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A Decision Support Model for Reservoir Operation

[1]V. Sudha and [2]N.K. Ambujam

[1]Department of Civil Engineering, NSS College of Engineering, Palakkad, Kerala, India
[2]Centre for Water Resources, Anna University, Chennai, India

Abstract: A user-friendly window based decision support model to support the reservoir operators for irrigation management is developed. Uncertainty is modeled by a data mining approach – Decision tree – in a multi stage environment, which includes different possible configurations of inflow in a wide time horizon. The aim is to identify different patterns and essential features on which to base a robust decision policy. Based on the results, it can be said that the developed decision support model is a user friendly model and can be used for the real time management of the reservoir.

Key words: Decision support model · Reservoir operation rule · Decision tree · Mixed Integer LP model

INTRODUCTION

A real world reservoir operation model plays an important role in the sustainable development of the water resource management. The system analysis technique has been widely applied to model the reservoir operation over the past decades. Despite the considerable progress in the research relating to reservoir operation, its application in to practice is very slow [1, 2]. The main reason for this is the complexities involved in the system analysis techniques [3].

Typical reservoir systems are usually subjected to thousands of constraints and variables and also the complexities due to the level of uncertainty about the modeling parameters such as hydrological exogenous inflows and demand patterns. These uncertainties may result in significant impact on system predictions and related decisions on system operation and management [4]. As a result, it is recognized that for an efficient real time operation of a reservoir, an easy to use decision support model, which also incorporates the uncertainties, is required. Therefore the objective of this work is to develop a relatively easy to use window based decision support model that can be distributed to the reservoir operator for real world application.

Background: The main challenges in developing optimal or near optimal reservoir operating rules lie in dealing with the uncertainty of the system variables. When one or more variables are uncertain or stochastic, we may need to consider explicitly the uncertainty in optimization. Even though the explicit stochastic models are the most effective, due to the complexities, they are not well known to the operators. An alternate method – implicit stochastic optimization – in which deterministic optimization is solved for a large number of samples and these results are used for inferring the operating rules. This approach is appealing, as it is simpler to understand and explain than the stochastic approach [5]. [6] initially proposed linear regression procedure to find the operational rules and [7] and [8] extended and improved the approach. [9] utilized multiple regressions and [10] used simple statistics and diagrams and tables to infer the operating policies. Lately, new methods like Genetic algorithm [11, 12], Fuzzy rule based techniques [5, 13-16], Artificial Neural Networks (ANN) [17-19] Bayesian Networks [20] and Decision tree approach [21, 22] have also proves to be successful. [23] demonstrates the use of ANN, Fuzzy logic and Decision tree algorithms for determining the reservoir operation rules. All the above models are the predictive models, which uncover the hidden relationships and patterns in the data using the methods such as statistics, machine learning or intelligent data analysis. Even though the predictive accuracy of these models are high, cases where these models are put into practices are rare. Hence there is an urgent need to improve the decision making process by using these developed prediction models.

Thus to aid the real time reservoir operator, an easy to use decision support model by bridging the gap between the predictive data mining model and decision

Corresponding Author: V. Sudha, Department of Civil Engineering, NSS College of Engineering, Palakkad, Kerala, India.

support is proposed here. The approach is based on a combination of an optimization method and learning method. Optimization automatically provides a data set for the learning method. Decision tree data mining predictive models are used as the learning method which develops crisp guide lines and they are encoded in Excel – VBA, a more accessible platform for the majority of model users.

MATERIALS AND METHODS

Proposed Approach: The proposed system is modular as shown in Fig. 1 and it consists of data selection, learning, knowledge base, prediction and display module.

Data Selection: One of the crucial points of learning methods is the construction of the data set from which the model has to learn. In order to have a good decision, the data set used for learning has to be from the solutions representing high performance system behavior. Also the data represented has to be diverse.

In reservoir operation models, generally optimization models are used to get the high performance solutions. Linear programming is probably the most flexible and most widely used technique for optimizing the planning and operation of water resource systems. Problems such as, determining the system yield, finding the size of the reservoir, determining optimum operating procedures are being handled frequently through LP application [24]. Here a mixed integer LP model is used for optimal operation of the irrigation reservoir.

In order to have more diversified data set, the optimization model is run using the historical net inflow data which contains both high flow and low flow periods and also with the generated net inflow data. For generating the net inflow data, the corresponding probability distribution function of the net inflow is used which is determined from the historical data.

