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Development of Reservoir Operational Policy Using Soft Computing

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ABSTRACT: Optimization models have proved to be powerful and useful methods to solve the design and operation problems associated with reservoir problems. A heuristic simulation based optimization model has been developed to optimize the operation of a multiple reservoir using dynamic programming and soft computing techniques. A combination of Simulation-based Controlled Optimization Model (SCOM) and Soft Computing techniques approach is proposed and developed to optimize the operation of the multi-reservoir systems to take their advantages and overcome their weaknesses. This heuristic approach involves three stages in the model development. In the first stage GA is used to develop initial trajectories for SCOM model and then SCOM model results were used to adopt training data set for ANFIS model. Finally, a general operating policy was developed for multi-reservoir system operations. The demonstration is carried out through application of Parambikulam Aliyar Project (PAP) systems in India. The performance of the proposed hybrid model was compared with current operating policies adopted for actual operation. Rule curves are developed for different scenarios like current operating policy, rezoning pattern, improved irrigation management and increase of available water potentials.

INTRODUCTION

The fact that the world faces a water crisis has become increasingly clear in recent years. Challenges remain widespread and reflect severe problems in the management of water resources in many parts of the world (Cosgrove and Rijsberman, 2000). Water experts define areas where per capita water supply drops below 1,700 m^3/year as experiencing a "water stress" situation in which disruptive water shortages can frequently occur. Many developing countries including India have difficulty in supplying this minimum annual per capita water requirement of 1,700 m^3. One of the justifications for constructing dams is to store the water during monsoon for use during non-monsoon months. However, if the dams have storage levels above 10 per cent of live capacity before the monsoon, it means that the waters have not been utilized to sub-optimal use of capacity created with colossal investments.

(Yeh, 1985) presented a comprehensive in-depth state of the art review of reservoir operation models, with a strong emphasis on optimization techniques and more recently, (Labadie, 2004) provided an extensive review of various optimization methods. Most applications to water resources systems analysis involve Linear Programming (LP) and Dynamic Programming (DP). Heuristic search algorithms may be set up in a number of ways, but as yet there is no standard procedure in implementing them and it is hard to perceive the best implementations for particular applications. Heuristic techniques do not guarantee the optimal solutions but many good solutions can be obtained which are practically useful in reality.

The method proposed in this study belongs to a relatively new research discipline called Soft Computing (SC), a name coined by (Zadeh, 1994). Soft computing attempts to integrate several different computing paradigms including Artificial Neural Networks (ANN), Fuzzy Logic (FL) and Genetic Algorithms (GA) etc. When utilized together, the strengths of each technique can be exploited in a synergistic manner for the creation of 'smart' systems. In this study different optimization models including heuristic search algorithms, combination of traditional and heuristic algorithms and artificial intelligence technique are proposed and integrated into a decision support system and examined for their performance in solving the multi-reservoir system operation problems.

Computerized decision support systems have been increasingly emphasized over the past two decades, for use both in planning-type reevaluation studies and real-time operations. A decision support system consists of integrated computer hardware and software packages readily useable by managers as an aid for making implementations and operations decisions. The present study is attempted to develop a decision making tool with the aid of DP and Nero-Fuzzy model

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for deriving operating rules for different time periods in an irrigation reservoir for the optimal use of available water resources. The aim of this research study is to develop a framework for adaptive reservoir management, which utilizes maximum available information. Proposed Simulation-based Soft Computing model will help to the change traditional reservoir operation by combining real-time data (reservoir levels and inflows) and inflow forecasts with historical data in order to optimize operation strategies, taking advantage of the rapid development in computational techniques.

STUDY AREA

The system considered for the study is the Parambikulam—Aliyar Project (PAP) located in the borders of the states of Tamilnadu and Kerala. This is a multi-purpose, multi-reservoir project with inter-basin transfer of water from one basin to another basin. PAP system consists of a number of finite-capacity storage reservoirs, river channels and man-made conduits delivering water to various destinations throughout the river basin (Figure 1; Table 1).

