latter demand includes the water volume demands such as industrial and municipal, irrigation, and cooling withdrawal and water quality control. The Water Resources Branch of the DNR of MB provided all this information (see Table 4.1). Subtracting the downstream tributaries inflow from demands gives the net demands.

4.3.3 Stochasticity Considerations.

A Deterministic model has a simpler model structure compared with stochastical models because it uses known long term data. Theoretically, the entire historical data record could be included in the optimization models. However, this may make the model size too large. In this case, 30 years of data under the MINSR models would result in 3666 variables and 6120 constraints. This is quite a heavy load even for a workstation. To avoid this problem while including enough historical and stochastical information in the input data, a new method is used to arrange the historical data. The method identifies three kinds of hydrologic year, namely wet, average, and dry year. The identification is based on inspection of the historical records of station MD004 and MD005 (from 1957 -1984) for these stations gauge the two largest tributaries to the reservoir. Since MD010 is comparatively much smaller in terms of the inflows, it is ignored. Then, add MD004 and MD005 together, and use the sum inflow values to identify each kind of year. The years in which the sum of the inflow shows a high Spring peak flow are assumed to be wet years; the years in which the sum of the inflow shows a low Spring peak flow are assumed to be dry years; and any year in which the Spring peak flow is neither high nor low is considered to be an average year. The years 1975, 1976, and 1979 were chosen to represent wet years; 1967, 1970, and 1983 represent average years, and 1961, 1963, and 1968 represent dry years. The graphs of inflow values for these years demonstrate the approach used in identifying wet, average, and dry years and are included in Appendix B.

The recorded inflow, evaporation, and tributary discharge for each of these years compose the data set used in the model. Combinations of these years are then compiled to produce scenarios which represent a possible history of record. These scenarios consist of one of the following combinations of wet, dry, and average years:

1. Three wet years followed by three average and three dry years.
2. Three dry years followed by three average and three wet years.

3. Nine years in which the series one dry, one average, and one wet year is repeat three times.

4. Similar to 3, but the series of one wet one average, and one dry year is repeated three times.

There are several merits to the approach taken herein. Firstly, stochastic information can be incorporated since each of the scenarios reflects a possible hydrological pattern. Secondly, the size of the models is kept to a reasonable size. Finally, models are still of deterministic type.

4.4 Optimization Results

Input all the hydrological data and demands data, above three models generate corresponding policies for each of the hydrological scenarios, as shown in Graph 4.4, 4.5, and 4.6.

1. Policies of MAXR Model

Figure 4.4 shows that the storage levels in most of the time periods are high (except for dry years of scenario 1 and 2). That result occurs because the MAXR model is constrained to have releases greater than the total water supply demands so the reservoir has to store enough water. The second phenomenon that can be seen is that the scenario 1 and 2 result in similar policies and so do the scenario 3 and 4. This similarity arises from the similarity of the inflow sequence construction. Scenarios 1 and 2 have more restrictive combinations of hydrological conditions (e.g., 3 wet or dry years come together consequently), while scenarios 3 and 4 present less severe hydrological conditions (wet, average, and dry year come alternatively). This phenomenon can also be seen in Figure 4.5 and 4.6.

The high levels of storage under the MAXR policies are neither good for reservoir safety nor for recreation. In the Figure 4.4, the storage level in most of the summer months is higher than the upper bound of preferred range (333 - 413 million cubic meters). Another

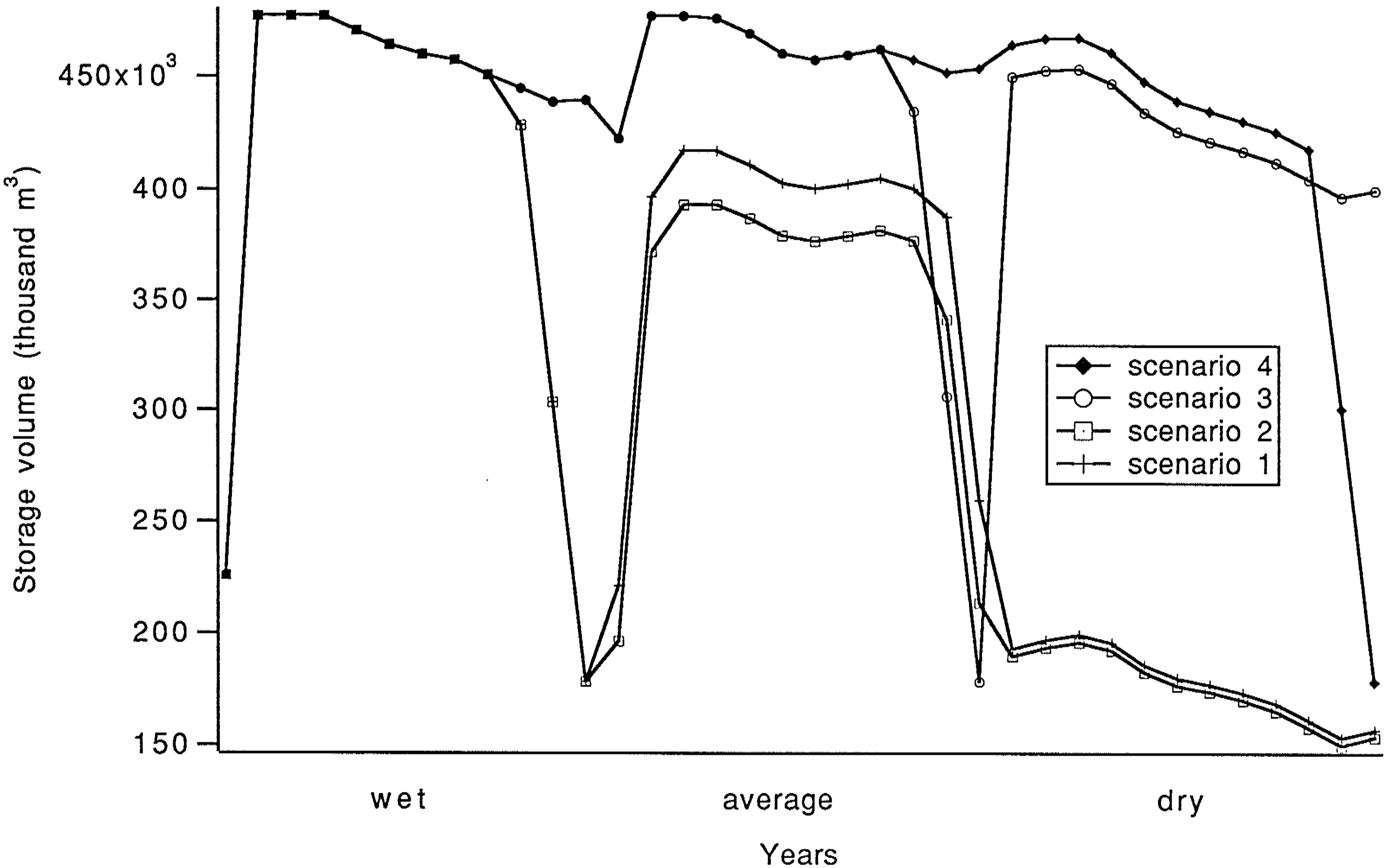


Fig. 4.4 Policy curves of MAXR

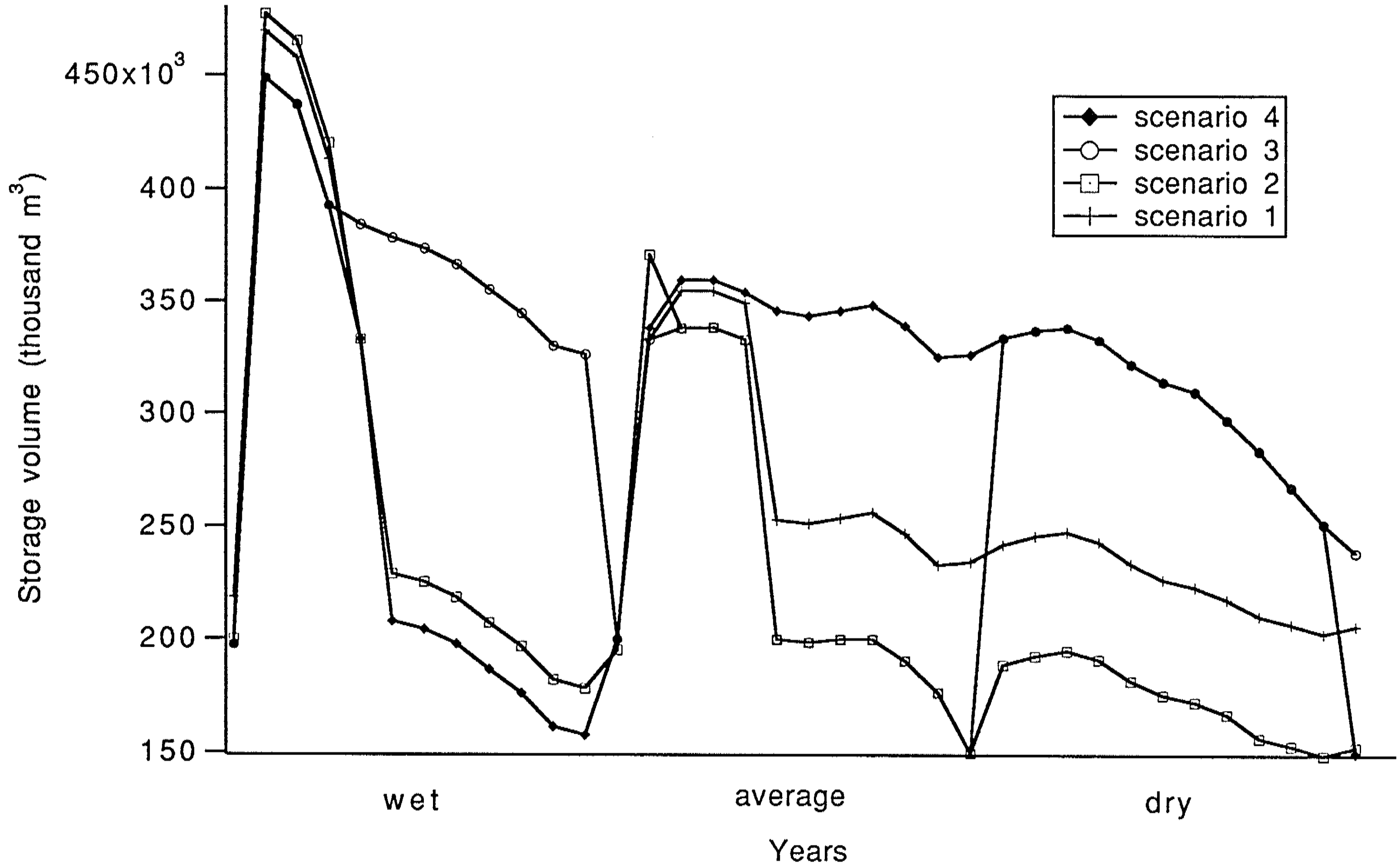


Fig. 4.5 Policy curves of MINSRA

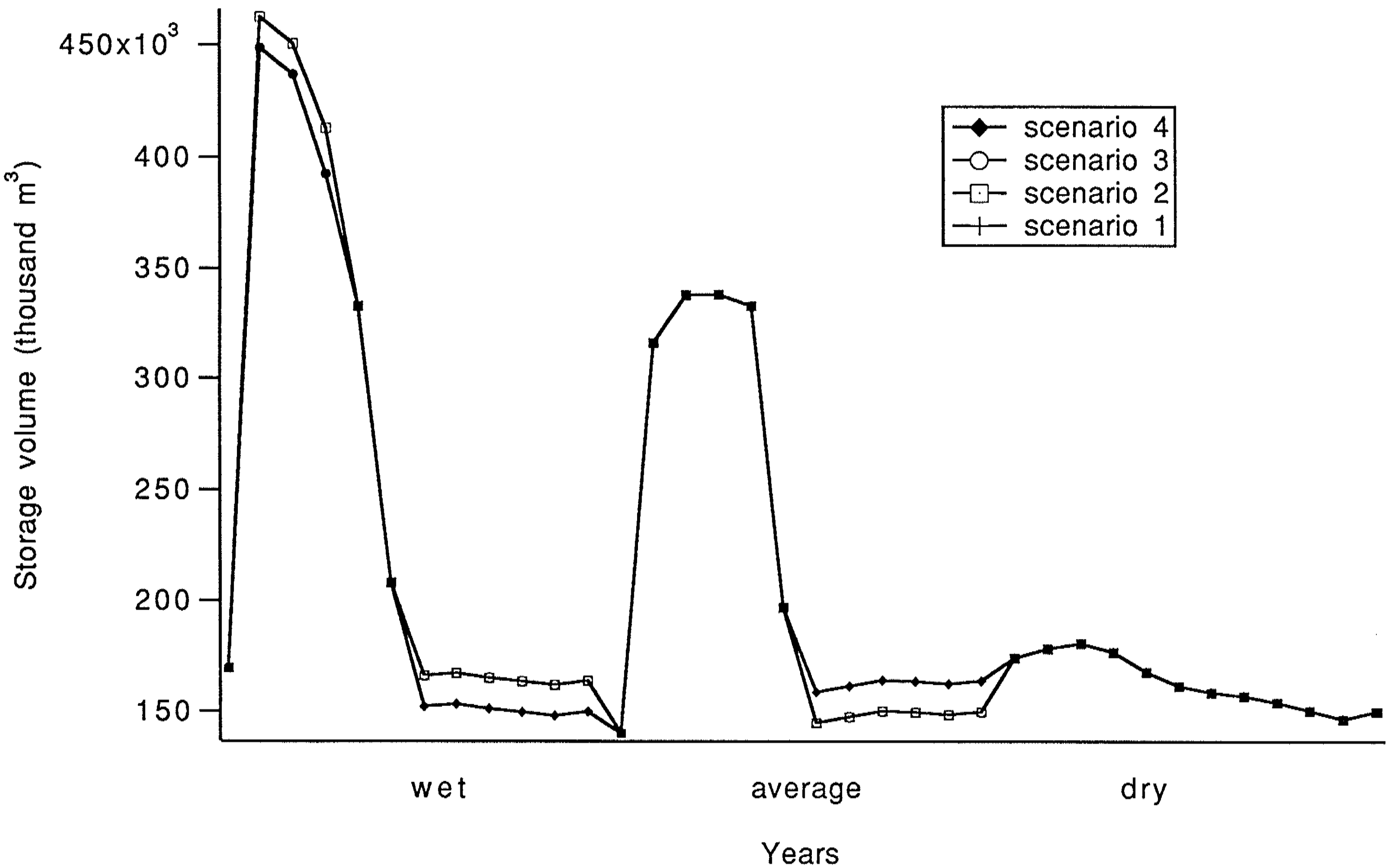


Fig. 4.6 Policy curves of MINSRB

disadvantage of high level policies is the larger evaporation losses since increased storage implies increased reservoir surface area and resulting increased evaporation loss.

2. Policies of MINSRA Model

An apparent characteristic of the MINSRA policies (Fig. 4.5) is the large amplitude of the operating policy trace curves (except for scenario 4). The storage level is high only in summer season. In the rest of the times it is lower. These policies are more reasonable because they only keep the storage level high in the summer season, which satisfies recreation demands, and then release water to downstream users. In scenario 4, the storage level for average years are high through out the whole year because the following year will be dry year, so that the water is stored for next year. The storage level is lowered down before early spring for coming flood season. This decreases the risk of flood and collapse of the dam.

3.Policies of MINSRB Model

The policies for the MINSRB (shown in Figure 4.6) have the very similar characteristics to the policies of MINSRA except for the dry years. It is understandable because the only difference of the two models is that MINSRB model has storage targets for whole year instead of only for the summer. The MINSRB model generates a very good uniformity in the storage level, but obtaining this uniformity sacrifices the benefit for a dry year. Any wetter year has a very limited ability to supply water for a subsequent dry year since the water is released to lower storage level down to the target. That is why dry years always have very lower storage levels. This certainly aggravates the shortage of water supply.

Chapter 5. Evaluation Of Operating Policies

Twelve policies have been generated arising from the combination of three models with four scenarios. Each of the operating policies presents a specific consideration of the objectives (defined by the objective function), the limits on the feasible space (defined by the constraints), and the hydrologic condition (defined by the hydrologic scenario). From the analyses of Section 4.4, some of the characteristics of each of the generated policies could be determined, but these analyses are mainly qualitative. A more clear quantitative analysis is still needed. For this purpose, a set of evaluation criteria must be selected, and then based on these criteria, each of the policies must be evaluated in accordance with the various aspects of the problem (such as water supply, flooding control, and meeting recreational storage targets). The results of this evaluation will form the basis for final policy selection.

5.1 The Criteria of Evaluation

Before discussing the criteria, the definition of a violation should be established. The target or threshold values for the three aspects (i.e., water supply, flooding control, and meeting recreational storage requirement) can be summarized as:

target of water supply:	WM + WI + WQ - TRI;
target of flooding control:	flooding threshold flow;
target of storage (1):	upper bound of preferred storage range for summer season;
target of storage (2):	lower bound of preferred storage range for summer season.

where

WM are municipal and industrial demands;

WI are irrigation demands;

WQ are water quality control (dilution) demands and cooling water withdrawal; and

TRI are the tributary inflows.

Define:

water supply violation (WS) as the deficit of the release relative to the water supply target, or

$$WS = \text{target of water supply - release} \qquad (5.1)$$

flood control violation (FLD) as the excess of the release relative to the flood control target, or

$$FLD = \text{release - flood control target} \qquad (5.2)$$

upper storage target violation (SU) as the excess of the storage level relative to the upper storage target (storage target 1), or

$$SU = \text{storage level - storage target 1} \qquad (5.3)$$

lower storage target violation (SL) as the deficit of the storage level relative to the lower storage target (storage target 2), or

$$SL = \text{storage target 2 - storage level} \qquad (5.4)$$

The units of variables in Equation (5.1) through (5.4) are million m^3. When any violation occurs, the reservoir is in a failure state; otherwise it is in a satisfactory state.

For evaluating a policy, the relevant factors are (1) how frequent a year the violations occur under that policy; (2) how large the violations occur under that policy; and (3) how quick the reservoir recovers from the failures under the selected policy.

In this work three criteria are invoked to address these concerns. The first criterion, Risk, measures the probability or the frequency of the reservoir being in a failure state.

$$\text{Risk} = \frac{\text{number of time periods during which violations occur}}{\text{total number of time periods in record}} \tag{5.5}$$

The second criterion is called Resilience which measures the ability of a system to recover from failures. Resilience will be measured using a modified version of the definition that Burn et al. (1991) used, resulting in:

$$\text{Resilience} = \frac{\text{number of time periods during which violations occur}}{\text{the number of times the reservoir went into failure}} \tag{5.6}$$

The slight difference is, Burn et al. (1991) used inverse value of that used here, i.e., their Resilience is equal to 1/ Resilience of Equation (5.6). The physical information included in both Resiliencies are equivalent.

The last criterion is vulnerability. It is a measure of the severity of violations. The sum of the maximum violations of each failure sojourn forms the definition of this index giving:

$$\text{Vulnerability} = \Sigma_n \text{ maximum violation}_n \tag{5.7}$$

where n denotes the ith failure state.

When compared, the smaller the index values the better. In the ideal situation, no violation would appear. Therefore, all of the criteria have optimal values of zero.

5.2 The Manner of Evaluation

The first step of the evaluation is to identify the violations or failures a policy causes, and then to characterize and evaluate this policy by the violations or failures it causes. For identifying failures, it is necessary to keep track of the performance of a reservoir system which is following the policy being evaluated. Simulation is the most appropriate technique for doing this because it is able to reproduce a system's performance in detail. In this work, two simulation models were developed. A monthly time step simulation model is built as the main evaluation tool. This model calculates the values of the Risk, the Resiliency, and the Vulnerability, and records the violations respectively, in terms of meeting the water supply, the flooding control, and the storage target needs. The second model is a daily time step model which examines the flooding situation in greater detail. The daily model strengthens the evaluation function for the flooding control item of the monthly time step model. This is necessary because the flooding is more a daily issue. In a monthly time step model, daily floods are very likely being hidden by monthly flood control index values. There could be some daily floods in a given month, but on the monthly average level, no flood may appear. To expose the daily floods, a daily time step simulation model is necessary.

Since the optimal operating policies generated from the optimization models are the guidelines of reservoir operation, as opposed to real-time rules that the reservoir has to obey, the storage level in any given month is not restricted to being exactly equal to the policy storage level. Instead, the reservoir will be run in a reasonable manner under the guidelines. To ensure reasonable operation of the reservoir, the following rules were built into the simulation model.

1. Simulation rules for the summer season

During the summer, the storage level targets have higher priority than non-basic water demands (i.e., water quality control and cooling water withdrawal). Therefore, when the policy level is above the upper bound of the preferred storage range, the rules try to lower the real storage level back into the range under the conditions of causing no downstream channel flooding. When the policy level is beneath the lower bound of the preferred range, the rules try to raise the actual level up into the preferred range while continuing to meet the basic water supply demands (irrigation, municipal and industrial demands). When the policy level is in the preferred range, the rules try to keep the storage at the policy level unless it causes either flooding or cannot meet water supply demands. In the case that flooding occurs, the storage is allowed to go up to the upper bound of the preferred range. In the case that water supply shortage happens, the storage is allowed to go down to the lower bound of the preferred range.

2. Simulation rules for non-summer seasons

The water supply demands have the priority during this time of the year. After all of these demands are satisfied, any remaining flexibility can be used to reach the policy level. It should be noticed that in order to avoid emergency situations (e.g., dam may be overtopped, or storage level may be lowered down to the dead storage level, or the basic demands may not be met), these rules can be broken.

Since the daily model is used only for testing the flooding control performance of the operating policies, it is only run during the flooding season comprising the late spring and early summer (in Assiniboine River basin, this is April and May). The operation rules are simply defined as (1) meet all water supply demands (because there is no storage target during that time) and (2) minimize flooding.

The structures of monthly time step simulation model is described in Figure 5.1. For the elaboration of Step 3, refer to Appendix C. The flow chart of the daily time step simulation model is in Appendix D.

5.3 The Data Used in Simulation

The hydrological data used in the monthly time step model are the same type as those used in the optimization models. However, in this case, the continuous series record is input into the model instead of the record for selected representative years. The available record is from 1971 (corresponding to the time the Shellmouth Reservoir was completed) to 1987, giving a 17-year record.

A 17-year period is generally not considered to be a sufficiently lengthy time period for

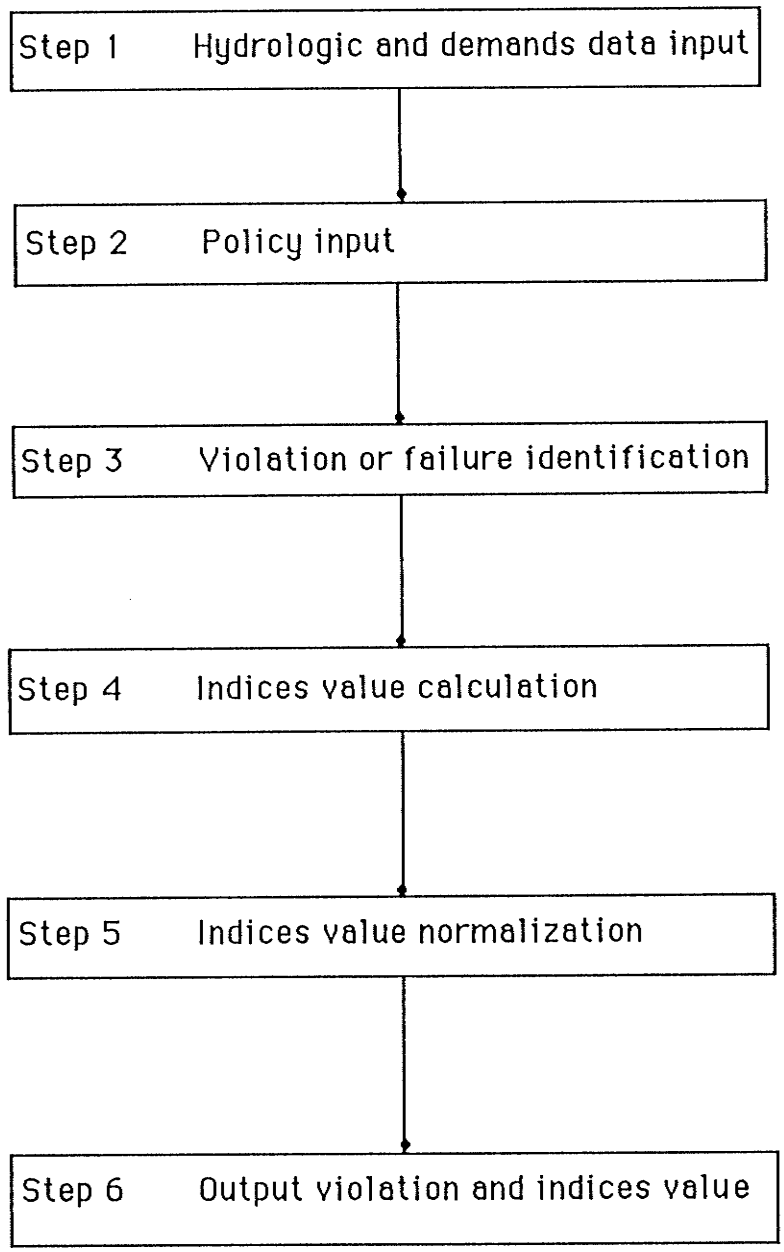


Figure 5.1 The structure of monthly time step simulation model

examining a reservoir's performance under stochastic hydrological conditions. Conventionally, the minimum record length is 30 years. If the actual record is not long enough, an extension of the historic record may be necessary. There are many methods to do this extension with random extension being one example. This method extends the record in a totally random way. When the historic data record is too short to fit a stochastic model, this is an attractive approach.

To extend historic records, a random generation model is used in this work to first generate the type for each of the extended years (i.e., wet, average, or dry). The order of these extended years is also randomly determined. Finally, samples from the actual historic record are selected and allocated to the corresponding extended years. To avoid bias associated with the particular generated record, seven sets of randomly generated data were input to the simulation model and the median result, in terms of the performance measures, was taken as the final result for this version.