Learning and Knowledge Modules: The methodology requires a learning approach which will induce an identification process for a solution class and also to induce a hierarchy of parameters according to their criticality and their impact on system performance. The classes produced by this learning method are the knowledge base. Machine learning or data mining methods can be used for this.

Data Mining Approach: Data mining is a recently emerging field, connecting the three worlds of Databases, Artificial intelligence and Statistics. It is typically used for generating information by discovering the patterns hidden in available data through some form of learning. In contrast to standard statistical methods, data mining techniques search for interesting information without demanding a priori hypotheses.

Data mining algorithms usually operate on data sets composed of vectors (instances) of independent variables (attributes). For example a database may describe a group of soil types in terms of their texture, lateral conductivity, maximum infiltration, porosity, field

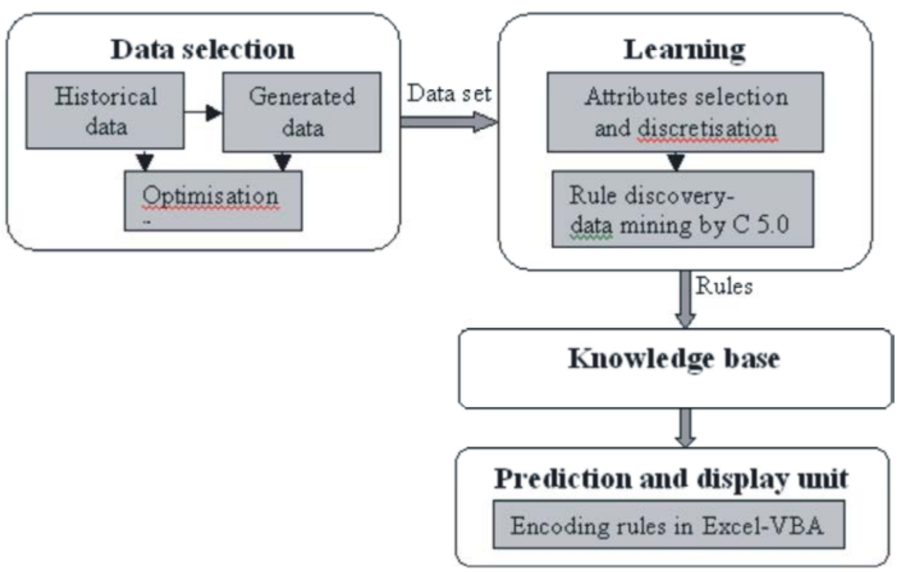

Fig 1: Proposed system architecture.

capacity and bulk density. In this case texture is an example of an attribute and each instance corresponds to a distinct soil type.

To discover the hidden patterns in data, it is essential to build a model consisting of independent variables that can be used to determine a dependant variable (also known as class or decision).Building such models therefore consists of identifying the relevant independent variables and minimizing the predictive error. Many methods of data mining exist. Among them neural networks and genetic based machine learning are generally used in water resource areas but still remains “black boxes”. Decision tree is another type of data mining approach which is used here as a learning module.

A decision tree is a model both predictive and descriptive [25]. It is one of the fundamental techniques employed in data mining whose major benefit is providing a visual representation of decision rules at the nodes used for making predictions [26]. The goal of this type of approach is to organize the parameters into a tree in which the more an attribute is relevant, the closer it is to the root. The relevance of an attribute is its capacity to classify an example.

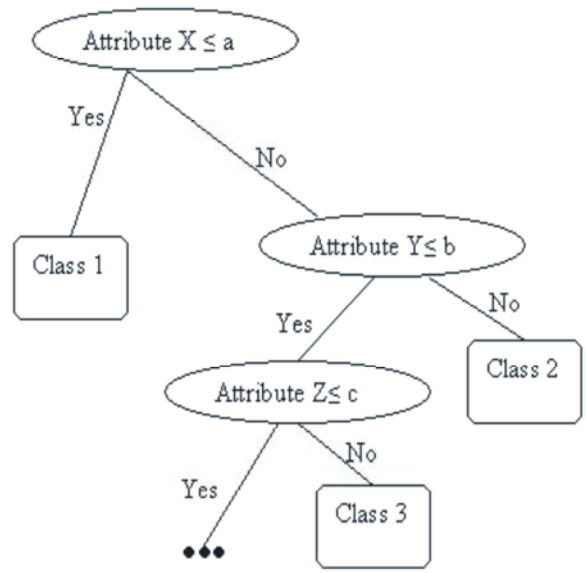

Fig 2: Decision tree abstraction showing how the values associated with certain features determine the class label.

