ARTIFICIAL NEURAL NETWORK MODELS FOR SHIVAJISAGAR LAKE EVAPORATION PREDICTION

Arunkumar R.[1], Jothiprakash, V.[2]

[1]Research Scholar, [2]Associate Professor, Department of Civil Engineering,
Indian Institute of Technology Bombay, Powai, Mumbai – 400 076, India.
Email: [1]arunkumar.r@iitb.ac.in, [2]vprakash@iitb.ac.in

ABSTRACT

Prediction of lake evaporation is very much essential for effective water resources planning, operation and management. In India, usually, the lake evaporation is estimated from the pan evaporation and the average water spread area. Accurate prediction of lake evaporation by conventional method is a cumbersome process, since it is in non-linear relationship with the storage and other meteorological parameters. The recently evolved soft computing techniques are proved to be efficient to model these non-linear hydrological processes. Thus in the present study, two artificial neural network algorithms (ANN) namely, multi-layer perceptron (MLP) and time lagged recurrent neural network (TLRN) are compared to predict the lake evaporation. The daily Shivajisagar lake evaporation data collected from the Koyna dam circle for a period of 49 years has been used in the modelling. About 70% of the dataset is used for training the ANN models and the remaining 30% is used for testing. It is found that both the ANN algorithms predicted the lake evaporation very well with a correlation coefficient around 0.99. This shows that, if the input data series exhibits good pattern with less noise, the soft computing techniques results in better performances.

Key words: lake evaporation, artificial neural network, multi-layer perceptron, time-lagged recurrent neural network, Koyna dam Shivajisagar Lake

I. INTRODUCTION

Evaporation is one of the significant hydrological processes need to be quantified accurately (1), for various purposes in hydrology and water resources. Prediction of lake evaporation is a challenging task and very much essential for effective water resources planning, operation and management. The estimation of evaporation from surface water lakes can be grouped into two methods, direct and indirect methods. The Pan Evaporimeter is one of the direct methods of measuring evaporation. The empirical temperature based methods (eg. (2)–(4)); radiation based methods (eg. (5), (6)) and the combined methods (eg. (7), (8)) constitute the indirect measurement of evaporation. In India, usually, the daily lake evaporation is estimated from the pan evaporation and the average water spread area of the lake in that day.

Literature survey shows that several studies have been reported in estimating the evaporation from surface water lakes using conventional empirical equations. The most popular method for estimating evaporation was developed by Penman (7), which includes various meteorological parameters. Later, several modifications have been made by various researches in Penman method for estimating the evaporation (eg. (1), (9)–(11)). Some researchers compared various evaporation estimation methods (eg. (12)–(18)). de Bruin (9) modified the Penman equation by combining with the Priestley and Taylor (5) model and developed a simple expression for estimating the evaporation in shallow lakes. Jarvinen (19) estimated the evaporation from four lakes using evaporimeters and water budget. The monthly evaporation from a lake was estimated by Omar and El-Bakry (20) using the heat budget and aerodynamic method. Vardavas and Fountoulakis (10) formulated a net heat model for estimating monthly lake evaporation using Penman method with standard meteorological data. The model was applied to four Australian lakes and reported that the model predictions agree well with the mean monthly measured evaporation of the four lakes.

Apart from using conventional empirical equations and instrument like evaporimeters, the lake evaporation was also estimated using isotope technique by Saxena (21). Finch (22) estimated the mean annual reservoir evaporation using sunshine hours, relative humidity, wind speed and average air temperature by the equilibrium temperature approach and compared the results with the measured data. All these empirical equations required measurement of numerous variables, making them relatively data intensive (16). A water budget of the reservoir is also in use to estimate the lake evaporation losses (23).

A simple Multiple Linear Regression (MLR) technique was applied by Murthy and Gawande (24) for predicting evaporation and proposed simple linear relationships between evaporation and other meteorological parameters. Recently, the soft computing techniques have been proved efficient for modelling complex hydrological processes. The daily evaporation of Lake Egirdir was estimated using various soft computing techniques like ANFIS, Decision Table, KStar, M5P, Pace Regression, Neural Network, Simple Linear Regression and SMO Regression algorithms (eg. (25)–(27)) and reported that soft computing techniques predicts better. A feed forward back propagation ANN algorithm was developed by Deswal and Pal [28] to predict the reservoir evaporation using meteorological variables and compared the results with the regression method developed by Murthy and Gawande (24). The parameters used were momentum rate as 0.1 and learning rate as 0.2 with six hidden layer nodes for 1000 iterations. It was reported that the ANN model resulted in highest correlation coefficient (0.96) along with lowest root mean square error (0.865).

