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Optimal operation of Multi-reservoir System using Dynamic Programming and Neural Network

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Abstract

A combined approach of a Dynamic Programming algorithm and Artificial Neural Network model is used for multi reservoir operation. The Dynamic programming algorithm is used for deriving optimum results for a four reservoir system and from the results, neural network is trained using back propagation algorithm to derive general operating policy for multi-reservoir operation. The performance is analyzed using a simulation model for the considered case study.

1 Introduction

In monsoon countries like India the availability of water with respect to time and space varies considerably. Rainfall, the major source of water in India, varies from 11000 mm at Cherrapunji in Assam State to 150 mm in the extreme west of Rajasthan State, due to orographic influence. Most of the reservoirs in India receive water during four monsoon months. Stored water is used for the rest of year. Hence efficient management of water becomes very essential. Optimization and simulation models for deriving rules for efficient water management are being applied increasingly in recent years.

1.1 Optimization and Simulation models

With the vast variation in availability of water in time and space, and increasing demand, it is very essential to find a solution of the given problem which should be feasible and also optimum under the given circumstances. One of the most important advancements made in the field of Water Resources Engineering during the last decade is the evolvement and application of optimization techniques for planning, design and management of complex Water Resources system. Optimization and simulation models used in water resources engineering have been reviewed by Yeh[8] and Wurbs[6] recently. The linear programming, non-linear programming, dynamic programming (DP) models used for various applications in water resources engineering were reviewed in detail in these papers. Yakowitz[7] exclusively reviewed various applications of DP models He discussed various advantages of DP models. The DP models can handle non-linear objective functions and also non-linearity in constraints. He also cited several attempts made to handle the curse of dimensionality problems.

1.2 Application of Artificial Neural Network in Water Resources

Artificial Neural Network (ANN) is a computational method modelled to mimic the functions of human brain and nervous systems. The pattern recognition approach with neural network procedure is applied to many problems related to water resources. They used a back propagation algorithm. Tang and Fishwick[5] used neural network procedure for time series modelling. Karunanithi et al.[2] used neural network using cascade correlation algorithm for river flow prediction. They demonstrated that neural network approach could be used as an adaptive model synthesiser as well as a predictor. Saad et al. [3] used NN for disaggregation of reservoir releases for hydropower systems in multi reservoir operation successfully. Smith and Eli[4] used ANN to model rainfall-runoff process. In this case, the network was trained using a back propagation algorithm to predict the peak discharge and the time to peak resulting from single rainfall pattern.

The combination of simplicity, interpolation, ability to provide conditional simulations and reasonably accurate prediction statistics suggest that the ANN can be a useful tool in Water Resources. In this study a multi- reservoir optimization model for a four reservoir system is developed using deterministic dynamic programming and general operating policies are derived by pattern mapping approach using neural network algorithm. The performance of the algorithm is studied using a simulation model.

2 System considered for case study

The system considered for case study is Parambikulam Aliyar project located in the border area of Tamil Nadu and Kerala states in South India. It diverts the excess water from west flowing rivers which goes to sea to eastern side of the western ghats which is drought-prone rain shadow region. This system inter-links three river basins namely Periyar river basin, Bharadapuza river basin and Chalakudy river basin by a series of reservoirs, tunnels and contour canal arrangement. This system consists of 8 reservoirs and a diversion weir. The system irrigates about 100000 ha of land in drought prone areas of the Tamil Nadu State. The system is being monitored on a fortnightly basis by a Joint Water Regulation Board organised by Governments of Tamil Nadu and Kerala states.

In this study four reservoirs in the project are considered which are formed by Tamil Nadu Sholayar dam, Parambikulam dam, Aliyar dam and Thirumurthy dam (hereinafter called as dam 1, dam 2, dam 3 and dam 4 respectively). The irrigation release is made from dam 3 and dam 4 only. Apart from irrigation release, a committed release to neibouring State Kerala is also made from Dam 3 which is monitored by Joint Water Regulation Board. Dam 1 and dam 2 are for diversion of water from west flowing rivers to dam 3 and dam 4 (Fig.1).

The daily irrigation requirement for the command area under each reservoir is computed using Modified Penman method (Doorenbos and Pruitt[1]) using ten years of daily meteorological data of the Coimbatore Station. maintained by Indian Meteorological Department. The demand is then aggregated to fortnightly values for the present study.