Decision Trees: Decision trees techniques build classification or regression models by recursive partitioning of data. A decision tree algorithm begins with the entire set of data, splits the data into two or more subsets according to the value of one or more attributes and then repeatedly splits each subset into finer subsets until the split size reaches an appropriate level. The entire modeling process can be represented in a tree structure, which consists of two types of nodes: *decision nodes*, which contains a question based on one or more attributes and *leaf nodes*, which contains the prediction (or classification) and the model generated can be summarised into a set of “If – Then” rules. These rules are the knowledge base for the problem. An example decision tree is shown in Figure 2. In this example, observations whose value for attribute X is less than the value are assigned a class label of Class1. Other classifications are based on the values of attributes Y and Z.

The training algorithm that creates the tree is referred to as induction. There are many decision tree induction algorithms. One particular group of algorithms, for generating decision trees, is ID3, C4.5 and C5.0 algorithms developed by [27, 28]. C5.0 decision tree algorithm, a widely used and tested implementation, is used here. The most important element of the decision tree estimation algorithm is the method used to estimate splits at each internal node of the tree. To do this C5.0 uses a metric called the information gain ratio that measures the reduction in entropy in the data produced by a split. In this framework, the test at each node within a tree is selected based on splits of the training data that maximize the reduction in entropy of the descendant nodes. Using these criteria, the training data is recursively split such that the gain ratio is maximized at each node of the tree. This procedure continues until each leaf node contains only examples of a single class or no gain in information is given by further testing. A decision tree at this stage is potentially an over fitted solution, i.e., it may have components that are too specific noise and outliers that may be present in the training data. If the training data contains errors, then over fitting the tree to the data in this manner can leads to poor performance on unseen data. To relax this over fitting, most decision tree methods go through a second phase called pruning that tries to generalize the tree by eliminating sub-trees that seem too specific. To address this problem C5.0 uses confidence-based pruning. A detailed explanation regarding this is given by [29].

Prediction and Display Module: The “If-Then” rules in the knowledge base can be utilized for the prediction. For easy use they can be encoded in Excel – VBA platform so it act as a data base and also a prediction model thus a DSS for the real time reservoir operation.

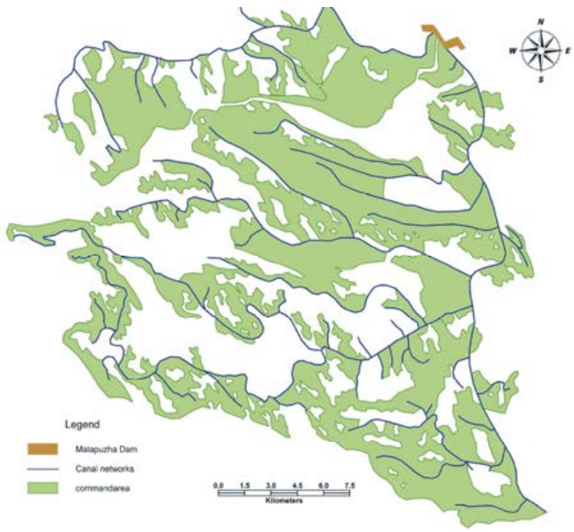

Fig 3: Malampuzha reservoir Irrigation system

Implementation of the Approach for Real Time Reservoir Operation:

Study site*:* The Malampuzha irrigation project of the Bharathapuzha river basin of Kerala in India covers an irrigable command area of 20,553 ha is taken as the study site. The catchment area of the dam is 147.63 sq. km. Its storage capacity is 236.69 cubic meters. The full reservoir level of the dam is 115.06 m and gross storage at FRL is 226 Mm3. The command area is served by the Left Bank Canal (LBC) and the Right Bank Canal (RBC). The LBC with a channel capacity 21.24 m^3/sec irrigates an area of 17,000 ha and RBC with 4.05 m^3/sec channel capacity irrigates an area of 3553 ha. Fig.3 presents the layout of canal network and command area in the Malampuzha irrigation project. There are mainly two cropping seasons and rice is the major crop grown. The first crop starts from May and is harvested in August-September and the second crop starts in September and harvested in January-February. The system is also supplying drinking water to the municipal area. The net inflows time series of the historical data show a high variability with a maximum value of 295 Mm^3 and a minimum seasonal value of 55.50 Mm^3 per year.

