International Journal of Engineering Research
Volume No.5, Issue Special 1 pp : 156-160
ISSN:2319-6890(online),2347-5013(print)
8 & 9 Jan 2016

Utility of Coactive Neuro-Fuzzy Inference System for Runoff Prediction in Comparison with Multilayer Perception

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Abstract : Modeling of hydrological process is important in view of many uses of water resources. This paper reports on an evaluation of the use of artificial neural network (ANN) models to forecast daily flows at single gauging station evaluation of the use of artificial neural network (ANN) models to forecast daily flows at single gauging station in Gunjvani watershed (Maharashtra, India). Two different neural network models, the multilayer perceptron (MLP) and coactive neuro-fuzzy inference system (CAN-FIS) models were developed to predict daily stream flow at gauging station were compared. Different scenarios using various combinations of data sets such as rainfall, meteorological parameters and stream flow were developed and compared for their ability to make flow predictions at gauging station. The input vector selection for both models involved quantification of the statistical properties such as cross-, auto- and partial autocorrelation of the data series that best represented the hydrologic response of the watershed. Measured data with 2860 patterns of input-output vector were divided into two sets: 2002 patterns for training, and the remaining 858 patterns for testing. The best performance based on the correlation coefficient (r), root mean square error (RMSE), and mean absolute error (MAE) was achieved by the MLP model with current and antecedent rainfall and antecedent flow as model inputs. The MLP model testing resulted in (R = 0.93, RMSE = 2.27, MAE = 2.52). Similarly, the results also showed that the most accurate daily flow predictions with a CANFIS model can be achieved with the Takagi-Sugeno-Kang (TSK) fuzzy model and the Gaussian membership function. Both models performed satisfactorily for flow predictions; however, the MLP model outperformed the CANFIS model. The results show that ANN models are useful tools for forecasting the hydrologic response at gauging points of interest in agricultural watersheds.

Keywords : Daily flow prediction, rainfall-runoff, multilayer perceptron, ANN.

I. Introduction

Over the last few decades, mathematical rainfall–runoff models have been developed to quantify and understand watershed-scale hydrologic processes. Based on the description of the governing processes, these models can be classified as either physics based or system theoretic. Physics based model involve a detailed description of various physical processes controlling the hydrologic behaviour of a system. However, system theoretic models do not consider the physical characteristics of the parameters; they map the data from input to output using transfer functions. Artificial neural network (ANN) models are example of system theoretic models that have gained considerable popularity in recent years in describing rainfall–runoff processes.

ANNs are artificial intelligence-based computational tools that can mimic the biological processes of a human brain. They are considered suitable tools for large search spaces where human expertise is needed. They do not require detailed knowledge of internal functions of a system in order to recognize relationships between inputs and outputs. For various complex nonlinear environmental problems, ANNs have an advantage over distributed parameter models in that the data requirements are usually less, and they are more suited for long-term forecasting.

System theoretic approach to forecasting runoff from a catchment is based on extracting and re-using information that is implicitly contained in hydrological data. The system theoretic models describe statistics and artificial intelligence arising from plethora of techniques (e.g. empirical regression, time series, fuzzy rule based systems and Artificial Neural Network modeling). System theoretic R-R models are quick and easy to develop and implement. Most of the drawbacks of physics based models overcome in this method. The disadvantages of this method lie in their low transparency and their limited range of application. Due to low transparency of these models it becomes difficult to interpret their internal workings in a physically meaningful way. And hence, they generally fail to give useful insights into the system under investigation. Furthermore, due to the limited range of application system theoretic models have validity over the range of the specific sample of the hydrological records that is used for model calibration.

Artificial Neural Network (ANN) modeling, a system theoretic technique, has gained significant attention in recent years. ANNs have proven to be good in simulating complex, non-linear systems in many fields. This inspired the hydrologists to carry out the experiments using ANNs in the first half of the 1990s. The promising results lead to the first studies specifically on ANNs in R-R modeling (i); (ii); (iii); (iv); and (v).

The ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (vi) gives good state-of-the-art reviews on ANN modeling in hydrology. The ability of ANNs to out-perform traditional statistical R-R techniques and produce comparable results to conceptual R-R models is proved by majority of studies, like (iii), (vii) (viii); (ix); and (x). The field of R-R modelings by means of ANNs is yet in an early stage of development and remains a topic of continuing interest (xi) and

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(xii). The two most-commonly used ANN methods for modelling rainfall–runoff processes are the multi layer perceptron (MLP) and radial basis function neural network (RBFNN) models. Many studies have reported on comparisons of the two models in simulating rainfall–runoff processes.