3 Model Formulation

The model developed is based on two algorithms. The first algorithm is a discrete deterministic DP optimization algorithm to solve four reservoir problem with an objective to minimize the squared deficit. The second one is a three layered neural network model with back propagation algorithm for training the patterns. The neurons in the hidden layer and output layers were sigmoidal activation functions. The optimization is done using the DP algorithm with four reservoir storages as four state variables. The results of the optimization model are printed in the form of patterns which is given as the training patterns to the Neural Network algorithm. Then neural network is trained with the patterns using back propagation algorithm to derive operating rules. (Fig.2)

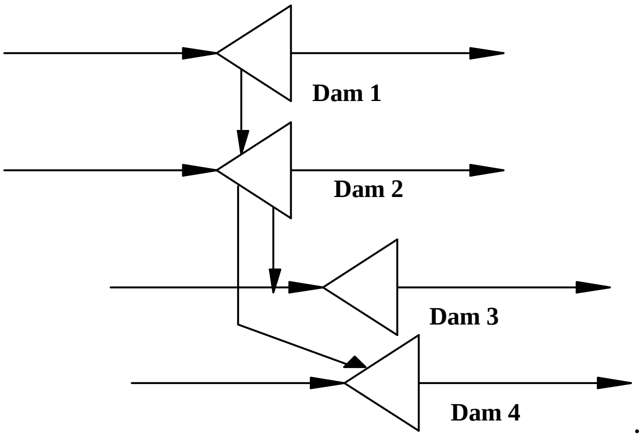

Fig.1. Four Reservoirs in Parambikulam-Aliyar Project, South India (Schematic)

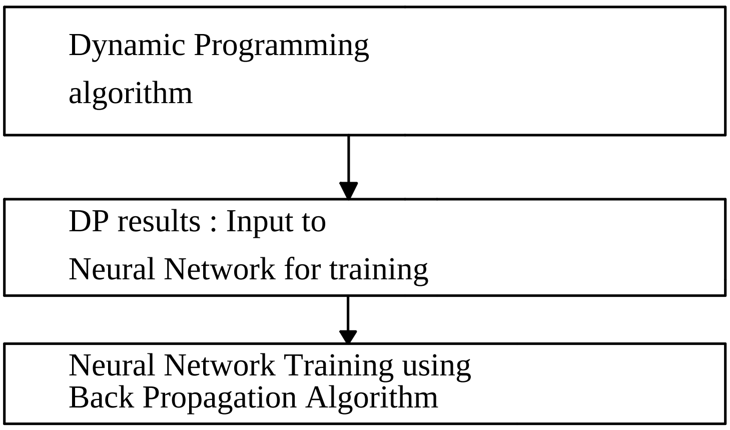

Fig.2. Model Construction

3. 1 Dynamic Programming Algorithm for Four Reservoir Problem

The reservoir system under study is mainly aimed for irrigation in drought-prone areas in the State of Tamil Nadu. Hence minimising the sum of squared deficit in the dams 3 and 4 is taken as the objective function for the optimization model . Mathematically it can be represented as

$$\text{minimize } Z = \sum_{t=1}^{T} ((D_{t,a} - R_{t,a})^2 + (D_{t,th} - R_{t,th})^2) \qquad (1)$$

where,

T = Number of fortnights

$R_{t,a}$, $R_{t,th}$ = Release during time period t from dam3 and dam4 respectively.

$D_{t,a}$, $D_{t,th}$ = Irrigation demand during time period t in dam3 and dam4 respectively.

The recursive equation for any time period t is,

$$f_t^{\,n}(S_{1t}, S_{2t}, S_{3t}, S_{4t}) = \min[Z_t + f_{t+1}^{\,n-1}(S_{1t-1}, S_{2t-1}, S_{3t-1}, S_{4t-1})] \qquad (2)$$

Where,

S_{1t},S_{2t},S_{3t},S_{4t} = Initial Storages during time period t in dam1, dam2, dam3 and dam4 respectively.

Z_t = objective function value for the period t.

The various constraints such as mass balance, storage and release constraints for each reservoir are incorporated in this formulation of the DP algorithm.

3.2 The neural network model

The neural network model considered has three layers. An input layer, a hidden layer and an output layer. The neural network has 10 input nodes, 4 output nodes and 23 hidden nodes in the hidden layer. The inputs and outputs given for training are listed in Fig.3.

