STREAMFLOW FORECASTING USING NEURO-FUZZY INFERENCE SYSTEM

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Abstract

This paper presents combined approaches of neural network analysis and fuzzy inference techniques to the problem of streamflow forecasting. In the present study, one step ahead forecasts are made for ten-daily flows, which are mostly required for short term operational planning of multipurpose reservoirs. A Neuro-Fuzzy model is developed to forecast ten-daily flows into the Hirakud reservoir on River Mahanadi in the state of Orissa. The input variables influencing the flows into the reservoir are identified using correlation analysis. The performance of the model is evaluated using various performance indicators and the results are presented. The results indicate that the Neuro-Fuzzy modeling technique is able to model the streamflow process with reasonable accuracy and can be used for real time forecasting of streamflows.

Keywords: Streamflow; Forecasting; Artificial Neural Networks; Neuro-Fuzzy Inference System; River Mahanadi

1. INTRODUCTION

The prediction of flow into a reservoir is fundamental in water resources planning and management. Prior knowledge of the arrival of flood can be used to route the flood safely through the reservoir. This reduces the danger of flood damage at the downstream region and ensures safety of the dam. Therefore, the need for timely and accurate streamflow forecasting is widely recognized and emphasized by many in water resources fraternity. Real-time forecasts of natural inflows to reservoirs are of particular interest for operation and scheduling. A variety of methods have been proposed for this purpose including conceptual (physical) and empirical (statistical) models (WMO 1975), but none of them can be considered as unique superior model (Shamseldin 1997). Owing to difficulties of formulating reasonable non-linear watershed models, recent attempts have resorted to Neural Network (NN) approach for complex hydrologic modeling (French et al. 1992; Hsu et. al. 1992; Karunanithi et. al. 1994; Raman and Sunil Kumar 1995; Saad et al. 1996; Clair and Ehrman 1998; Thirumalaiah and Deo 1998; Jain et al. 1999; Coulibaly et al. 2000).

In recent years the use of soft computing in the field of hydrological forecasting is gaining ground. This is one of the latest approaches for the development of systems armed with computational intelligence. It attempts to integrate several different computing paradigms such as Neural Networks (NN) and fuzzy logic (Jang 1993; Jang et al. 1997). The objective of this paper is to develop Adaptive Neuro-Fuzzy Inference System (ANFIS) for the prediction of inflows into a reservoir. ANFIS based ten daily flow forecasting model is developed for Hirakud Reservoir on River Mahanadi in the State of Orissa. The performance of this model is evaluated to validate the applicability of ANFIS technique for modeling the streamflow series. An overview of ANFIS is given in the next section, while the details of the present study along with the results and discussion are presented in the subsequent sections.

2. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The Adaptive Neuro Fuzzy Inference System (ANFIS) incorporates the concepts of neural network learning in fuzzy inference systems and has the ability to model any nonlinear function (Jang et al, 1997). ANFIS models are being employed in a wide variety of applications of modelling, decision making, signal processing and control. The basic features of ANFIS are described in the following sections.

2.1 FUZZY INFERENCE SYSTEMS

The fuzzy inference system is a popular computing framework based on the concepts of fuzzy logic. Fuzzy logic is based on the mathematics of fuzzy set theory where the classical notion of binary set membership has been modified to include partial membership ranging between 0 and 1 (Kosko, 1994). Fuzzy sets have ambiguous boundaries and therefore gradual transtions between defined sets. The fuzzy logic has ability to model human reasoning and linguistic concepts associated with it.

The basic structure of a fuzzy inference system consists of conceptually three components namely a rule base, a data base and a reasoning mechanism. The rule base contains a selection of fuzzy if-then rules, while the database defines the membership functions used in the fuzzy rules. The reasoning mechanism performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion. The fuzzy inference system used in this study is Sugeno fuzzy model. A typical fuzzy rule in a two inputs Sugeno fuzzy model has the form

if x is A and y is B then $z = f(x,y)$ …(1)

where A and B are fuzzy sets over inputs x and y respectively, while $z = f(x,y)$ is a crisp function which is the output of the system. If $f(x,y)$ is a first order polynomial of x and y then the fuzzy inference system is called a first-order Sugeno fuzzy model. In the present study the architecture of ANFIS model used represents a first-order Sugeno fuzzy model.