Three categories of constraints have been considered in the PAP Systems: (a) Physical and technical constraints, e.g. sizes of reservoirs and of connecting conduits, temporal maximum and minimum water levels; (b) Interstate Agreements between Tamilnadu and Kerala concerning specified releases to Kerala at specified locations and their timing, specified maximal diversions and specified reservoir levels;

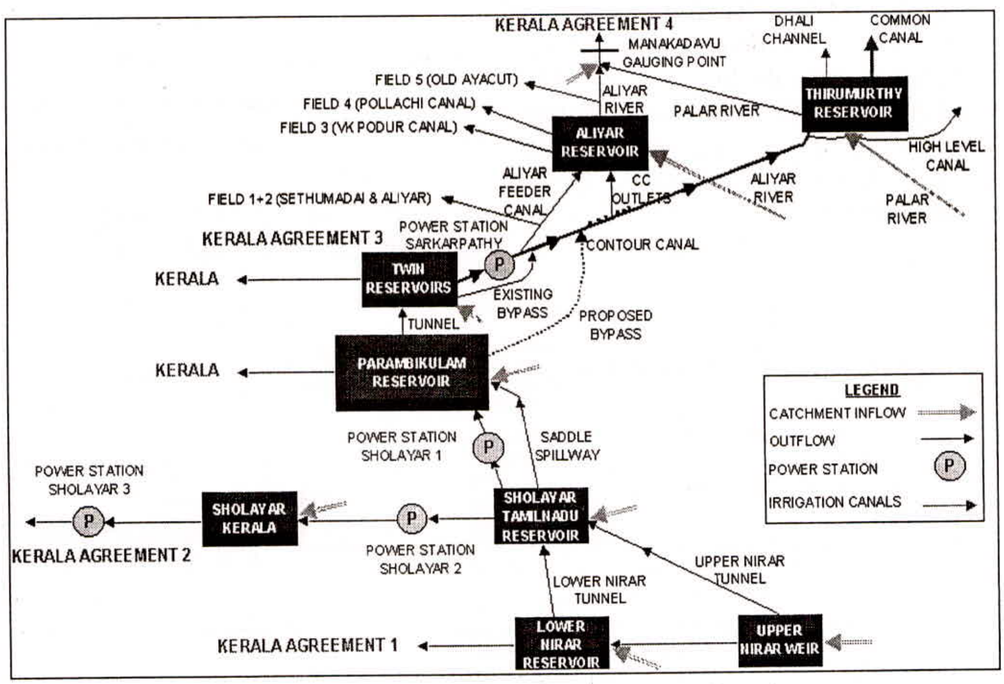

Fig. 1: PAP schematic layouts of multi-reservoir systems

Table 1: Characteristics of PAP Reservoir Systems

Reservoir System	*Reservoir Name*	*Capacity in Mm^3*	*Objectives*
1	Upper Nirar weir	1.12	Water diversion as per inter-state agreements
2	Lower Nirar	7.76	Diversion reservoir
3	Tamilnadu Sholayar	152.70	Storage & Hydro power as per interstate agreements
4	Kerala Sholayar	153.48	Storage as per interstate agreements.
5	Parambikulam	504.66	Storage reservoir with annual utilisation constraints as per inter-state agreements
6	Thunakadavu and Peruvaripallam	33.33	Twin reservoir and hydro power generation
7	Aliyar	109.43	Irrigation releases
8	Thirumurthy	54.80	Irrigation releases

(c) Environmental Constraints such as specifying allowable maximal drawdown for the protection of fish life. The hydro power is generated as an incidental kind of situations when the storage water is diverted to meet the irrigation demands.

METHODOLOGY

The proposed hybrid model has been developed in three stages and in each stage module has been developed for a specific objective in orders to tackle the complexity nature in the model development of multi reservoir operation. First the sub optimal feasible trajectories solution is obtained with help of **SIM**ulation-based **G**enetic **A**lgorithm **(SIMGA)** model. Secondly the suboptimal feasible trajectories are used as initial trajectory solution in the **S**imulation-based **C**ontrolled **O**ptimization **M**odel (**SCOM**) to tackle the curse of dimensionality issue and solution approximation issues. The solution results from the SCOM will be the training data set for Adaptive Neuro Inference System (ANFIS) model development. In the third stage, **S**imulation based controlled optimized **NE**uro **F**uzzy (**SNEF**) model is developed and the operating rules are trained through back-propagation algorithm and least square methods. The general outline of the proposed Soft Computing based decision support system model is presented in a flow chart (Figure 2).