Even though several studies have been reported on conventional empirical equations, all these studies require extensive data such as radiation, temperature, change in heat storage and vapor pressure. Measuring these data itself a complicated process and also it requires various instruments and technical labor. The operation and maintenance of these instruments is also a cumbersome process. In addition, all these parameters that affect the evaporation have many assumptions and phenomenal constraints. It is also reported that soft computing techniques are very efficient in modeling complex non-linear processes. Application of artificial neural networks in water resources system analysis is fast growing. An artificial neural network is a model inspired by the structure of the brain that is well suited for complicated tasks (29). Thus, in the present study, to overcome the difficulties of conventional techniques, it is aimed to apply soft computing techniques to predict the lake evaporation. Two different Artificial neural network algorithms namely, multi-layer perceptron and time lagged recurrent neural network are applied to predict the lake evaporation and the results are compared.

II. STUDY AREA

The Koyna dam Shivajisagar Lake situated on the West Coast of Maharashtra, India, with a global coordinates of $17° 24' N$ latitude and $73° 45' E$ longitude is considered for the study. The location of Shivajisagar Lake is shown in Fig. 1. The Shivajisagar Lake receives inflow from its catchment area of about 891.78 km^2. The catchment is elongated leaf shaped with about 64 km in length and about 13 km in width. The rainfall in the catchment is almost entirely due to the southwest monsoon during June to October and amounts between 3180 mm to 6350 mm in the valley, average annual being 5080 mm. Thus, the whole catchment area lies in a very heavy rainfall area. The water spread area of the Shivajisagar Lake at full lake level is about 115.35 km^2 which is about 13% of the catchment area. The gross storage of the lake is $2797 \times 10^6\ m^3$. The daily lake evaporation data for a period of 49 years (1961-62 to 2009-10) has been collected and used in the present study. The time series plot of the daily volume of evaporation from Shivajisagar lake is shown in Fig. 2. From Fig. 2, it can be seen that there exists a well-defined sinusoidal pattern in the time series of Shivajisagar lake evaporation. Also, it is observed that after 12 years of initial operation, the evaporation has been stabilized and shows a good sinusoidal pattern. For better view of short lags, the correlation between various lags of time series is given in Table 1. From the figure and table, it can be seen that there exists good correlation between the data of various lags. This leads to higher difficulties in estimating the number of input variables required.

III. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) attempts to model the functioning of the human brain. It is a massively parallel distributed information processing system, which consists of group of interconnected artificial neurons, and processes information through connection links (29). Haykin (29) stated that the ANN is based on the following rules:

1. Information processing occurs at many single elements called nodes, also referred to as units, cells, or neurons,

2. Signals are passed between nodes through connection links
3. Each connection link has an associated weight that rep- resents its connection strength
4. Each node typically applies a nonlinear transformation called an activation function to its net input to determine its output signal.

They are adaptive systems capable of modifying their internal structure, typically the weights between nodes in the network, allowing them to be used for a variety of function approximation problems such as classification, regression, feature extraction and content addressable memory (29).

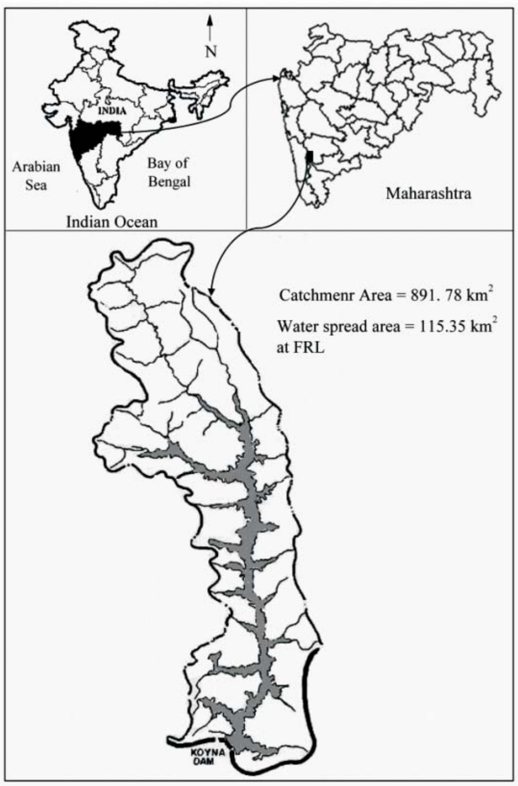

Fig. 1. Location of Shivajisagar Lake

Table 1. Correlation of various lags

	t	t-1	t-2	t-3	t-4
t	1				
t-1	0.999	1			
t-2	0.998	0.999	1		
t-3	0.996	0.998	0.999	1	
t-4	0.994	0.996	0.998	0.999	1

