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ANFIS MODEL FOR BARAK RIVER SYSTEM

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ABSTRACT
In a flood affected region quick and accurate flood forecasting is essential to save life and property of inhabitants by issuing prior warning. Model for flood forecasting has been developed using Adaptive network based fuzzy inference system (ANFIS) for multiple inflows in a river network. Fuzzy logic toolbox of Matlab is the software used for this purpose. The root mean square error (RMSE) is used to evaluate the adequacy of the model. Concurrent hourly discharge data from 3 input and 1 output stations of Barak river network were collected and used to develop Sugeno model for flood forecasting at a downstream location. The forecasting model developed was used to predict flood discharge at the downstream point using flood flows measured at 3 upstream statons. The result obtained is compared with the observed discharge and model performances were evaluated using statistical measures, co-efficient of efficiency and difference in peak time and peak discharge. Performance measures evaluated indicate satisfactory model performance. Results obtained shows that predicted discharge at the outflow station and time to peak for two flood events used in the study match closely with the observed values.

KEYWORDS- *Flood, Forecasting,Model,Fuzzy,Matlab,Performance.Predicted.*

1. INTRODUCTION

Flood is an unsteady flow in a river reach where inflow, outflow, and reach storage change continuously with time. The storage in the river reach comes back to its initial state at the end of the flood. Flood is devastating. The impact of flood could be reduced but couldn't be eliminated totally.

2. OBJECTIVES

Different flood control measures are adopted to reduce the impact of flood. These are, Structural and Non-structural flood control measure.

Structural measure require huge fund and involves construction of reservoirs, diversions, levees' or marginal bund and channel improvement. It may also cause environmental degradation and ecological change on-structural measures involve prediction of flood, so that habitants could get sufficient time to save their life and property. It also involves modification of damage susceptibility of the socio-economic system and environment to flood. Flood forecasting method reduces the damage caused by flood. Forecasting is done in advance and issues warning to the habitants likely to be affected by flood. This method is important and relatively inexpensive. The correct and advanced flood warning is essential for evacuation of life and property of people of flood affected region.

Based on system analysis, the flood forecasting models in a channel is of two major types, Conceptually based model and Empirical model.

In conceptually based model, flood propagation process is usually described by Saint Venant equation comprising partial differential equation of continuity and momentum. These equations are not responsive to analytical solution. It requires a large number of data (e.g. characteristic of terrain and river network, rainfall and runoff) for calibration. In many occasions, these datas may not be available or it may be expensive and time consuming to collect data.

Empirical models are based on evidence of relationships maintained in historical records of input and output without analyzing the internal structure of the physical process.

Objective of the present study - It is observed from study that ANFIS model for single inflow –single outflow problem has been studied, but so far there is no attempt in modelling multiple inflow problems using ANFIS.

The objective of the present study is to develop a flood forecasting model using ANFIS that can be used to predict downstream flow using multiple inflows in a river network.

3. METHODOLOGY

Adaptive Neuro Fuzzy Inference System (ANFIS)

Jang (1993) introduced architecture and learning procedure for the FIS that uses a neural network learning algorithm for constructing a set of fuzzy if-then rules with appropriate Membership functions from the specified input–output pairs. This procedure of developing a FIS using the framework of adaptive neural network is called adaptive neuro-fuzzy inference system.

The basic structure of ANFIS is a model that maps input characteristics to input membership functions, input membership functions to rules, rules to a set of output characteristics, output characteristics to output membership functions and output membership function to a single valued output or a decision associated with the output.

There are two methods that ANFIS learning employs for updating MF parameters (1) Back propagation for all parameters and (2) Hybrid method consisting of back propagation for the parameters associated with the input MF and least square estimation for the parameter associated with the output MF. As a result training error decreases, at least locally throughout the learning process. Therefore, the more the initial MF resembling the optimal ones, the easier it will be for the model parameter training to converge. Human expertise about the target system to be modeled may aid in setting up these initial MF parameters in FIS structure.

Fuzzy rule base models **-** Fuzzy rule base models are of two types (1) Additive rule model and (2) Non- additive rule model. Additive rule model is of two types (a) Sugeno model and (b) Kosoko's model. Non-additive rule model is Mamdani model.

Sugeno model

Sugeno or Takagi-sugeno-Kang model is simple and the no. of rule is less. The main feature of this model is that the output MF is either linear or constant. ANFIS is a graphical network representation of Sugeno type fuzzy model.
A typical Sugeno model has the form,

Output=**Z=ax+by+c**, where, Input 1=x and Input 2=y.

For a zero order Sugeno model, the output level Z is a constant (a=b=0).

For the first order Sugeno fuzzy model a typical rule set with two fuzzy If-then rule can be expressed as,

Rule 1. If x is A_1 and y is B_1, then, f1= $p_1x+ q_1y+r_1$.

Rule 2. If x is A_2 and y is B_2, then, $f_2= p_2x+q_2y+r_2$.