The indices used to identify the better performance of the model is mean square error and mean relative error values. The mean square error can be defined as

$$mse = \frac{1}{pq} \sum_{q} \sum_{j=1}^{p} (y_j^{(t)} - y_j)^2 \qquad (3)$$

Mean Relative error (*mre*) is defined as

$$mre = \frac{1}{pq} \sum_{q} \sum_{i=1}^{p} \left| \frac{(y_j^{(t)} - y_j)}{y_j^{(t)}} \right| \times 100 \tag{4}$$

in which

$y_j^{(t)}$ = target output value

y_j = output from NN

p = number of patterns

q = number of output nodes

The *mse* and *mre* are good measures for indicating goodness of fit at high and moderate output values respectively (Karunanithi et al.1994).

The input patterns were normalized by dividing the values by a higher value 600 and the output pattern values are normalised using a higher value 120. The number of neurons in the hidden layers and the normalising values are decided after examining different combinations. The trial is started with 2 neurons in the hidden layer and tried upto 25 neurons in the hidden layer. The selected architecture gave better performance. The inter-connecting weights are initialised by random numbers between -1 to +1. The weights will be re-adjusted while training by the back propagation algorithm. The neurons in the output layer and in the hidden layers are activation functions whereas the input neurons simply acts as a buffer.

In this study sigmoidal function is used as the activation function in the hidden layer and output layer. The output from the neuron y_j

$$y_j = \frac{1}{1+e^{-net_j}} \tag{5}$$

where, net_j is the sum of weighted inputs from the previous layer.

The knowledge gained by training neural network model is stored in the form of weights interconnecting neurons. This back propagation algorithm is a steepest gradient descent procedure to minimize the mean square error. The updating of weights will be done by the rule

$$\Delta w_{ji}(s+1) = -\eta \delta_j x_i + \alpha \Delta w_{ji}(s) \tag{6}$$

where,

η is the learning rate, α is the momentum factor, s is the sweep number and derivative δ is a factor depending on whether neuron j is an output neuron or a hidden neuron. The value of η is kept at 0.4 and α is kept at 0.6. The values of η and α are also arrived after examining different combinations. In this study, the selected values results in faster convergence in less number of sweeps.

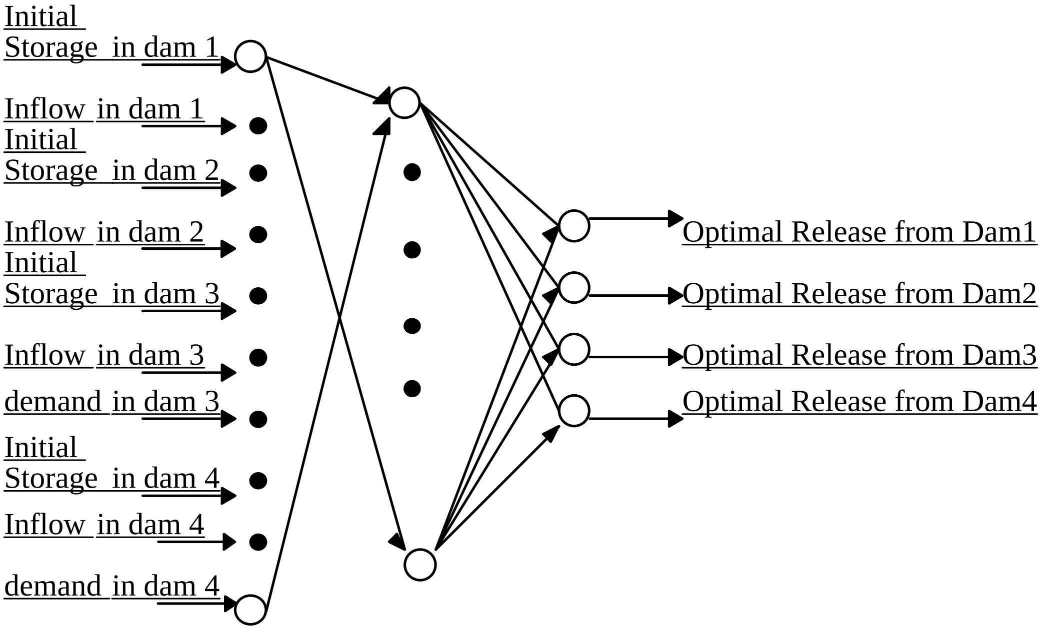

Fig.3 Neural Network

4. Results and Discussions

The performance of the four reservoir optimization model based on DP and NN algorithms (model 2) is compared with the performance of the simulation model (model 1) based on Standard Operating Policy (SOP) which is being practised in the field. According to SOP, when water available is less than the demand, the available water will be released. When the water available is equal to or greater than demand, quantity equal to demand will be released and the excess will be stored. If the excess is more than the storage available, water will be spilled. This procedure has no hedging to benefit future requirement.