The reservoir operation problem has been developed in a deterministic environment. In this formulation rainfall-inflow into the reservoir is considered as a known quantity. If we consider a reservoir with rainfall-inflow as a known quantity, the aim of the reservoir operation is to find the optimal release to maximize the given objective function. Dynamic programming (DP) effectively exploits the sequential decision structure of reservoir system optimization problems. As originally developed in its general form by (Bellman, 1957), DP decomposes the original problem into sub problems that are solved sequentially over each stage i.e., time period. Various modifications have been performed on the original DP formulation to mollify the *curse of dimensionality* of discrete dynamic programming.

- Coarse grid/interpolation techniques;
- Dynamic Programming Successive Approximations DPSA; and
- Incremental Dynamic Programming (IDP) or Discrete Differential Dynamic Programming (DDDP).

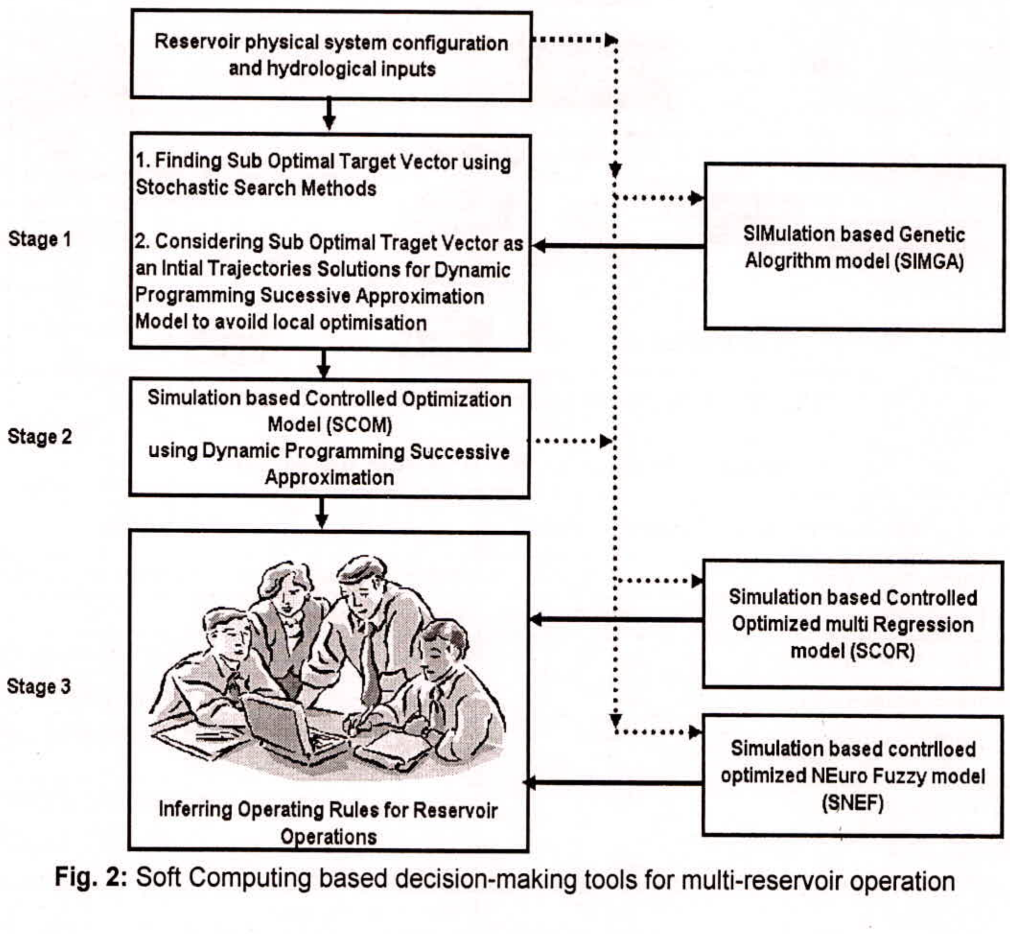

Fig. 2: Soft Computing based decision-making tools for multi-reservoir operation

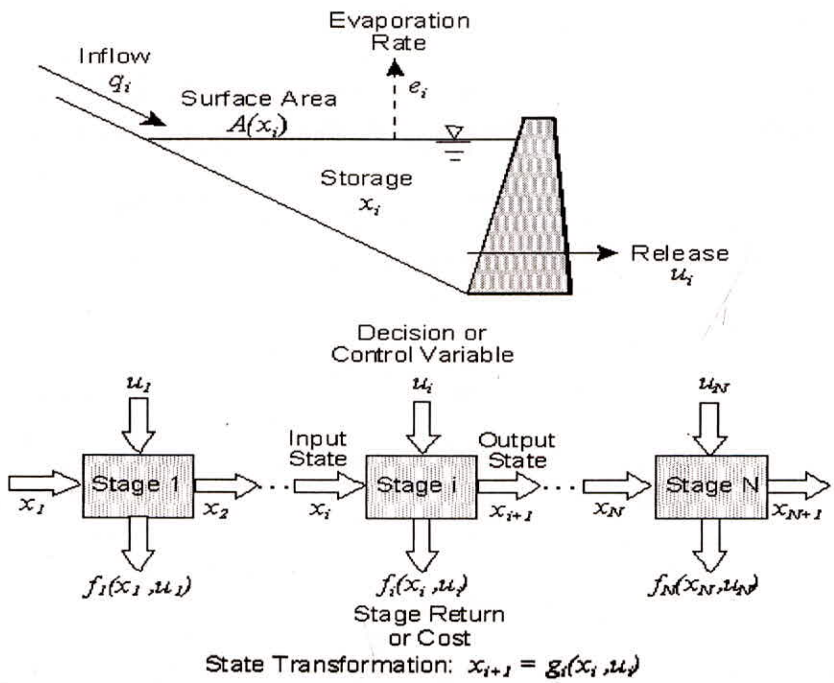

Fig. 3: Reservoir system state transformation—Sequential decision proces

(Bellman and Dreyfus, 1962) originally suggested the dynamic programming successive approximations (DPSA) technique, later generalized by (Larson, 1968). DPSA decomposes the multidimensional problem into a sequence of one-dimensional problems by optimizing over one state variable at a time, with all other state variables maintained at given current values. Accurate calculation of evaporation losses without the need for iterative procedures, and allows for the development of optimal storage release policy curves. DPSA was applied by (Shim *et al.*, 2002) for real-time flood control operations in the Han River Basin, Korea. (Janejira *et al.*, 2005) applied DDDP model for multi-reservoir systems.