Where, A_1, A_2 and B_1, B_2 are Input parameters for input x and y respectively. p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters of the output function. The functioning of the ANFIS is described as,

<u>Layer 1.</u> Every node in this layer produces MF grades of an input parameter. The node O_1 is explained by,

$O_{1,i}= \mu_{Ai}(x)$ for, i= 1, 2 $O_{1,i}=\mu_{Bi}(y)$ for, i= 1,2.

Where x (or y) is the input to the node I, A_i (or , B_i) is a linguistic fuzzy set associated with the node O_{1i}, is the membership function grade of a fuzzy set and it specifies the degree to which the given input x (or y) satisfies the quantities.
MFs can be any functions that are Gaussian, Generalized bell shaped, Triangular, Trapezoidal shaped function.
A generalized bell shaped function can be selected within this membership function and described as,

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

Where (a_i, b_i, c_i) are the parameter set which changes the shape of membership degree with maximum value equal to 1 and minimum 0.

Layer 2. Every node in this layer is a fixed node labeled π, whose output is the product of all incoming signals.
$O_{2i}= w_i= \mu_{Ai}(x).\ \mu_{Bi}(y)$, for,i=1,2 -------------

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Layer 3. The ith node of this layer labeled N, calculates the normalized firing strength as,

$O_{3i} = \overline{w_i} = \frac{w_i}{w_1+w_2}$ Where, i=1, 2, 3 ----------

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

$O_{4i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i)$
Where,$\overline{w_i}$ *is the output of layer* 3 *and* $\{p_{i,} q_{i,} r_i\}$ *is theparameter set of this node.*

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

$$Overall\ output = O_{5i} = \sum \overline{w_i}\, f_i = \frac{\sum w_i f_i}{\sum w_i}$$

Evaluation criteria for model performance:-

The performance of the model resulting from training, testing and validation is evaluated by RMSE (Root mean square error) and Nash-Sutcliffe co-efficient of efficiency using the following formulas,

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}\left[Q_i^o - Q_i^p\right]^2}{n}}$$

$$\text{C.E=Nash-Sutcliffe co-efficient of efficiency, } = 1 - \frac{\sum_{i=1}^{n}\left[Q_i^o - Q_i^p\right]^2}{\sum_{i=1}^{n}\left[Q_i^o - \bar{Q}_i^o\right]^2}$$

Where, Q_i^o =Measured discharge or, Discharge obtained from data.
Q_i^p = Predicted discharge.
$\bar{Q}_i^o = \frac{\sum Q_i^o}{\text{No. of data pairs}}$ =Mean value of measured discharge.
n= Total no. of data pairs considered.

RMSE furnishes a quantitative indication of the model error in units of the variable with the characteristics that larger error receives greater attention than smaller ones. The quantitative evaluation of model performance is made in terms of co-efficient of efficiency between the measured and simulated data.

Discharge and time difference of two major peaks are also obtained.

4. GEOGRAPHICAL AREA

The Multiple inflow Barak river is considered here for analysis. The river Barak originates from the state of Nagaland (India) and traverses through Manipur, Mizoram and Assam in India before entering into neighbouring country Bangladesh. The catchment of the river system is approximately 26,139 Sq. Km. in India through its main channel.

For the present study, datas from four gauging stations has been collected. Three stations, namely, Fulertol, Tulargram and Matijuri are considered as input stations and Badarpurghat as output station. The approximate distances of the stations from Badarpurghat are, Fulertol 90 Km., Tulargram 50 Km. and Matijuri 15 Km.

5. DATA MINING

Concurrent hourly recorded river stage data pairs from all the four stations of the flood events during 2002 and 2003 have been collected from Central water commission.

A total number of 6775 stage data have been collected and converted to discharge data by regression analysis .
Out of these data, 4000 data have been used for the purpose of training, checking and testing.

6. DIVISION OF DATA

In this study the data are divided into three sets, training, checking and testing as per Sahin as follows,Out of 4000 data 75% (3000) data are kept for training, 25% (1000) data used for checking. The training data are further divided into 2/3 (2000) for training set and 1/3 (1000) for the testing set.

7. Results - Fuzzy logic toolbox of MATLAB is the software used for modeling. In general a higher no. of categories will provide higher accuracy, but with the disadvantage of longer rule base as well as more computation time. For example, with 5 fuzzy

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categories for each of the 3 variables, would involve a set of 5^3=125 rules, which is too much to allow pattern to be easily discerned. The parameters from premises and consequences are increased significantly and the computation time is rather long , while the performance might only be improved slightly. A testing set is adopted in order to overcome overfitting. By trial and error method appropriate no. of variables categories are selected. The no. of parameters increases remarkably from 2 to 5 categories, while the training time increases significantly from 10 to 25 secs. Although more subspaces for the anfis model will generally results in better performance. Cautious treatment has been made to avoid overfitting. When both the computation time and RMSE testing are considered, an optimal no. of categories of 3 (Low, Medium and High) is adopted with their fuzzy membership function as shown in figure.