On average, a random extended series has the same stochastic parameters as its parent-sample does. For testing the robustness of the policies under different meteorological patterns, another two input versions were prepared. These two new versions assume that the meteorological patterns will be either wetter or drier than the historic period. The wetter pattern is structured by taking two extreme dry years' records away from the historic record and randomly extending the rest into 51 years; the drier pattern is structured by taking two extreme wet years' records away from the historic record and randomly extending the rest into 51 years.

These considerations result in four different arrangements of input data as following:

using actual historical record (the 17-year record);

using extended historical record (historical record is randomly extended into 51 years);

using extended historical record after two recorded extreme wet years are taken away;

using extended historical record after two recorded extreme dry years are taken away.

5.4 The Identification of the Policies

All of the optimal policies obtained from the optimization models have three storage traces; one for wet years, one for average years, and one for dry years. The input hydrological record (historical or extended) is a mixture of all kinds of years. Therefore, before the start of the simulation, a storage trace should be allocated to each year. Obviously, this allocation depends on the forecasting for each year. Four forecasting methods are designed to allocate policies:

1. Perfect forecasting. The steps involved are to first classify each of the historical years as wet, average, or dry, using the same technique that was used in defining the three kinds of hydrologically representative years (see Section 4.3.3). It is then necessary to assign corresponding storage traces for each of the years (i.e., assign storage trace for wet year to wet years and so on). This is equivalent to having a perfect forecast of the hydrologic conditions. Each of the storage traces operates in the hydrological environment for which the storage trace has been generated. Under this set of conditions, the policy should be able to obtain its best performance.

2. Forecasting provided by the Water Resources Branch (WRB). Since this method is currently used by the reservoir operator, it is a more realistic method. This method forecasts the inflow from October up to early summer. (Early summer, according to WRB, has no fixed definition. Generally, it means early May). From a rough study of the hydrological record, it could be found that in the Shellmouth region, the hydrological type of each year has an obvious relation with the spring and early summer inflow characteristics (mainly the volume of the inflow). Therefore, at a satisfactory acceptance level, it allows us to forecast the type of year according to the inflow volume for spring and early summer. However, since only 10 years of forecasting information was obtained (1980 - 1989), and since the other input data are available up to 1987, only eight years

could be used. (i.e., 1980 to 1987).

3. Random forecasting. A random generation model is used to identify the hydrologic type for a coming year, and then allocate storage traces according to the random identification.

4. Totally incorrect forecasting. In this approach, it is assumed that the forecast for the extreme types of year is totally wrong (for instance, if the coming year is a wet year then the forecast will assume dry year, or vice versa). An incorrect storage trace is therefore allocated to each of the extreme years. This type of situation could occur if the forecasting technique was not particularly good. By this way, the flexibility, or robustness, of the policies is examined with respect to mis-specification of the type of hydrologic year.

Combined with the input data versions outlined above, a total of seven versions are prepared for the simulation model:

1. using actual historical record (the 17-year record), and perfect forecasting;
2. using extended historical record after two recorded extreme dry years are taken away, and perfect forecasting; the extended length is 51 years.
3. using extended historical record after two recorded extreme wet years are taken away, and perfect forecasting; the extended length is 51 years.
4. using actual historical record (the 8-year record), and forecasting method of WRB;
5. using actual historical record, and random forecasting;
6. using extended historical record (historical record is randomly extended into 51 years), and perfect forecasting;
7. using actual historical record (the 17-year record), and totally incorrect forecasting.

5.5 The Results of Simulation

The simulation model gives two kinds of results, for all of the seven versions of input arrangement, which are called the violation record and the indices values. The violation record is a record of the time the violations happened and the magnitude of violations. The indices values are the calculated values of the Risk, the Resiliency, and the Vulnerability, (defined as RK, RE, and VN in related graphs).

Figures 5.2 (a) - (d) show the comparisons of the indices values for Version 1 for the three kinds of policies under the four hydrological scenarios, in terms of water supply (WS), flood control (FLD), and storage targets (STG, upper and lower). The results of the remaining versions are in the Appendix E. From the physical meanings of these three indices (Section 5.1), the smaller these indices values, or the shorter the bars, the better.

From Figures 5.2 (a) - (d) and Figures in Appendix E, the constancy of the results among seven versions can be seen. For example, if one policy is better in one version than others with respect to a certain aspect with a given scenario, it is better than others in all seven versions under the same conditions. (The significance of this point will be discussed later). This makes it possible to summarize the results using an example version. The actual historical data and perfect forecasting version is chosen as the analysis base.

Figures 5.2 (a) - (d) display the characteristics of each of the policies in twelve aspects, that is: four functions (water supply, flood control, upper and lower storage targets, respectively) times three criteria (risk, resilience, vulnerability).

Figure 5.2 (a) displays the three criteria associated with water supply function (WS), Figure 5.2 (b) displays the three criteria associated with flood control function (FLD), and Figure 5.2 (c) and 5.2 (d) display the three criteria associated with upper and lower storage targets (STG), respectively. In each of the graphs, the results of each of the aspects are ranked scenario by scenario. In each scenario, the policies derived from three optimization models are displayed from left to right. Based on these three graphs, the following observations are made.

(1). MAXR policies. These policies have better performance in water supply and lower storage target violations because of the high policy storage levels which result in more water available to meet the demands. This is indicated by the shorter Risk (RK), Resilience

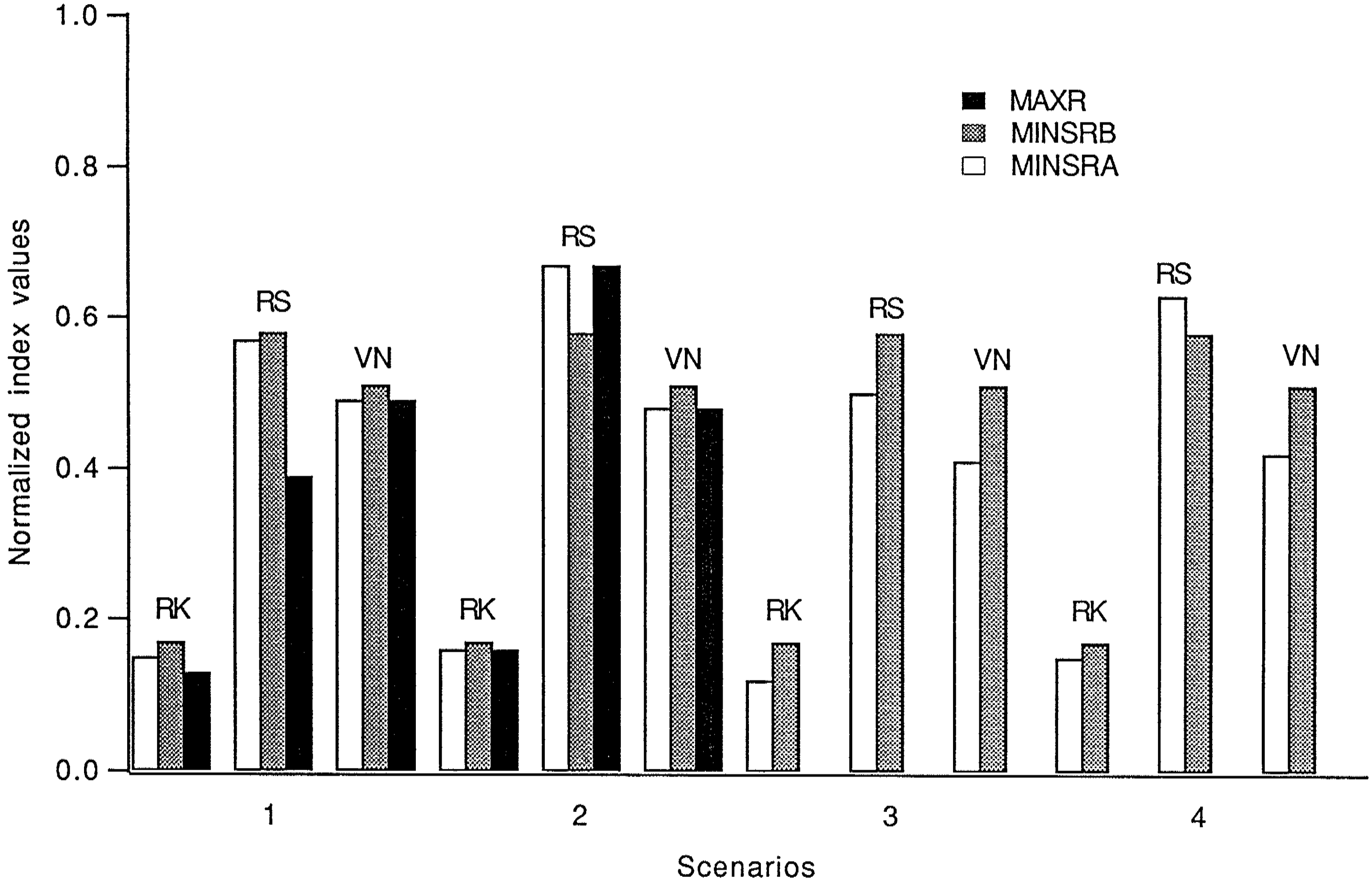


Fig. 5.2(a) Policy evaluation for water supply.
Version 1: use historic data and perfect forecasting

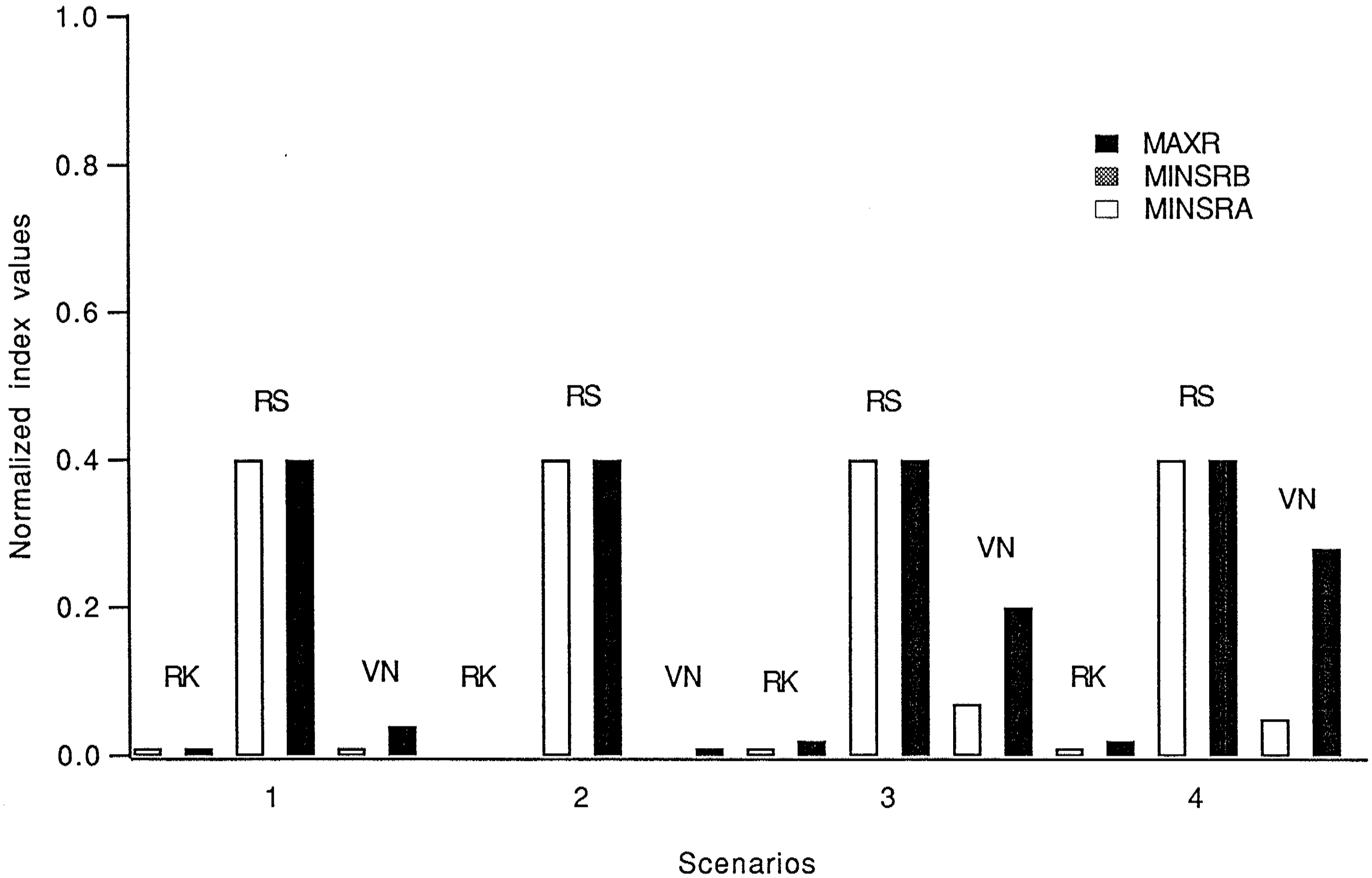


Fig. 5.2(b) Policy evaluation for flood control.
Version 1: use historic data and perfect forecasting

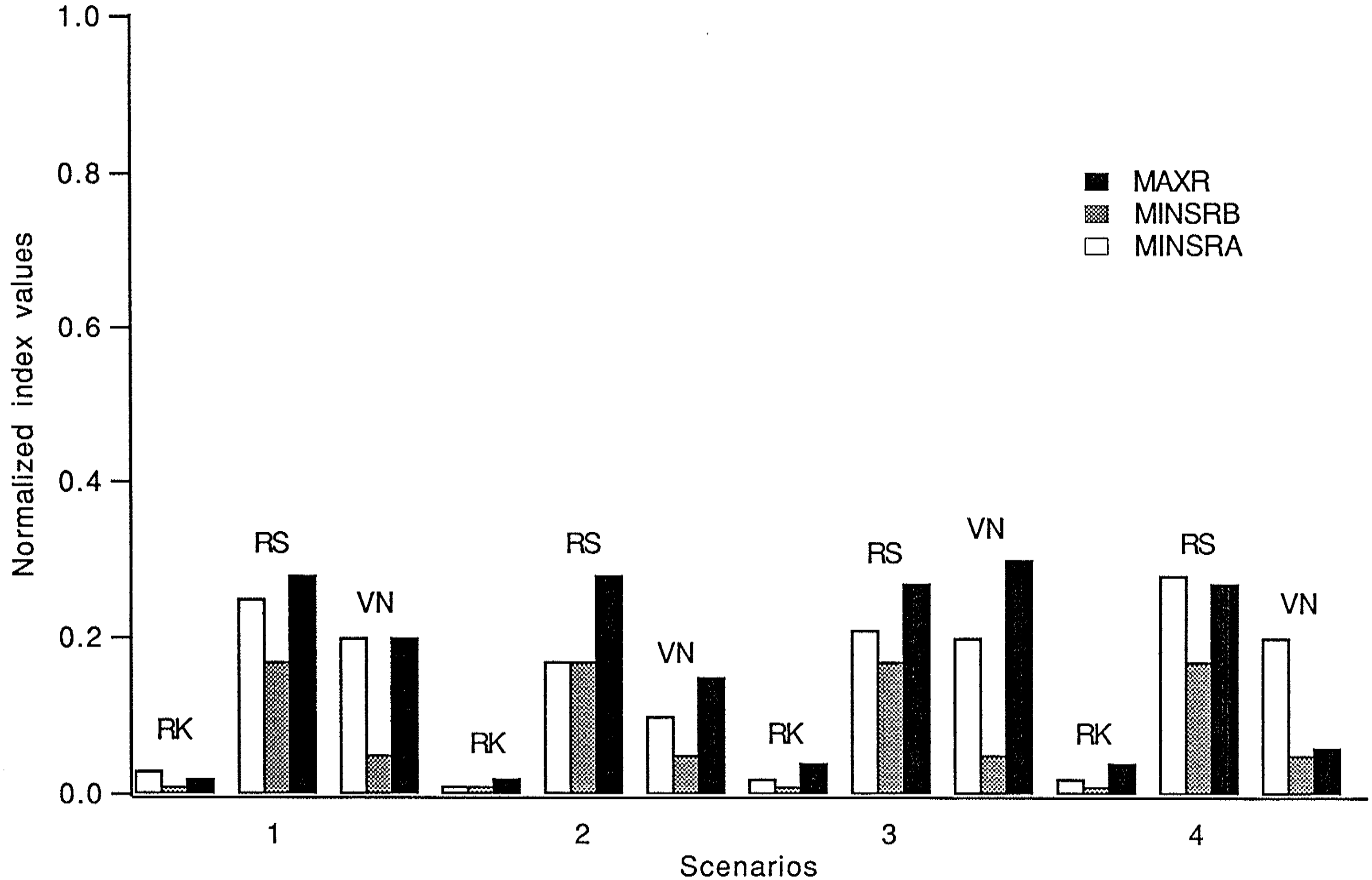


Fig. 5.2(c) Policy evaluation for upper storage target.
Version 1: use historic data and perfect forecasting

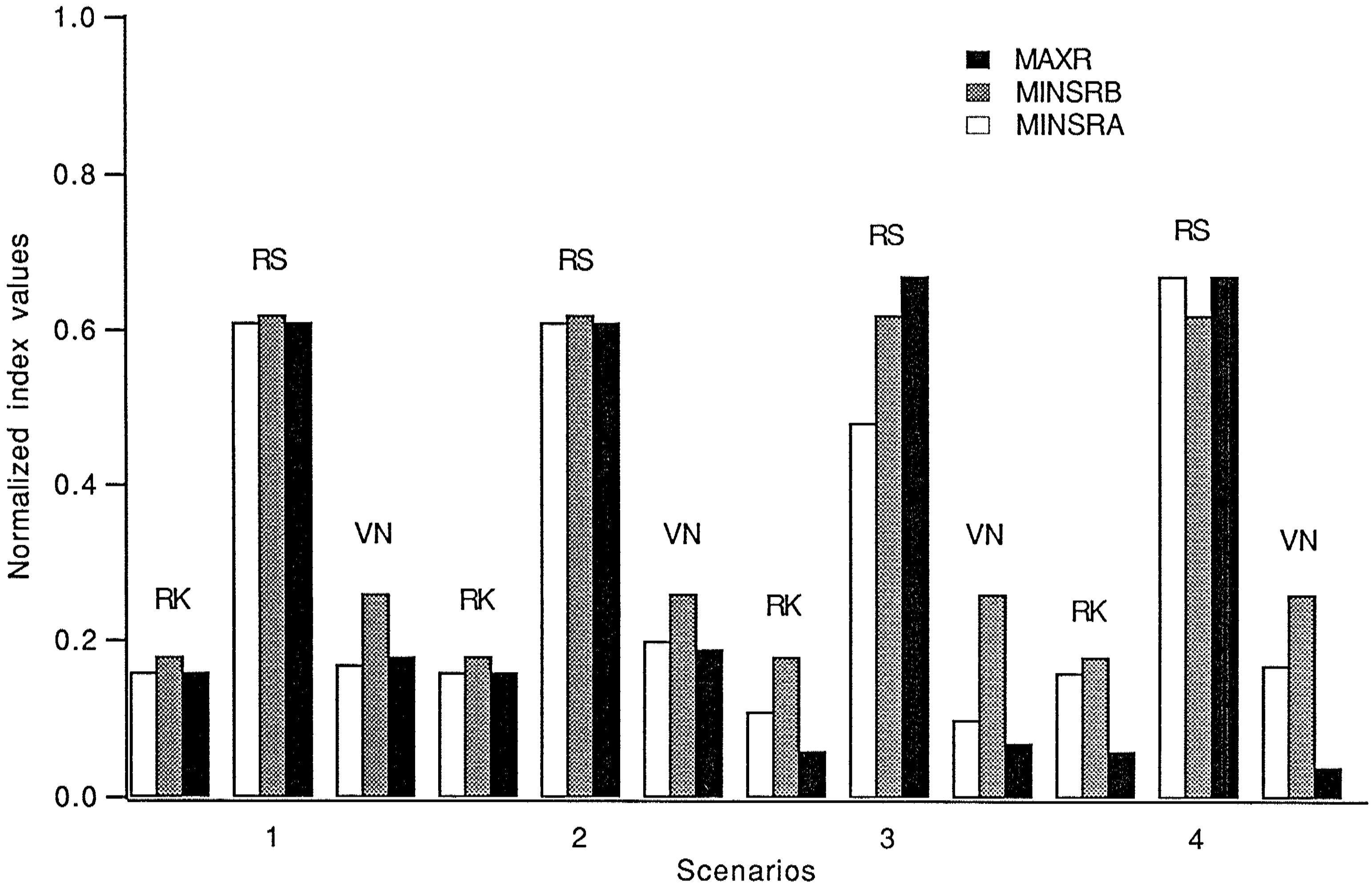


Fig. 5.2(d) Policy for lower storage target.
Version 1: use historic data and perfect forecasting

(RS), and Vulnerability (VN) bars under the MAXR model for water supply and storage. But in return the policies of the MAXR model have almost exclusively the highest violations in flood control and upper storage target.

(2). MINSRA policies. These policies seem to be the median of the MINSRB and the MAXR models. Compared with the MAXR policies, they are better in flood control and in meeting upper storage target; compared with the MINSRB policies, they are better in meeting the lower storage target and in meeting water supply. The MINSRB model is sometimes better than the MINSRA model in terms of Resilience of water supply. From the definitions of Risk and Resilience, it is known that RK reflects the number of violations that happened and RS can reflect the number and length of discrete failure states. Therefore, a shorter RK bar and a longer RS bar here implies fewer but more concentrated failures and vice versa.

(3). MINSRB policies. These policies have comparatively the lowest storage levels so that they have the best characteristics in flood control and upper storage target violation. But this advantage is obtained by sacrificing performance on the water supply function and the goal of meeting the lower storage level target in summer.

Figure 5.3 summarizes the results of the daily time step model. As indicated before, daily floods could be concealed by monthly flooding indices. Therefore, it is necessary to examine the flood control characteristics by the results of daily time step model. The graph shows that the MINSRB policies are still better according to the daily flooding and accumulated excess deviations about upper storage target which is defined as the sum of all of the daily excess deviations about the upper storage target. The MINSRA policies are somewhat poorer, followed by the MAXR policies. This outcome agrees with the ranking from the monthly time step model.

All of these observations coincide with the appearance of policy curves and the analyses made in Section 4.4.

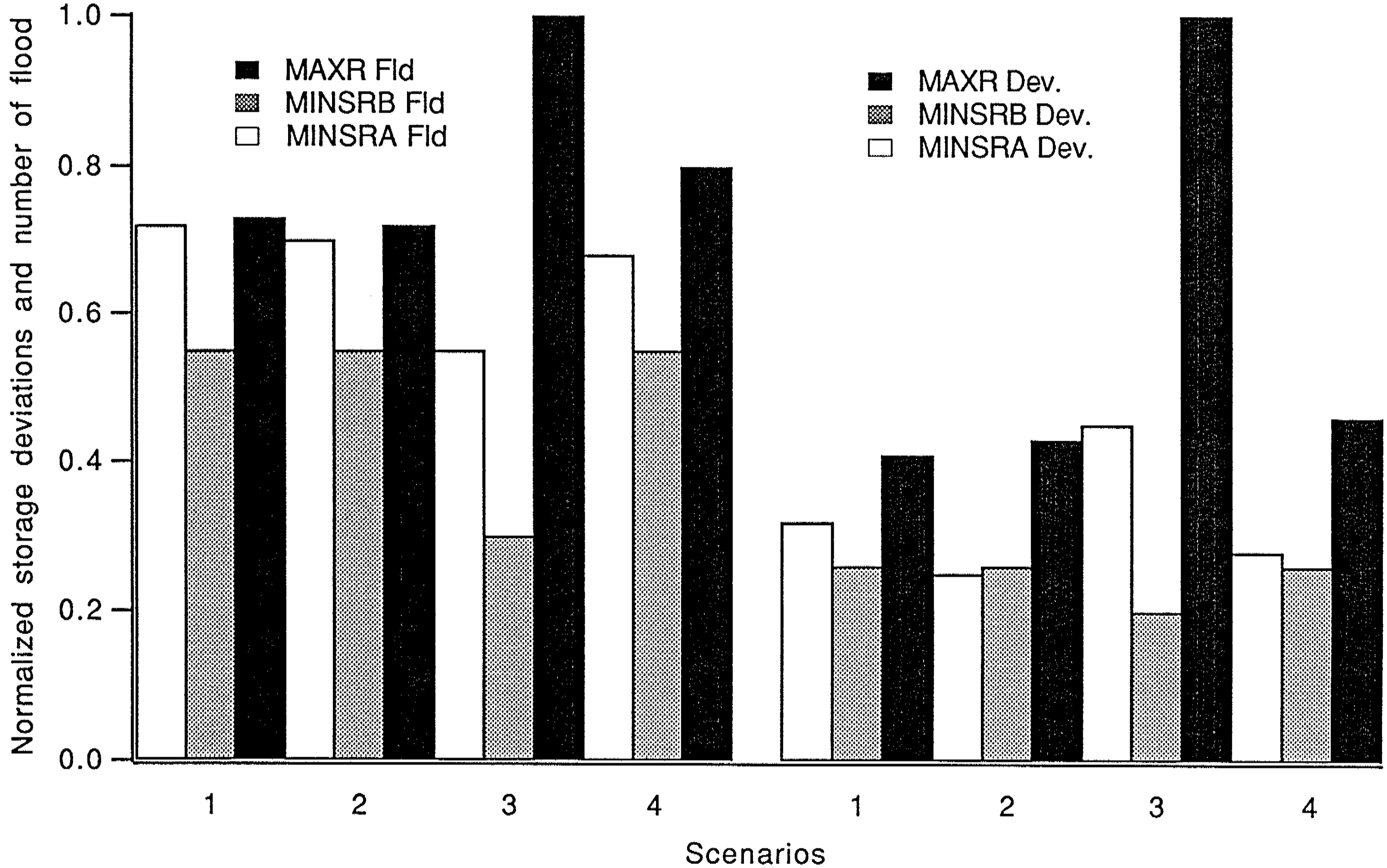


Fig. 5.3 The results of daily simulation model.

