India Water Week 2012 – Water, Energy and Food Security : Call for Solutions, 10-14 April 2012, New Delhi

STREAM FLOW FORECASTING USING ANN AND FUZZY LOGIC

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ABSTRACT

In this paper, methodologies has been presented for daily flow forecasting, considering different lead periods, using artificial neural networks (AAN) and Fuzzy Logic. Historical daily discharge data for Hiran river (a tributary of River Narmada) at Patan are utilised for training and validating the ANN and Fuzzy logic based models in the real time flood forecasting mode. The performance of the methodology has been evaluated based on graphical and numerical criteria for training as well as calibration. The results illustrate good potential of the two soft computing methods i.e. ANN and Fuzzy Logic for daily flow forecasting for different lead periods. For the larger lead periods, the performance of the models becomes poorer. For improving the performance of the model for high lead periods, ANN and Fuzzy model Structures considering forecasted rainfall as an additional input need to be developed.

INTRODUCTION

Stream flow forecasting is of vital importance for the planning, operational analysis and efficient management of reservoirs. In general the hydrological forecasting is done in two stages, the first stage corresponds to the system identification or model development and the second stage to optimal forecasting. Traditionally, regression or a time series model is used to carry out stream flow forecasting. Numerous stochastic models have been proposed for modelling and forecasting hydrological time series. These comprise auto regressive moving average (ARMA) models [1], models based on the concept of pattern recognition [2] and deaggregation models [3]. Performance of five different models for stream flow simulation has been studied by Stedinger and Taylor [4]. In some cases statistical correlation techniques have been employed for direct prediction of water levels [5]. Most of these available models assume linear relationships among variables. Such models do not attempt to represent the non-linear dynamics inherent in the hydrologic processes, and may not always perform well. Such models do not attempt to represent the non-linear dynamics inherent in the hydrologic processes, and may not always perform well. On the other hand, ANNs can approximate virtually any (measurable) function up to an arbitrary degree of accuracy. The advantage of ANN is that one need not have a well defined physical relationship for converting an input to an output and it provides a quick and flexible means of creating models for hydrological forecasting.

During the last decade the artificial neural networks and fuzzy logic techniques have become popular in hydrological modeling, particularly in those applications in which the deterministic approach presents serious drawbacks, due to the noisy or random nature of the data. Recently use of fuzzy set theory has been introduced to inter-relate variables in hydrologic process calculations and modeling the aggregate behavior. Further, the concept of fuzzy decision making and fuzzy mathematical programming have great potential of application in water resources management models to provide meaningful decisions in the face of conflicting objectives. Fuzzy Logic based procedures may be used, when conventional procedures are getting rather complex and expensive or vague and imprecise information flows directly into the modeling process.

The present paper describes the concept of ANN and fuzzy logic. Furthermore, this paper also presents a general review of the applications of ANN and fuzzy logic in hydrological modelling and a methodology has been presented for daily stream flow forecasting, considering different lead periods, using artificial neural networks

(AAN) and Fuzzy logic techniques. Historical daily discharge data of Hiran river (a tributary of River Narmada) at Patan are utilised for training and validating the ANN model in the real time flow forecasting mode. The performance of the methodologies has been evaluated based on graphical and numerical criteria for training as well as validation. The results illustrate good potential of the ANN and Fuzzy models for daily flow forecasting for different lead periods. However, for the larger lead periods, the performance of the model becomes poorer.

BRIEF REVIEW AND SCOPE OF PRESENT STUDY

Hydrological forecasting using time series analysis is one of the methods to quantify predictions and it can be interpreted as an output of an unknown system [6]. In situations when both the system characteristics and the input functions are not known, a time series analysis provides future output values by means of extrapolation from their own past. Many of the time series analysis techniques assume linear relationships among variables. For describing time series data using linear relationship is often found to be inadequate. ANN model generally offers several advantages over the more conventional approaches to computing. The most frequently cited of these are their ability to develop a generalised solution to a problem from a set of examples. The attribute of generalisation permits them to be applied to problems other than those used for training and to produce valid solutions even when there are errors in the training data [7,8]. A number of studies showed the applicability of ANN in hydrological modeling and forecasting. For forecasting rainfall in space and time, French et al. [9] developed an ANN model. Kang [10] used multi-layer perception model to forecast stream flows at Pyunchang river basin in Korea. Buch et al. [11] have used ANN in runoff simulation of a Himalayan glacier. An ANN model for the simulation and prediction of daily flow of Huron river at Dexter sampling station was developed by Karunanithi et al. [12]. Raman and Sunil Kumar [13] compared the performance of neural network with the statistical method for synthesising monthly inflow records for two reservoir sites.