2.2 ARCHITECTURE OF ANFIS MODEL

ANFIS, proposed by Jang (1993), is based on the first-order Sugeno fuzzy model. The neural network paradigm used is a multi-layer feed-forward back propagation network.

For simplicity, let the fuzzy inference system under consideration is assumed to have two inputs, x and y, and one output z. For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy if then rules can be expressed as

Rule 1: If x is A_1, and y is B_1, then $f_1 = p_1x + q_1y + r_1$

Rule 2: If x is A_2 and y is B_2 then $f_2 = p_2x + 1_2y + r_2$

Figure1 illustrates the fuzzy model and the corresponding equivalent ANFIS architecture.

In the ANFIS, nodes in the same layer have similar functions as described below. The output of node i in layer l is denoted as O_{li}.

Layer 1: Every node in this layer is an adaptive node with a node output defined as

$O_{1,i} = \mu_A(x)$ for i=1,2 …(2)

$O_{1,i} = \mu_{Bi-2}(y)$ for i=3,4 …(3)

where x (or y) is the input to the node; and A_i (or B_{i-2}) is fuzzy set associated with this node.

Layer 2: Every node in this layer is a fixed node labeled **Π,** which multiplies the incoming signals and outputs the product. For instance

$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y)$, i=1,2 …(4)

Each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is a fixed node labeled N. The ith node calculates the ratio of ith rule's firing strength to the sum of all rules' firing strengths.

$O_{3,i} = W_i = \dfrac{w_i}{w_1 + w_2}$, i=1,2 …(5)

Layer 4: Every node in this layer is an adaptive node with a node function

$O_{4,i} = W_i f_i = W_i (p_ix + q_iy + r_i)$ …(6)

Where W_i is output of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set.

Layer 5: The single node in this layer is fixed node labeled ∑, which computes the overall output as the summation of the incoming signals

$O_{5.1}$ = overall output = $\sum_i \mathbf{W}if_i = \dfrac{\sum_i wif_i}{\sum w_i}$ …(7)

Thus, an ANFIS network is functionally equivalent to a Sugeno fuzzy model. This network can easily be extended to a Sugeno fuzzy model with multiple inputs and rules.

The output f of a ANFIS network shown in Figure 1 can be written as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$

$$= W_1f_1 + W_2f_2$$

$$= (W_1x)p_1 + (W_1y)q_1 + (W_1)\, r_1 + (W_2x)p_2 + (W_2y)q_2 + (W_2)r_2 \quad …(8)$$

where p_1, q_1, r_1, $p_{1,}$ q_2 and r_2 are the parameters of the model. From Equation (8), it is observed that the output is linear in the parameters p_1, q_1, r_1, $p_{2,}$ q_2 and r_2, which are known as consequent parameters.

The nodes in layer 1 are adaptive nodes with a node function given by Equation (2). The output, $O_{1,i}$ of node i in this layer is the membership grade of a fuzzy set A (=A_1, A_2 , B_1 or B_2) and it specifies the degree to which the given input x (or y) satisfies the quantifier A. The membership function for A can be any appropriate parameterized membership function. If generalized bell function is used, the membership function is given by

$$\mu_{Ai}=(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}} \qquad \ldots(9)$$

where $\{a_i , b_i , c_i \}$ is the parameter set. These parameters are referred as premise parameters. The output of the network f is obviously non-linear in premise parameters. Thus the set of total parameters S can be partitioned into two subsets: a set of premise (non linear) parameters S_1 and a set of consequent (linear) parameters S_2.

2.3 LEARNING ALGORITHM

Jang (1993) proposed a hybrid learning algorithm for training ANFIS. The learning takes place in two stages. In the forward pass of the hybrid learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent, similar to back propagation algorithm. The hybrid approach is much faster in training the network than the strict gradient descent or back propagation algorithm.