5.6 The Stability of the Policies

The simulation results also tell us some other characteristics of the policies.

1. Climate condition change does not greatly affect the number and distribution of the violations. This can be observed by comparing the results of version 2 (wetter), 3 (drier), and 6 (historic). The magnitude of the bars of RK and RS are not significantly changed. However, the magnitude of the water shortage should be smaller in wetter weather (water supply bars of VN are obviously shorter under wetter climate condition). This results implies that the policies are hydrologically stable, (i.e., the characteristics of policies, shown through the performance of the reservoir, do not greatly vary with the change of the hydrologic conditions).

2. The forecasting methods affect the performance of the policies. Table 5.1 displays the relative accuracy of the various forecasting methods (assuming version 1 has the perfect forecasting). In the Table 5.1, the extreme mis-forecasting means forecasting a wet year to be a dry years, or vice versa; the common mis-forecasting means forecasting a wet or dry year as an average year, or vice versa. This table indicates that the order of the relative accuracy of various forecasting methods referring to version 1 is version 5, 4, and then 7.

3. Generally, different input versions (implies different operating conditions) result in different violation magnitudes. However, the distribution of relative performance among the policies of each versions are identical. This is the constancy observed in Section 5.5. This indicates that the relative performance is inherent and true, or in other words, the simulation model does explore the inherent characteristics of the policies.

It is still not possible, however, to tell which policy is best because of the obvious trade-offs among the policies in connection with the twelve aspects. Therefore, the multiobjective selection approach is necessary.

Table 5.1 The Relative Accuracy of Forecasting Methods

	number of extreme mis-forecasting	number of common mis-forecasting
version 1	0	0
version 4	0	8.5*
version 5	<2 (average)	0.5 (average)
version 7	12	0**

* The results of version 4 are based on eight years data and prorated to the 17-year scale.

** Version 7 only relates the accuracy of the forecasting about wet or dry years. The forecasting about average years is assumed always correct.

Chapter 6. The Multiobjective Selection

In Chapter 5, twelve evaluation aspects were developed and the policies were evaluated according to these twelve aspects. From these twelve aspects, it can be seen that the aspects can be divided into two groups: (1) flooding and violation about the upper bound of preferred storage range; and (2) violations about the water supply target and about the lower bound of preferred storage range. The aspects in the first group imply the impacts related to safety (i.e., safety of the dam and safety with respect to downstream flooding). The aspects in the second group represent the impacts related to water supply and recreation. Since the reservoir was initially built for flood control, it is reasonable to give the aspects in the first group a higher priority and according to them, screen out those policies which have the poorest index values. This is called the first screening step. From the remaining policies, the best policy will then be identified. This is the second screening step.

From Figures 5.2 and Appendix E, an almost dominated phenomena can be observed, that is the policies of the MAXR model are inferior to the others, in terms of all of the index values related with flooding and upper storage target. From the Figure 4.4 and Section 4.4, the high violations about flood targets (both in the reservoir and downstream channel) of the MAXR policies arise from the high storage levels. The high storage levels arise from constraint Equation (4.9), which requires that the release meet all of the downstream net demands. To achieve this, a large amount of water must be stored in the reservoir, resulting in high storage levels. Since a high risk of flooding is not acceptable, the MAXR policies are eliminated from further consideration.

This leaves the MINSRA and MINSRB policies. Figures 4.5 and 4.6 show that the MINSRA and MINSRB models generate similar policies except in dry years. In addition, Figure 5.2 and Appendix E show the trade-offs in terms of all of the twelve evaluation aspects. For further screening, a multiobjective model was developed.

6.1 Multiobjective Modelling

The second screening procedure employs a mathematic model called Discrete Compromise Programming model.

Compromise Programming ranks the options according to their "distances" to the "ideal situation". For problem in this work, the "ideal situation" corresponds to the case of no violations, and the "distance" to the "ideal situation" is measured by the recorded violations. The common form of a Compromise Programming model is:

$$Ls = [\Sigma_i A_i*(X_i - X0_i)^p]^{(1/p)} \qquad (6.1)$$

where

Ls is the compromise distance measure;

X is the vector of violations;

X0 is the vector presenting ideal situation;

A is a parameter vector which presents the relative importance of different violations. (Larger weights are assigned to the more important types of violations), and

p is an exponent parameter representing the preference of decision maker regarding the magnitude of the deviations from the ideal situation.

Ls reflects all of the relevant characteristics of the evaluated polices. All of the options are ranked according to the magnitudes of Ls, with a smaller value of Ls implying better performance.

In this work, X is the deviation from the ideal situation, and therefore the X0 should be zero. The Equation (6.1) reduces to

$$Ls = [\Sigma_i A_i*X_i^{\,p}]^{(1/p)} \qquad (6.2)$$

To rank policies, not only the largest violations, but also the distribution of violations and also the number of times the violations occurred should be considered. To do this, the records of violations are used. The first step is to divide the violations into five classes and place each of the violations into one of the resulting classes. For example, divide all violations with respect to the water supply goal into five classes, from zero violation through the maximum violation that occurred. Each class possesses an equal portion of the maximum violation (20%, in this work). The next step is to locate all real violations into these five classes and record the number of violations in each class. Only those numbers are used to calculate the Ls values. By doing this, it is able to address the number of times violations appeared (this is the numbers in all classes), the distribution of violations (the five classes give discrete distribution of the violations), and the largest violations (the violations in the top class). An additional merit of doing this is avoiding the difficulty arising from the discrepancy of units of different kinds of violations. For instance, violation about storage target could be an order of magnitude different from the violation about water supply. In such a case, it is difficult to balance the violations' magnitudes and the effect of the one which has smaller magnitude will be diminished when calculating the Ls value.

Each of the five classes selected indicates a kind of deviations from the ideal situation. To represent this discrepancy, different p values are assigned to each of the classes. The larger the deviations, the larger the p values. The classes and corresponding p values are shown below:

Class	violation range	p value
1	0 - 20% of maximum violation	1
2	20% - 40% of maximum violation	2
3	40% - 60% of maximum violation	3
4	60% - 80% of maximum violation	4
5	80% - 100% of maximum violation	5

The parameter vector of weights, A, must also be determined. As mentioned above, this weight reflects the relative importance of different kinds of violations. If the order of relative importance associated with each aspect cannot be pre-determined, a sensitivity analysis should be made, (i.e., change the weights assigned to each of the aspects and determine a reasonable distribution of the weights). Five options for the weights were designed for the sensitive analysis:

(1) assign a 70% weight to the water supply and 10% to the rest;

(2) assign a 70% weight to the flood control and 10% to the rest;

(3) assign a 70% weight to the upper storage target and 10% to the rest;

(4) assign a 70% weight to the lower storage target and 10% to the rest; and

(5) assign equal a weights to water supply, flood control, upper and lower storage target goals.

These five designs have covered four extreme cases, (i.e., when the water supply aspect, the flood control aspect, the upper storage target, or lower storage target, respectively, are primarily concerned), and a median case, (i.e., when all of them are equally concerned).

Finally, the Compromise Programming model of this work becomes:

$$Ls = \Sigma_k \{ [\Sigma_i A_i * X_{i,k}^{p(k)}]^{(1/p(k))} \} \qquad (6.3)$$

where

k denotes the violation classes.

6.2 Discussion of Results

Corresponding to each weighting vector, the model ranks the policies according to the Ls values. The results are tabulated in Table 6.1. The policy ranked first has the smallest Ls value, and so on.

The ranks can be seen to vary with changes to the weights. However, the recommendation with four of the five weightings remains the same, that is the policy derived from MINSRA model under scenario 3. With weighting vector 4, the recommendation is MINSRA under scenario 2. It is reasonable to conclude that the MINSRA policy under scenario 3 is the most robust one and should be recommended for implementation.

An interesting observation from this table is that the policies generated under hydrologic scenarios 3 or 4 occur more frequently in the top three ranks. The multiobjective selection process compares not only the policies derived from different models, but also the hydrologic scenarios under which those policies were derived. If a scenario is closer to the real world hydrologic condition, the policies derived from this scenario should exhibit better performance. Since the historic data record, or its extension, is used in the evaluation process, this phenomenon infers that scenarios 3 and 4 are more realistic compared to scenarios 1 and 2. This conclusion can be understood from the arrangement of the data of these four scenarios. Three extreme years (that is scenario 1 or 2) appearing sequentially is

Table 6.1 The Results of the Multiobjective Selection

		Weight version				
Policy of	Scenario	1	2	3	4	5
MINSRA	1	1.77	0.63	0.70	0.95	0.57
	2	1.84	0.56	0.56	**0.90**	0.56
	3	**1.28**	**0.41**	**0.42**	1.14	**0.41**
	4	1.78	0.62	0.62	0.91	0.56
MINSRB	1	2.05	0.64	0.70	1.05	0.64
	2	2.06	0.65	0.77	1.11	0.65
	3	2.05	0.64	0.70	1.10	0.64
	4	2.05	0.64	0.70	1.05	0.64

rare. A more frequent situation might be the alternative occurrence of wet, average, and dry years.

Figure 6.1 displays the storage and release traces when the reservoir is operated following the policy MINSRA under scenario 3, using historic data and perfect forecasting. Observations from this graph include:

1. The actual storage trace follows the policy trace well except in a dry period (1980 through 1984). According to the definition of hydrologic years, this period corresponds to average, dry, dry, average, and dry years. The storage trace comparison implies that the policy is reasonable over the period of record.

2. The summer storage targets are satisfied in most years. Even during the dry period, the preferred summer range is not obtained during only two dry years. In the remaining three years, it is either met or very close to being met. In three wet years, the summer storage levels are kept in the preferred range instead of above the range as dictated by the policy.

3. In the whole operating period, there are only three flood events. These floods appear during extremely wet years (1975, 1976, and 1979). From the storage trace, it can be seen that in these years the summer storage levels are higher than the upper storage target, implying that the reservoir does not have sufficient capacity to handle such a large event. In other years, flooding has been effectively controlled.

4. The releases from the reservoir satisfy the water demands quite well. Most of these demands are easily satisfied. Large releases only occur in early spring, or in the time periods when a high storage level has to be lowered, as happens in the summer. The period for high channel water level is from spring through to summer. For the rest of the time, the releases are kept at a lower level. Water shortage is observed to occur only in dry years, where most of the shortages occur during the dry period of 1980 through 1984.

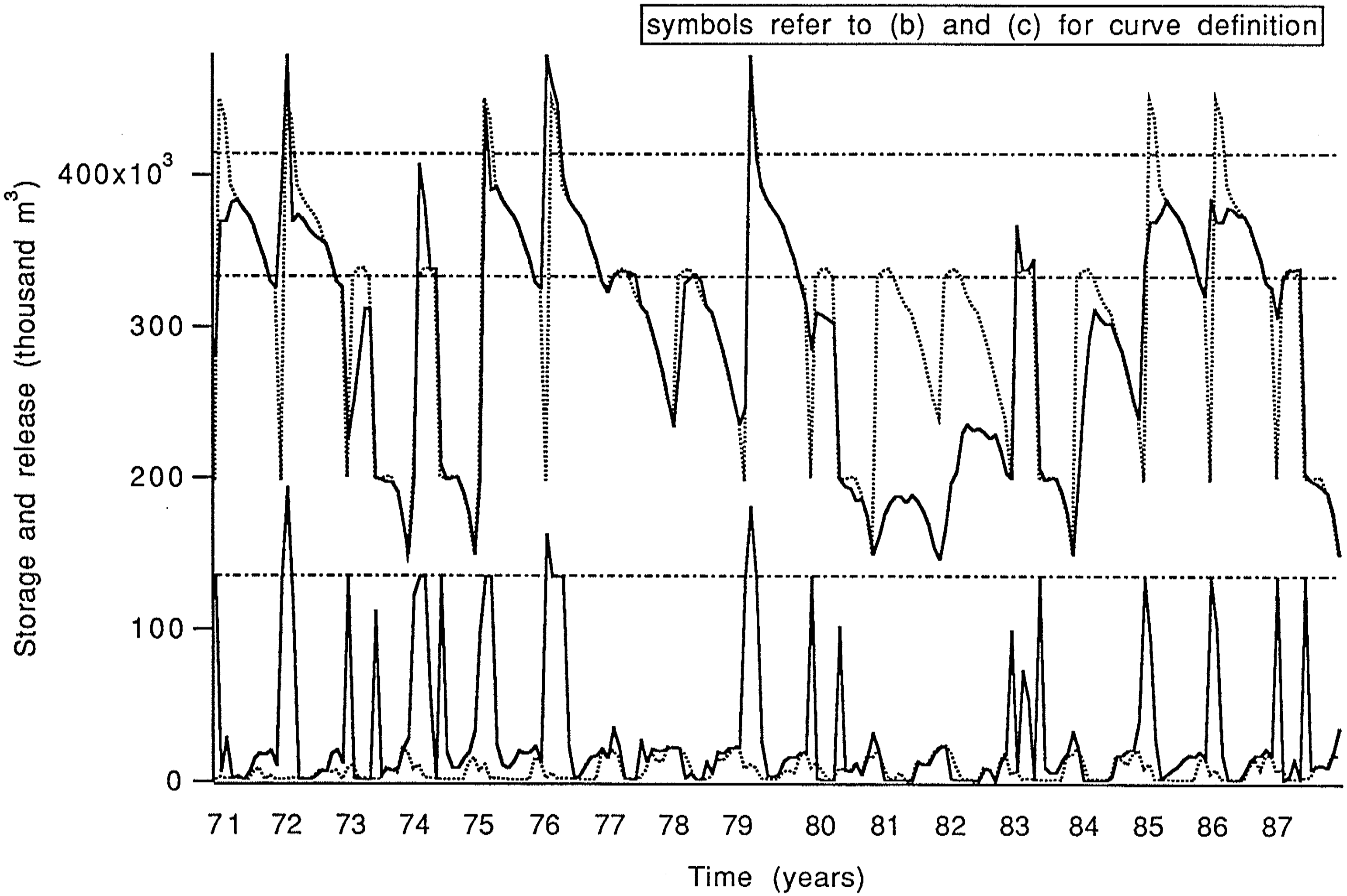


Fig. 6.1(a) The storage and release traces of MINSRA at scenario 3

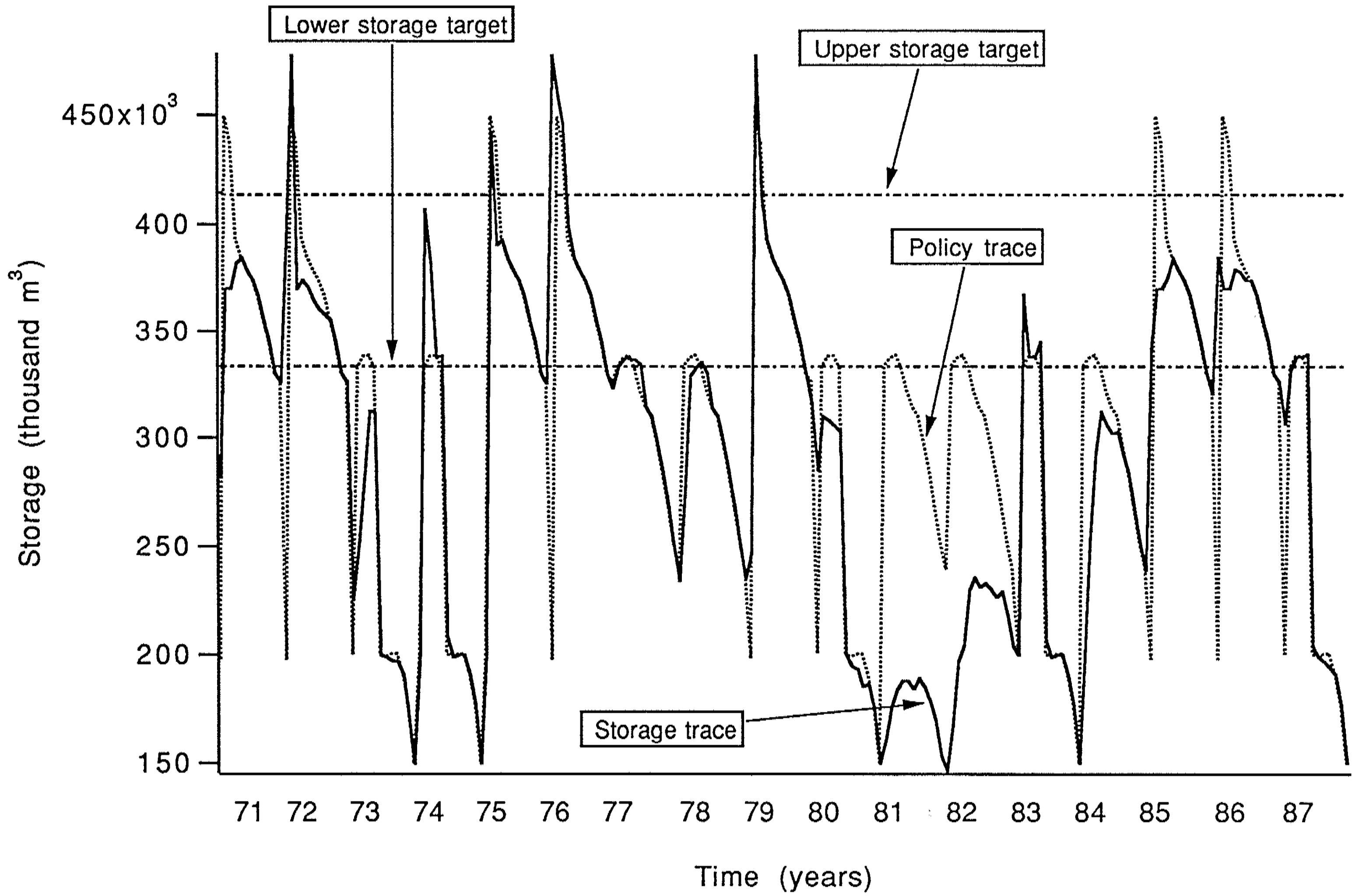


Fig. 6.1(b) The storage traces of MINSRA at scenario 3

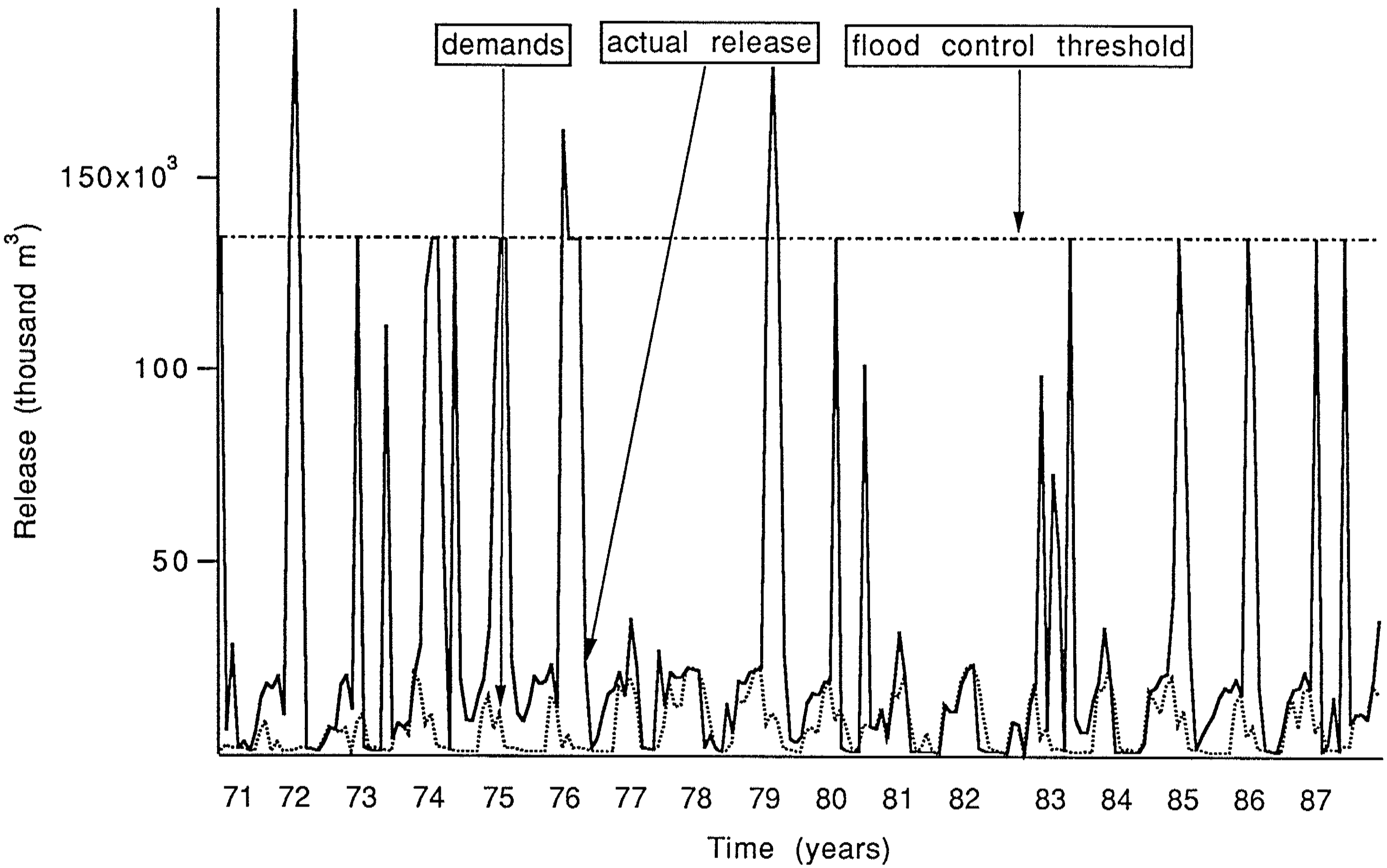


Fig. 6.1(c) The release traces of MINSRA policy at scenario 3

Chapter 7. Conclusions and Recommendations

This thesis has presented the development of a methodology for identifying operating policies for a multipurpose reservoir. An application of this developed methodology to a case study, based on the Shellmouth Reservoir, is also provided.

The methodology includes three steps:

1. The generation of optimal policies. Optimization models were formulated and solved to determine operating policies. The operating policies for reservoir operation were generated under various hydrological scenarios, by altering the input flow data to the models.

2. The evaluation of the optimal policies. The generated policies were evaluated by simulation, in terms of the risk, the resilience, and the vulnerability to violations of the policies.

3. The selection of the best policy. A multiobjective model, the modified Compromise Programming model, was used to fulfill this task. The selection was based on the performance of allocating water to the users, preventing flooding, and maintaining storage levels.

The first optimization model examined was a linear deterministic model (MAXR) which had the objective function of maximizing the total release from the reservoir. This model had the most restrictive constraints on the releases.

The second optimization model, the MINSRA model, was a linear Goal Programming model. This model had explicit storage targets, besides the release targets, in its objective function. Unlike MAXR model, it allowed the occurrence of the deficit deviations from the release targets. But these deficits were minimized.

The third model (MINSRB) was a variation on MINSRA in which storage targets were set for the whole year.

All of three models were demonstrated to be able to generate long term optimal operating policies for a multipurpose reservoir. The requirements of the reservoir system can be efficiently incorporated in both objective function and constraints. From the analysis conducted, the generated policies can be said to reflect the requirements of the reservoir system.

Comparing Maximize Release model (MAXR) with Minimizing storage and release deviation models (MINSRs), the former is inferior to the latter because of its higher risk of both flooding and endangering the safety of the dam. This disadvantage comes from the strictness of its constraints. Therefore, in similar application, the Goal Programming approach is recommended.

The policies of MINSRB model for wet and average years are as good as those of MINSRA model. But for dry years, MINSRB' policies are unreasonable.

According to the multipurpose selection results, the best policy for the given reservoir is the policy generated from MINSRA model under scenario 3.

This thesis has demonstrated that a deterministic type model can also handle hydrological uncertainty well. In this work, each hydrological scenario presents a possible hydrological condition. Theoretically, many more scenarios can be constructed in order to check all of the effects of hydrological uncertainty on the generation of the optimal policy. But realistically, some of the reasonable conditions may be enough. In this methodology, the reality of the scenarios are not judged by frequency analysis, but more straightforwardly by their agreement with real world conditions. This judgement is carried out in the multiobjective selection step. According to the results of the judgement, the most realistic and efficient scenario is identified.

Recommendations

Hydrological scenarios were used to reflect the hydrological uncertainty. This improves the ability of handling stochasticity of a deterministic model. To examine the efficiency of this approach, it would be desirable to compare these results with results from stochastic optimization models.

REFERENCES

1. Askew, A. J., "Chance-Constrained Dynamic Programming and the Optimization of Water Resources System", Water Resources Research, Vol. 10, No. 6, December, 1974.

2. Burn, D. H., Venema, H. D., and Simonovic, S. P., "Risk-Based Performance Criteria for Real-Time Reservoir Operation", Canadian Journal of Civil Engineering, Vol. 18, No. 1, February, 1991.

3. Changchit, C., and Terrell, M. P., "CCGP Model for Multiobjective Reservoir System", ASCE, Journal of Water Resources Planning and Management, Vol. 115, No. 5, September, 1989.

4. Collins, M. A., "Implementation of an optimization Model for Operation of a Metropolitan Reservoir System", Water Resources Bulletin, Vol. 13, No. 1, February, 1977.

5. Colorni, A., and Fronza, G., "Reservoir Management via Reliability Programming", Water Resources Research, Vol. 12, No. 1, February, 1976.

6. Curry, G. L., Helm, J. C., and Clark, R. A., "Chance-Constrained Model of System of Reservoirs", Journal of Hydraulics Division, Vol. 99, No. HY12, December, 1973.

7. Dagli, C. H., and Miles, J. F., "Determining Operating Policies for a Water Resources System", Journal of Hydrology, Vol. 47, No. 3/4, July, 1980.

8. Eisel, L. M., "Chance Constrained Reservoir Model", Water Resources Research, Vol. 8, No. 2, April, 1972.

9. Georgakakos, A. P., and Marks, D. H., "A New Method for the Real-Time Operation of Reservoir Systems", Water Resources Research, Vol. 23, No. 7, June, 1987.