A simple ANN, consists three layers, namely, input layer, hidden layer and output layer is shown in Fig. 3. The input layer is a transparent layer in which the information is fed to the network. The output layer consists of values to be predicted by the network and usually determined by trial and error procedure. The data which is used to train the network, constitutes input for which the correct output is known. The network initially starts with random weights as connection strengths and predicts the output. The weights are then adjusted such that the error between the predicted and the actual is minimized. In this study, the multi-layer perceptron (MLP) and time lagged recurrent networks (TLRN) are applied and its is working principle is discussed in the following sections.

A. Multi Layer Perceptron

The Multi-layer Perceptron (MLP) is an example of an artificial neural network that is used extensively for the solution of a number of different problems, including pattern recognition and interpolation. A MLP is a feedforward network that maps sets of input data onto a set of appropriate output. Except the input nodes, each node in the hidden layer consists of a non-linear activation function. For training the network, MLP utilizes a supervised learning technique called back-propagation (29). With back-propagation, the input data is repeatedly presented to the neural network. With each presentation, the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back-propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output.

B. Time Lagged Recurrent Network

The Time lagged recurrent network (TLRN) is a dynamic recurrent neural network provided with static short-term memory, Global feedback connections from output to hidden layer and back propagation through time (BPTT) algorithm. Contrary to feedforward networks, recurrent neural networks (RNN) are models with bi-directional data flow (29). In a feedforward network, data flows in unidirectional from input to output, whereas RNN propagate data from later processing stages to earlier stages.