Jang et al (1997) have shown that ANFIS has unlimited approximation power for matching any non linear function arbitrarily well, provided the number of rules is not restricted. Thus ANFIS can be considered as a universal approximator. This property of ANFIS is very useful in modeling highly non linear systems. ANFIS can also be used in control systems. Jang (1993) and Jang et al (1997) presented four examples to demonstrate the applicability of ANFIS. In the first two examples, ANFIS is used to model two non linear functions and the results are compared with those achieved by neural networks and fuzzy modelling. In the third example, ANFIS is used for on-line identification of a nonlinear component in a discrete control system. In the last example, a chaotic time series is predicted using ANFIS, and its superiority over standard statistical and neural network methods is demonstrated. All these examples demonstrate the capabilities of ANFIS.

3. STUDY AREA

The study area is situated in the eastern part of India, in a region with varied landscapes and hydrological regimes. The streamflow into the Hirakud reservoir, which is a multipurpose project built across river Mahanadi at latitude 21° - 32′ N, longitude 63° - 52′ E about 15 km upstream of Sambalpur town of Orissa State, is considered. This project provides flood protection to 9500 km^2 of Mahanadi delta in Cuttack and Puri districts. The Hirakud catchment receives 75 to 90% of total rainfall during south-west monsoon starting from the third week of June to the end of October. The maximum precipitation is usually observed in the month of July, August and first half of September.

There are more than 200 rain gauge stations in Mahanadi basin which are maintained by different agencies including Indian Meteorological Department. Rainfall observations are twice in a day. There are 34 gauge stations available over the basin. Normally gauges are observed every 3 hourly. In high flood periods hourly gauges are observed.

Flow data at different stream-gauging stations and rainfall data at raingauge stations located in the Mahanadi catchment upstream of Hirakud dam are collected from Hirakud Dam Circle, Upper Mahanadi Basin, Burla, Water Planning Organisation, Department of Water Resources, Government of Orissa, Bhubaneswar and Central Water Commission, Bhubaneswar. The database is divided into two periods: monsoon and non-monsoon. The reservoir operation during monsoon is complicated due to conflicting objectives like flood control, irrigation, power generation and conservation at the end of the period. The non-monsoon operation is relatively simple. Hence, only monsoon period is considered in this study, which starts on 21st June and continues up to 31st October.

Before starting the training, the collected data are standardized so that the transformed values lie between 0 and 1. The standardization of the data is done as per the following formula.

$$(x_i)_{std} = \left[0.1 + \frac{(x_i)_{act}}{1.2(x_{\max})}\right] \qquad \ldots(10)$$

where $x_i \in X(x_i)$ is the i-th standardized value of the variable x, $(x_i)_{act}$ is the actual i-th value, and $x_{\max}$ is the maximum value of the variable x over the available data length, and $(x_i)_{std}$ is the standardized value of the data.

4. MODEL IDENTIFICATION

The physical system of the basin that takes the rainfall as an input and produces the runoff at the basin outlet as the output, is highly non-linear, complicated and very difficult to fully comprehend. The system is influenced by large number of factors and variables. The ANFIS can learn and generalize highly non-linear and uncertain phenomena due to the embedded neural network, which is efficient in learning and generalization. Further the fuzzy system mimics the cognitive capability of human brain. Hence together, they can learn the complicated processes involved in the basin and correlate the discharge to the corresponding precipitation.

Ten-daily precipitation over the whole upstream catchment and ten-daily inflow into the Hirakud reservoir during the monsoon season for the years 1981 to 1999 are collected to implement the ANFIS model. Correlation analysis is performed to identify the input variables to model the ANFIS network. The variables used in model identification and the corresponding notations used to represent them in the representative equation are shown in Table 1.

Table 1. Notations for variables of ANFIS models

Sl.No.	Variable	Notation used
1.	Flow at previous period Q(t-1) (one lag)	ql1
2.	Flow over two lags Q(t-2)	ql2
3.	Flow in the previous year in the time period t, $Q(t)_{y-1}$	qpy
4.	Flow with one lag, one year ago, $Q(t-1)_{y-1}$	qlpy
5	The time period (at which forecast is needed)	time
6.	The rainfall in the previous period R(t-1) (one lag)	rl1
7.	The rainfall over two lags R(t-2)	rl2
8.	The rainfall in the same period one year ago, $R(t)_{y-1}$	rpy
9.	The rainfall with one lag, one year ago, $R(t-1)_{y-1}$	rlpy

The ANFIS model adopted for the investigation depends upon the number of input variables. The variables are attached with two qualifications, i.e. low and high. So the number of membership functions attached to each variable is two in number. Generalized bell function, as defined earlier is adopted as the type of membership function.