In the context of flow forecasting use of the previous time period discharge as input to the ANN model is considered in this study. Flow forecasting using univeriate series can further be improved by continuous updating the forecast values through real time error updating module. In the present study flow forecasting along with real time error updating is coupled with the ANN for deriving more real estimates of the daily river flows.
Although ANN is quite powerful for modelling various real world problems, it also has its shortcomings. If the input data are less accurate or ambiguous, ANN would be struggling to handle them and a fuzzy system might be a better option. Fuzzy logic and fuzzy set theory, founded by Zadeh [14], are used to identify the characteristics of decision making through a set of logical rules. Fuzzy logic based modeling approaches have recently got attention in hydrological modeling and reservoir operaton (See & Openshaw [15]; Xiong *et al*.[16] Shrestha *et al*. [17], Fontane *et al*. [18], Yu and Chen [19], Chang and Chen [20], Lohani et al. [21, 22,23, 24].

STUDY AREA AND DATA USED

Hiran is the biggest right bank tributary of Narmada which rises in the Bhaner range in Jabalpur district of Madhya Pradesh. It drains a total of 4,792 sq km. The location of sub basin is shown in Figure 1. The outlet gauging station is at Patan road bridge. Daily values of flow for a continuous period of 7 year (1993-1997) at Patan gauging site were available and have been used in the current study. The data were divided into two sets: a training data set consisting of daily river flow for three years (1993-95) and a testing data set of two years (1996-97).

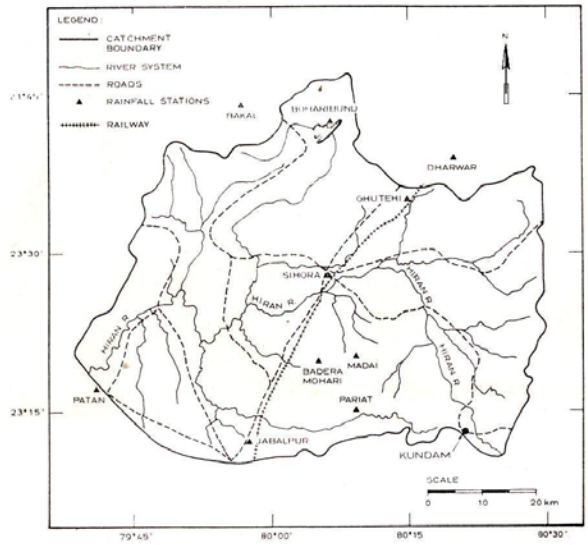

Figure 1: Hiran subbasin of Nramada river up to Patan gauging site

ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network (ANN) was first introduced as a mathematical aid by McCulloch and Pitts [25]. Neural networks are composed of many simple elements operating in parallel. These elements are inspired by biological nervous systems. The network function is determined largely by the connections between elements. It is claimed that the human central nervous system is comprised of about 1,3x1010 neurons and that about 1x1010 of them takes place in the brain. At any time, some of these neurons are firing and the power dissipation due to this electrical activity is estimated to be in the order of 10 watts. A neuron has a roughly spherical cell body called soma. The signals generated in soma are transmitted to other neurons through an extension on the cell body called *axon* or *nerve fibres.* Another kind of extensions around the cell body like bushy tree is the ***dendrites***, which are responsible from receiving the incoming signals generated by other neurons.

The transmission of a signal from one neuron to another through synapses is a complex chemical process in which specific transmitter substances are released from the sending side of the junction. The effect is to raise or lower the electrical potential inside the body of the receiving cell. If this graded potential reaches a threshold, the neuron fires. It is this characteristic that the artificial neuron model proposed by McCulloch and Pitts, (McCulloch and Pitts 1943) attempt to reproduce.