Data Collection and Analysis*:* The irrigation demands are calculated using historical weather data. To evaluate the irrigation demand the following procedure is used. The monthly average reference evaporation (ET_o) is used to calculate the crop water requirement. For that, monthly climatic data are collected and used in the CROPWAT model. Since rice is the prominent crop in the system, the crop coefficient value K_c for rice recommended by [30] is used to determine the crop evapotranspiration (ET_c). The other water requirement for rice, such as land preparation, nursery, seepage and percolation losses etc are accommodated according to [31] Effective rainfall is estimated based on the total rainfall in that period following the procedure suggested by [32]. By following the above procedure and taking into account the conveyance and distribution losses, monthly average gross water demand is calculated and is shown in Table 1. From the 24 years of historical records monthly net inflow data, which includes the evaporation loss also is calculated and its probability distribution is computed.

Table 1: Statistics of historical and generated net inflows.

Statistics	Historical inflows (Mm)	Generated inflows (Mm)
Mean	164.18	161.3
SD	50.8	45.15
CV	0.3	0.28

Reviewing the past release records, it was observed that the release made from the reservoir are not based on the crop water requirement. Also the traditional reservoir operation, based on rules of thumb, result in uneven inter- temporal allocation of water leading to failure of crops during the drought period. These follow-ups lead to suboptimum levels of economic return. These are the points to be addressed in this paper.

Reservoir Operation Rule Generation Using Decision Tree Approach: Preparing the data for the modeling is an important step in data mining [33]. The following stages are important (i) data selection. (ii) Preprocessing, (iii) modeling and & evaluation

Data Selection: As it is a reservoir operation model, prediction of releases based on the information at the beginning of the month is required. Since there is no inflow forecast model, the attributes used for decision tree generation are previous month's inflows, beginning storage and releases. Historical releases are based on the thumb rule hence an optimization model is used here to obtain the optimal releases.

Mixed Integer LP Model: The objective function considered is to maximize the irrigation releases. The objective function and constraints of the model can be mathematically presented as follows.

$$\text{Max } \sum_i \sum_j IR_{i,j} \quad i = 1, 2,\ldots..n,\ j = 1,2,\ldots..12. \qquad (1)$$

Subjected to

$$S_{i,j+1} = S_{i,j} + I_{i,j} - E_{i,j} - IR_{i,j} - DR_{i,j} - V_{i,j} \quad (2)$$

$$IR_{i,j} \le D_{i,j} \quad (3)$$

$$S_{i,j} \le S_{\max}$$
$$S_{i,j} \ge S_{\min} \quad (4)$$

where, i represents year with total number of years being 'n', j represents month

$IR_{i,j}$ is the irrigation release, $S_{i,j}$ is the beginning storage in the reservoir, $I_{i,j}$ is the inflow to the reservoir, $E_{i,j}$ is the evaporation from the reservoir, $DR_{i,j}$ is the drinking water supply from the reservoir, $V_{i,j}$ the spill from the reservoir. $S_{\max}$ and $S_{\min}$ are the maximum and minimum storage volumes of the reservoir. $D_{i,j}$ is the irrigation demand,

To ensure that the reservoir does not spill before reaching its capacity, there must be an explicit constraint in the formulation. [34] attempted to incorporate such a constraint for spill using a zero-one integer variable acting as a spill indicator. They proposed the following constraint, which are also included here.

$$a_{i,j} \le S_{i,j+1} / S_{\max} \quad (5)$$

$$V_{i,j} \le a_{i,j} \times B \quad (6)$$

$$a_{i,j} = 0 or 1 \quad (7)$$

where, B is a very large number.

By solving the above optimization model the optimal releases can be determined. Mixed integer LP model is run first for the 24 years of historical data with different initial storage values. Then using probability distribution function of each month the net inflow is generated for 100 years. Table 1 compares the statistics of the generated and historical net inflows and as can be noticed that, these statistics are very close to each other. Figure 4. shows the time series plot of the generated and historical net inflows, for the month July as an example. Using the generated data the optimization model is run again for different initial storage values. Thus the data set that have used for the rule generation is comprised of 744 data points.

Table 2: Class for release attribute.