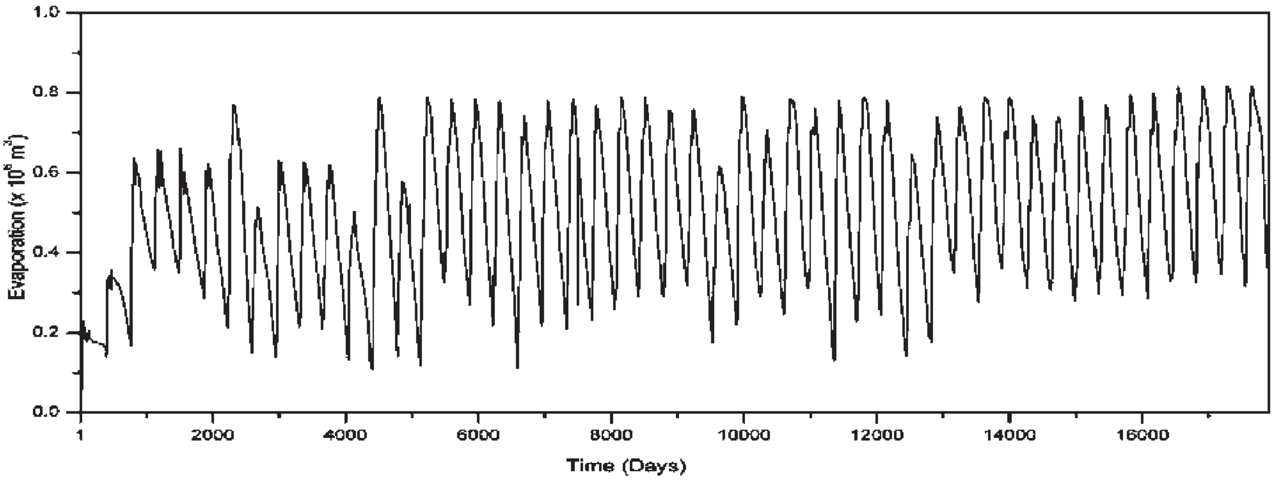

Fig. 2. Time series of Shivajisagar lake evaporation

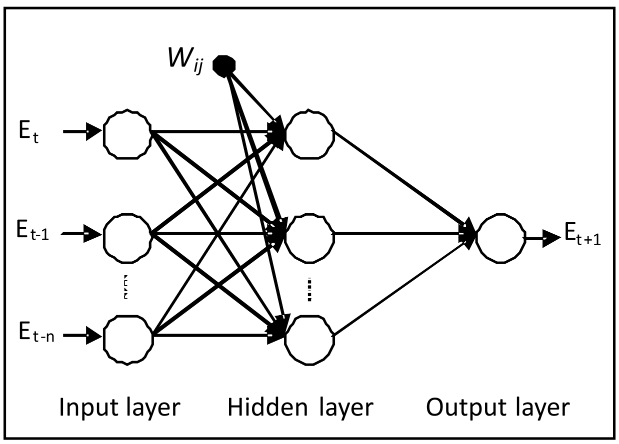

Fig. 3. A simple ANN architecture

These recurrent networks can have an infinite memory depth and thus find relationships through time as well as through the instantaneous input space (30). Most of the real-world data are temporally varied. Hence, the temporal pattern need to be recognized and it requires processing of patterns that evolve over time, with the response at a particular instant of time depending not only on the present value of the input but also on the past values (30). Basically TLRN is an extension of MLP with short-term memory structures of time delay, gamma, and Laguerre learning rule. Fig. 4 shows the sample architecture of TLRN. The main advantage of TLRN is the smaller network size required to learn temporal problems when compared to MLP that use extra inputs to represent the past. An added advantage of TLRN is their low sensitivity to noise (30).

The application of ANN in Hydrology and water resources is very wide and can be found in ASCE ((31), (32)). Fairly a large amount of work has been reported on the application of ANN for forecasting reservoir inflow (30), rainfall-runoff modeling (33), river stage prediction, pan evaporation prediction (34), etc.

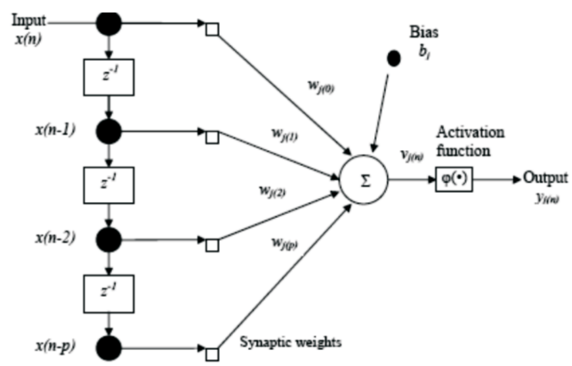

Fig. 4. Architecture of TLRN (Haykin (29))

IV. RESULTS AND DISCUSSION

In the present study, two ANN algorithms namely, multi-layer perceptron and time lagged recurrent neural networks has been compared in predicting the Shivajisagar lake evaporation. All the daily time series lake evaporation prediction models are developed using 49 years (1961-62 to 2009-10) of daily historical data. The data is split in to two parts for training and testing based on the trial and error procedure. About 70% of the data was used for training the model and the remaining 30% of the data was used for testing the developed the models. The number of input variables are determined by lagging the previous time period data $(T(t), T(t-1), T(t-2) \ldots)$ based on trial and error approach. The non-linear activation function is optimized by varying different types.

The developed models are evaluated using standard performance criteria namely, mean square error (MSE), mean absolute error (MAE), root mean square error (RMSE), error in estimating peak values (%MF), Nash-Sutcliffe efficiency (E) and correlation coefficient (R). The MSE is a good measure for indicating the goodness-of-fit at high output values and it is a commonly used error index. MAE measures the fit to mean values and indicates the goodness-of-fit for moderate output values. The %MF shows how effectively the peak values are predicted. The values of %MF closer to zero indicates that the values are predicted with less deviation.

The models are developed using NeuroSolutions version 5.0 software package (http://www.neurosolutions.com/). For both the algorithms, different models are developed by varying the numbers of input variables. The number of inputs is varied by lagging the observed evaporation data up to a maximum of five days. After fixing the hidden nodes by trial and error in a three layered network, the ANN models are developed with *Tanh* transfer function, Laverenberg-Marquardt learning rule and run for 1000 epochs. The Laverenberg-Marquardt algorithm is one of the most appropriate higher-order adaptive algorithms for minimizing the MSE of a neural network (29).