In the Table 1, q stands for discharge, r for rainfall, l for lag, y for year and py for previous year. The correlation analysis showed that the variables ql1, rl1, rl2, qlpy and rlpy are influential on outflow in a decreasing order of significance. However, the combination of different inputs may yield a better correlation, though individually, the influence may be less. Hence, various combinations of inputs are taken. Table 2 shows the various combinations of inputs considered in the present study. For the first set, the form of the equation is,

$$Q = f(ql1, ql2, qpy, rpy) \tag{11}$$

The networks are first trained for 150 epochs. Then the network performing best among the lot is chosen for further analysis. The performance criteria, as discussed earlier are considered for comparing the networks. Once the satisfactory performance level is achieved, the network parameters are saved.

5. RESULTS AND DISCUSSIONS

For ease in comparison of performance of the models, each one is trained for 150 epochs. The total data is partitioned into two sets, one set for training the network and the other for testing the network. The training set consists of 207 pairs of input output observations, while the testing set consists of 26 data pairs. The ANFIS model is trained using the training data set, while the performance of the trained model is tested with testing set. The ANFIS network parameters and performance measures such as Root Mean Square Error (RMSE), Correlation Coefficient (CORR) and coefficient of efficiency R^2 are computed for training and testing phases of the model. Table 4 shows the performance of the different models studied. The network that performs best is chosen as the final model for prediction of ten daily flow. As seen from Table 4, the model number 22, which considers q11, r11, r12 and qpy as inputs gave the best performance and hence is chosen as the final model. The coefficient of efficiency in training and testing for this model are 0.8891 and 0.9649 respectively. The minimum *RMSE* achieved at 680th epoch are 0.0542 and 0.0238759 for training and testing phases respectively. This model has 55 nodes and 104 parameters, out of which 80 are linear and 24 are non-linear.

The time series plot of the observed and modeled flows for training set is shown in Figure 2, while that of the testing set is shown in Figure 3. These two graphs show that the ten-daily forecasting model is efficient in predicting the high and medium flows with reasonable accuracy. The forecast of low flows is associated with less efficiency.

Table 2. Input variables for ANFIS models

Model No.	Input variables	Model No.	Input variables
1	ql1, ql2, qpy, rpy	14	ql1, rl1, time
2.	ql1, ql2, qpy, time	15	ql1, time, rl1, rpy
3	ql1, ql2, rl1, rl2	16	ql1, ql2, rl1, time
4	ql1, qpy, rl1, rl2	17	ql1, rl1, rl2, time
5	ql1, qpy, rl1, time	18	rl1, rl2, time
6	ql1, ql2, rl1, rpy	19	ql1, rl1,qlpy, rlpy
7	ql1, rl1, rl2, rpy	20	ql1, qlpy, rl1
8	ql1, ql2, qpy, rpy	21	ql1, rl1, rlpy
9	ql1, ql2, rl1, rpy, time	22	ql1, rl1, rl2, qpy
10	ql1, rl1, rpy, time	23	ql1, rl1, rl2, rlpy
11	ql1, rl1, rpy		
12	ql1, ql2, rpy, time		
13	ql1, rl1		

6. CONCLUSIONS

The results of the study indicate that the ANFIS model developed in this study for forecasting ten daily flow into Hirakud reservoir performed well. The model is able to forecast the ten daily flow reasonably well as indicated by the high R^2 value in both training as well as testing and also the low RMSE values. It is observed from Figs. 2, and 3 that the model is able to forecast peak flows more effectively than the low flows. The results of this study show that ANFIS is suitable for modeling streamflow series.