10. Goulter, I. C., and Castensson, R., "Multi-Objective Analysis of Boating and Fishlife Interests In Lake Sommen, Sweden", Water Resources Development, Vol. 4, No. 3, September, 1988.

11. Hall, W. A., Harboe, R. C., Yeh, W. W-G., and Askew, A. J., "Optimum Firm Output Power From a Two Reservoir System by Incremental Dynamic Programming", Contribution 130, Water Resources Center, University of California, Los Angeles, October, 1969.

12. Hogan, A. J., Morris, J. G., and Thompson, H. E., "Decision Problem Under Risk and Chance Constrained Programming: Dilemmas in the Transition", Management Science, Vol. 27, No. 6, June, 1981.

13. Houck, M. H., "A Chance Constrained Optimization Model for Reservoir Design and Operation", Water Resources Research, Vol. 15, No. 5, October, 1979.

14. Houck, M. H., and Datta, B., "Performance Evaluation of a Stochastic Optimization Model for Reservoir Design and Management With Explicit Reliability Criteria", Water Resources Research, Vol. 17, No. 4, August, 1981.

15. Huang, W-C., Harboe, R., and Bogardi, J. J., "Testing Stochastic Dynamic Programming Models Conditioned on Observed or Forecasted Inflows", Journal of Water Resources Planning and Management, ASCE, Vol. 117, No. 1, January/February, 1991.

16. Joeres, E. F., Seus, G. J., and Engelmann, H. M., "The Linear Decision Rule (LDR) Reservoir Problem With Correlated Inflows. 1, Model Development", Water Resources Research, Vol. 17, No. 1, February, 1981.

17. Karamouz, M., and Houck, M. H., "Comparison of Stochastic and Deterministic Dynamic Programming for Reservoir Operating Rule Generation", Water Resources Bulletin, Vol. 23, No. 1, February, 1987.

18. Loucks, D. P., "Some Comments on Linear Decision Rules and Chance Constraints", Water Resources Research, Vol. 6, No. 2, April, 1970.

19. Loucks, D. P., and Dorfman, P. J., "An Evaluation of Some Decision Rules in Chance-Constrained Models for Reservoir Planning and Operation", Water Resources Research , Vol. 11, No. 6, December, 1975.

20. Loucks, D. P., Stedinger, J. R., and Haith, D. A., "Water Resources Systems Planning and Analysis", Prentice-Hall, N. J., 1981.

21. Lucas, N. J. D., and Perera, P. J., "Short-Term Hydroelectric Scheduling Using the Progressive Optimality Algorithm", Water Resources Research, Vol. 21, No. 9, September, 1985.

22. Marino, M. A., and Mohammudi, B., "Reservoir Management: A Reliability Programming Approach", Water Resources Research, Vol. 19, No. 3, June, 1983.

23. Marino, M. A., Loaiciga, H. A., "Dynamic Model for Multireservoir Operation", Water Resources Research, Vol. 21, No. 5, May, 1985.

24. Nopmongcol, P., and Askew, A. J., "Multilevel Incremental Dynamic Programming", Water Resources Research, Vol. 12, No. 6, December, 1976.

25. Papageorgion, M., "Optimal Multireservoir Network Control by the Discrete Maximum Principle", Water Resources Research, Vol. 21, No. 12, December, 1985.

26. Paudyal, G. N., and Shrestha, D. L., "Optimal Hydropower System Configuration Based on Operational Analysis", Journal of Water Resources Planning and Management, ASCE, Vol. 116, No. 2, March/April, 1990.

27. ReVelle, C. S., Joeres, E. F., and Kirby, W., "The Linear Decision Rule in Reservoir Management and Decision. 1, Development of the Stochastic Model", Water Resources Research , Vol. 5, No. 4, August, 1969.

28. ReVelle, C. S., and Kirby, W., "The Linear Decision Rule in Reservoir Management and Decision. 2, Performance Optimization", Water Resources Research , Vol. 6, No. 4, August, 1970.

29. ReVelle, C. S., and Gundelach, J., "The Linear Decision Rule in Reservoir Management and Decision. 4, A Rule That Minimizes Output Variance", Water Resources Research, Vol. 11, No. 2, April, 1975.

30. Simonovic, S. P., and Marino, M. A., "Reliability Programming in Reservoir Management. 1, Single Multipurpose Reservoir", Water Resources Research, Vol. 16, No. 5, October, 1980.

31. Simonovic, S. P., and Marino, M. A., "Reliability Programming in Reservoir Management. 2, Risk-Loss Functions", Water Resources Research, Vol. 17, No. 4, August, 1981.

32. Stedinger, J. R., Sule, B. F., and Loucks, D. P, "Stochastic Dynamic Programming Models for Reservoir Operation Optimization", Water Resources Research, Vol. 20, No. 11, November, 1984.

33. Stedinger, J. R., "The Performance of LDR Models for Preliminary Design and Reservoir Operation", Water Resources Research, Vol. 20, No. 2, February, 1984.

34. Strycharczyk, J. B., and Stedinger, J. R., "Evaluation of A 'Reliability Programming' Reservoir Model", Water Resources Research, Vol. 23, No. 2, February, 1987.

35. Tai, F-K, and Goulter, I. C., "A Stochastic Dynamic Programming Based Approach to the Operation of A Multi-Reservoir System", Water Resources Bulletin, Vol. 23, No. 3, June, 1987.

36. Takeuchi, K., "Chance-Constrained Model for Real-Time Reservoir Operation Using Drought Duration Curve", Water Resources Research, Vol. 22, No. 4, April, 1986.

37. Trezos, T., and Yeh, W. W-G., "Use of Stochastic Dynamic Programming for Reservoir Management", Water Resources Research, Vol. 23, No. 6, June, 1987.

38. Turgeon, A., "An Application of Parametric Mixed-Integer Linear Programming to HYdropower Development", Water Resources Research, Vol. 23, No. 3, March, 1987.

39. Wasimi, S. A., and Kitamidis, P. K., "Real-Time Forecasting and Daily Operation of A Multireservoir System During Floods by Linear Quadratic Gaussian Control", Water Resources Research, Vol. 19, No. 6, December, 1983.

40. Windsor, J. S., "Model for the Optimal Planning of Structural Flood Control System", Water Resources Research, Vol. 17, No. 2, April, 1981.

41. Yeh, W. W-G., "Reservoir Management and Operation Models: A State-of-the-Art Review", Water Resources Research, Vol. 21, No. 12, December, 1985.

42. Zessler, U., and Shamir, U., "Optimal Operation of Water Distribution Systems", Journal of Water Resources Planning and Management, ASCE, Vol. 115, No. 6, November, 1989.

APPENDIX A. THE DERIVATION OF REGRESSIVE PARAMETERS FOR THE GENERATION OF THE LOCAL INFLOWS

APPENDIX A. THE DERIVATION OF REGRESSIVE PARAMETERS FOR THE GENERATION OF THE LOCAL INFLOWS

To estimate the regressive parameters, a least square model is built:

$$\text{Min } \Sigma_j (LINFE_{ij} - LINF_{ij})^2$$

subject to

$$LINFE_{ij} = a_i{*}INF4_{ij} + b_i{*}INF5_{ij} + d_i$$

$$LINFE_{ij} \geq 0$$

where

$LINF_{ij}$ is the real local inflow calculated by

$$LINF_{ij} = INFE_{ij} - INF4_{ij} - INF5_{ij} \qquad (A.1)$$

where

$INFE_{ij}$ is the inflows recorded by station ME001 which is immediately downstream of the Shellmouth Dam.

Others are as defined in Chapter 5.

The records of MD010 are ignored because they are much smaller than that of station MD004 and MD005.

Form this model, the regressive parameters are obtained as listed in Table A.1:

Table A.1 Regressive Parameters

Month	a	b	d
Jan.	1.162		1932.4
Feb.	2.01	0.03	1174.2
Mar.	0.03	0.03	4169.2
Apr.		0.03	9658.7
May	0.255	0.964	
Jun.	0.077	0.03	4826.1
Jul.	0.265	0.235	2629.2
Aug.	0.03	0.742	988.9
Spe.	0.03	0.169	1455.3
Oct.	0.03	0.03	2237.4
Nov.	0.03	0.2	1733.3
Dec.	0.128		2228.1

APPENDIX B. THE IDENTIFICATION OF WET, AVERAGE, AND DRY YEARS

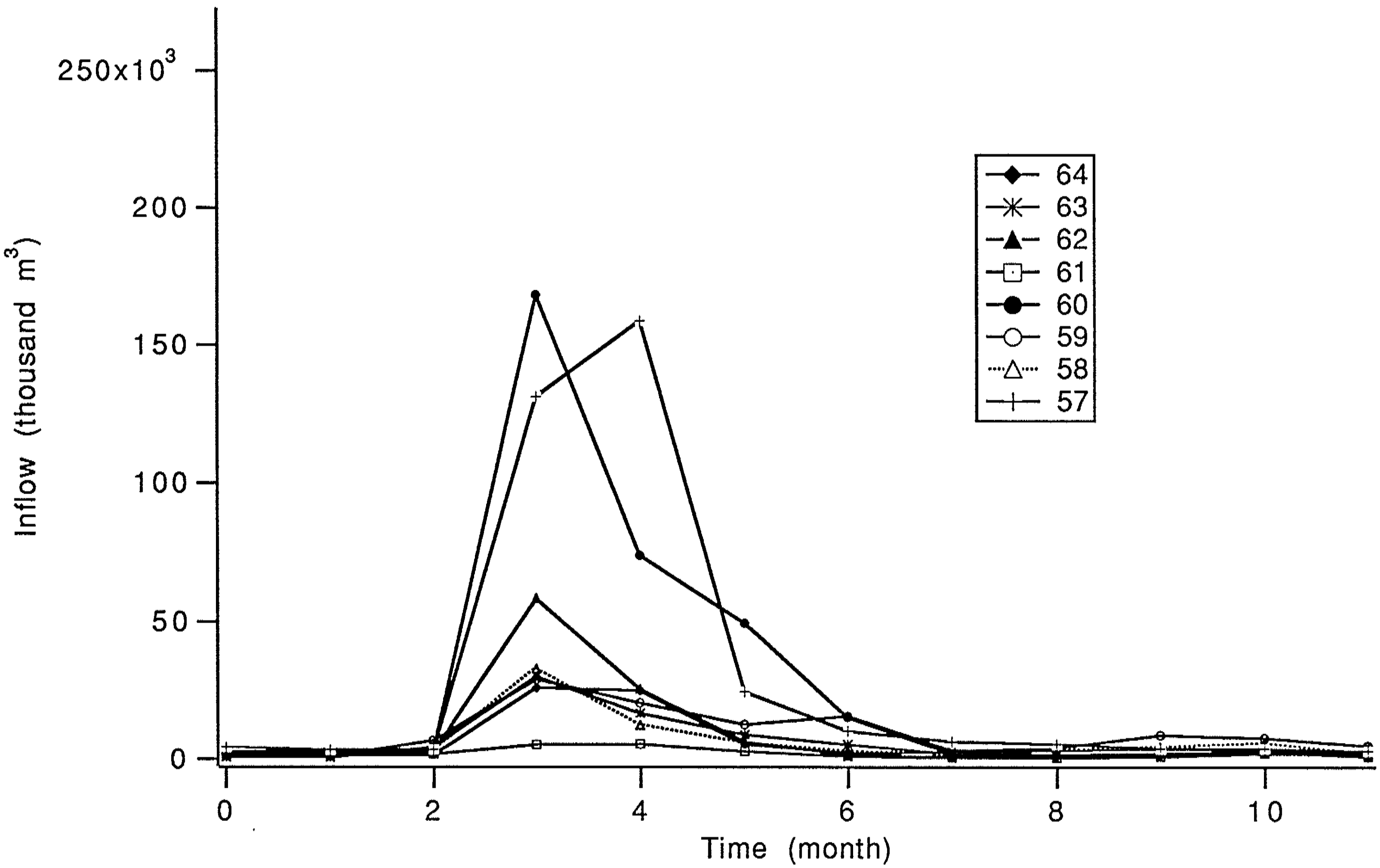


Fig. B.1(a) Sum of the inflows of Station 05MD004 and 05MD005. 1957 - 1964

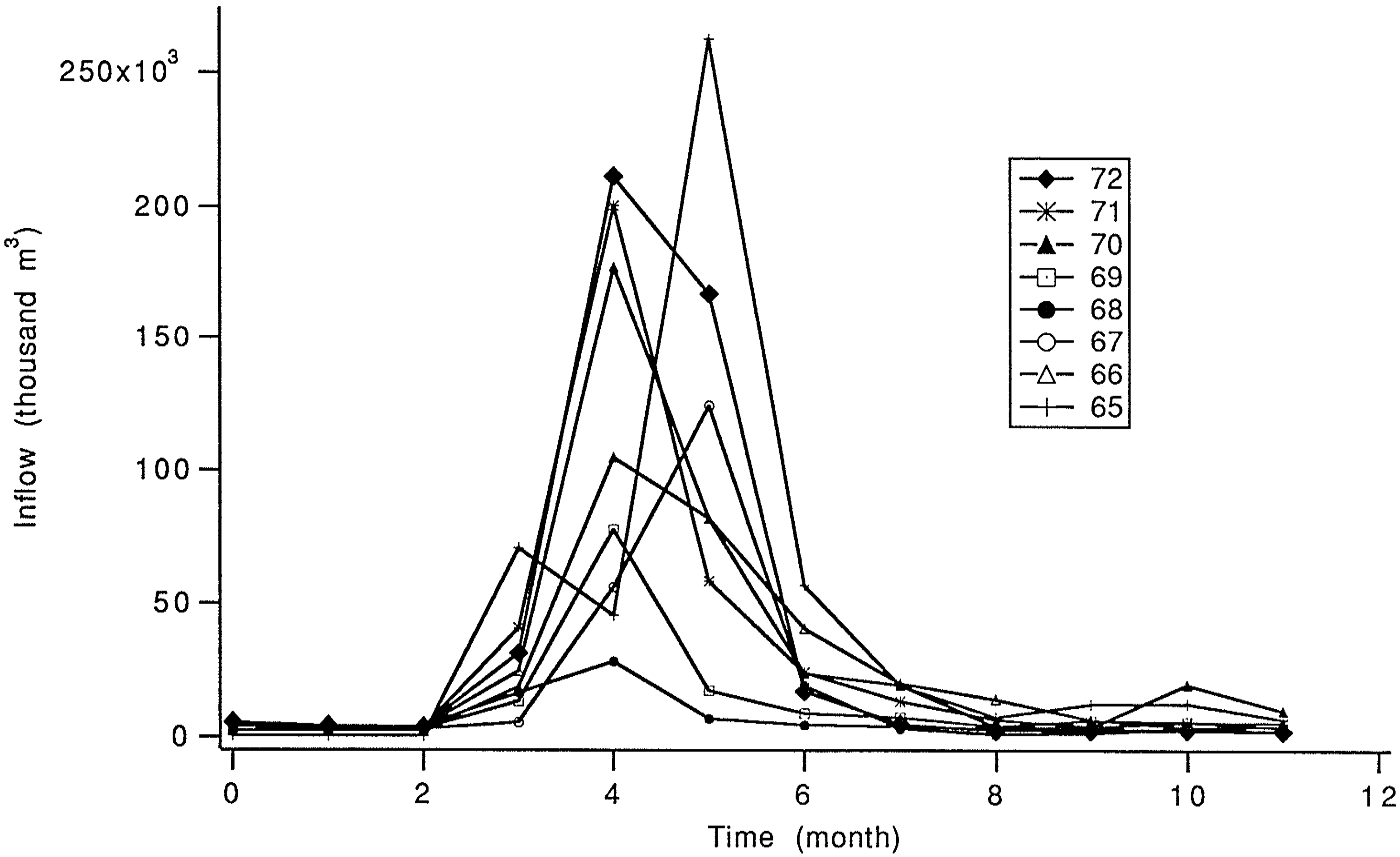


Fig. B.1(b) Sum of the inflows of Station 05MD004 and 05MD005. 1965 - 1972

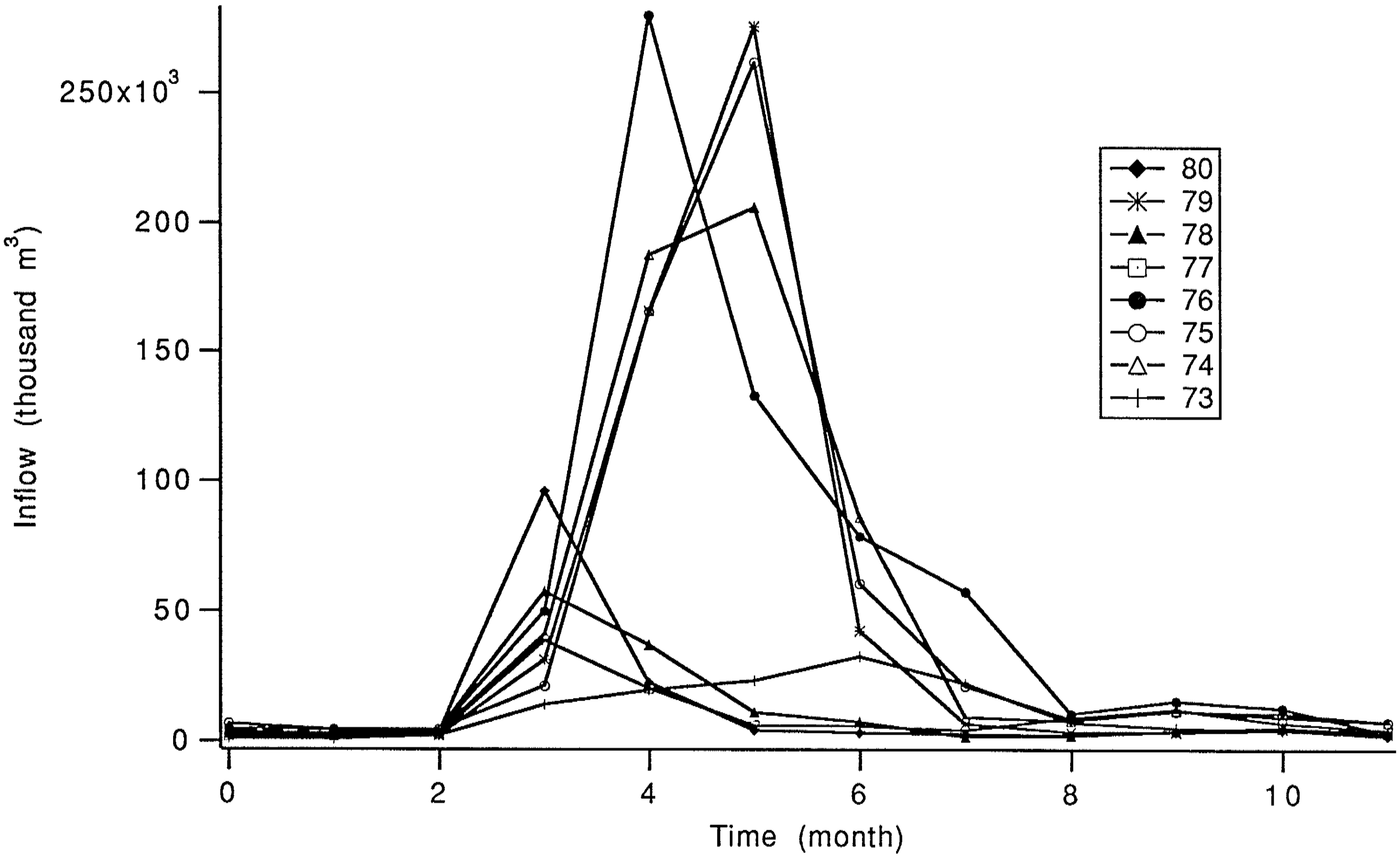


Fig. B.1(c) Sum of the inflows of Station 05MD004 and 05MD005. 1973 - 1980

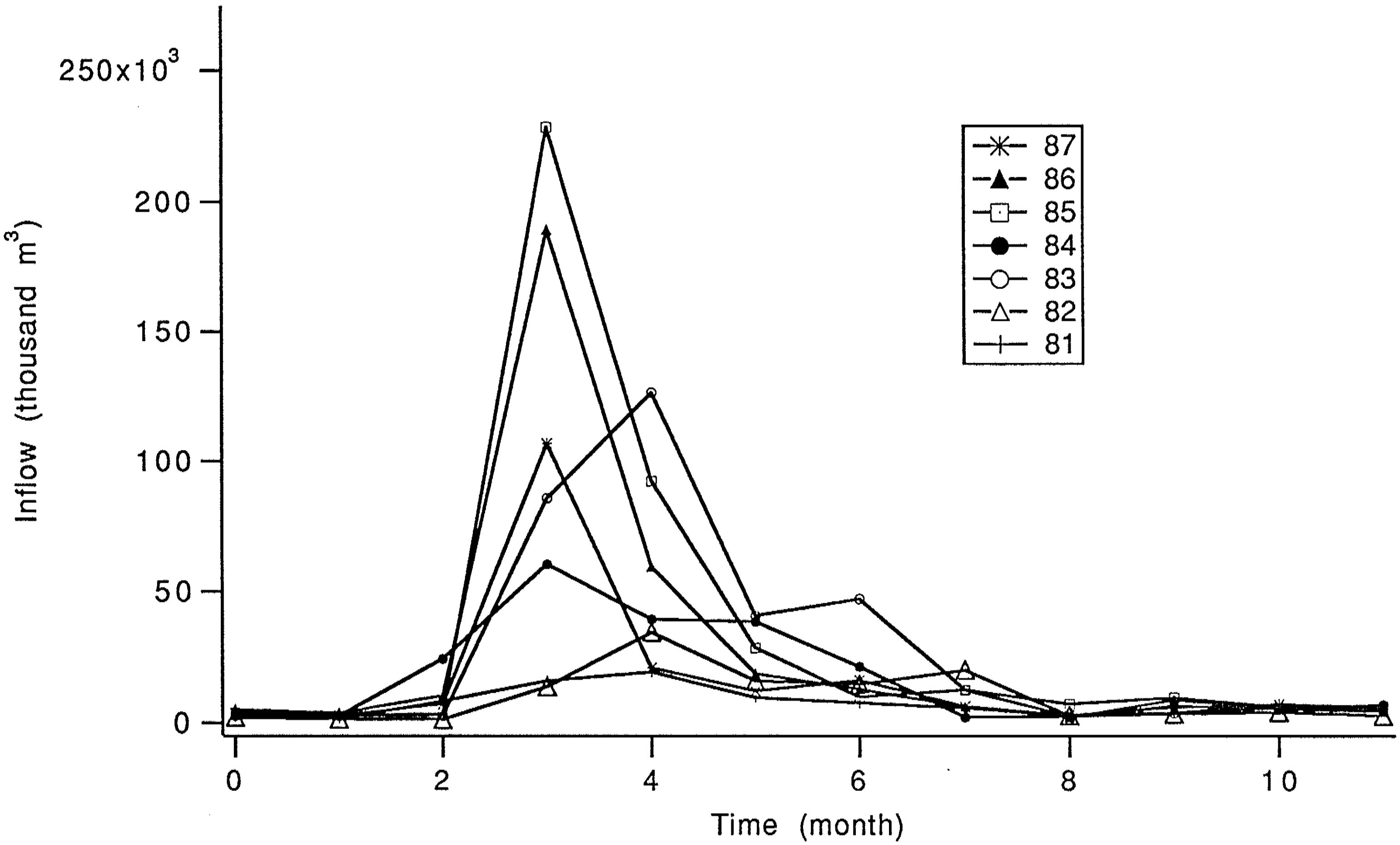
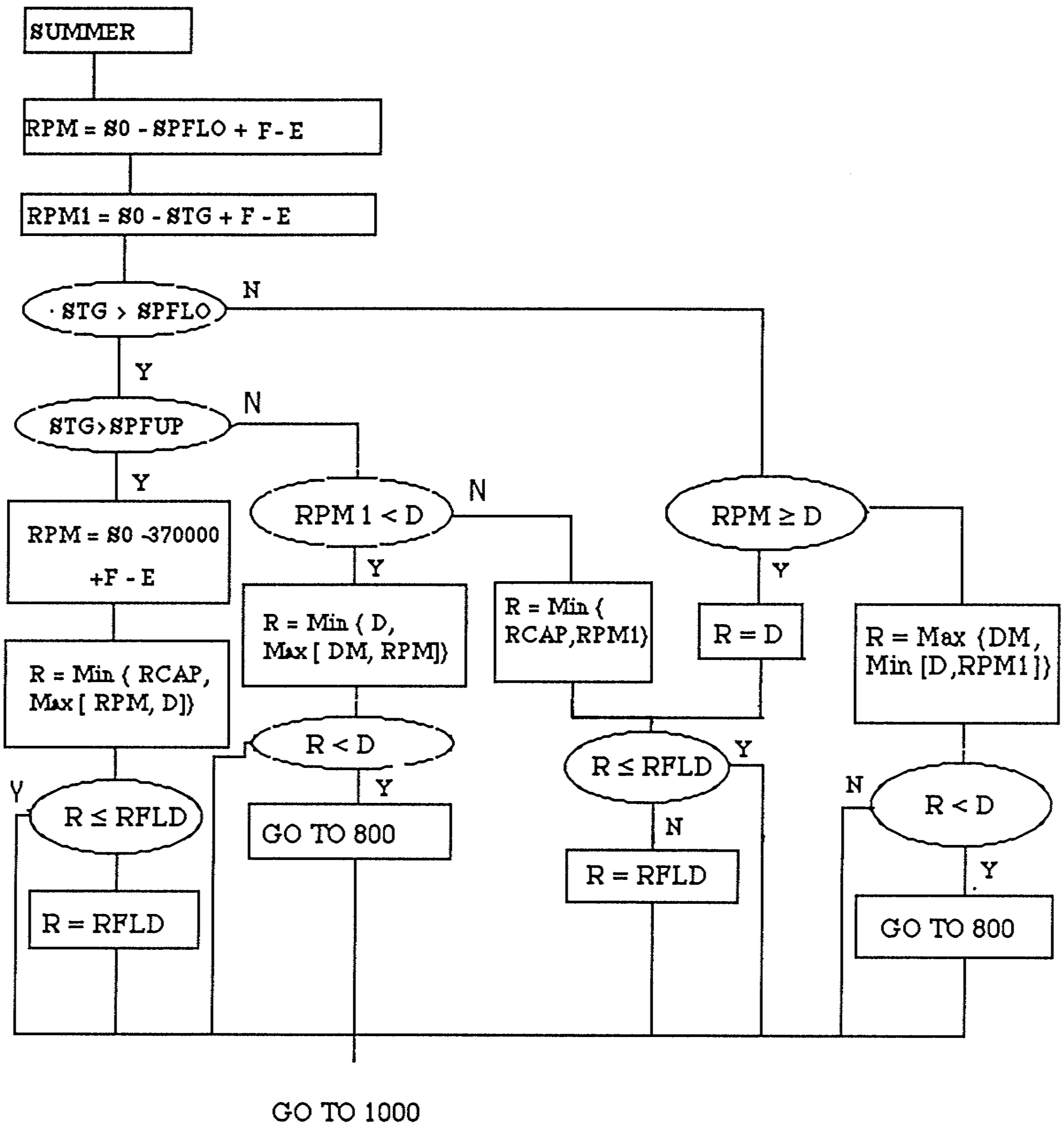
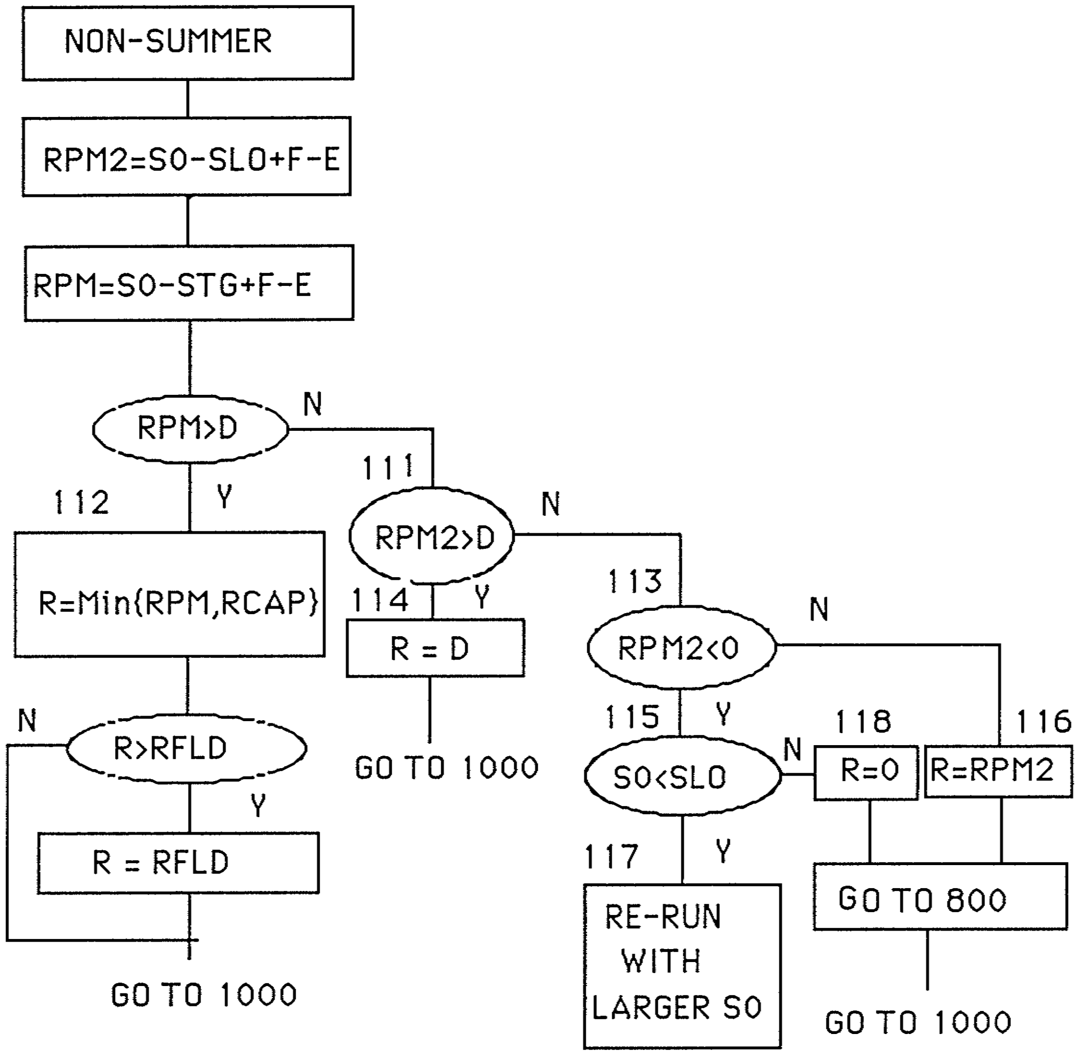