(Labadie, 2003) describes a generalized DP package developed at Colorado State University called CSUDP that provides a general framework for building a DP model for a particular application. Figure 3 presents a typical a multistage problem, where the transition from stage to stage is embodied in specification of state variable x_i as the input state to stage i, with independent decisions or controls u_i exercised at each is stage i, $i = 1, \ldots, N$. A cost or return $f_i(x_i, u_i)$ produced at each stage i, and is assumed independent of decisions made in other stages. The inverted form of the state transformation relation is,

$$u_i = g_i^{-1}(x_i, x_{i+1}) \qquad \ldots (1)$$

The state transformation relation describing mass balance on the reservoir contents is,

$$x_{i+1} = x_i - u_i + q_i - e_i \bar{A}(x_i, x_{i+1}) \qquad \ldots (2)$$

Alternatively, this relation is easily inverted as follows,

$$u_i = x_i - x_{i+1} + q_i - e_i \bar{A}(x_i, x_{i+1}) \qquad \ldots (3)$$

Optimization can be performed directly with respect to x_{i+1} for a given discrete x_i. Constraints on the state and decision variables must be simple upper and lower bounds in DP problems. More complicated constraints can be considered indirectly through the use of penalty terms. In the DPSA application, only one of the reservoir storages is allowed to vary at a time while all others are kept constant, and thus all the reservoirs are treated likewise to obtain better solutions by successive approximations and this continues until no further improvement is achieved. In this way, a multi-dimensional problem is reduced to a series of one-dimensional problem and provided that reasonable initial operational policies are adopted, computational load is significantly reduced.