The performances of the MLP models during training and testing are given in Table 2. From the table, it can be observed that all the MLP models are equally performing better. The model with five inputs (lagged up to four days) with five hidden nodes resulted better than other MLP models with a correlation coefficient of 0.998 during testing. It can be also seen that, the percentage peak error is close to zero for the model MLP (5-5-1), indicates that the peak values are well predicted. The MSE and MAE are also minimum for the model when compared with other MLP models. The time series and scatter plot of MLP (5-5-1) during testing is given in Fig. 5. From the figure, it can be seen that the predicted values exactly matches with the observed data. Even the peak values are also having good agreement with the observed data.

The performance of the TLRN models during training and testing is given in Table 3. From the table, it is observed that the TLRN models are also performed equally well. Among the TLRN models, model (5-5-1) performed better with an correlation of 0.969 during testing. However, the peak values are not predicted better, which can be observed from %MF. The time series and scatter plot of TLRN (5-5-1) is show in Fig. 6. From the figure, it can be seen that the peak values are not predicted well.

On comparing MLP and TLRN models, MLP models resulted slighted better than TLRN models. In both the algorithms, the model with five input variables performed better than other models. This shows that the number of hidden nodes equivalent to number of input variables results better. Then with the increase in the number of input variables, the performance of the models declines. The MLP models resulted in higher correlation than TLRN models. The %MF values are also very much deviated from zero for TLRN models, which indicates that peak values are not predicted well This result shows that for simple time series modeling, the simple MLP technique is good enough to model the processes.

Table 2. Performances of ANN-MLP models

	2-5-1		3-5-1		4-5-1		5-5-1		6-5-1	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
MSE	0.002	0.001	0.008	0.012	0.001	0.001	0.001	0.001	0.010	0.053
MAE	0.036	0.028	0.079	0.099	0.020	0.019	0.024	0.019	0.088	0.067
RMSE	0.043	0.035	0.091	0.112	0.022	0.020	0.027	0.023	0.098	0.229
%MF	1.080	1.005	22.380	24.200	0.340	1.880	0.220	1.440	22.380	24.200
E	0.941	0.951	0.735	0.499	0.984	0.983	0.976	0.979	0.723	0.776
R	0.995	0.994	0.987	0.986	0.994	0.993	0.998	0.998	0.988	0.983

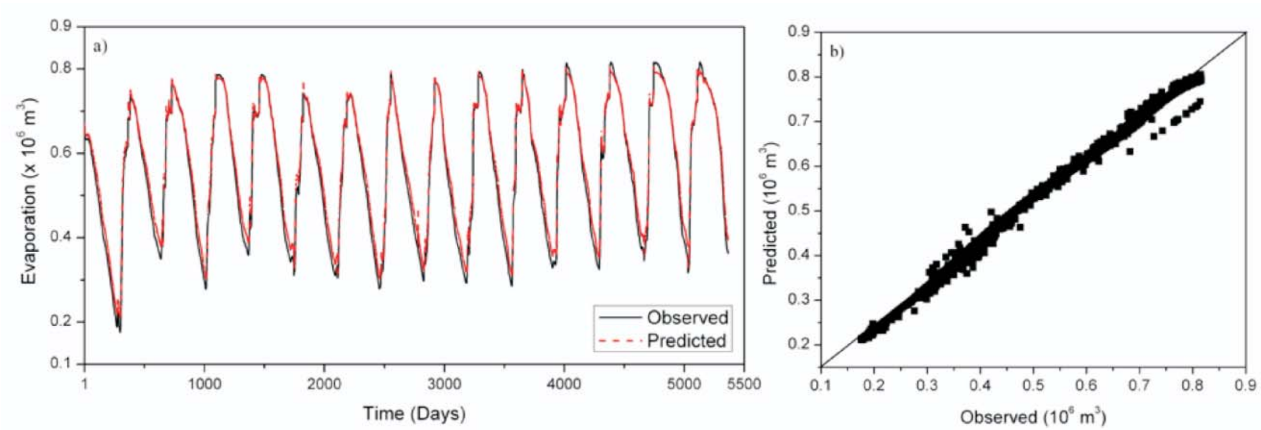

Fig. 5. Time series and scatter plot of MLP (5-5-1) during testing

Table 3. Performances of ANN-TLRN models

	2-5-1		3-5-1		4-5-1		5-5-1		6-5-1	
	Training	Testing	Training	Testing	Training	Training	Testing	Training	Testing	Training
MSE	0.003	0.002	0.005	0.005	0.003	0.004	0.002	0.002	0.006	0.005
MAE	0.040	0.032	0.045	0.046	0.037	0.043	0.039	0.039	0.054	0.0536
RMSE	0.057	0.041	0.069	0.074	0.058	0.065	0.048	0.046	0.076	0.072
%MF	2.6	6.25	-12.98	13.210	10.960	15.820	6.590	10.910	16.25	12.6
E	0.895	0.932	0.843	0.783	0.890	0.831	0.926	0.914	0.951	0.895
R	0.967	0.979	0.921	0.904	0.948	0.934	0.976	0.969	0.931	0.944