This study was conducted to evaluate black-box models to provide a guideline for choosing the best method for prediction of one step ahead runoff from the available rainfall and runoff data. The aims of this study were (1) to evaluate the performance of coactive neuro-fuzzy inference system (CANFIS) model with various membership functions and fuzzy models and different combinations of input parameters to predict one step ahead runoff, (2) to examine the potential of MLP model for runoff prediction, and (3) to compare the performances of the MLP and CANFIS models for one step ahead runoff prediction.

II. **Material and Methodology**

II.1 Data

Daily meteorological data from 1 March2000 to 31 December2007 were collected from Sakhar station. The collected meteorological variables were: daily rainfall in mm; relative humidity (RH) in percent evaporation in mm; temperature in ^{0}c; and runoff in m3/s. The station was equipped with meteorological instruments. The present study was conducted with the help of data obtained at Gunjvani river watershed up to Velhe on river Kanand that is a tributary to Gunjvani in western- ghats of Maharashtra, India and located South-West of Pune city. The watershed is covered between latitudes 18016’N and 18020’N, and longitudes 73030’E and 73040’E. Gunjvani watershed has an area of 62.95 sq.km. up to the Velhe river gauge site. Length of main river is about 14.7 km with highest peak elevation of 1403 m above MSL at Torna Fort situated south of villages Velhe Budruk and the headwater of the watershed is at an elevation of 1186 m above mean sea level. There are four stations with Standard Rain Gauges in the watershed. The data collected for the studies include hydrological data and maps. The hydrological data is obtained from the Hydrological Project, Nashik Maharashtra India

II.2 Artificial neural network

II.2.1 Multilayer perceptron

There are many types of ANN for various applications available in the literature. The MLP is a widely used ANN configuration and has been frequently applied in the field of hydrological modeling (xiii); (xiv); and (xv). This study evaluates the utility of MLP neural networks for estimating runoff. Figure 1 provides an overview of the structure of this network. Generally, the MLP consists of three layers of neurons: an input layer, output layer and intermediate or hidden layer. Each neuron has a number of inputs and a number of outputs. A neuron computes its output response based on the weighted sum of all its inputs according to an activation function. Data flow in one direction through this kind of network—starting from external inputs into the first layer that are transmitted through the hidden layer, and then passed to the output layer from which the external outputs are obtained. The network is trained by adjusting the weights that connect the neurons using a procedure called error back propagation. In this procedure, the network is presented with a series of training examples and the internal weights are adjusted in an attempt to model the input/output relationship. This procedure must be repeated many times before the network begins to model the relationship (vi).

II.2.2 ANN structure and training

The training of the ANN was carried out using the Neuro solutions software as developed by Neuro dimensions Inc. of Florida (Neuro Dimension, Inc. 2005). Data were pre-randomized before divided into training data set and testing dataset. The first 70 % of rows were used for the training and the 30 percent were testing data. Randomization of all available data was done in each of these two groups, so that the probability of representation of data for the entire range of operation was increased.

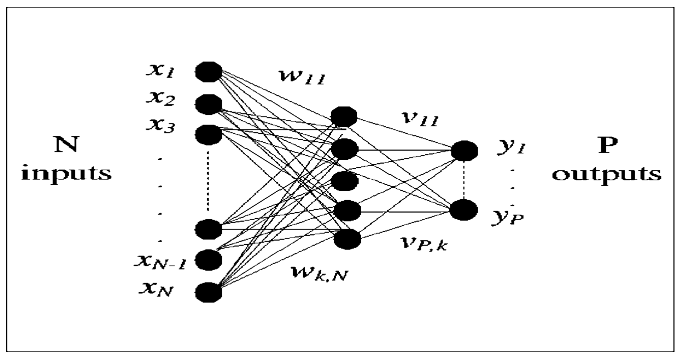

Figure 1 Architecture of MLP model

The development of an ANN model consists of proper selection of input and output parameters, defining ANN structure specified by the type of activation function, number of hidden layers, number of neurons, etc. For this purpose, the data used as inputs were transmitted through the network, layer by layer, and a set of output data were obtained. The obtained outputs were compared with the desired output values and, as a backward pass; the difference between desired outputs and calculated outputs (error) was used to adjust the weights of the network to reduce the level of the error. The learning is an iterative process, which continues until an acceptable level of errors is obtained. Each time the network processes the whole set of data (both a forward and a backward pass), is called an epoch. The network was trained in this way and the error was reduced by every epoch until an acceptable level of error was obtained (xvi). On the other hand, the training of the network is carried out for a considerable number of patterns until the network reaches the point where the weights no longer undergo significant changes. Four learning algorithms namely Levenberg– Marquardt, Step, Momentum, and Conjugate Gradient were tested to identify the one which trains a given network more efficiently. More about the learning algorithms can be found in (xiv).