DPSA technique offers rapid convergence characteristics, but without assurance of convergence to discrete local optima. The iterations are done for one state variable at a time. While fixing the corridor around trial trajectory for first iteration, the entire possible grid points for the first state variable only are considered and the trajectory of all the remaining state variables is kept fixed. Then DP is run through this corridor. The best trajectory, obtained in first iteration will be the new trajectory for second iteration. In second iteration, second state variable is considered as the first state variable. In this way, first set of iterations continues till all the state variables are considered. Then, next set of iterations is done similar to the first one, with new trajectories. This process stops when two sets of consecutive iterations yield nearly same trajectories. So, it is very that DPSA solution convergence depends on the proximity of the initial trial trajectory. Potentially, this technique has tremendously reduced computational requirements over other dynamic programming methods; these requirements grow linearly with the number of state variables rather than exponentially.

Since the Dynamic Programming algorithm is a sequential kind of system approach, the complexity effect of different interstate agreements and other constraints are written in the simulation model routine within the optimization algorithm. That is simulation model routine is incorporated within the optimization model system. It needs special attention while writing the algorithms. This kind of approach is relatively new in the water resources model development applications. This model herein after referred as **S**imulation based **C**ontrolled **O**ptimization **M**odel (**SCOM**). Mathematically the objective function can be represented as,

$$\text{minimize } Z = \sum_{t=1}^{T}\left(\left(D_{7,t} - R_{7,t}\right)^2 + \left(D_{8,t} - R_{8,t}\right)^2\right) \quad \ldots (4)$$

where $R_{7,t}$ and $R_{8,t}$ = releases during time period t from Reservoirs 7 and 8, respectively; and $D_{7,t}$ and $D_{8,t}$ = irrigation demand during time period t in Reservoirs 7 and 8, respectively. The recursive equation for a given time period t is,

$$f_t^n\left(S_{3,t}, S_{5,t}, S_{7,t}, S_{8,t}\right) = \underset{R_{3,t}, R_{5,t}, R_{7,t}, R_{8,t}}{\text{minimize}} \left[z_t + f_{t+1}^{n-1}\left(S_{3,t+1}, S_{5,t+1}, S_{7,t+1}, S_{8,t+1}\right)\right] \quad \ldots (5)$$

Non-dominated Sorting Genetic Algorithm-II (Deb, 2000) is modified to suit our case study problem and then used to run the model with the same formulation as that used for SCOM model development. In the irrigation based multi-reservoir systems, the flow of water will be only in one direction (i.e. flow of water from upstream to downstream reservoir systems). In the PAP system (Figure 1), the release decisions of Thirumurthy reservoir system could be made based on the Parambikulam reservoir system storage. (Jang, 1993) introduced a hybrid-learning algorithm called ANFIS in which the premise parameters (parameters defining the shape of the membership functions) are identified by the back-propagation and consequent parameters by the least-squares method. This allows the fuzzy systems to learn from the data being modeled.

(Raman and Chandramouli, 1996) developed a Dynamic Programming-neural Network (DPN) model, which used neural network for deriving general operating policies from the deterministic dynamic programming optimization algorithm. The ANFIS system used three input variables (initial storage, inflow and demand during the periods), and an output layer (release to be made from the reservoir). The SNEF uses the SCOM results as an input training dataset (storage, inflow, demand) and output (release) and was optimized within the ANFIS framework.