% demand met	100	90	80	70	< 70
Class	Full	High	Medium	Low	Nil

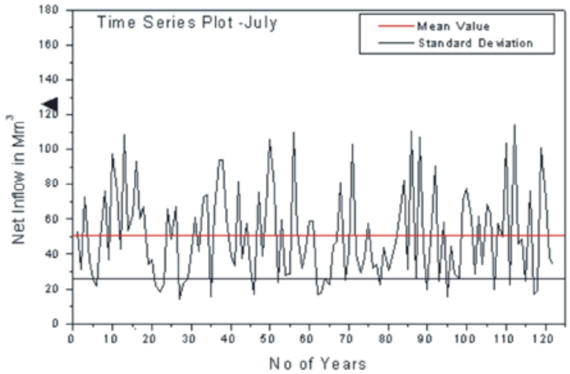

Fig 4: Time series plot of net inflow for the month July.

Data Preprocessing: In this step, if the class label attribute is continuous it has to be divided to discrete classes. The attribute release is taken as the class label attribute and it is continuous, hence by analyzing the optimization result, it is divided into different classes according to the percentage of demand met as shown in the Table 2. By taking percentage demand met less than 70 as no release class, according to the generated rules there will not be any releases when the available releases is less than 70% demand. This will help in efficient water management for irrigation.

Modeling: The 744 data were split into two parts one part is used for development of rule and the other part for evaluation. The rules produced from the training set is tested with unseen test cases to know how accurate the classifier. Different pruning option is also tested and which gives more accuracy in both training and testing data set is taken as the final rule set.

In the system, irrigation releases are for certain months only according to the crop water needs hence the decision rule model is prepared for the months which require the irrigation release. The attributes used for modeling is the previous year inflow with lag1, lag2, lag3 (I_{t-1}, I_{t-2}, I_{t-3}), sum of the inflows from the starting month May to the month considered(PMNI) (water year is taken as May to April, hence if it is the month September then sum of the 4 months inflow and for the month May no such attribute), initial storage of each month (S_t), sum of the previous months release(PMNR) and previous years release (R_{t-1}). For all the other months except May one more attribute is also considered, that is the initial storage of the year (S_{may}).For the month May, as the value of S_{may}

and S_t are the same, only one of them is considered and also the attribute sum of previous months release is not there. The decision trees and rule sets constructed by C5.0 do not generally use all of the attributes. This ability to pick and choose among the predictors is an important advantage of tree-based modeling techniques. For example the decision tree obtained for the months May and September are shown in Appendix. From the tree it can be seen that for the month May, the release depends on the initial storage and previous year inflow with lag1, lag2 and lag3. This is because; the May release is for the crop 1 and hence it mainly depends on the inflow during the year because more importance is given to the second crop. The inflow during the year is not predicted and given as the attribute in the model. As the inflow during the year depends on the previous year inflows, the model automatically selected I_{t-1}, I_{t-2} and I_{t-3} as the attribute. For the month September, the release for the second crop, which depends on the inflow during the monsoon season starting from June to September. Thus the release mainly, depends on the sum of the previous month's inflows and releases during the year and not the previous year's inflow and the model also selected the attribute like that. The next advantage of the model is we can convert the rules into "If-Then" rules which may be easier to understand and adopt. For example the rule 1 for the month September can be written as "If previous four months inflow (PMNI) is greater than 178.00 Mm^3 then release the full demand". Now these rules for each month are the knowledge base and this can be encoded in Excel –VBA platform. The display unit of the model is as shown in Fig.5 in which the user can calculate the release for each month with the known attributes.

RESULTS

Validation: The validation of the proposed model is done on the basis of the following performance indicators as proposed by [35-38].

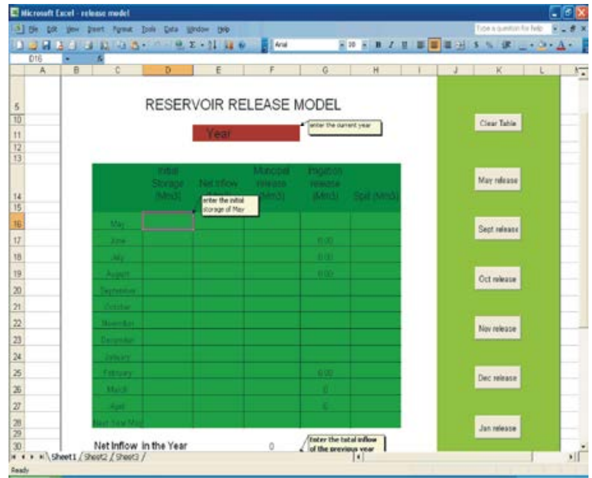

Fig 5: Display unit of reservoir release model

Reliability: The probability that the system actual demand is satisfactory.