Table 4. Comparision of the performance of difference ANFIS models

Model No.	Inputs	Epochs	RMSE		CORR		R^2(Efficiency)	
			trn	tst	trn	tst	trn	tst
1	4	150	0.058	0.094	0.878	0.37	0.771	0.137
2	4	150	0.051	0.178	0.910	0.090	0.828	0.008
3	4	150	0.052	0.078	0.91	0.433	0.828	0.187
4	4	150	0.055	0.074	0.895	0.524	0.801	0.275
5	4	150	0.050	0.182	0.910	0.140	0.828	0.020
6	4	150	0.054	0.108	0.900	0.314	0.810	0.099
7	4	150	0.055	0.135	0.890	0.124	0.792	0.0154
8	3	150	0.071	0.077	0.814	0.471	0.663	0.222
9	4	150	0.050	0.088	0.908	0.506	0.824	0.256
10	4	150	0.050	0.140	0.910	0.129	0.828	0.017
11	3	150	0.040	0.100	0.932	0.223	0.869	0.050
12	4	150	0.050	0.142	0.912	0.130	0.832	0.017
13	2	150	0.085	0.084	0.720	0.420	0.518	0.176
14	3	150	0.067	0.095	0.834	0.496	0.695	0.246
15	4	150	0.050	0.142	0.910	0.130	0.828	0.017
16	4	150	0.049	0.150	0.915	0.190	0.837	0.036
17	4	150	0.051	0.088	0.907	0.506	0.824	0.256
18	3	150	0.068	0.072	0.833	0.609	0.694	0.371
19	4	150	0.060	0.100	0.865	0.254	0.748	0.065
20	3	150	0.073	0.099	0.800	0.330	0.640	0.109
21	3	150	0.073	0.099	0.700	0.360	0.490	0.130
22	4	150	0.054	0.028	0.889	0.964	0.791	0.931
23	4	150	0.050	0.100	0.900	0.153	0.797	0.255

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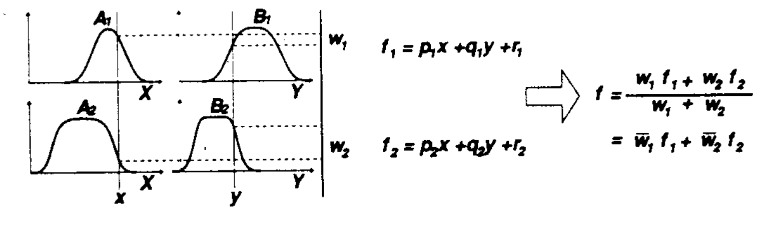
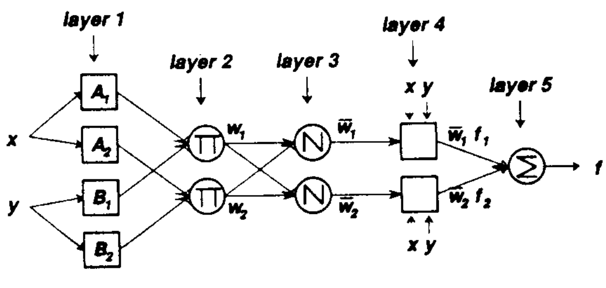


(a)



(b)

Fig. 1 (a) Sugeno type fuzzy inference system with two inputs and two membership functions
(b) Architecture of the corresponding ANFIS model