Mathematical models of biological neurons (called artificial neurons) mimic the functionality of biological neurons at various levels of detail. A typical model is basically a static function with several inputs (representing the dendrites) and one output (the axon). Each input is associated with a weight factor (synaptic strength). The weighted inputs are added up and passed through a nonlinear function, which is called the *activation function* (ASCE, 2000). The value of this function is the output of the neuron (Figure 2).

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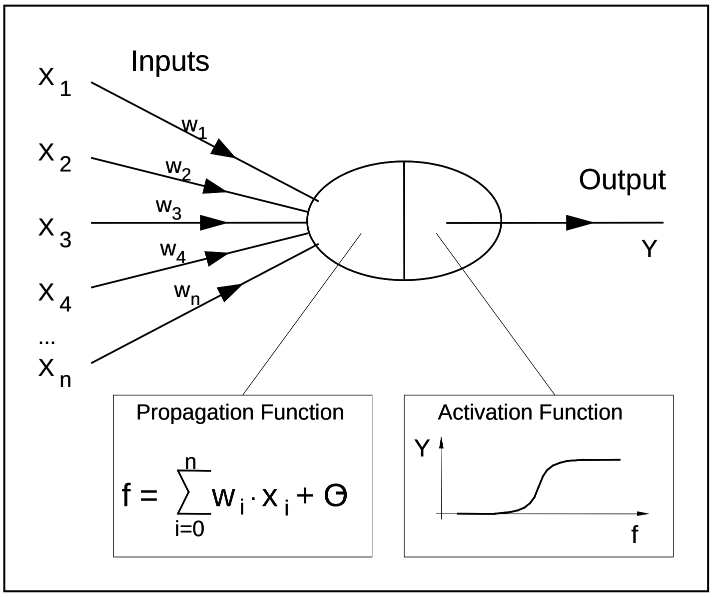

Figure 2: Processing Element of ANN

A typical ANN model consists of number of layers and nodes that are organised to a particular structure. There are various ways to classify a neural network. Neurons are usually arranged in several *layers* and this arrangement is referred to as the *architecture* of a neural net. Networks with several layers are called *multi-layer* networks, as opposed to *single-layer* networks that only have one layer. The classification of neural networks is done by the number of layers, connection between the nodes of the layers, the direction of information flow, the non linear equation used to get the output from the nodes, and the method of determining the weights between the nodes of different layers. Within and among the layers, neurons can be interconnected in two basic ways: (1) *Feedforward networks* in which neurons are arranged in several layers. Information flows only in one direction, from the input layer to the output layer, and (2) *Recurrent networks* in which neurons are arranged in one or more layers and feedback is introduced either internally in the neurons, to other neurons in the same layer or to neurons in preceding layers. The commonly used neural network is three-layered feed forward network due to its general applicability to a variety of different problems and is presented in Figure 3.

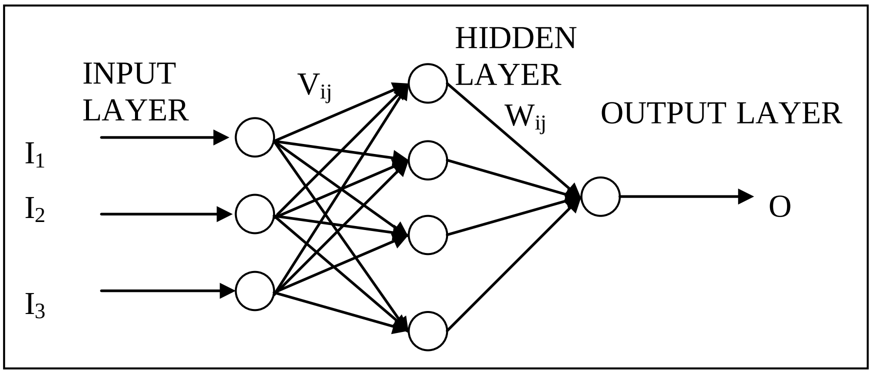

Figure 3: A Typical Three-Layer Feed Forward ANN (ASCE, 2000a)

The ability of a neural network to process information is obtained through a learning process, which is the adaptation of link weights so that the network can produce an approximate output(s). In general, the learning process of an ANN will reward a correct response of the system to an input by increasing the strength of the current matrix of nodal weights [27]. The learning process in biological neural networks is based on the change of the interconnection strength among neurons. Synaptic connections among neurons that simultaneously exhibit high activity are strengthened. In artificial neural networks, various concepts are used. A mathematical approximation of biological learning, called Hebbian learning is used, for instance, in the Hopfield network. Multi-layer nets, however, typically use some kind of optimization strategy whose aim is to minimize the difference between the desired and actual behavior (output) of the net. Two different learning methods can be recognized: supervised and unsupervised learning:

Supervised learning: the network is supplied with both the input values and the correct output values, and the weight adjustments performed by the network are based upon the error of the computed output.