Fig.4 shows the demand pattern in Dam 3 and Dam 4. The demand for Dam 3 also includes the committed release to Kerala State. Fig.5 shows the average fortnightly inflows into the four reservoirs. This figure shows that the average annual inflow in Dam 4 is very minimum and it depends mainly on the diversion water from Dam 1 and Dam 2. The water is shared between the two

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reservoirs Dam 4 and Dam 3 from Dam 2 in the ratio of 75 % and 25 % respectively in this study.

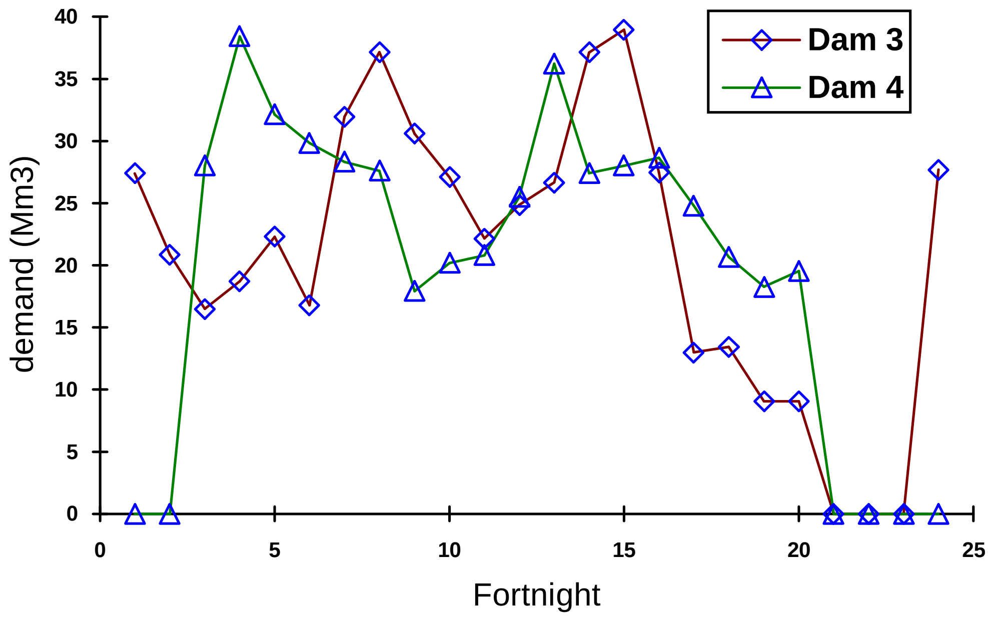

Fig4. Dam and Pattern in Dam 3 and Dam 4

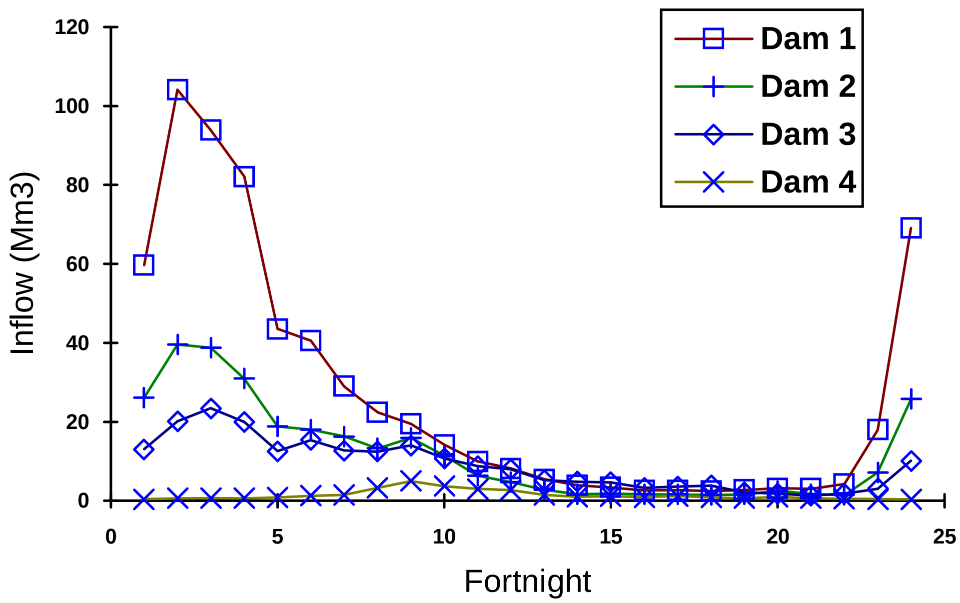

Fig.5 Average inflow into the Dams

Another study is also made with single reservoir DP algorithm with NN for deriving operating rules. The optimization model is solved for single reservoir case with single state variable and the results were trained using back propagation algorithm. Using this procedure the operating rules are derived for dam 3 and dam 4 separately. A simulation model is constructed in which dam1 and dam 2 are operated using SOP and dam 3 and dam 4 are operated using rules derived by single reservoir algorithm (model 3).

Nineteen years of fortnightly historical data are used to study the performance. The objective function used for this purpose is square of the deficit [$(D_t - R_t)^2$ where D_t is the demand and R_t is the release during the time period t].