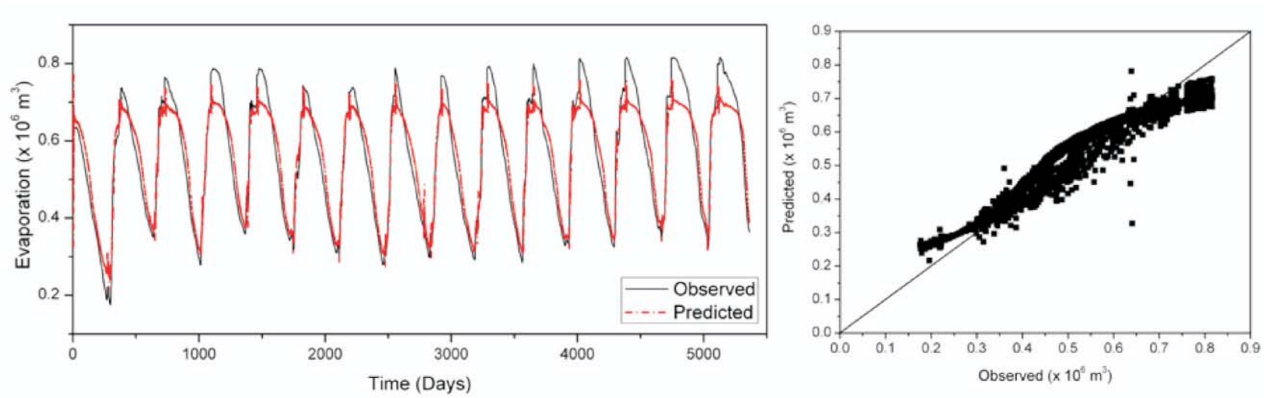

Fig. 6. Time series and scatter plot of TLRN (5-5-1) during testing

V. CONCLUSION

Prediction of lake evaporation is very much essential for effective water resources planning, operation and management. In India, usually, the lake evaporation is estimated from the pan evaporation and the average water spread area. Accurate prediction of lake evaporation by conventional method is a cumbersome process, since it is in non-linear relationship with the storage and other meteorological parameters. Hence, in the present study, two types of artificial neural network algorithms are compared in predicting the lake evaporation. The models are developed using times series Shivajisagar Lake evaporation data. In both the algorithms, different models are developed by varying the number of input variables. The developed models are evaluated using standard statistical performance criteria namely, MSE, MAE, RMSE, %MF, E and R. Based on the performance, it is found that the model with five input variables predicts better for both the two algorithms. Even though both the algorithms equally performed better in terms of correlation, MLP models edged better in predicting peak values. Thus this study shows that, if the data exhibit very good pattern and correlation among different lags, the soft computing techniques can produce more accurate results.

VI. ACKNOWLEDGEMENT

The authors gratefully acknowledge the Ministry of Water Resources, Government of India, New Delhi, for sponsoring this research project through the Indian National Committee on Hydrology. The authors also thank Chief Engineer, Koyna Hydroelectric Project and Executive Engineer, Koyna Dam for providing the necessary data.

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R. Arunkumar is graduated in Agricultural Engineering from Tamil Nadu Agricultural University in 2007 and post graduated in Irrigation Water Management from Anna University Chennai. He has received Dr. Jayasekhar Endowment award for getting I Rank in M.E (IWM) for the year 2009. Presently he is doing his PhD Research in the Civil Engineering Department at Indian Institute of Technology Bombay.

Dr. V. Jothiprakash is currently working as Associate Professor of Civil Engineering Department, Indian Institute of Technology Bombay. He has carried out various major research projects in water resources planning and management using Soft Computing Techniques. He has authored or co-authored of more than 56 research papers in referred journal and more than 122 conference papers. He has received five best paper awards published in journals and various awards for his notable contributions in the field of water resources.