Fig. B.1(d) Sum of the inflows of Station 05MD004 and 05MD005. 1981 - 1987

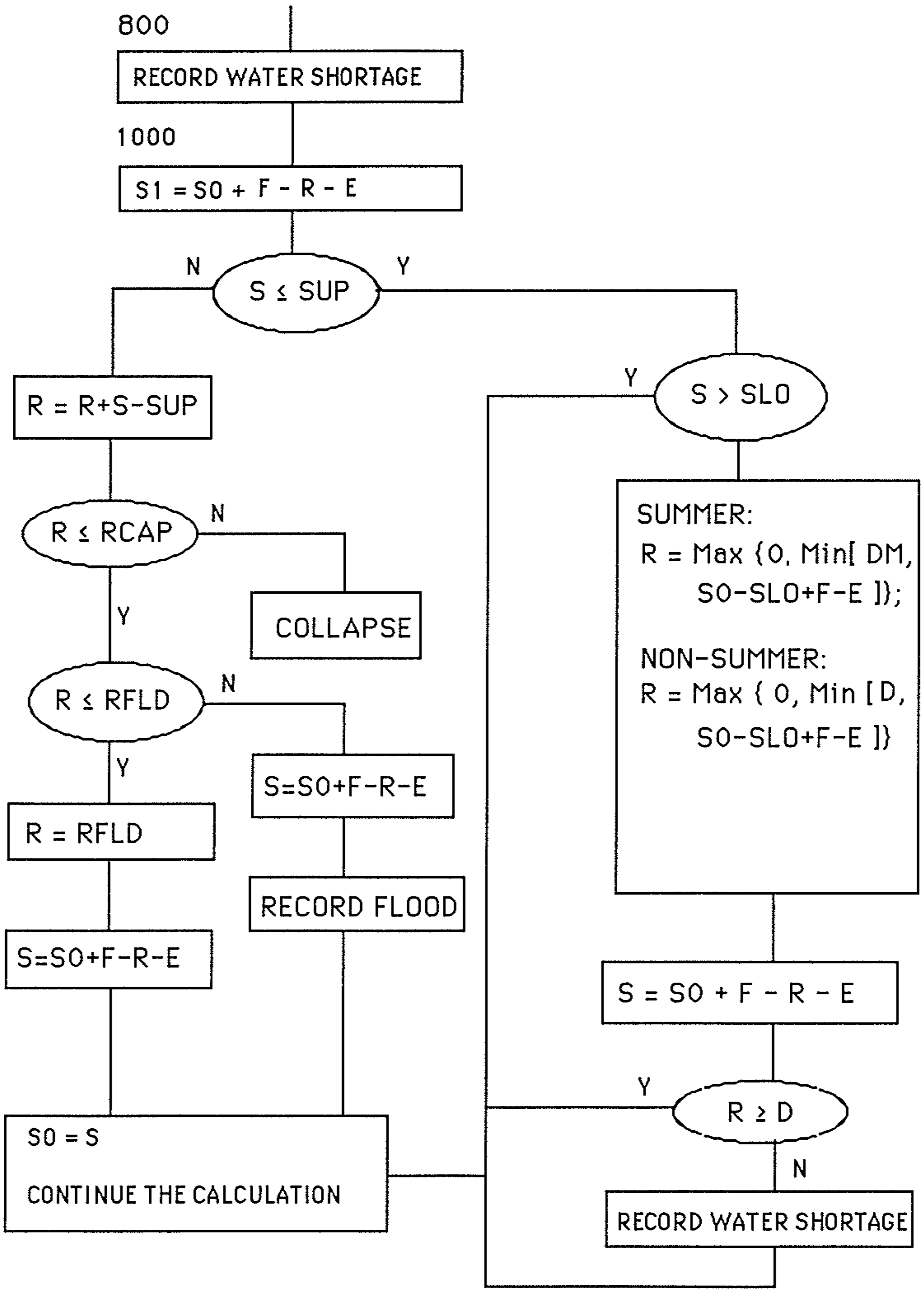
APPENDIX C. THE FLOW CHART OF THE MONTHLY TIME STEP SIMULATION MODEL: STEP 3


SUMMER
RPM = S0 - SPFLO + F - E
RPM1 = S0 - STG + F - E
STG > SPFLO
N
Y
STG>SPFUP
N
Y
RPM = S0 -370000 +F - E
R = Min { RCAP, Max [RPM, D]}
R ≤ RFLD
Y
R = RFLD
RPM 1 < D
N
Y
R = Min { D, Max [DM, RPM]}
R < D
Y
GO TO 800
R = Min { RCAP,RPM1}
RPM ≥ D
Y
R = D
R ≤ RFLD
Y
N
R = RFLD
R = Max {DM, Min [D,RPM1]}
R < D
N
Y
GO TO 800
GO TO 1000

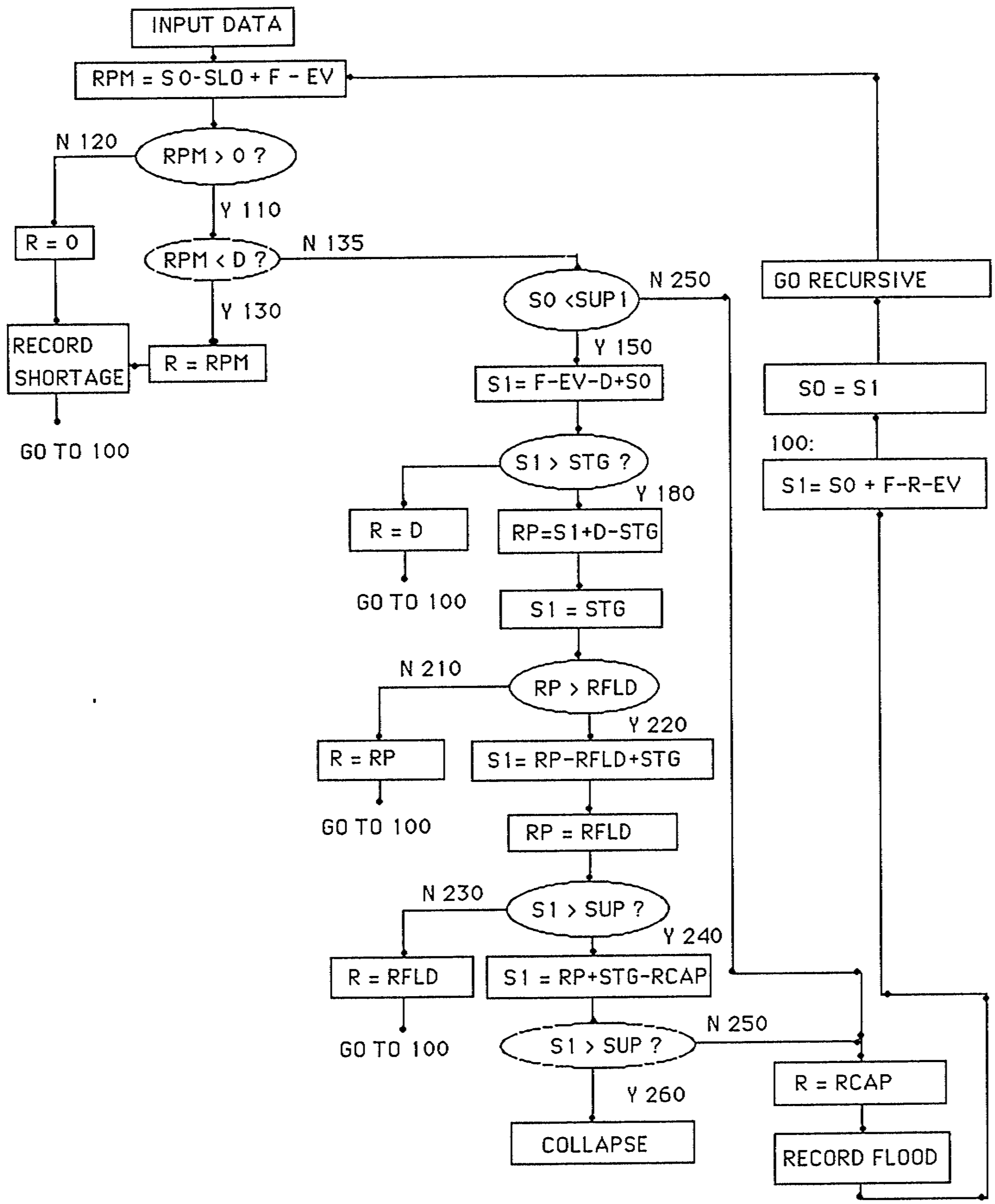


800: RECORD WATER SUPPLY SHORTAGE.

1000: CALCULATE S1=S0+F-E-R


800
RECORD WATER SHORTAGE
1000
S1 = S0 + F - R - E
S ≤ SUP
N
Y
R = R+S-SUP
R ≤ RCAP
N
COLLAPSE
Y
R ≤ RFLD
N
S=S0+F-R-E
RECORD FLOOD
Y
R = RFLD
S=S0+F-R-E
S0 = S
CONTINUE THE CALCULATION
S > SLO
Y
SUMMER:
R = Max {0, Min[DM, S0-SLO+F-E]};
NON-SUMMER:
R = Max { 0, Min [D, S0-SLO+F-E]}
S = S0 + F - R - E
R ≥ D
Y
N
RECORD WATER SHORTAGE

APPENDIX D. THE FLOW CHART OF THE DAILY TIME STEP SIMULATION MODEL.


INPUT DATA
RPM = S0-SL0 + F - EV
N 120
RPM > 0 ?
Y 110
R = 0
RPM < D ?
N 135
Y 130
RECORD SHORTAGE
R = RPM
GO TO 100
S0 <SUP1
N 250
Y 150
S1= F-EV-D+S0
S1 > STG ?
Y 180
R = D
RP=S1+D-STG
GO TO 100
S1 = STG
N 210
RP > RFLD
Y 220
R = RP
S1= RP-RFLD+STG
GO TO 100
RP = RFLD
N 230
S1 > SUP ?
Y 240
R = RFLD
S1 = RP+STG-RCAP
GO TO 100
S1 > SUP ?
N 250
Y 260
COLLAPSE
R = RCAP
RECORD FLOOD
GO RECURSIVE
S0 = S1
100:
S1= S0 + F-R-EV

APPENDIX E. THE RESULTS OF SIMULATION: VERSION 2 THROUGH VERSION 7.

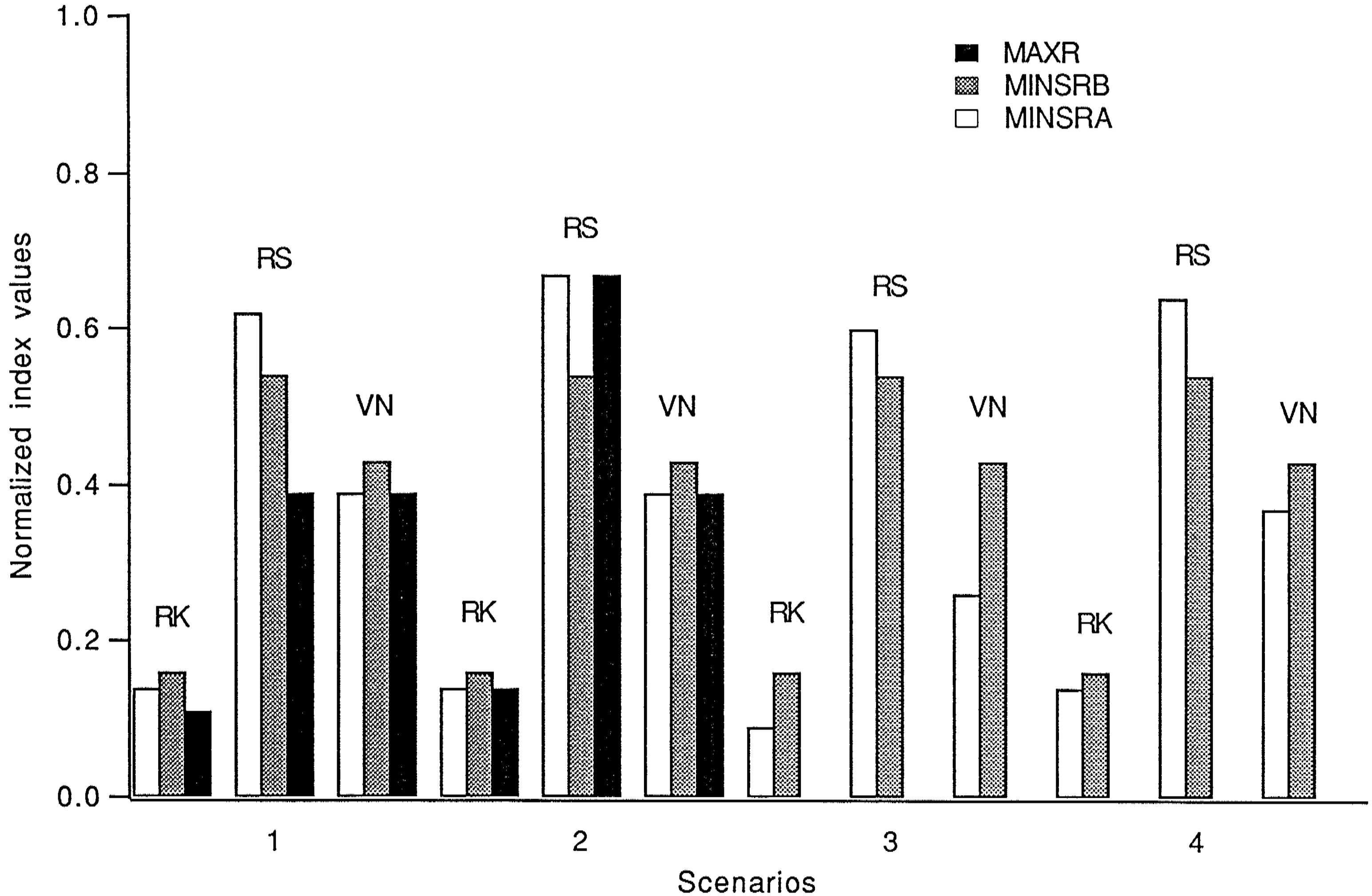


Fig. E.1(a) Policy evaluation for water supply.
Version 2: use randomly extended historic data assuming 2 dry years missed and perfect forecasting

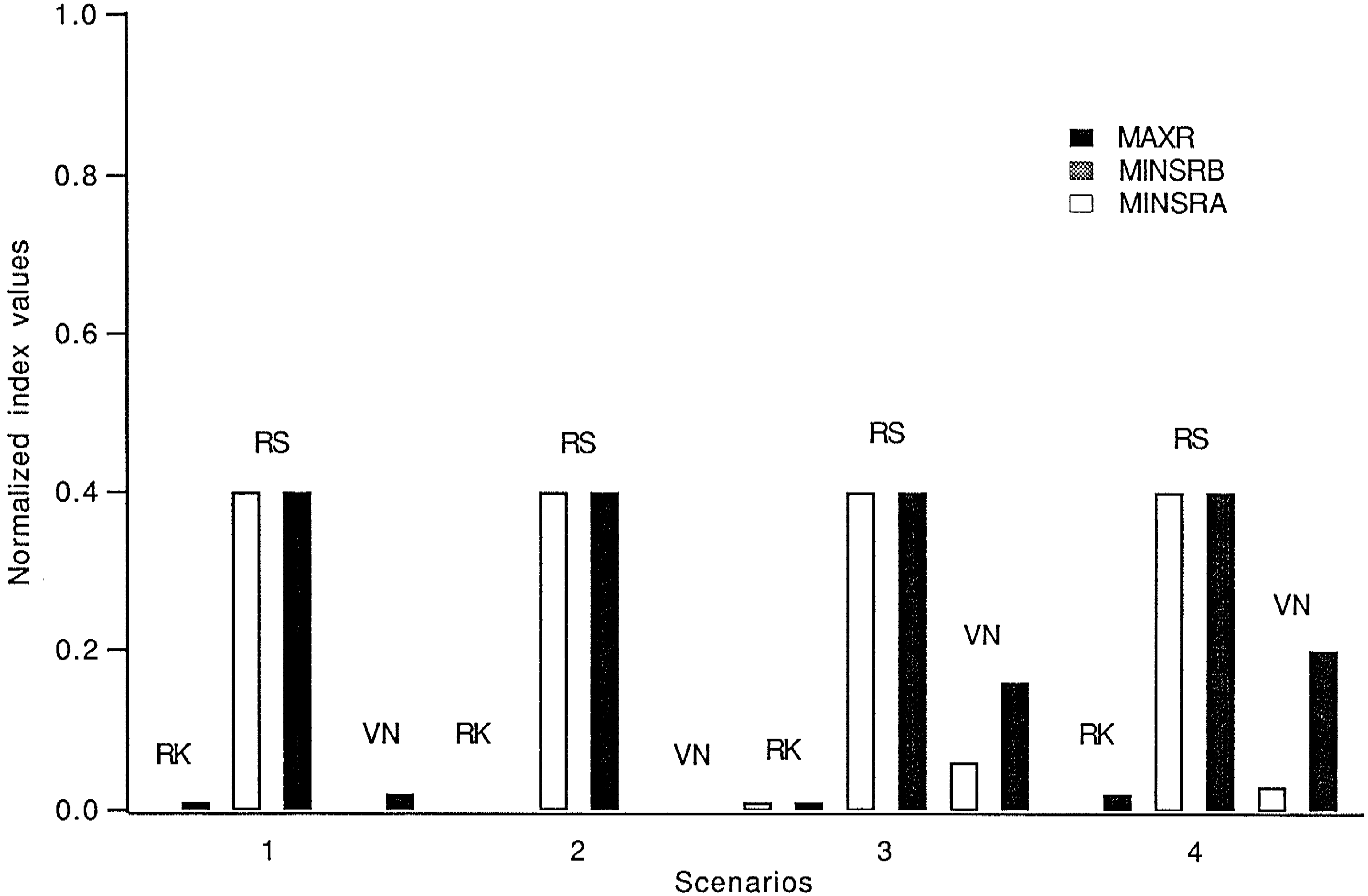


Fig. E.1(b) Policy evaluation for flood control.
Version 2: use randomly extended historic data assuming 2 dry years missed and perfect forecasting

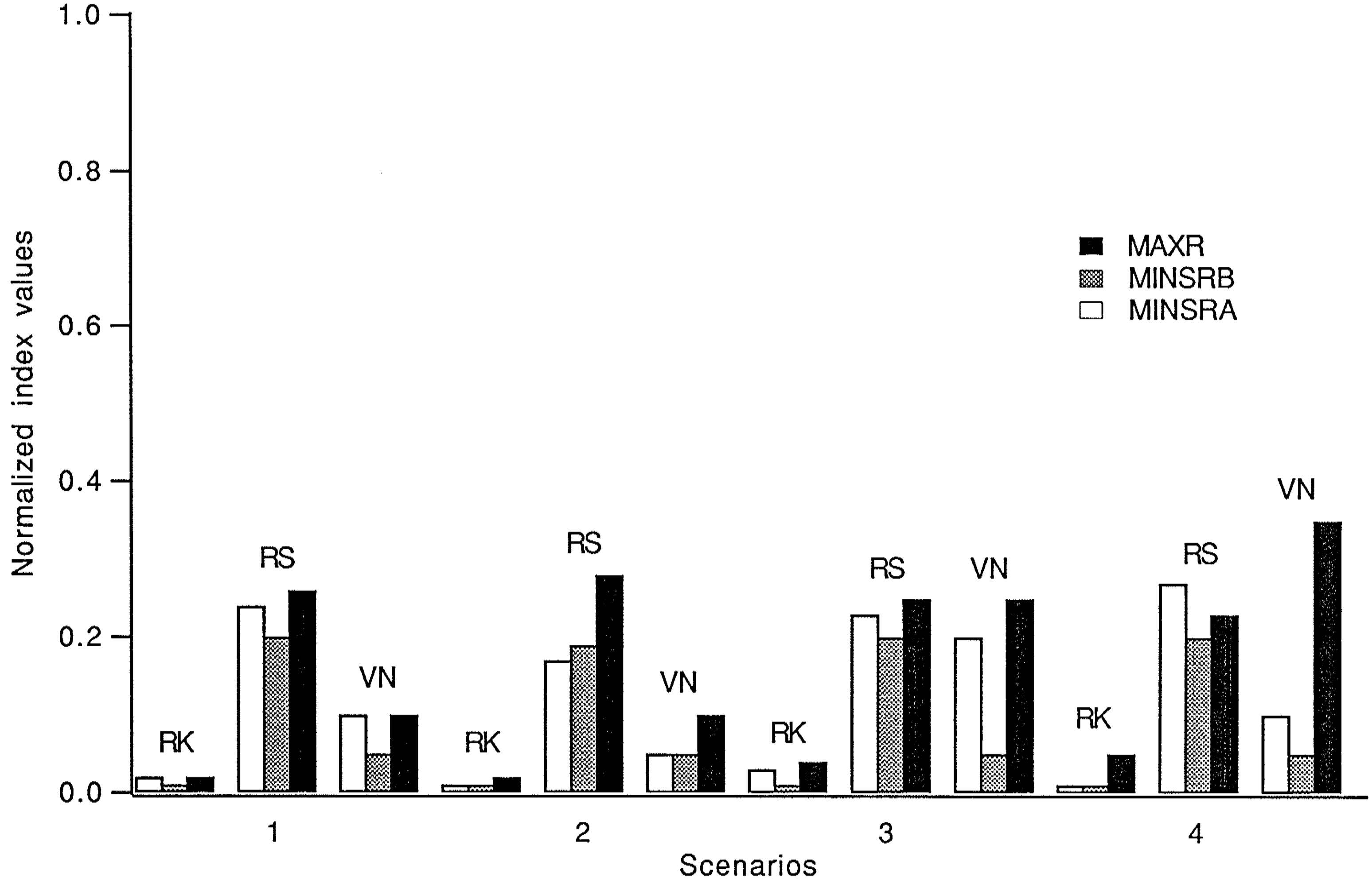


Fig. E.1(c) Policy evaluation for upper storage target.
Version 2: use randomly extended historic data assuming 2 dry yeras missed and perfect forecasting