Both model 2 and model 3 perform better than that of model 1. (Fig. 4) This may be due to the hedging by the rules derived from the optimization algorithm using NN. The Fig. 4 shows higher values of objective function for model 1 in years of water shortage. The performance of the model 2 and model 3 are similar and the multi reservoir model does not give considerable improvement. Further, the total value of the squared deficit also indicates model 3 performs slightly better than the model 2. Model 2 performs better than model 3 during water scarce years and does not give higher deviation during these periods. Further the model 2 gives slightly higher values during good years. This may be due to the fact that the Model 3 does not hedge water in Dams 1 and 3 since these two are operated by SOP in this model. Further there is no irrigation release from the Dams 1 and 2.

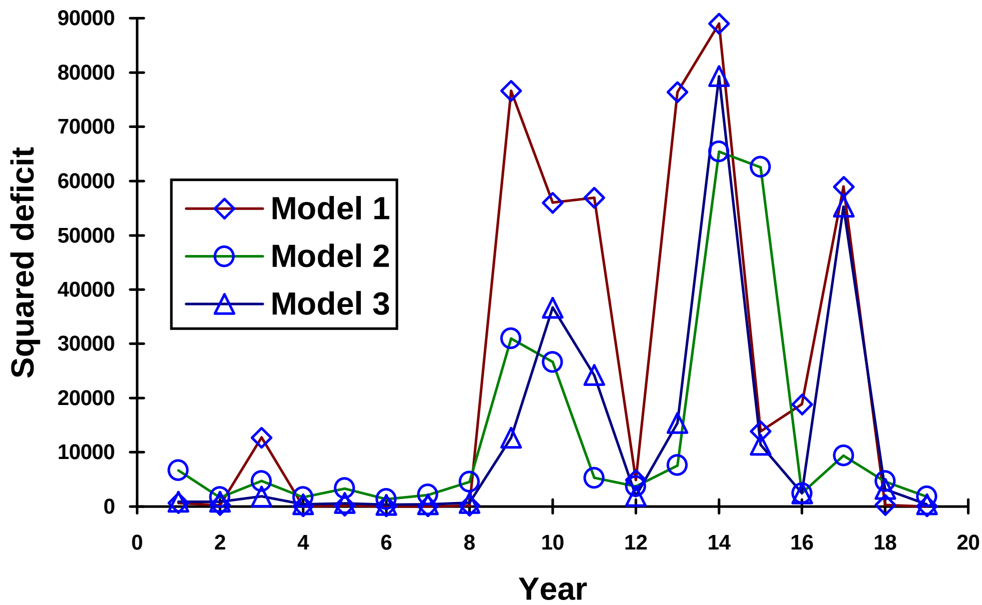

Fig.6 Performance of the Models

5 Conclusions

The application of neural network procedure in deriving rules for multi reservoir operation from a deterministic optimization model works better than the SOP based model. The model 3 based on single reservoir operation algorithm performs similar to the model 2 with multi reservoir operation in this case study.

Key Words :

Artificial Neural Network, Dynamic programming, Water Resources.

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