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II.2.3 Activation functions

The activation function is the formula used to determine the output of a processing neuron. In this study, three different functions (i.e. Sigmoid, tanh and Linear) were tested to identify the one which shows the best results in depicting the non-linearity of the system following by the trial and error approach. The main selection criterion here was to increase the neural network accuracy. The Linear scaled and biased sigmoid function to each neuron in the layer. The scaling factor and bias are inherited from the linear function. The range of values for each neuron in the layer is between 0and 1. The tanh function applies a bias and tanh function to each neuron in the layer. This will squash the range of each neuron in the layer to between -1 and 1.

II.3 Coactive neuro-fuzzy inference system

Coactive neuro-fuzzy inference system belongs to a more general class of adaptive neuro-fuzzy inference systems (ANFIS). The CANFIS model integrates adaptable fuzzy inputs with a modular neural network to rapidly and accurately approximate complex functions. The characteristics of CANFIS are emphasized by the advantages of integrating ANN with fuzzy inference systems (FIS) in the same topology. The powerful capability of CANFIS stems from pattern-dependent weights between the consequent layer and the fuzzy association layer. The architecture of CANFIS is illustrated in Fig. 2. The fundamental component for CANFIS is a fuzzy neuron that applies membership functions (MFs) to the inputs. Basically, two membership function types can be used: general bell and Gaussian. The network also contains a normalization axon to expand the output into a range of 0–1. Fuzzy axons are valuable because their MF can be modified through back-propagation during network training to expedite the convergence. The second major component of CANFIS is a modular network that applies functional rules to the inputs. The number of modular networks matches the number of network outputs, and the number of processing elements in each network corresponds to the number of MFs. The CANFIS also has a combiner axon that applies the MFs outputs to the modular network outputs.

Finally, the combined outputs are channeled through a final output layer and the error is back propagated to both the MFs and the modular networks. The function of each layer is described as

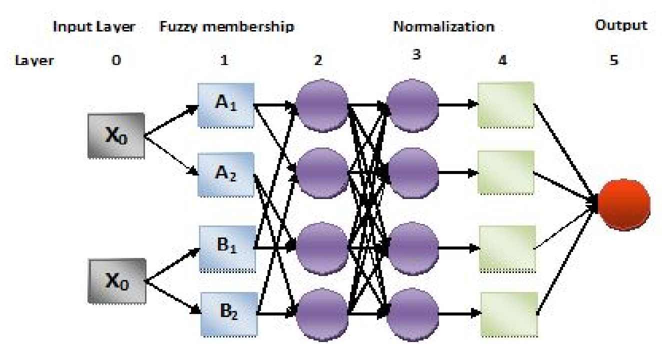

Figure 2 Architecture of the CANFIS model

follows. Each node in Layer 1 is the membership grade of a fuzzy set (A1, A2, B1, or B2) and specifies the degree to which the given input belongs to one of the fuzzy sets. The fuzzy sets are defined by three membership functions. Layer 2 receives input in the form of the product of all output pairs from the first layer. The third layer has two components. The upper component applies the membership functions to each of the inputs, while the lower component is a representation of the modular network that computes, for each output, the sum of all the firing strengths. The fourth layer calculates the weight normalization of the output of the two components from the third layer and produces the final output of the network. Two fuzzy models are mainly used: the Tsu-kamoto model and the Sugeno (TSK) model (Aytek 2009).In this study, the both fuzzy models were used.

II.4 Performance evaluation parameters

The performances of the models used for runoff prediction were assessed using various standard statistical performance evaluation criteria. The statistical measures considered were correlation coefficient (r), root mean square error (RMSE) and mean absolute error (MAE). The three criteria are calculated according to the following equations:

$$r = \frac{\sum_{i=1}^{n}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\bar{X})^2(Y_i-\bar{Y})^2}} \quad \text{(i)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_i-Y_i)^2}{n}} \quad \text{(ii)}$$

$$MAE = \frac{\sum_{i=1}^{n}|X_i-Y_i|}{n} \quad \text{(iii)}$$

where, X_i and Y_i are the ith observed and estimated values, respectively; $\bar{X}$ and $\bar{Y}$ are the average of X_i and Y_i, and n is the total numbers of data.