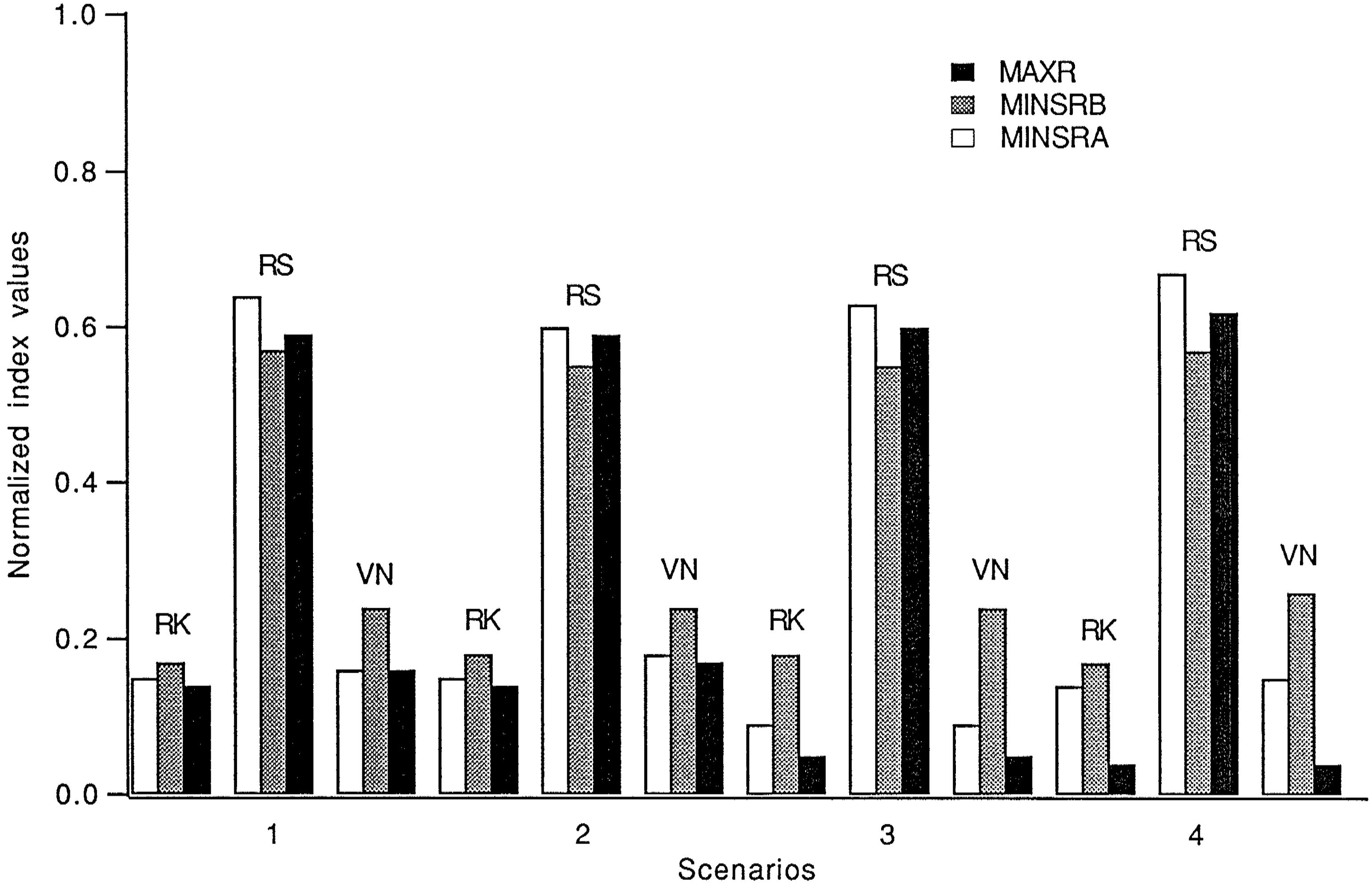


Fig. E.1(d) Policy evaluation for lower storage target.
Version 2: use randomly extended historic data assuming 2 dry years missed and perfect forecasting

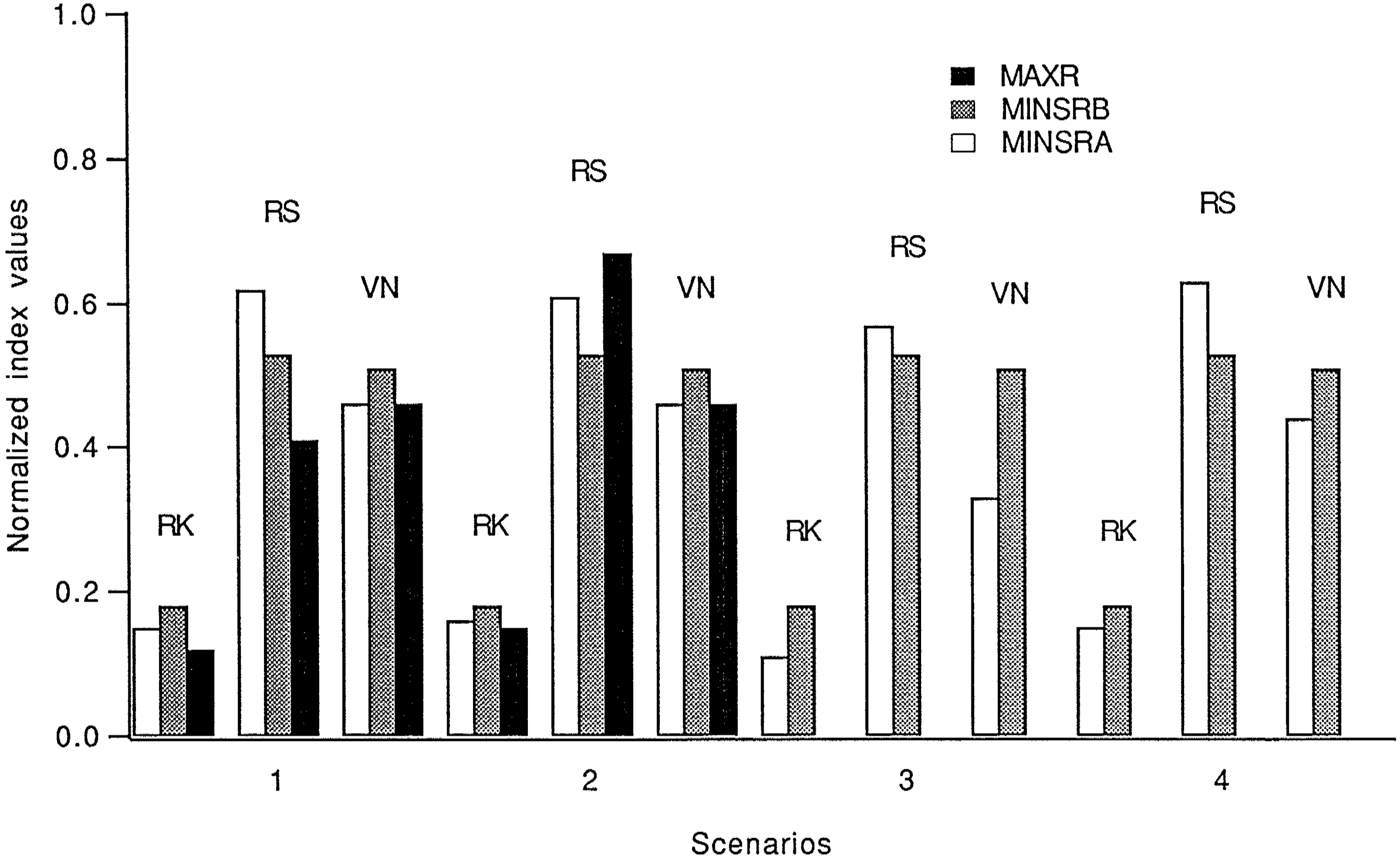


Fig. E.1 (a) Policy evaluation for water suply
Version 2: use randomly extended historic data assuming 2 wet years missed and perfect forecasting

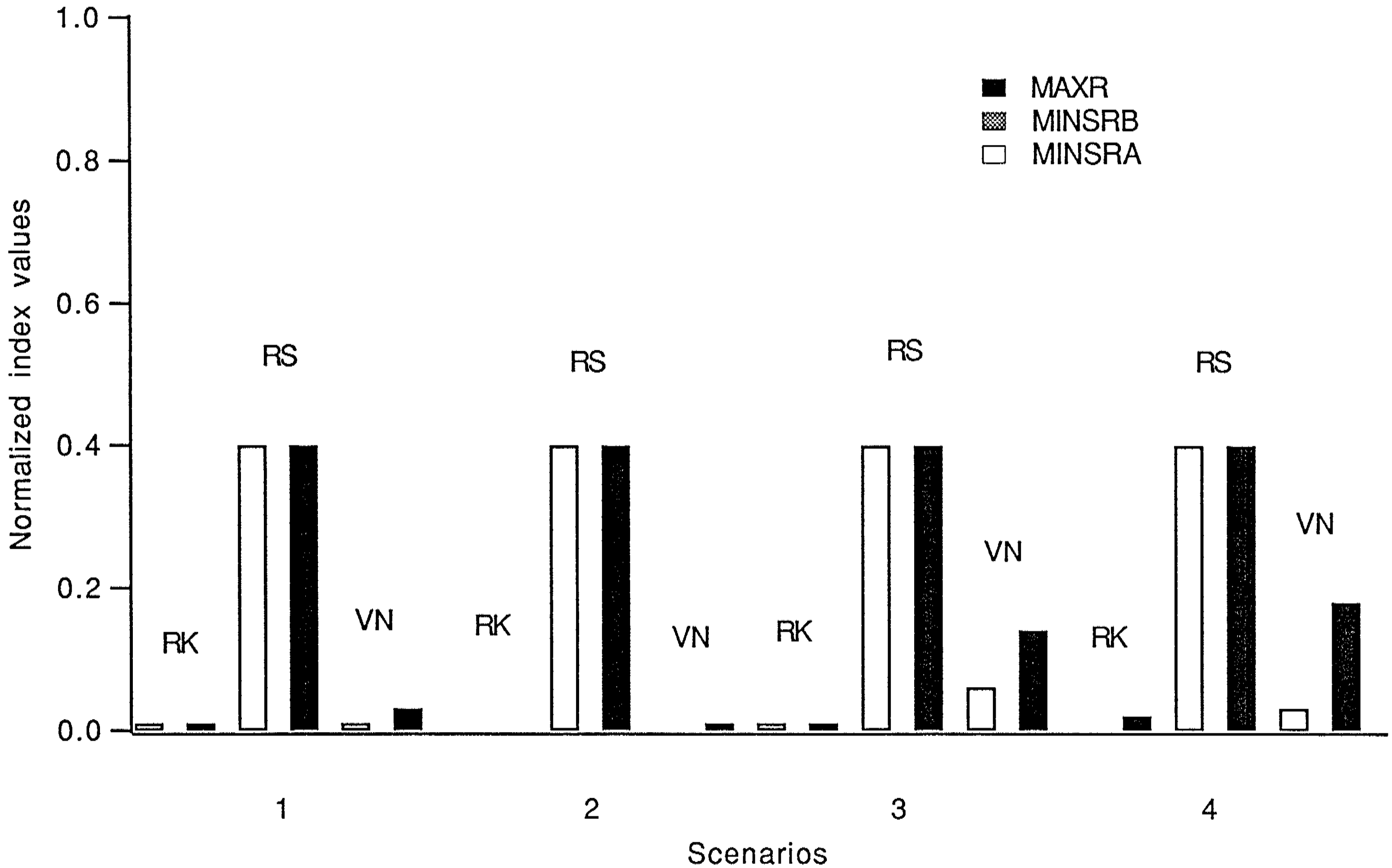


Fig. E.2(b) Policy evaluation for flood control.
Version 3: use randomly extended historic data assuming 2 wet years missed and perfect forecasting

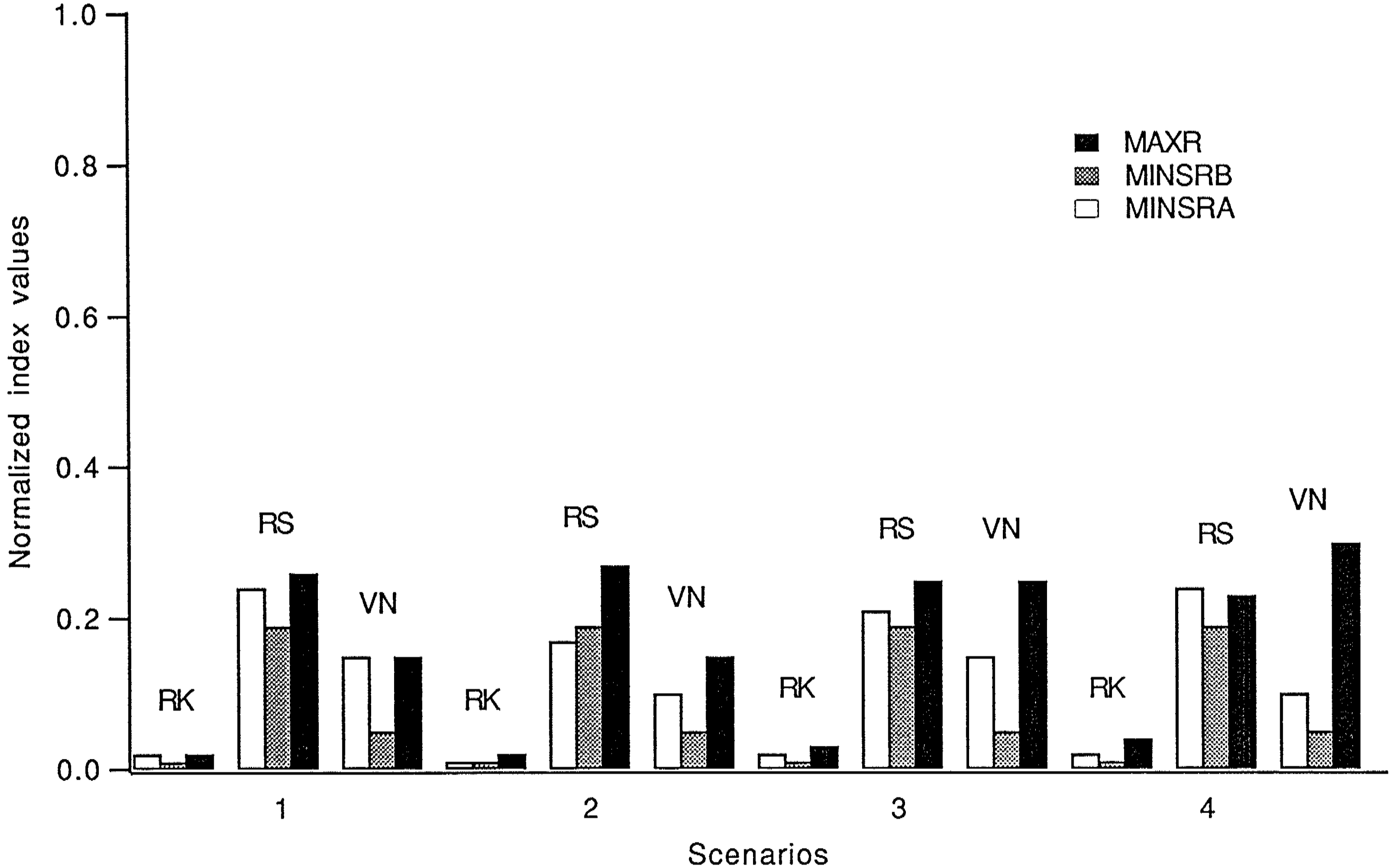


Fig. E.2(c) Policy evaluation for upper storage target.
Version 3: use randomly extended historic data assuming 2 wet years missed and perfect forecasting

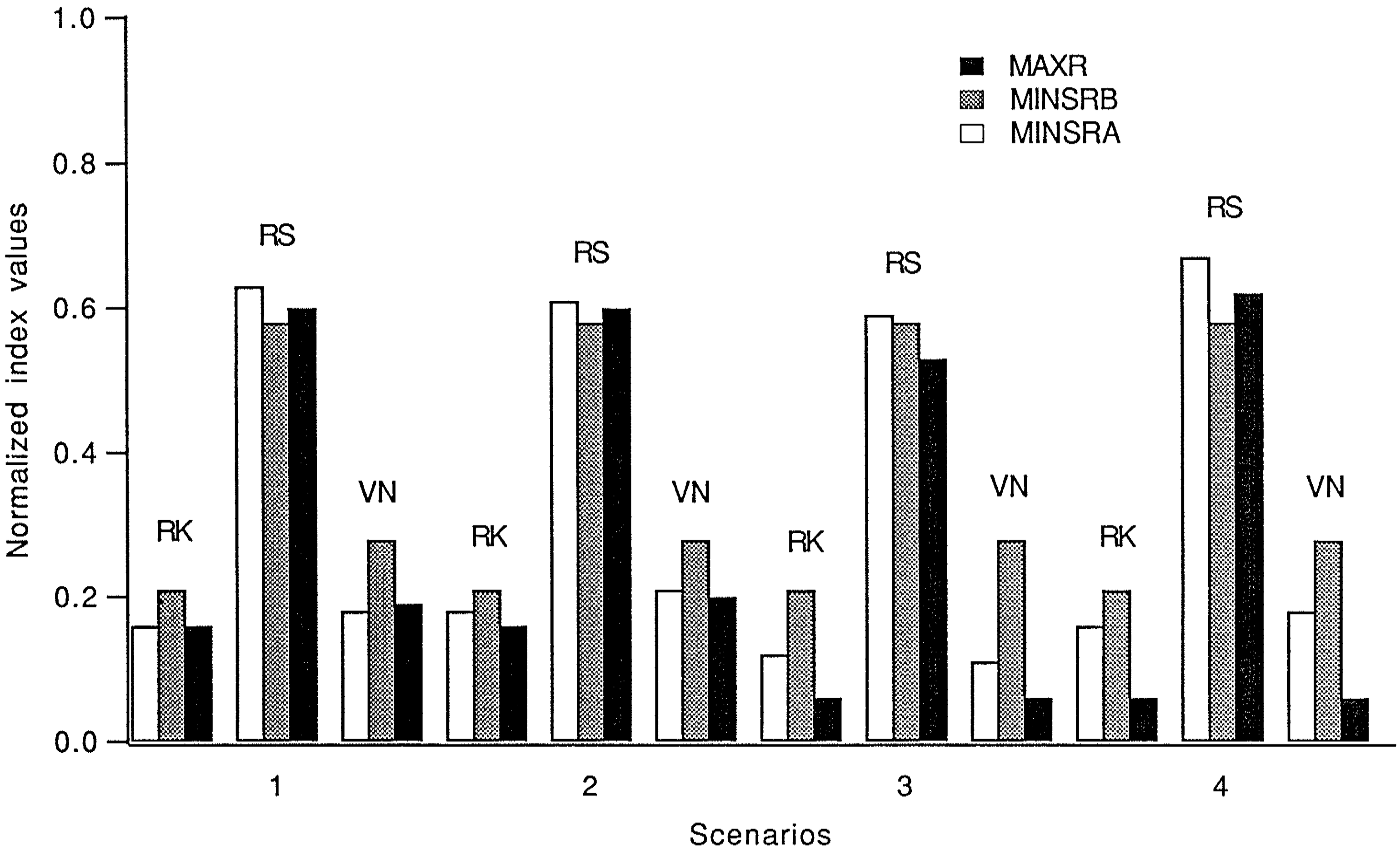


Fig. E.2(d) Policy evaluation for lower storage target.
Version 3: use randomly extended historic data assuming 2 wet years missed and perfect forecasting

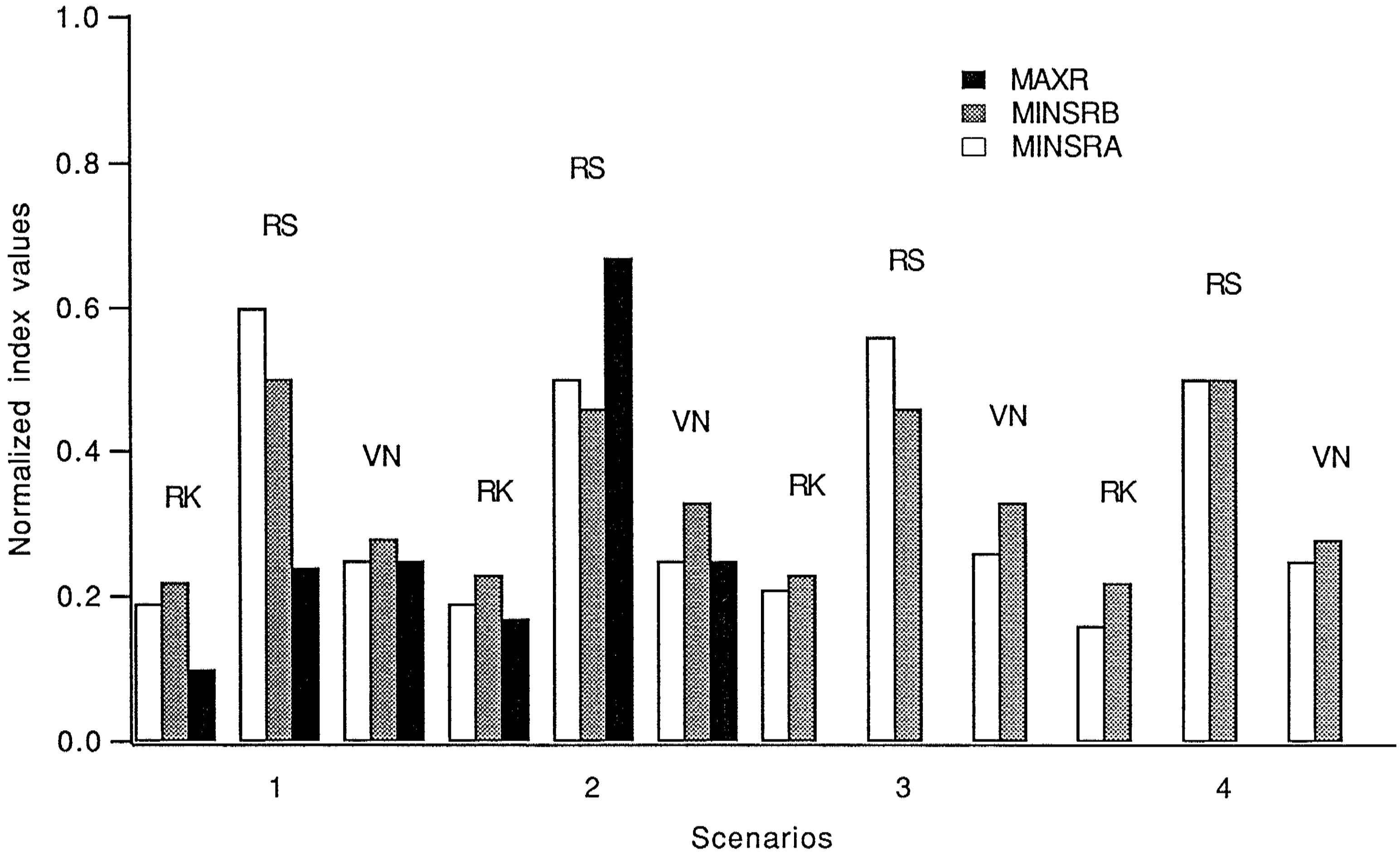


Fig. E.3(a) Policy evaluation for water supply.
Version 4: use historic data and forecasting of WRB