Unsupervised learning: the network is only provided with the input values, and the weight adjustments are based only on the input values and the current network output. Unsupervised learning methods are quite similar to clustering approaches.

A multi-layer neural network (MNN) has one input layer, one output layer and a number of hidden layers between them. In a MNN, two computational phases are distinguished:

1. *Feedforward computation.* From the network inputs (xi, $i = 1, \ldots, n$), the outputs of the first hidden layer are first computed. Then using these values as inputs to the second hidden layer, the outputs of this layer are computed, etc. Finally, the output of the network is obtained.

2. *Weight adaptation.* The output of the network is compared to the desired output. The difference of these two values called the error, is then used to adjust the weights first in the output layer, then in the layer before, etc., in order to decrease the error. This backward computation is called error backpropagation.

There are several features in ANN that distinguish it from the empirical models. First, neural networks have flexible nonlinear function mapping capability which can approximate any continuous measurable function with arbitrarily desired accuracy [28,29], whereas most of the commonly used empirical models do not have this property. Second, being non-parametric and data-driven, neural networks impose few prior assumptions on the underlying process from which data are generated. Because of these properties, neural networks are less susceptible to model.

FUZZY LOGIC

The origin of the fuzzy logic approach dates back to 1965 since Lotfi Zadeh's [14] introduction of the fuzzy set theory and its applications. Since then the fuzzy logic concept has found a very wide range of applications in various domains like: estimation, prediction, control, approximate reasoning, pattern recognition, medical computing, robotics, optimization and industrial engineering, etc.
Fuzzy logic is a powerful problem-solving methodology with a myriad of applications in embedded control and information processing. Fuzzy provides a remarkably simple way to draw definite conclusions from vague, ambiguous or imprecise information. In a sense, fuzzy logic resembles human decision making with its ability to work from approximate data and find precise solutions.

Unlike classical logic which requires a deep understanding of a system, exact equations, and precise numeric values, Fuzzy logic incorporates an alternative way of thinking, which allows modeling complex systems using a higher level of abstraction originating from our knowledge and experience.

In ordinary (non fuzzy) set theory, elements either fully belong to a set or are fully excluded from it. Recall, that the membership $\mu_{\square}$(x)of $\square$of a classical set A, as a subset of the universe x, is defined by:

$$\mu_A(x) = \begin{cases} 1, & \text{iff } x \in A \\ 0, & \text{iff } x \notin A \end{cases}$$

Step by step procedure for developing a fuzzy model is given below:

- Define the model objectives and criteria: What am I trying to model? What do I have to do to model the system? What kind of response do I need? What are the possible (probable) system failure modes?
- Determine the input and output relationships and choose a minimum number of variables for input to the Fuzzy Logic (FL) system.
- Using the rule-based structure of FL, break the modelling problem down into a series of IF X AND Y THEN Z rules that define the desired system output response for given system input conditions. The number and complexity of rules depends on the number of input parameters that are to be processed and the number of fuzzy variables associated with each parameter. If possible, use at least one variable and its time derivative. Although it is possible to use a single, instantaneous error parameter without knowing its rate of change, this cripples the system's ability to minimize overshoot for a step inputs.
- Create FL membership functions that define the meaning (values) of Input/Output terms used in the rules.
- Create the necessary pre- and post-processing FL
- Test the system, evaluate the results, tune the rules and membership functions, and retest until satisfactory results are obtained.