III. Results and discussion

III.1 Selection of input vectors for MLP and CANFIS models

Proper selection of data representing complete range of operating conditions may lead to the successful training of ANN with a smaller number of data sets even for a complex system and thus saving computation time as a whole. Therefore, careful selection of data is more important than the amount of data for training. Determination of significant input variables is one of the most important steps in the model development process. All the potential input variables will not be equally useful since some may not be correlated, noisy or have no significant relationship with the output variables being modeled. Generally, some degree of priorities knowledge is used to specify the initial set of candidate inputs (ix). When the relationship to be modeled is not well understood, then an analytical technique, such as cross correlation, is often employed. The current study employed a trial and error approach to identify the appropriate input vector.

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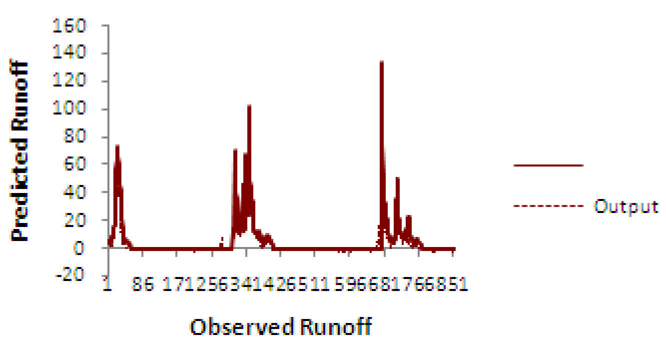
III.2 Performances of MLP models

In this study, a number of networks were constructed, each of them was trained separately, and the best network was selected based on the accuracy of the predictions in the testing phase. This way of defining the topology takes a considerable amount of time, and it is nevertheless quite likely that an untested combination might have a better response to the expected generalization and convergence time than the one selected.

The performance evaluation criteria of the MLP models at testing phase are presented in Table 1. The Table 1 indicates that the MLP model whose inputs are the rainfall P(t), temperature T(t), evaporation E(t), humidity H(t), and runoff Q(t) . MLP6 has the smallest RMSE (2.27 m3/s), MAE (2.12 m3/s), and the highest r (0.93). This emphasizes the factors influencing estimation of runoff, since the model considered all the variables. The comparison of the runoff predicted by the MLP5 model and observed values at testing phase showed good agreement (Figure 3). As seen from Table 1, using only the rainfall [MLP1] input gave the poorest runoff estimates. Therefore, it is pertinent to take into account the combined influence of all the meteorological variables, although the MLP models with limited meteorological data estimated runoff with reasonable accuracy.
Although several tests were carried out using one, two and three hidden layers, a single hidden layer with three neurons was found to be sufficient for the runoff estimation. The simulations showed that an increase in the hidden layer and the number of neurons in the hidden layer has brought nearly no significant improvement to the runoff forecast. For the 5–3–1 architecture, the Momentum learning algorithm and the Tanh activation function have shown the highest correlation coefficient and minimum errors.

Table 1 MLP models performance in testing phase

Sr. No.	Model	Input combination	r	RMSE	MAE
1	MLP1	$P_{(t)}$	0.743	8.28	5.88
2	MLP2	$P_{(t)}$, $T_{(t)}$	0.782	7.06	5.18
3	MLP3	$P_{(t)}$, $H_{(t)}$, $E_{(t)}$	0.828	5.57	4.35
4	MLP4	$P_{(t)}$, $H_{(t)}$, $E_{(t)}$, $T_{(t)}$	0.864	4.41	3.70
5	MLP5	$Q_{(t)}$, $P_{(t)}$, $H_{(t)}$, $E_{(t)}$, $T_{(t)}$	0.930	2.27	2.12



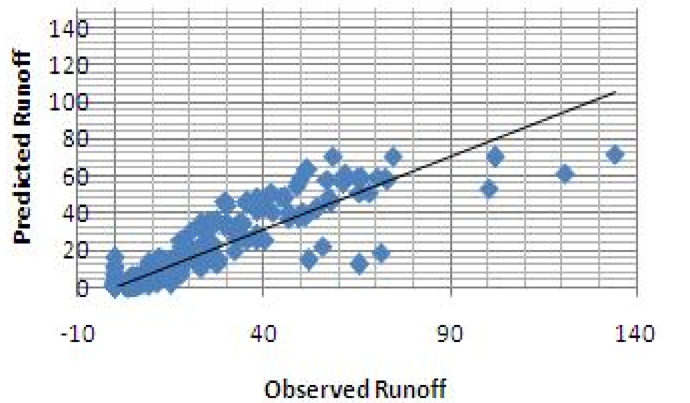


Figure 3 Time series and scatter plot of best model MLP5 (5-3-1)