The developed **S**imulation based controlled optimized **NE**uro **F**uzzy (SNEF) model is applied to the Thirumurthy reservoir system for rule curve development. The SNEF uses the SCOM results as an input to train the dataset (initial storage of Thirumurthy reservoir, initial storage of Parambikulam strorage, rainfall-inflow of Thirumurthy reservoir system, demand pattern of Thirumurthy reservoir) and output (release decision of Thirumurthy reservoir) and they were optimized within the ANFIS framework. (Raman and Chandramouli, 1996) considered initial storage, inflow and demand as input variable for the development of multiple linear regressions as follows,

$$R_t = aI_t + bS_t + cD_t + d \quad \ldots (6)$$

In this study, the optimal release is expressed as a multiple linear regression function of initial storage (S), inflow (I), demand (D) and storage position of upstream reservoir ($Upstream\_res\_stor$),

$$R_t = aI_t + bS_t + cD_t + d(\text{Upstream\_res\_stor})_t + e \quad \ldots (7)$$

where a, b, c, d and e are regression coefficients. The SCOM model results are regressed using the least-square method. The developed regression equation was then used in the simulation model. These results were compared with that of the proposed SNEF model. Since the PAP systems is so complex in nature, simulation based optimized routine is used in the model development. Hence, this multiple regression model may be refereed as **S**imulation based **C**ontrolled **O**ptimized multiple **R**egression model (**SCOR**).

RESULTS AND DISCUSSION

The PAP system is modeled in accordance with the inter-state agreement with Kerala and fortnightly time step was used. The developed model is used to simulate the reservoir operation using DPSA for 25 years of hydrologic data. The initial trail trajectories solutions were obtained from the SIMGA model. The SNEF model uses the SCOM results as an input to train the dataset (storage, inflow, demand and storage of upstream reservoir) and output (release) and it was optimized within the ANFIS framework. The developed SNEF model results are compared with SCOR results of Reservoir 8 and the typical model results are plotted in the Figure 4. It is observed that both models are performing well during normal flow period. The overall deficit index of the systems in the case of SNEF model is less than the SCOR model results in particular of deficient rainfall situation.

Scenario analysis has been carried out in the PAP systems to operate the reservoir best of its efficiency and in particular to meet out the shortage in supply during the dry season (Jan–June). The common canal shows maximum shortage of about 52% during the dry season period. The current operating policy results reveal that it is necessary to reduce the shortage of supply in the common canal during the dry season period. Since command areas under common canal are mostly dry crop area, supplemental water can get from North-East rainfall during wet season period. Hence, rezoning of irrigation area from dry season to wet season analysis was carried out. The results were presented in the Table 2 and Figure 5.

Scenario 2, 3 and 4 involves rezoning of command area which can be implemented by taking concerns of farming communities of that command area. Scenario 5, 6, 7, and 8 involves relaxing the inter-state agreement of Nirar weir node which can be implemented only after taking concerns of inter-state officials. Scenario 9 involves improvement of irrigation system efficiency and periodical maintenance of the systems. Scenario 9 can be addressed without much difficulty which involves only the financial budgetary provisions for maintenance of the irrigation systems. Scenario 4, 8 and 9 are comparatively more efficient than other scenario options.

CONCLUSIONS

The purpose of this research study was to develop heuristic optimization algorithms for the integrated optimization of irrigation reservoir system operation, to synthesize these models with appropriately modified existing techniques and to satisfactorily solve multi-reservoir irrigation optimization problem. A combination of DPSA, GA, and ANFIS model is developed and applied to a case study of multi-purpose multi reservoir systems. Several alternative operation procedures were simulated by using proposed simulation based Soft computing models in order to determine ways and means to improve the performance of the existing system of operation.

The complexity involved in the development of multi-reservoir optimization model was effectively handled by incorporating the simulation model routine into the optimization routine. This kind of novel approach helps to handle the system constraints and thereby reduction of curse of dimensionality problems at a considerable amount. When SCOM, SNEF and SCOR models are compared based on the objective