ANN AND FUZZY MODEL DEVELOPMENT

ANN and fuzzy model structures for river flow forecasting have been developed for five different lead times viz. 1 day, 2 day, 3 day, 4, day and 5 days. The input data vectors for the models were selected based on the auto-correlation and partial auto correlation analysis of the flow data series. Figure 4 shows the autocorrelation plot of river flow series. On the basis of the results of these correlation analyses, four significant flow values of previous time steps were identified as input vector to the ANN and fuzzy models:

$$Q(t+k) = f(Q(t-1), Q(t-2), Q(t-3), Q(t-4)) \quad (1)$$

where, Q(t) is the river flow at time period t and k is the lead period.

The modelling is initiated with the normalization of input and output. The input-output data i.e. the daily river flow series is normalized between the range 0 to 1. After the input and output variables were selected, the ANN architecture based on three layer feed forward back propagation neural network having single hidden layer is used. The various network parameters e.g. connection weight, threshold, number of neurons in the hidden layer were adjusted during the training process through minimization of mean square errors using Levenberg Marquardt back propagation algorithm in MATLAB.

Similarly, for developing a fuzzy rule based model, different membership functions are trialed and finally Triangular membership function has been selected. To describe the relation between inputs and output rules are formed. Based on the inputs, membership functions and associated rules, a fuzzy output is computed. The input and fuzzy output is defuzzified to crisp output by using centroid method. The conceptual crisp outputs provide the flood forecast at forecasting site. The defuzzified results are compared with observed values in order to calibrate and validate the model.

The ANN and Fuzzy rule based models are trained on calibration data set and tested on another set of data for generalization of the results. Finally, the model is tested using various performance criteria both for calibration and validation data sets.

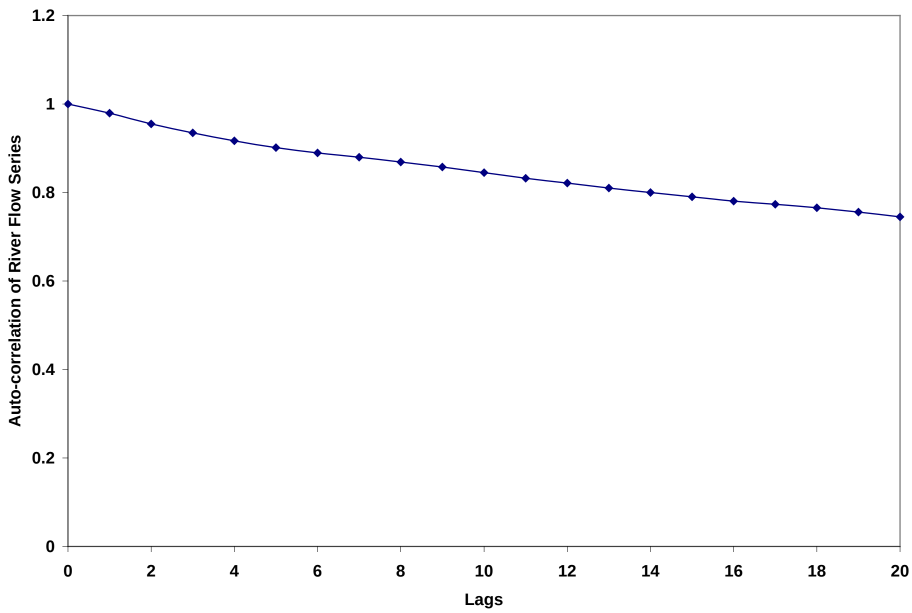

Fig.4: Auto-correlation plot of river flow series

PERFORMANCE EVALUATION CRITERIA

In order to evaluate the efficiency of the ANN and fuzzy rule based models in river flow forecasting, three performance criteria have been introduced and investigated for both calibration and validation of the model. The whole data length is divided into two parts, one for calibration and another for validation of fuzzy logic model. Performance criteria such as RMSE, model efficiency (Nash and Sutcliffe [30]) and coefficient of correlation (R) are applied to evaluate the performance during calibration and validation. The higher values of coefficient of correlation and efficiency and lower values of RMSE would indicate better model performance. These performance criteria are defined by the following equations:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (Q_{oi} - Q_{pi})^2}{N}} \qquad (3)$$

$$\text{Efficiency} = \left[1 - \frac{\sum_{i=1}^{N} (Q_o - Q_p)^2}{\sum_{i=1}^{N} (Q_o - \overline{Q}_o)^2} \right] \qquad (4)$$

$$\text{Coefficient of Correlation} = \frac{\sum_{i=1}^{N} (Q_o - \overline{Q}_o)(Q_p - \overline{Q}_p)}{\sqrt{\sum_{i=1}^{N} (Q_o - \overline{Q}_o)^2 \sum_{i=1}^{N} (Q_p - \overline{Q}_p)^2}} \qquad (5)$$