The program then instructed to run for 800 epochs. The error was measured for each run of the epoch number. Training should be stopped when the error remains unchanged for a given number of epochs. This is done in order to avoid overtraining, in which case the model memorizes the training values and is unable to make predictions when an unknown example is presented to it. In this study, 650 epochs were found adequate for the best topology. The performance of the model deteriorated for fewer and higher epochs than 650.

III.3 Performance of CANFIS model

The ability of the CANFIS model to achieve the performance goal depends on the internal CANFIS parameters such as the number and shape of membership functions and the type of fuzzy model. In this study, a great amount of CANFIS models were developed by varying the number and structure (Bell and Gaussian) of the MF and the fuzzy model (TSK and Tsukamoto) in order to determine the best topology. In the CANFIS models, increasing the number of membership functions on the input variables will increase the number of fuzzy if–then rules; simultaneously it increases the model complexity and hence affects the model parsimony (xvii). Furthermore, a fuzzy model with a large number of rules often encounters the risk of over fitting the data. Simulation results of CANFIS models are summarized in Table 2. The input combinations of variables to CANFIS models consist of the same meteorological variables used for the MLP models. As shown in Table 2, the CANFIS model which requires all input parameters ($Q_{(t)}$, $T_{(t)}$ $P_{(t)}$, $H_{(t)}$, and $E_{(t)}$) performed the most accurate predictions for daily runoff. The results showed that the Gaussian membership function and TSK fuzzy model had the highest correlation coefficient and minimum errors. It was found that a CANFIS with three membership functions for each input variable gave the best results. No significant improvement in the performances of the CANFIS models was achieved with respect to the change in number of membership functions. However, with increasing the number of membership functions, the time taken for model training increased considerably. Similar to the MLP models, different numbers of epochs were tested for the CANFIS models. The optimum number of epoch was obtained 750 for the best topology.

doi : 10.17950/ijer/v5i1/036

Table 2 CANFIS models performance in testing phase

Sr. No.	Model	Input combination	r	RMSE	MAE
1	CANFIS1	$P_{(t)}$	0.724	8.95	8.35
2	CANFIS2	$P_{(t)}$, $T_{(t)}$, $E_{(t)}$	0.768	7.52	7.02
3	CANFIS3	$P_{(t)}$, $H_{(t)}$, $E_{(t)}$	0.806	6.29	5.87
4	CANFIS4	$P_{(t)}$, $H_{(t)}$, $E_{(t)}$, $T_{(t)}$	0.847	4.96	4.63
5	CANFIS5	$Q_{(t)}$, $P_{(t)}$, $H_{(t)}$, $E_{(t)}$, $T_{(t)}$	0.905	3.08	2.87

IV. Conclusion

The main purpose of this paper was to estimate one day ahead runoff using the MLP and CANFIS models for the meteorological station in India. The MLP models using varied input combinations of meteorological variables have been trained using various training algorithms. Also, the CANFIS models with various membership functions and fuzzy models and different combinations of input parameters were examined to predict one day ahead runoff. The results showed that the MLP model whose inputs are the $Q_{(t)}$, $T_{(t)}$ $P_{(t),}$ $H_{(t)}$, and $E_{(t)}$ (MLP5) was the best model among the input combinations tried in the study. It was also found that a single hidden layer with three neurons was the best architecture. For the best architecture, the Momentum learning algorithm has shown the highest correlation coefficient and minimum errors. The activation function was set to a Tanh function as this proved by trial and error to be the best in depicting the non-linearity of the modeled natural system.

The results revealed that the TSK fuzzy model was more efficient than the Tsukamoto fuzzy model for prediction of one day ahead runoff by the CANFIS models. Moreover, the Gaussian function performed better than the Bell function. Comparing the MLP and CANFIS models, it was found that the MLP models were more adequate than the CANFIS models for estimating one day ahead runoff. In addition, the run time of the MLP models was much less than that of the CANFIS models.

The results of this study can be helpful for filling the runoff measurements. The findings of this study are based on a single case study. Therefore, the findings reported in this paper need to be thoroughly explored and reinforced through further rigorous research by carrying out similar studies in other regions of varying hydrologic and climatic conditions.

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