Table 2: Scenario Analysis Results of PAP Common Canal Systems

S.No.	*Scenario Description*	*Reliability of Irrigation Supply (%)*		
		Annual (July–June)	*Wet (July–Dec)*	*Dry (Jan–June)*
1.	Current Operating Policy	69.8	100.0	51.7
2.	Rezoning of irrigation area by 25% from dry to wet	76.8	99.8	53.1
3.	Rezoning of irrigation area by 35% from dry to wet	81.5	97.7	59.4
4.	Rezoning of irrigation area by 50% from dry to wet	86.9	92.7	73.5
5.	Relaxing Diversion Constraints at Upper Nirar Weir and without change in command area distribution	69.6	100.0	56.6
6.	Relaxing Diversion Constraints at Upper Nirar Weir and rezoning of irrigation by 25% from dry to wet	83.6	99.8	66.9
7.	Relaxing Diversion Constraints at Upper Nirar Weir and rezoning of irrigation by 35% from dry to wet	86.8	92.7	89.6
8.	Relaxing Diversion Constraints at Upper Nirar Weir and rezoning of irrigation by 50% from dry to wet	80.7	79.9	86.4
9.	Improved Irrigation Management by reduction of conveyance losses in the main as well as in the distributary's systems and improved irrigation application systems without rezoning the command area.	86.2	100.0	77.5

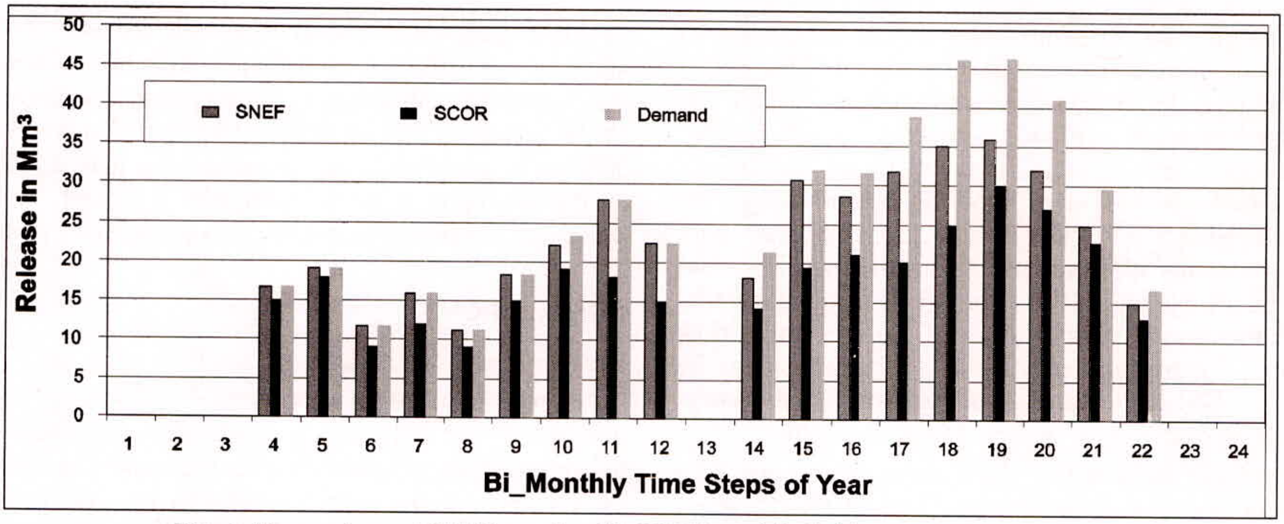

Fig. 4: Comparison of SNEF results with SCOR model of Thirumurthy (Reservoir 8)

function values, SCOM and SNEF model performs better than SCOR model.This is because neuro-fuzzy approach allows better modeling than the regression method. The reservoir operating policies were inferred from DP based neuro-fuzzy systems. Rule curves are developed for different scenarios like current operating policy, rezoning pattern, improved irrigation management and increase of available water potentials. In the current operating policy, the reliability of water supply is very low and only up to 52% in the common canal systems during the dry season period when compare to other PAP canal systems. Rezoning of 50% command area from dry season to wet season could be adopted in the common canal systems to reduce the shortage supply.

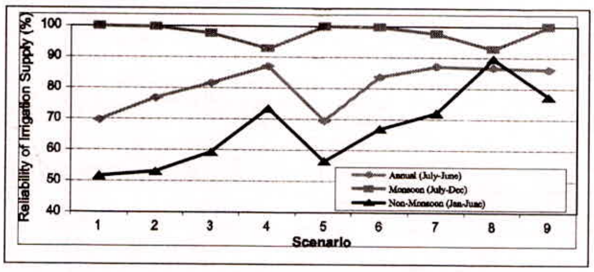

Fig. 5: Scenario Analysis results of PAP Common Canal Systems

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