Where, N is the number of observations; Q_o is the observed flow; Q_p is predicted flow; $\overline{Q}_o$ is the mean of the observed flow; and $\overline{Q}_p$ is the mean of the predicted flow.

RESULTS AND DISCUSSION

The results of flow forecasting model in terms of the various performance evaluation statistics for different lead periods are presented in Table 1 and 2. It can be seen from Table 1 that the performance of the ANN model for calibration and testing stage are very similar in nature. From the calibration results it is evident that the model performs well for small lead periods. However, the forecasting for higher lead periods shows very poor performance. For one day lead period the model correlation and efficiency values have been obtained as 0.965 and 0.926 respectively during calibration and 0.962 and 0.926 respectively during validation. While, for 5 day lead period correlation coefficient and efficiency reduces to 0.941 and 0.403 during calibration and 0.538 and 0.394 respectively during validation respectively.

Table 1: Performance evaluation statistics for ANN model for different lead periods

Lead Period	Without Error Modelling					
	Calibration			Validation		
	R	RMSE	Efficiency	R	RMSE	Efficiency
1	0.965	30.24	0.926	0.962	31.19	0.926
2	0.840	60.65	0.701	0.840	61.53	0.702
3	0.831	66.52	0.640	0.822	66.61	0.639
4	0.728	80.38	0.505	0.717	80.61	0.502
5	0.541	99.06	0.403	0.538	99.79	0.394

Table 2: Performance evaluation statistics for Fuzzy rule based model for different lead periods

Lead Period	Without Error Modelling					
	Calibration			Validation		
	R	RMSE	Efficiency	R	RMSE	Efficiency
1	0.972	29.02	0.931	0.970	29.39	0.929
2	0.851	57.34	0.741	0.849	58.21	0.735
3	0.840	64.71	0.678	0.837	64.97	0.665
4	0.738	77.39	0.581	0.734	78.67	0.579
5	0.549	97.27	0.488	0.544	98.32	0.471

Table 2 presents the results of the fuzzy forecasting model. For one day lead period the fuzzy model correlation and efficiency values have been obtained as 0.972 and 0.931 respectively during calibration and 0.970 and 0.929 respectively during validation. While, for 5 day lead period correlation coefficient and efficiency reduces to 0.949 and 0.488 during calibration and 0.544 and 0.471 respectively during validation respectively. It can be seen from Table 2 that the performance of the forecasting improves when fuzzy logic based model are used. There is significant improvement in the flow forecasting for small lead periods. Figure 5 shows the scatter plot of observed and forecasted flows from ANN and fuzzy rule based models for 1 day lead period. The scatter plot indicates a definite improvement in the forecast by using fuzzy rule based model. This can be represented by a graphical comparison (Figure 6) of the observed flows with those forecasted using ANN and Fuzzy models. The time series comparison of the observed and forecasted flow shows that the fuzzy rule based model is capable of forecasting of flows for monsoon as well as non-monsoon periods as depicted from Table 2 and

Figure 6 and Figure 7. Thus, it is observed that the performance of the developed fuzzy is reasonably good for forecasting daily flows.

Furthermore, the results indicates that the flow forecasting model based on previous time steps flow only is not capable to forecast at higher lead periods. However, it can be produce a very useful model for small lead periods. Poor performance of the models for higher lead period may be due to univeriate series of flow considered in the present study. If the forecasted catchment rainfall is also available the flow forecasting results may be further improved.