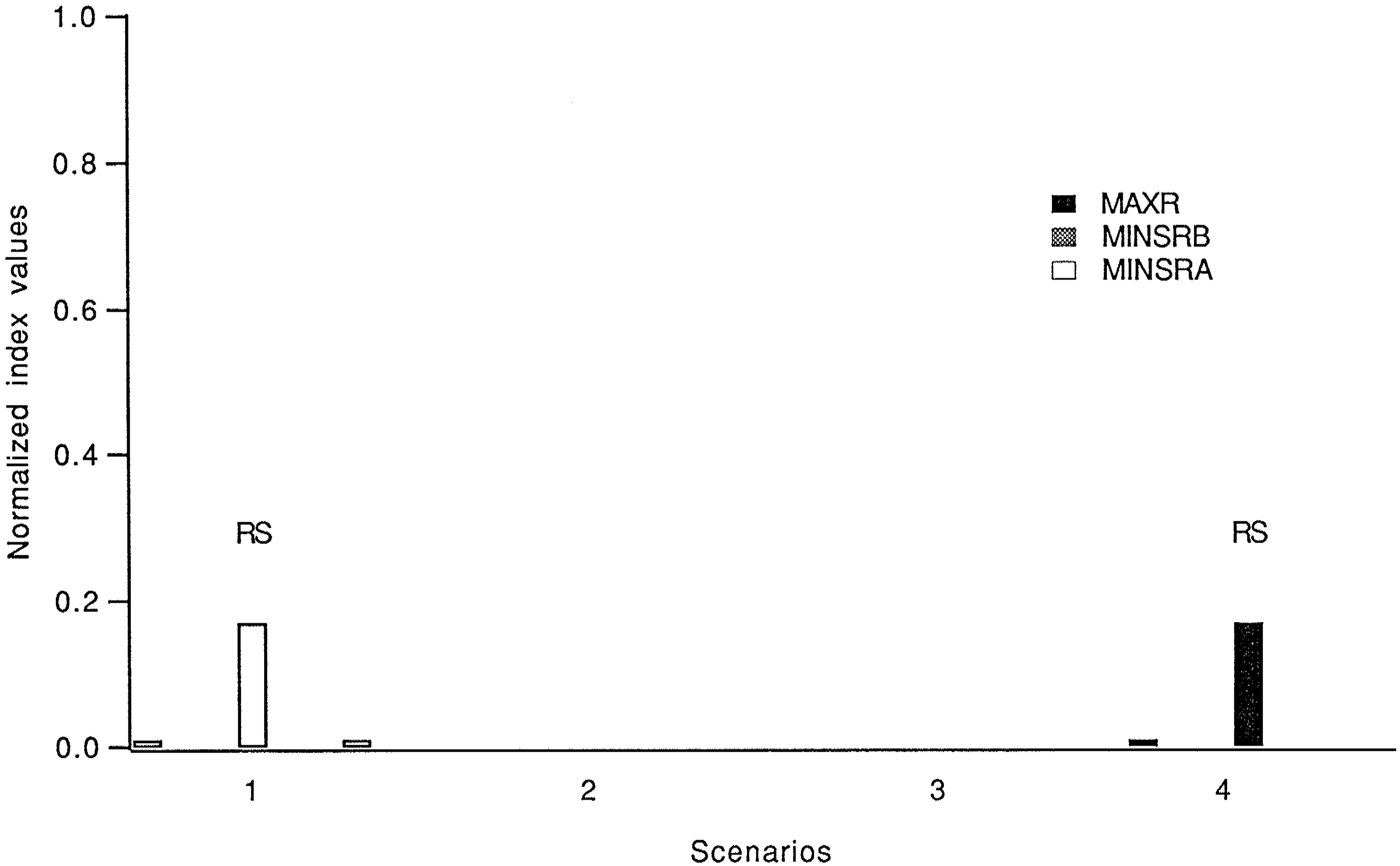


Fig. E.3(c) Policy evaluation for upper storage target.
Version 4: use historic data and forecasting of WRB

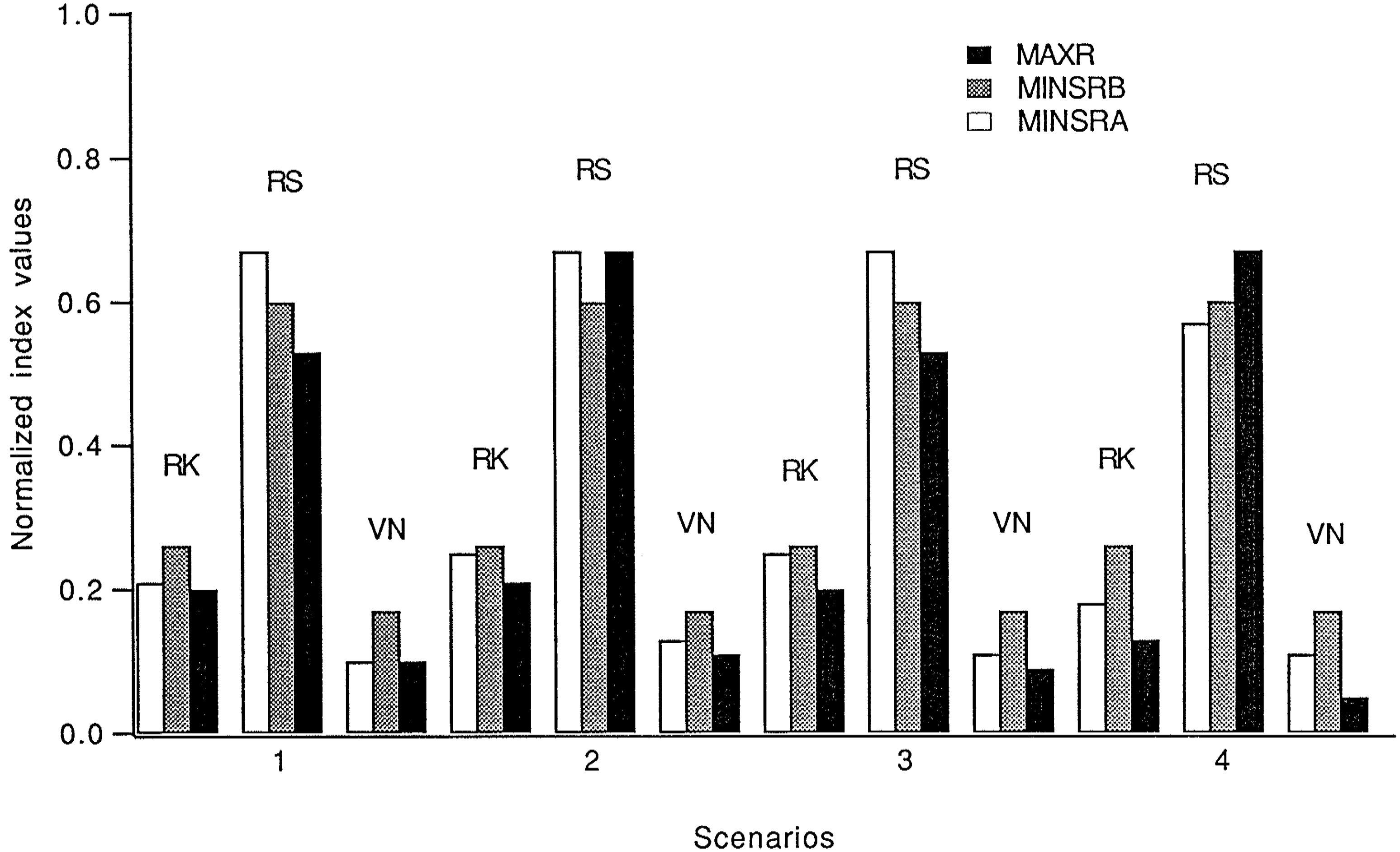


Fig. E.3(d) Policy evaluation for lower storage target.
Version 4: use historic data and forecasting of WRB

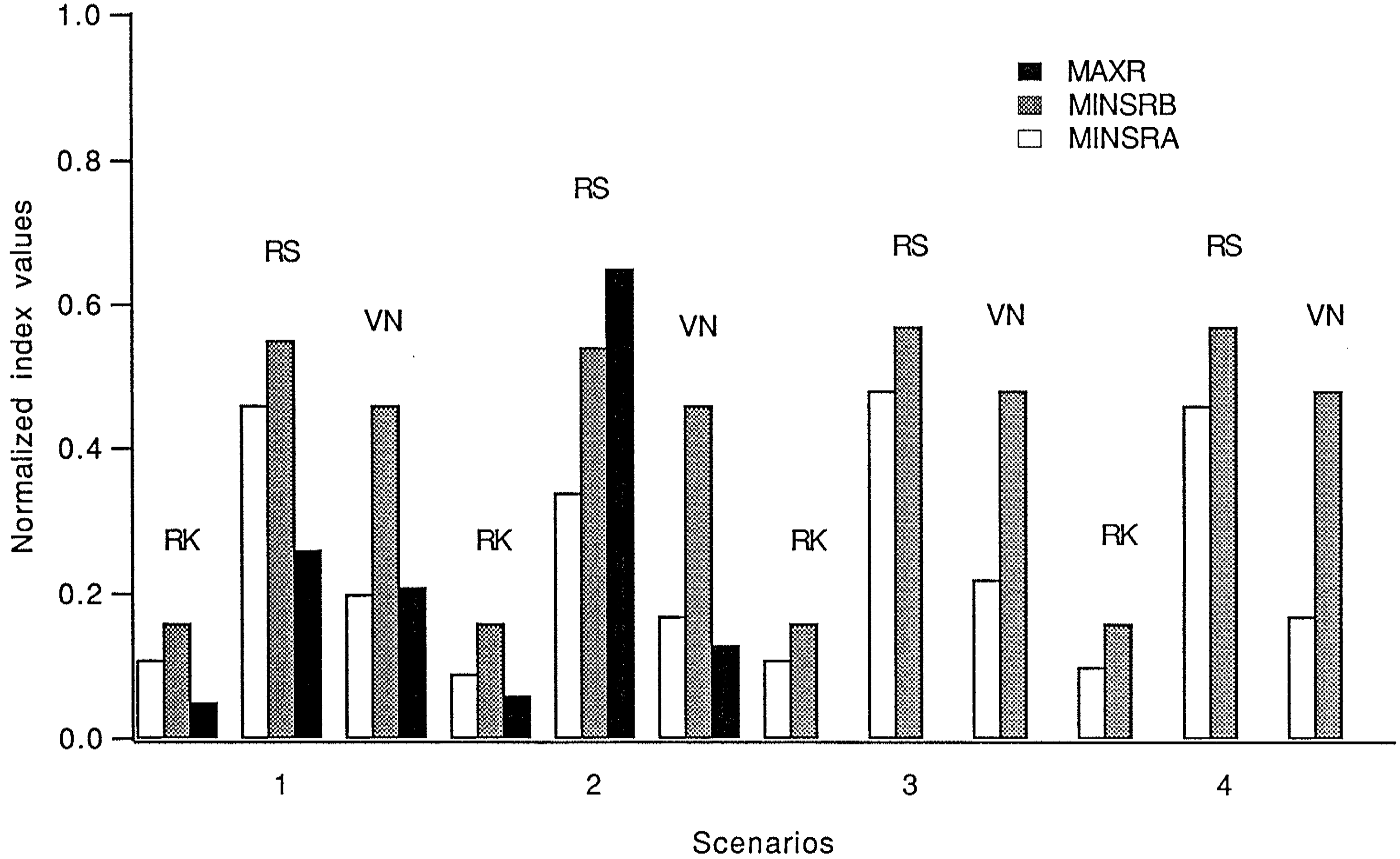


Fig. E.4(a) Policy evaluation for water supply.
Version 5: use historic data and random forecasting

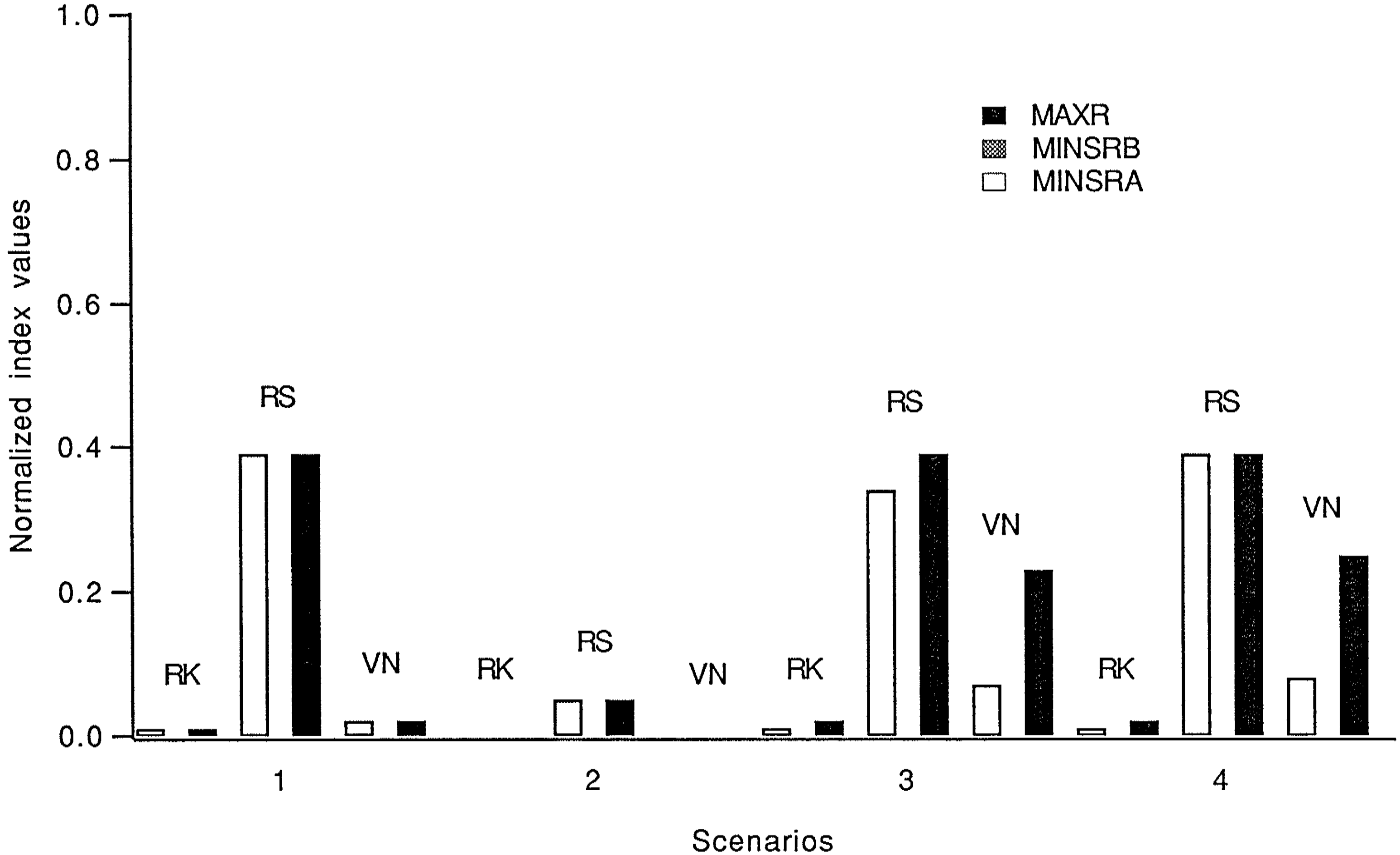


Fig. E.4(b) Policy evaluation for flood control.
Version 5: use historic data and random forecasting

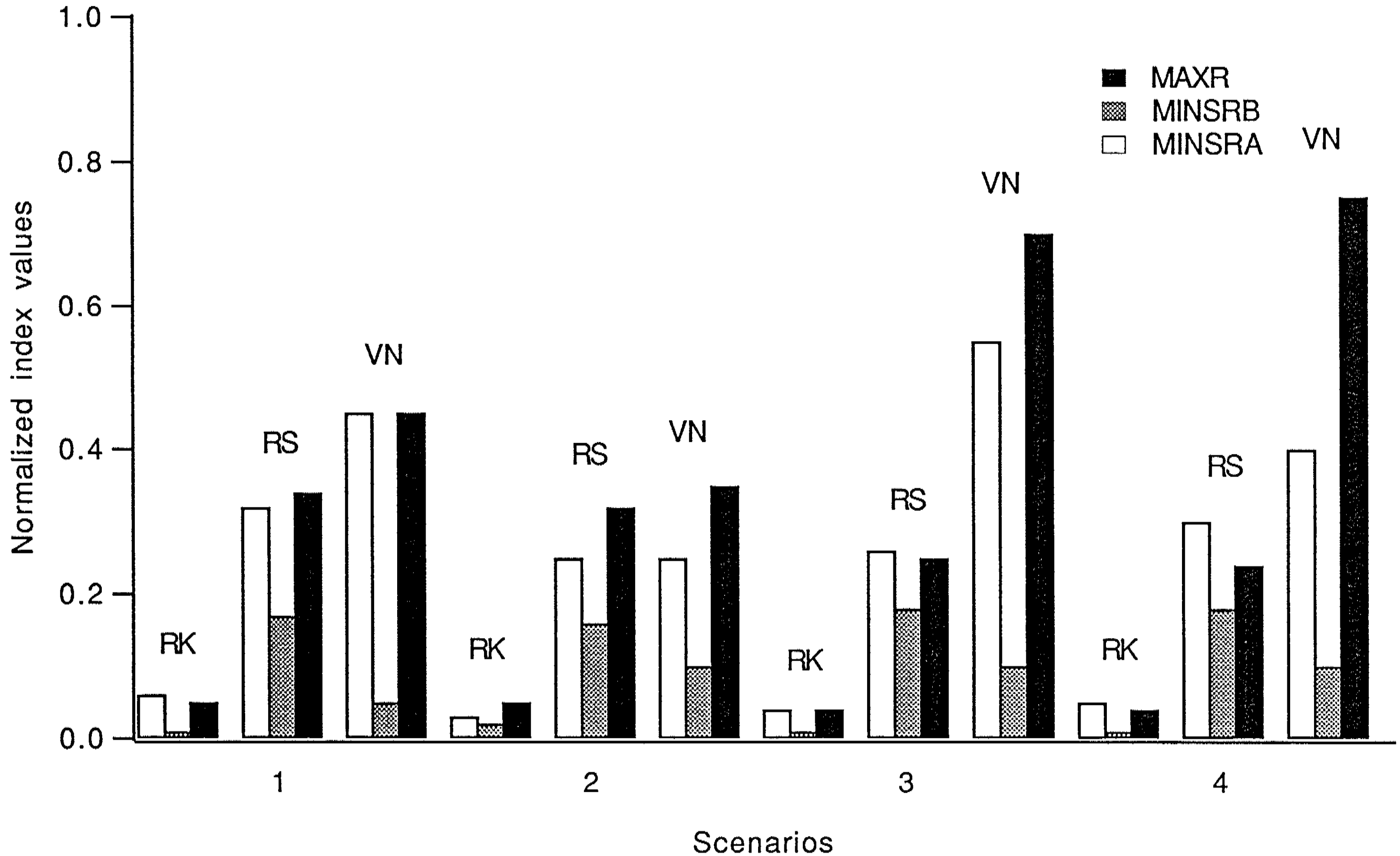


Fig. E.4(c) Policy evaluation for upper storage target.
Version 5: use historic data and random forecasting

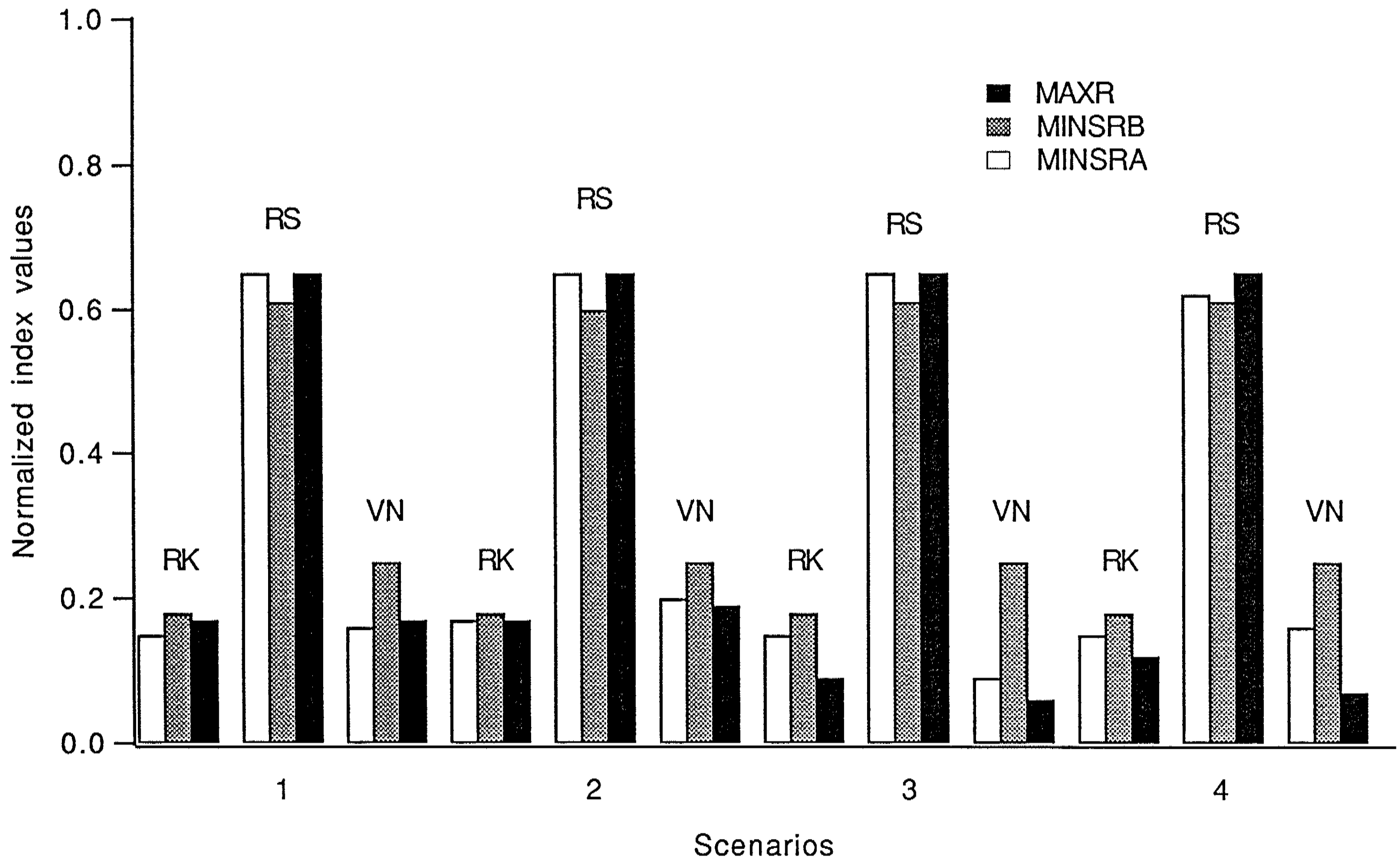


Fig. E.4(d) Policy evaluation for lower storage target.
Version 5: use historic data and random forecasting

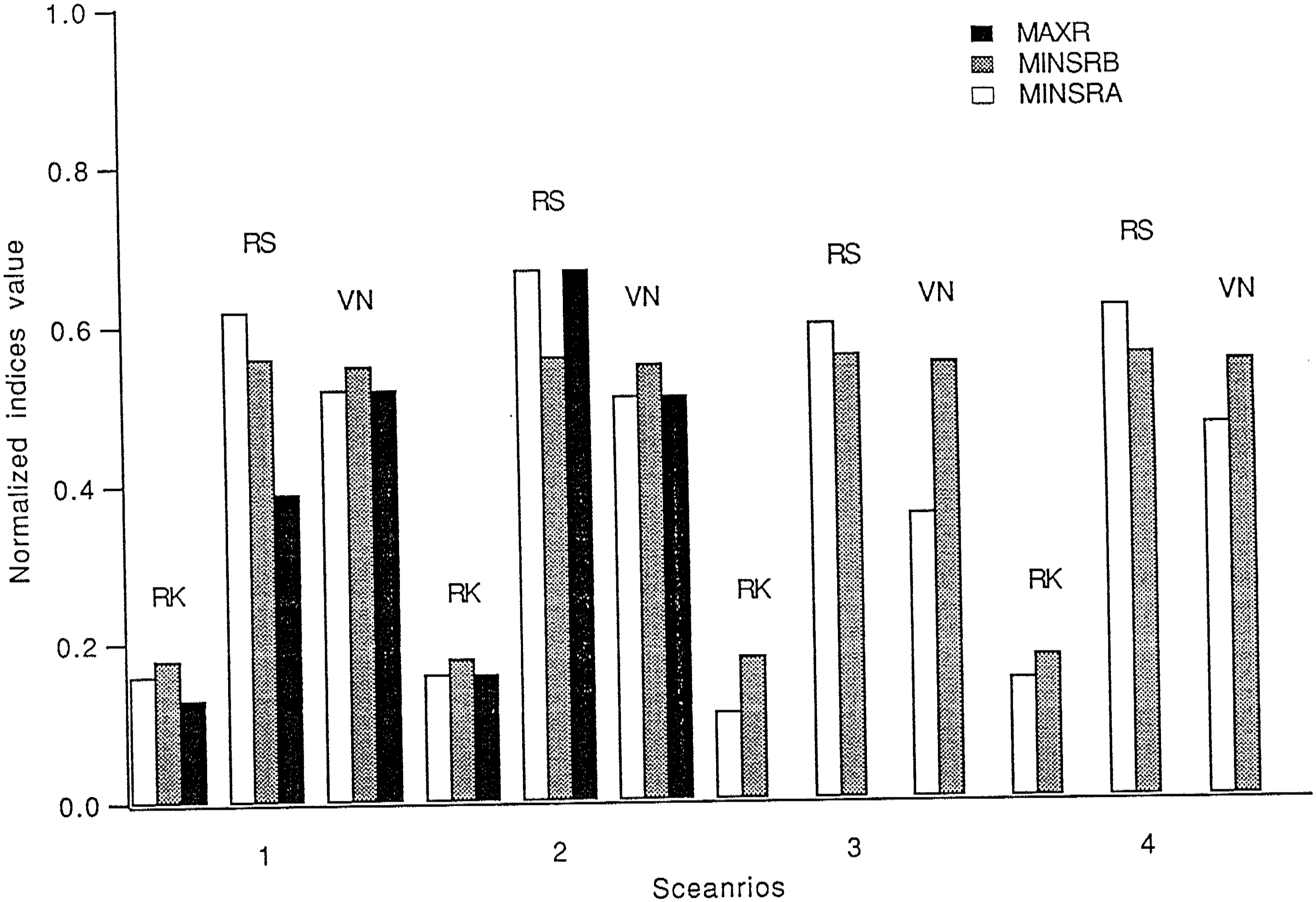


Fig. E.5(a) Policy evaluation for water supply.
Version 6: use randomly extended historic data and perfect forecasting