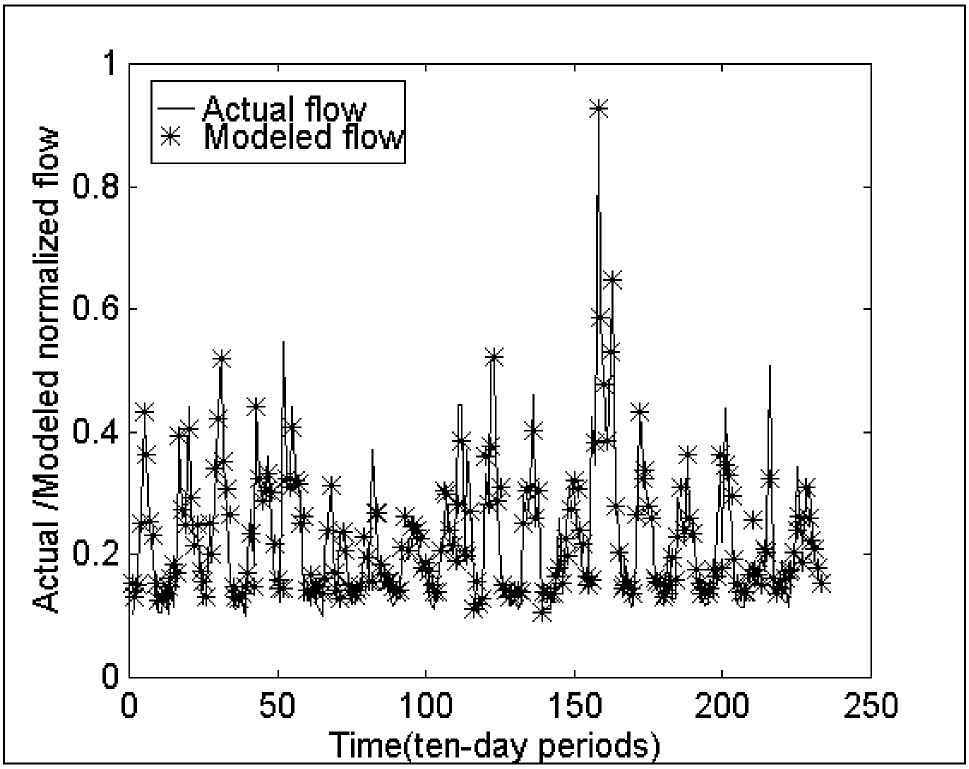


Fig. 2 Time series plot of actual and modeled 10-daily flows (training)

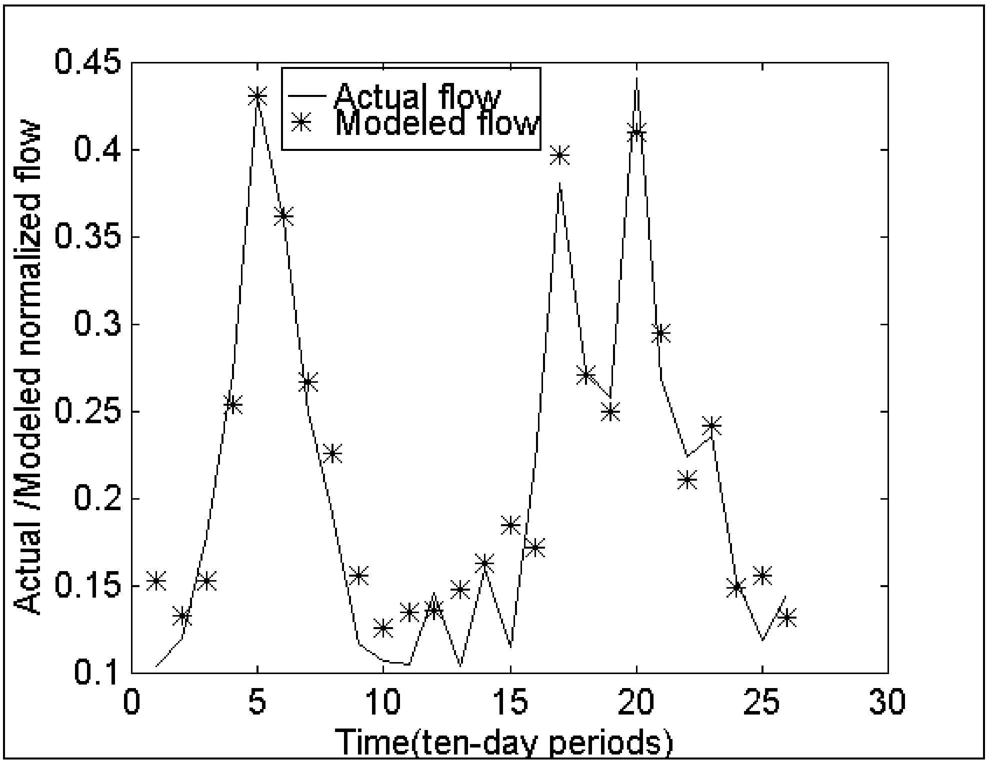


Fig. 3 Time series plot of actual/ modeled 10-daily flows (testing)