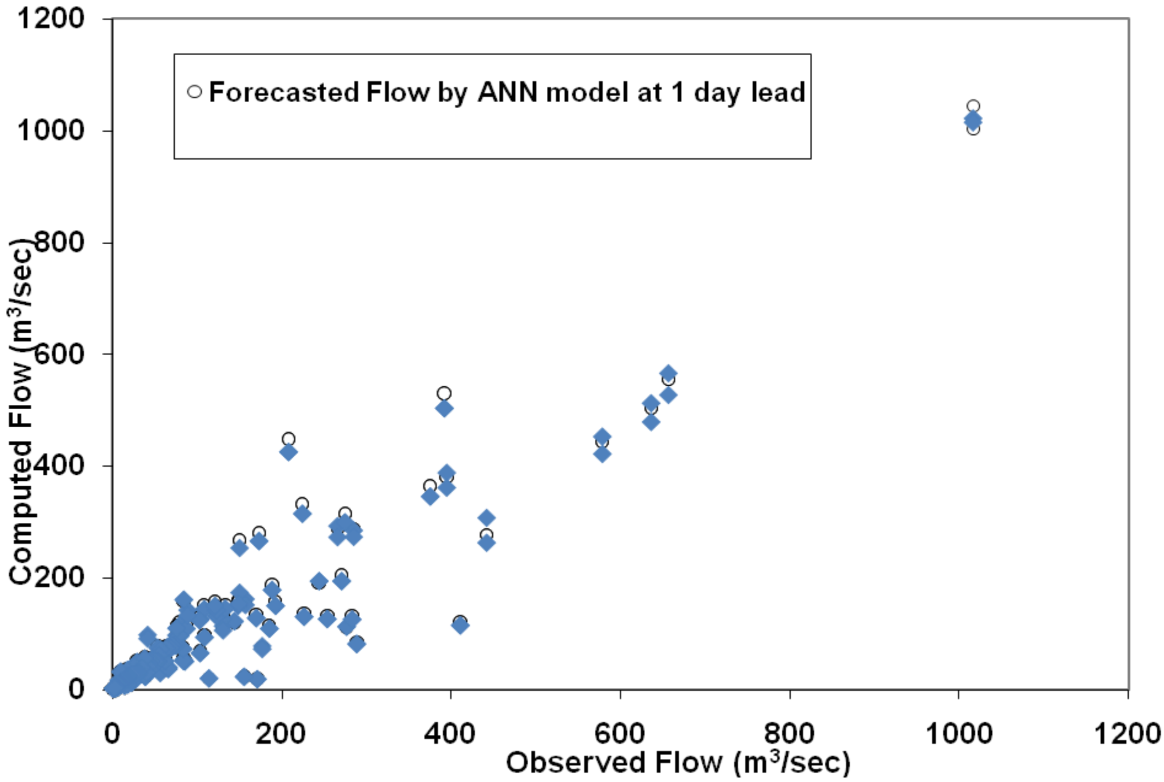

Fig. 5: Scatter Plot of observed and forecasted flow (Lead Period 2 days)