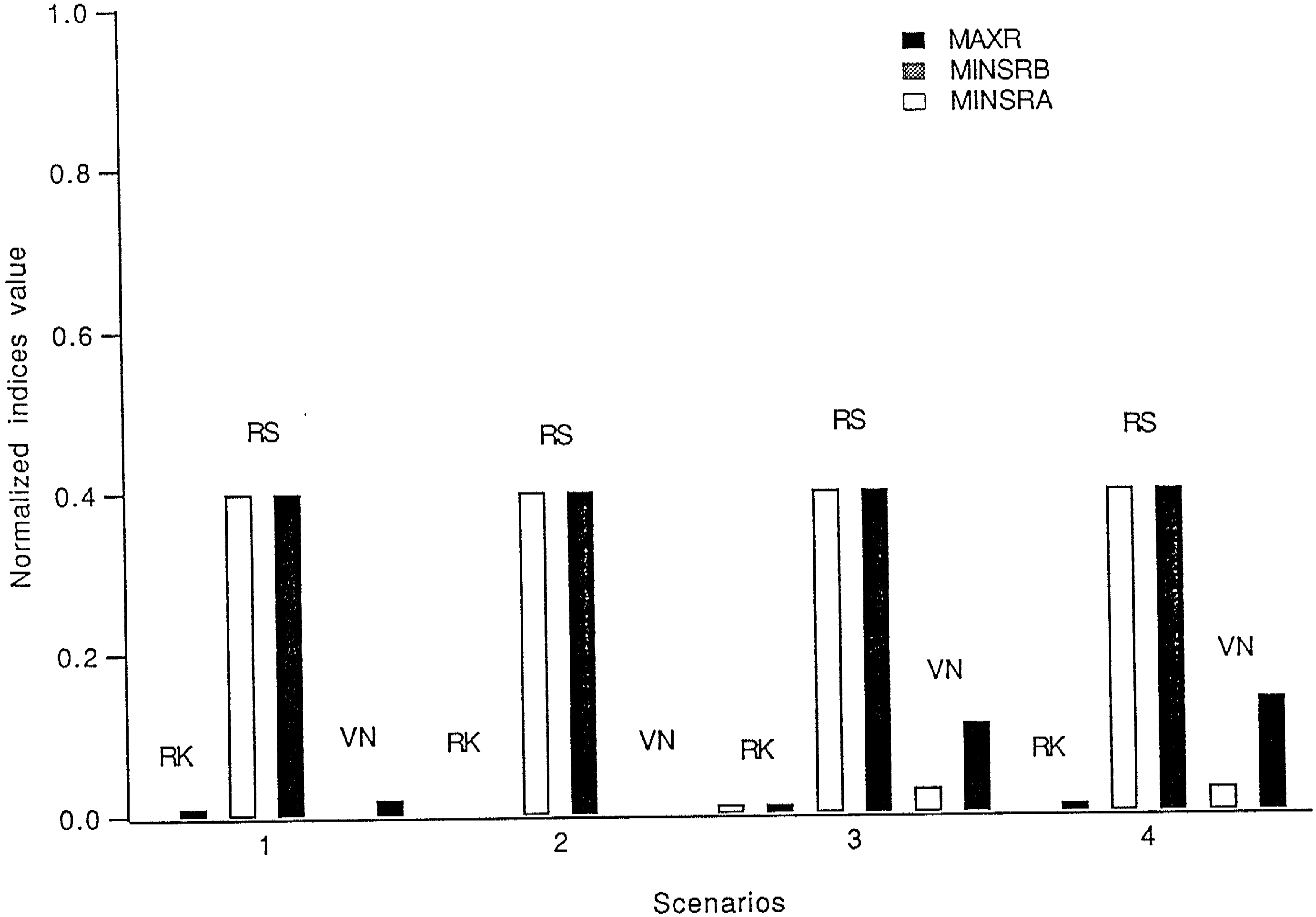


Fig. E.5(b) Policy evaluation for flood control.
Version 6: use randomly extended historic data and perfect forecasting

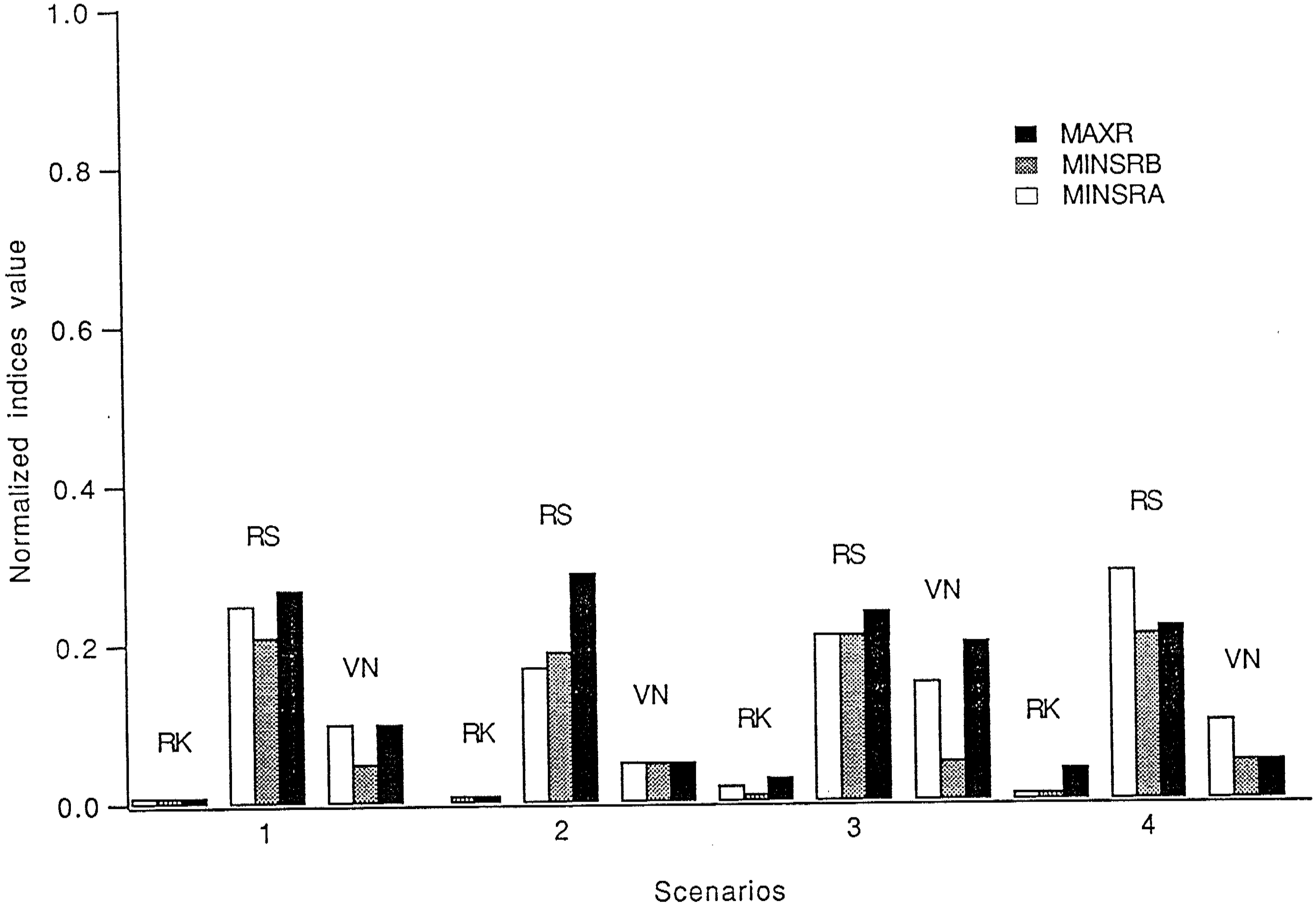


Fig. E.5(c) Policy evaluation for upper storage target.
Version 6: use randomly extended historic data and perfect forecasting

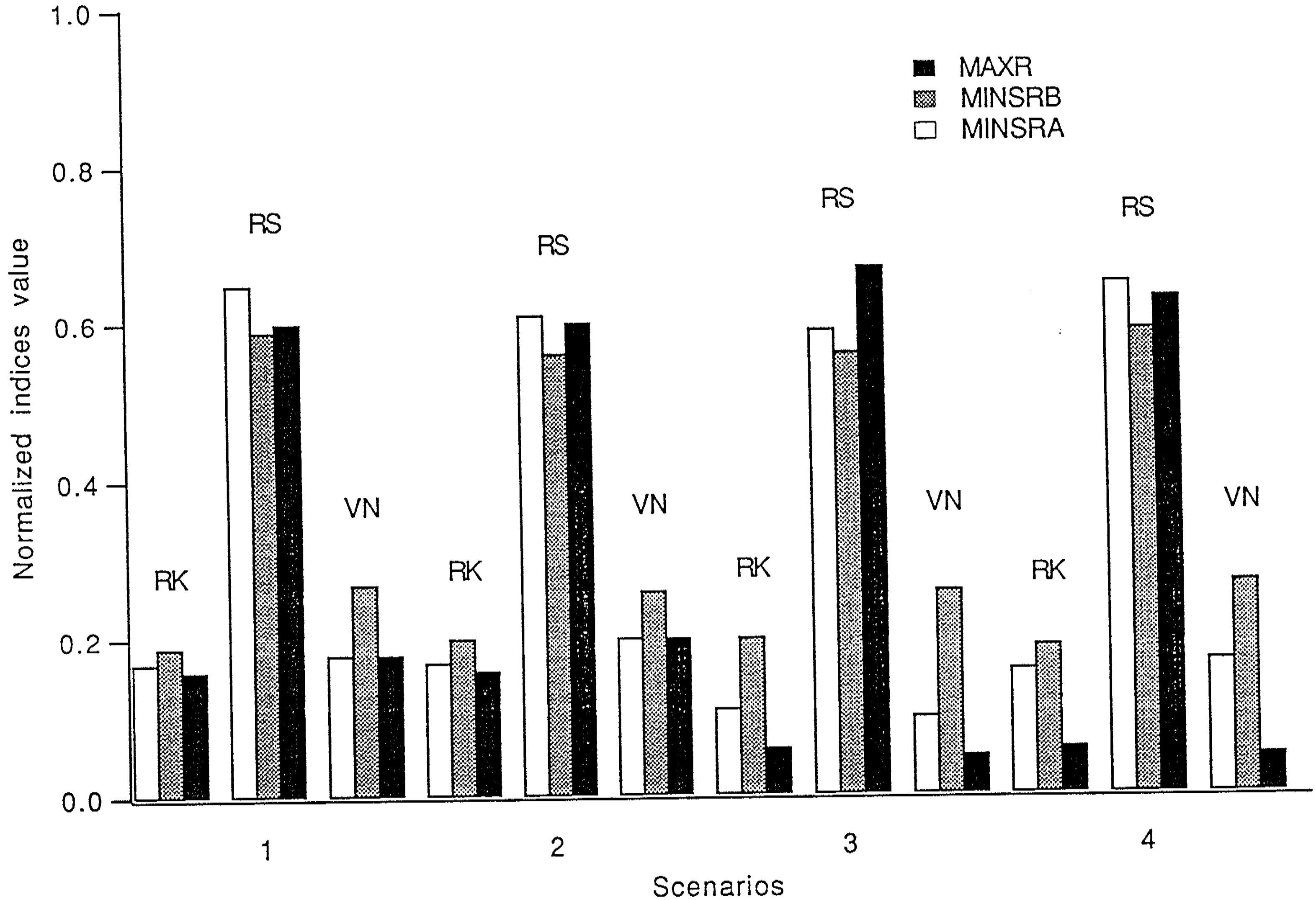


Fig. E.5(d) Policy evaluation for lower storage target.
Version 6: use randomly extended historic data and perfect forecasting

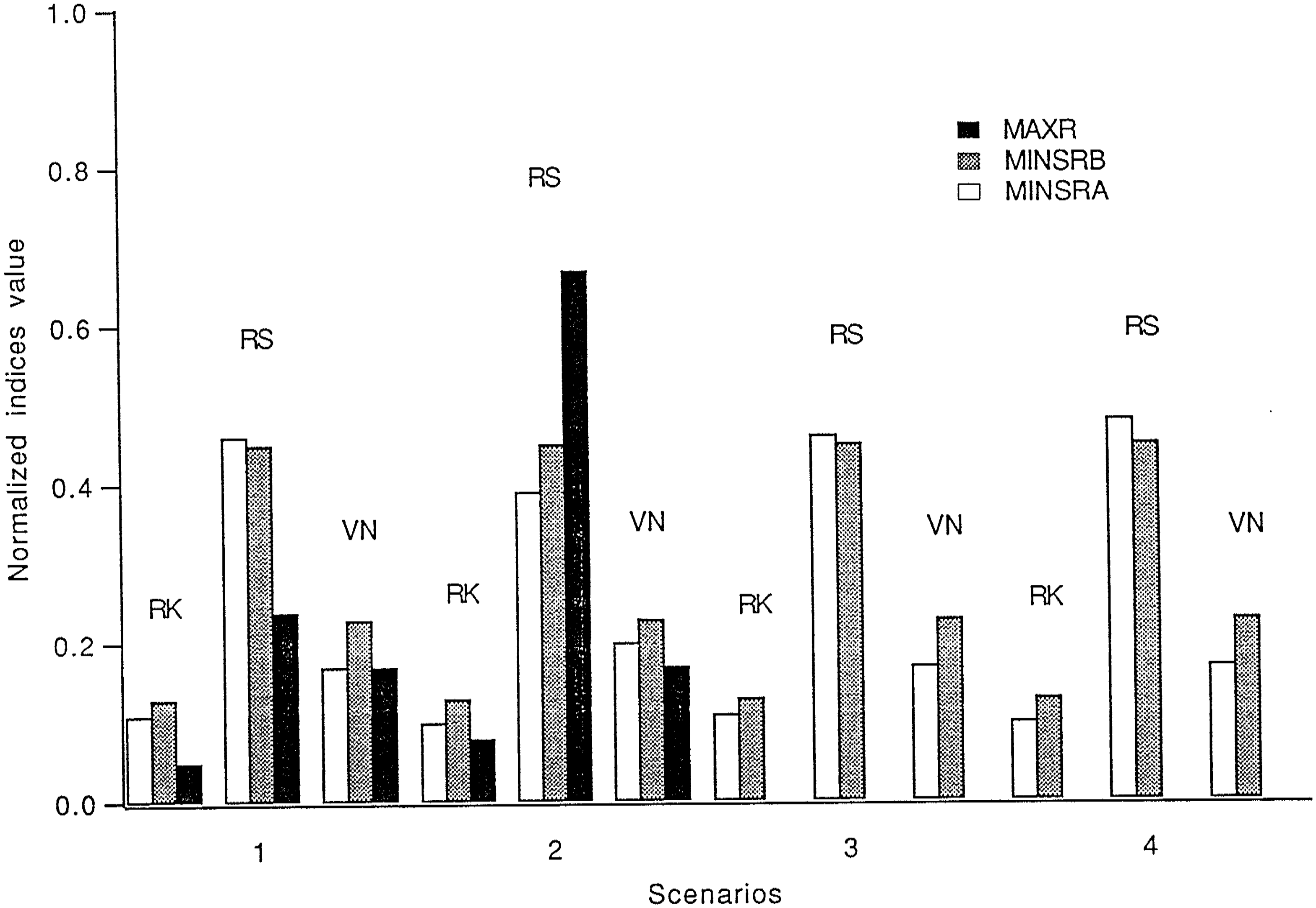


Fig. E.6(a) Policy evaluation for water supply.
Version 7: use historic data and incorrect forecasting

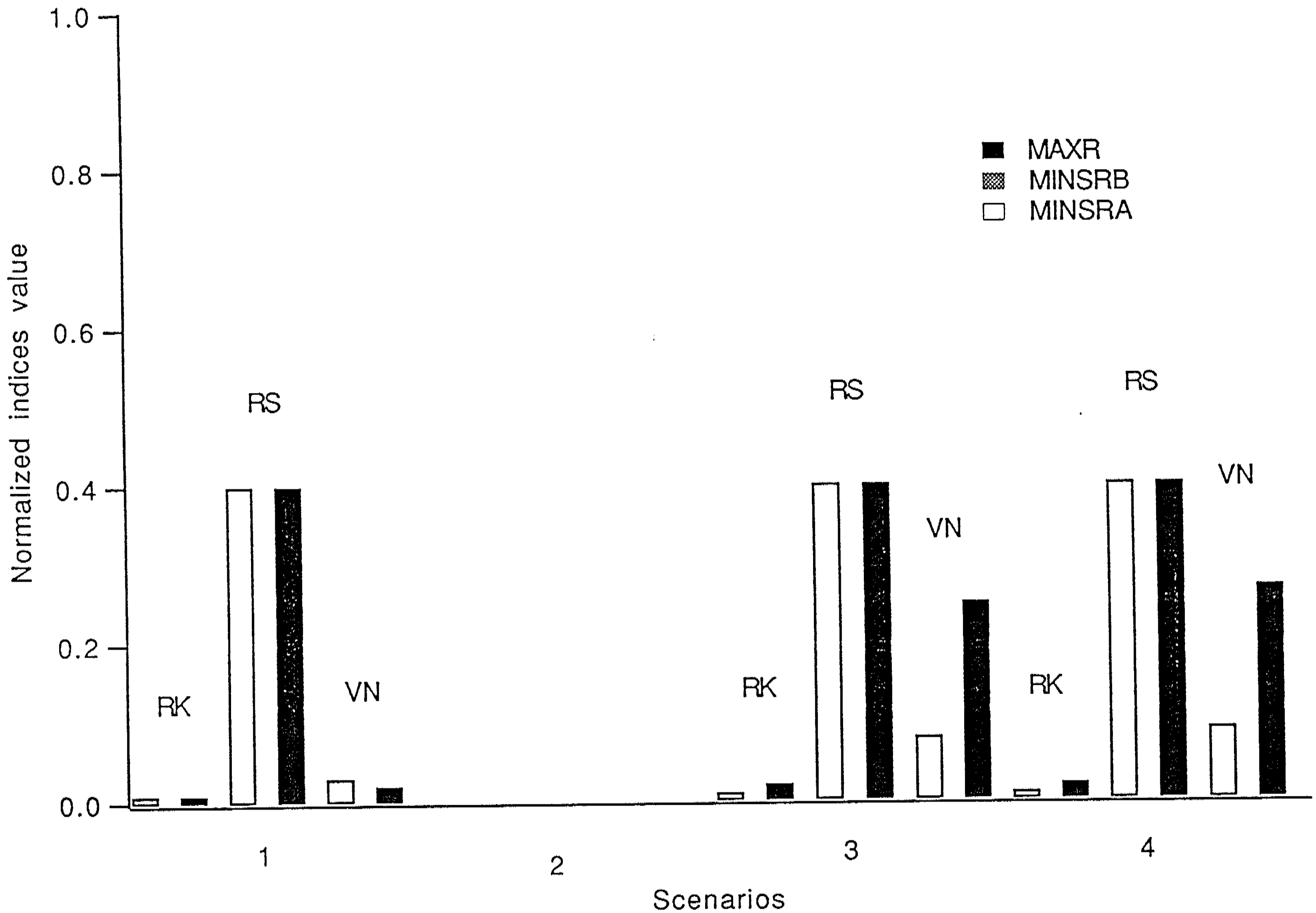


Fig. E.6(b) Policy evaluation for flood control.
Version 7: use historic data and incorrect forecasting

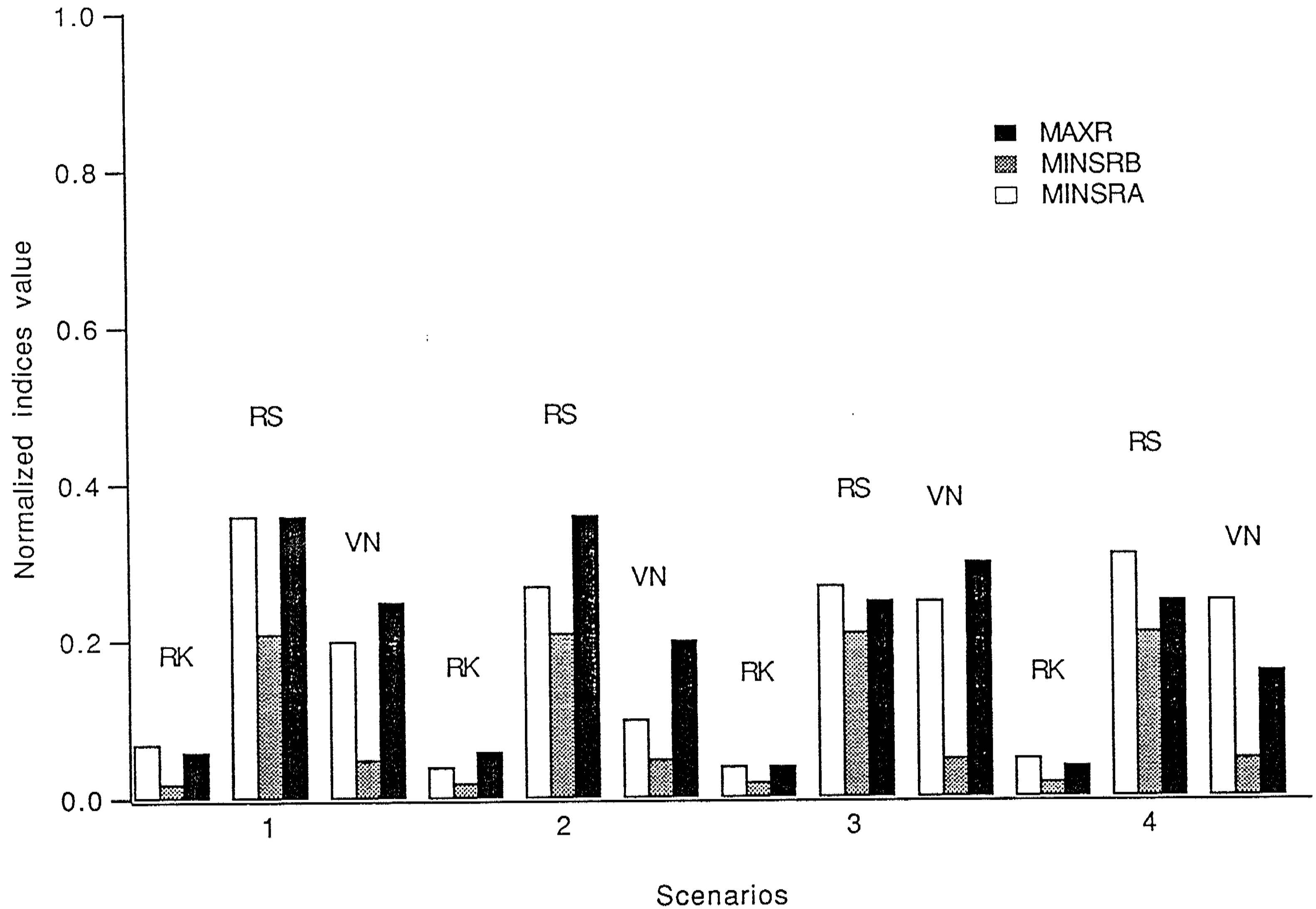


Fig. E.6(c) Policy evaluation for upper storage target.
Version 7: use historic data and incorrect forecasting

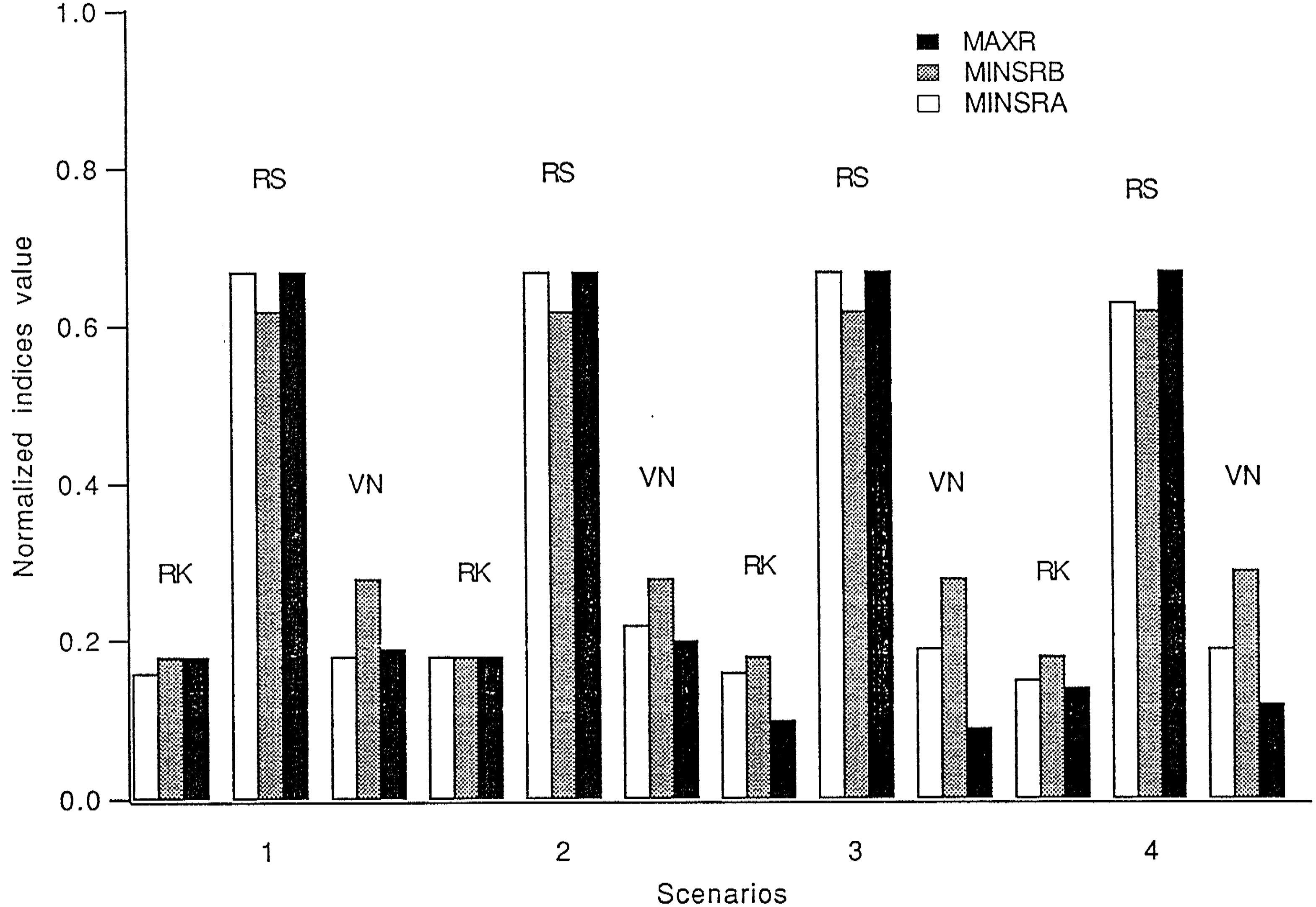


Fig. E.6(d) Policy evaluation for lower storage target.
Version 7: use historic data and incorrect forecasting