- Resiliency: The probability that the system actual demand in period t+1 is satisfactory, given that it is unsatisfactory in period t
- Maximum seasonal deficit in %
- Mean value of deficit in time and space given by the following formula.

$$\frac{\sum_{t=1}^{24}(D_t - V_t)}{24 \times 20553}, deficit(Mm^3/ha)$$

Where D_t is the total demand during the period and V_t the release from the reservoir during that period.

As the system is mainly for the second crop, all the above performance indicators are done for the second crop. To test the model performance for the first crop another performance indicator, the No of years failed to supply for first crop (%Years) is calculated. To check the overall performance total spill is also determined. The results of the proposed model, optimization model and the historical releases are compared on the basis of the above performance indices and are given in Table 3. The results

Table 3: Performance Indices.

Model	Reliability	Reseliency	Maximum seasonal deficit (%)	Mean value of deficit (Mm^3/ha)	No of years failed to supply for first crop in %	Spill in Mm^3
Proposed DSS	0.71	0.57	43.00	10.71×10^{-4}	38	57.50
Optimization	0.75	0.50	46.30	9.26×10^{-4}	42	50.00
Historical	0.63	0.22	75.00	13.81×10^{-4}	75	128.00

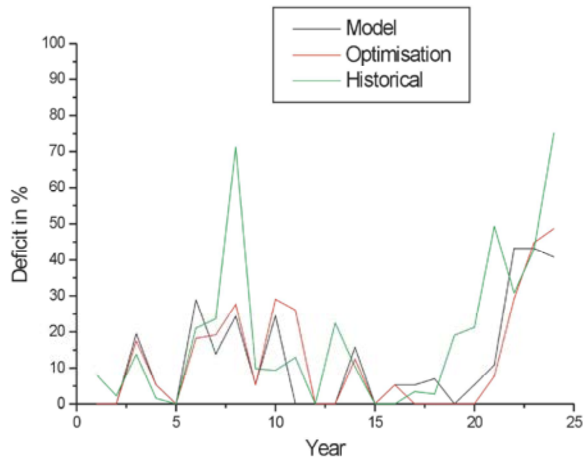

Fig 6: Deficits in % of the second crop for 24 years for different models

are expressed in terms of frequency rather than probability, since the simulations were implemented over a short period of time (24 years).

From the above results it can be inferred that both the proposed DSS and optimization model outperform the historical releases. While comparing the optimization and the DSS, the best result is from the optimization model, which is obvious because the optimization results represent theoretical optimal management under the perfect knowledge of the future. The results of the DSS model, which is a predictive model that predicts the future release from the available data, are also very close to the optimization model. This shows the prediction capacity of the model. Also, in terms of resiliency and for the first crop supply the DSS model give better results than the optimization. The deficits in % of the second crop for 24 years are shown in Fig 6. Historical Deficit is also shown for comparison and it can be seen that the deficit by the model and optimization is distributed among years thus maximum deficit is less than that of the historical. This shows the ability of the DSS and the optimization model to reduce the maximum deficit, which is the requirement for the irrigation water management.

CONCLUSIONS

A three step DSS model for the reservoir operation is presented and tested in this paper. The proposed methodology is based on the work in synergy of an approach of optimization and an approach of learning by data mining. With this methodology it is possible to extract and use knowledge on the best system solutions. By coding the rules in the knowledge base in an easy to use and readily available decision support shells may help to advance the acceptance and use of predictive models in real world reservoir operation.

The better value of the performance indices shows the capability of the proposed model in satisfying the objective of the system when compared to the historical method. Also the results show that the methodology adopted here improves the performance during drought condition, thus confirming the general enhancement achieved by using this method in reservoir operation. Thus the model performance in a real-world reservoir operation problem is promising.

There are several limitations of this study. First, the historical data collection period was only 24 years and so it is insufficient to support. Second, the system performance can be improved by using other optimization methods via stochastic dynamic programming. It is possible; as the developed model's modular architecture allows incorporating alternate generation modules and optimization procedures. Thirdly the spatio-temporal variation of irrigation demands is not considered here, which is also to be considered for further enhancement.

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