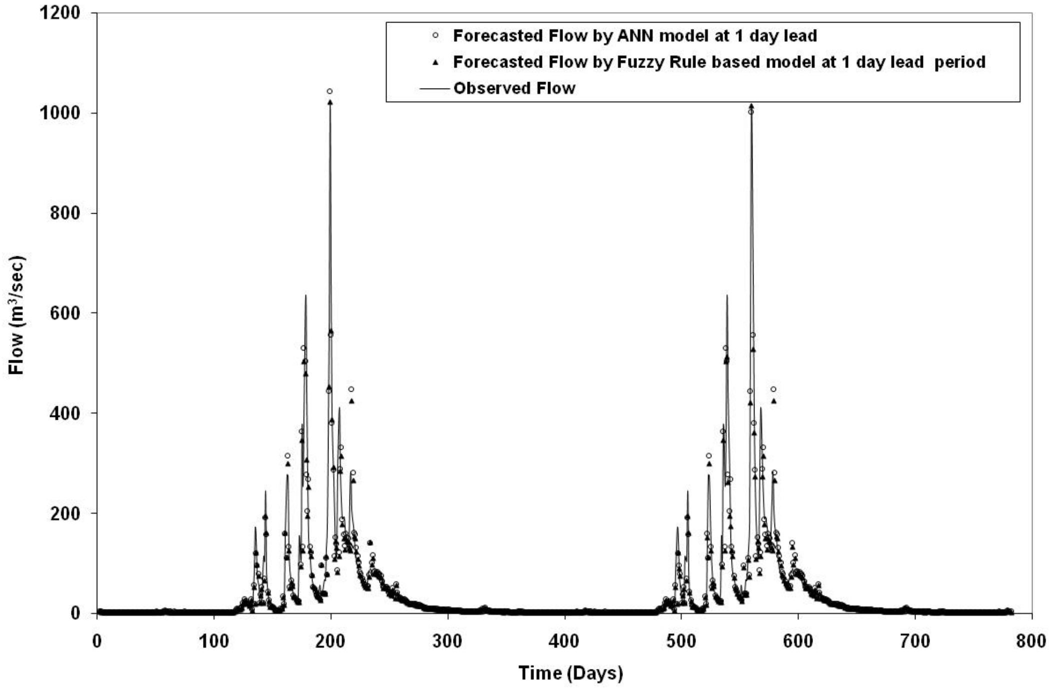

Fig. 6: Comparison of observed and forecasted flows (Lead Period 1 Days)

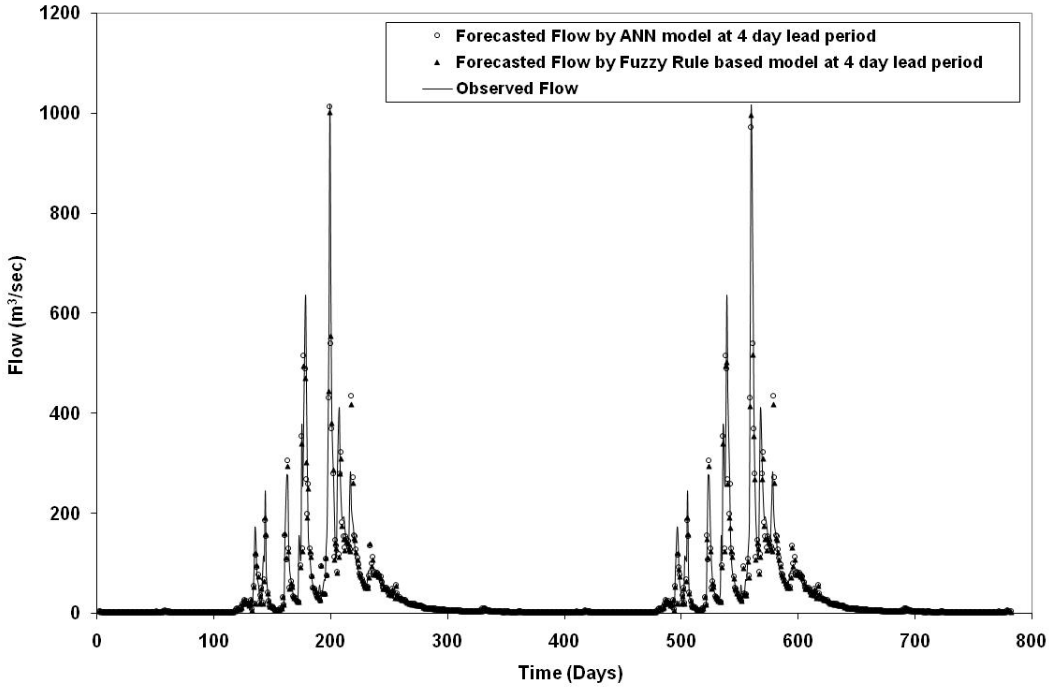

Fig. 7: Comparison of observed and forecasted flows (Lead Period 4 Days)

CONCLUSIONS

The daily flow forecasting model based on ANN and Fuzzy logic techniques have been developed. The models have been successfully applied for formulating the daily flow forecasts for different lead periods at Patan gauging site of Hiran River, which is a tributary of River Narmada. The performance for the developed forecasting models are evaluated by comparing the observed and forecasted flows. The results of the application of the developed ANN and Fuzzy models indicate a definite improvement in the model performance at different lead periods when fuzzy model is used. It is observed that the model performs very well for forecasting the flow at small lead periods (1 day, 2 day and 3 day). However, the performance of the model deteriorates with increase in the lead period (4 day, 5 day etc.). Thus, for larger lead period a suitable ANN or Fuzzy rule based model structure has to be evolved incorporating the forecasted rainfall as additional input variable.

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