By trial and error method different parameters are selected as follows,

1. FIS is generated using the default Grid partitioning method.
2. Optimization method considered here is Hybrid.
3. Error tolerance is considered as zero.
4. No. of Input membership function(MF) ,Type of Input membership function and Type of Output membership functions are selected from a chart as shown below,

No. of input MF	Type of input MF	Type of output MF	Epochs	RMSE			Difference of RMSE between	
				Training	Checking	Testing	Training & Checking	Training & Testing
3 3 3	Triangular	Constant	3	205.82	229.45	232.05	**23.63**	**26.23**
4 4 4	Triangular	Constant	3	166.9	396.95	477.29	203.05	310.39
5 5 5	Triangular	Constant	3	153.56	698.47	324.17	544.91	170.61
6 6 6	Triangular	Constant	3	139.2	787.25	398.5	648.05	259.3
No. of Input MF selected is 3 3 3,for input MF type, consider the following,								
3 3 3	Trapezoidal	Constant	3	335.17	410.49	497.19	75.32	162.02
3 3 3	Gbell	Constant	3	191.98	182.97	370.64	9.01	178.66
3 3 3	Gauss	Constant	3	185.41	222.27	382.31	36.86	196.9
3 3 3	Gauss2	Constant	3	311.4	354.0	414.42	42.6	103.02
3 3 3	Pi	Constant	3	409.53	464.89	492.78	55.36	83.25
3 3 3	Dsig	Constant	3	222.16	203.36	279.68	18.8	57.52
3 3 3	Psig	Constant	3	222.08	210.2	281.86	11.88	59.78
Triangular MF selected, corresponding to minimum error. For Output MF,consider the following,								
3 3 3	Triangular	Linear	3	165.76	27595.2	361.95	27233.2	196.19
Constant type Output MF selected. For no. of epochs, the following parameters has been selected for trial,								
3 3 3	Triangular	Constant	4	205.82	229.45	232.05	23.63	26.23
3 3 3	Triangular	Constant	6	205.82	229.45	232.06	23.63	26.24
3 3 3	Triangular	Constant	20	205.82	229.47	232.09	23.65	26.27

From the table above, corresponding to minimum difference between the errors the following parameters are selected,

1. No. of Input MF =3.
2. Type of Input MF , Triangular.
3. Type of Output MF , Constant.
4. Epochs =3.

Model has been developed using all the above parameters. The root mean square error for training, checking and testing are found out respectively as, 205.82, 229.45 and 232.05. Crisp output is obtained by defuzzification method using 4000 input data.

Nash-Sutcliffe co-eff. of efficiency=0.96.

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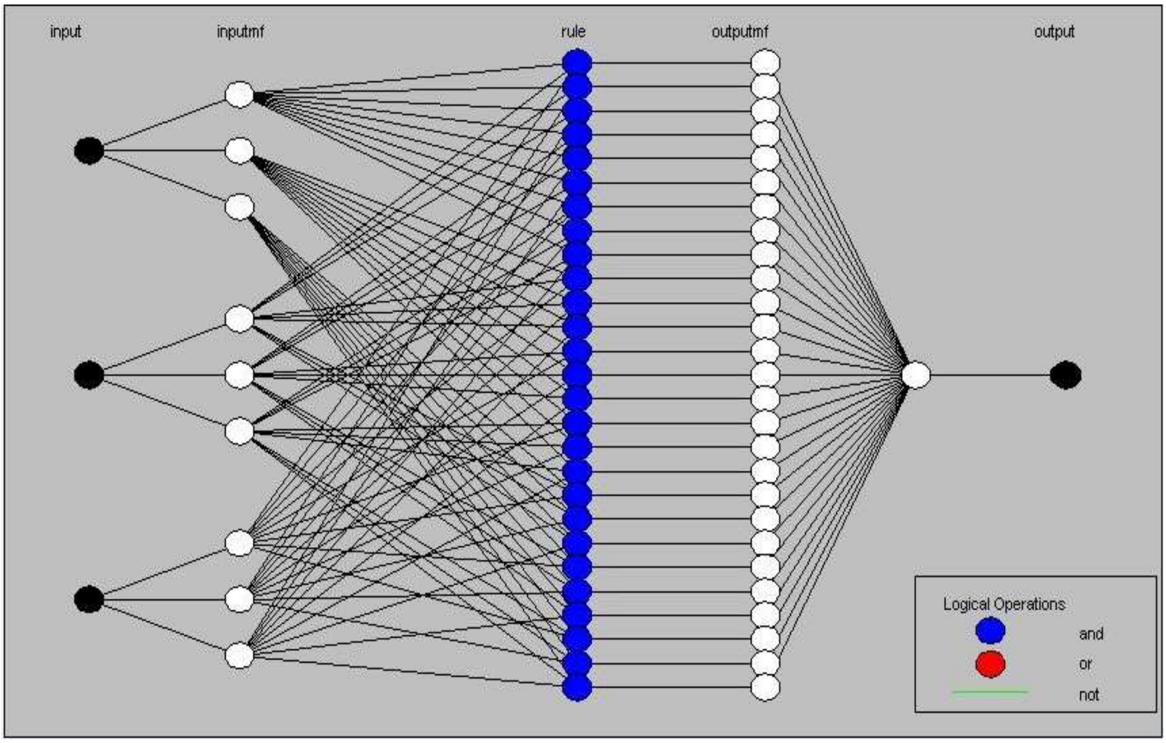
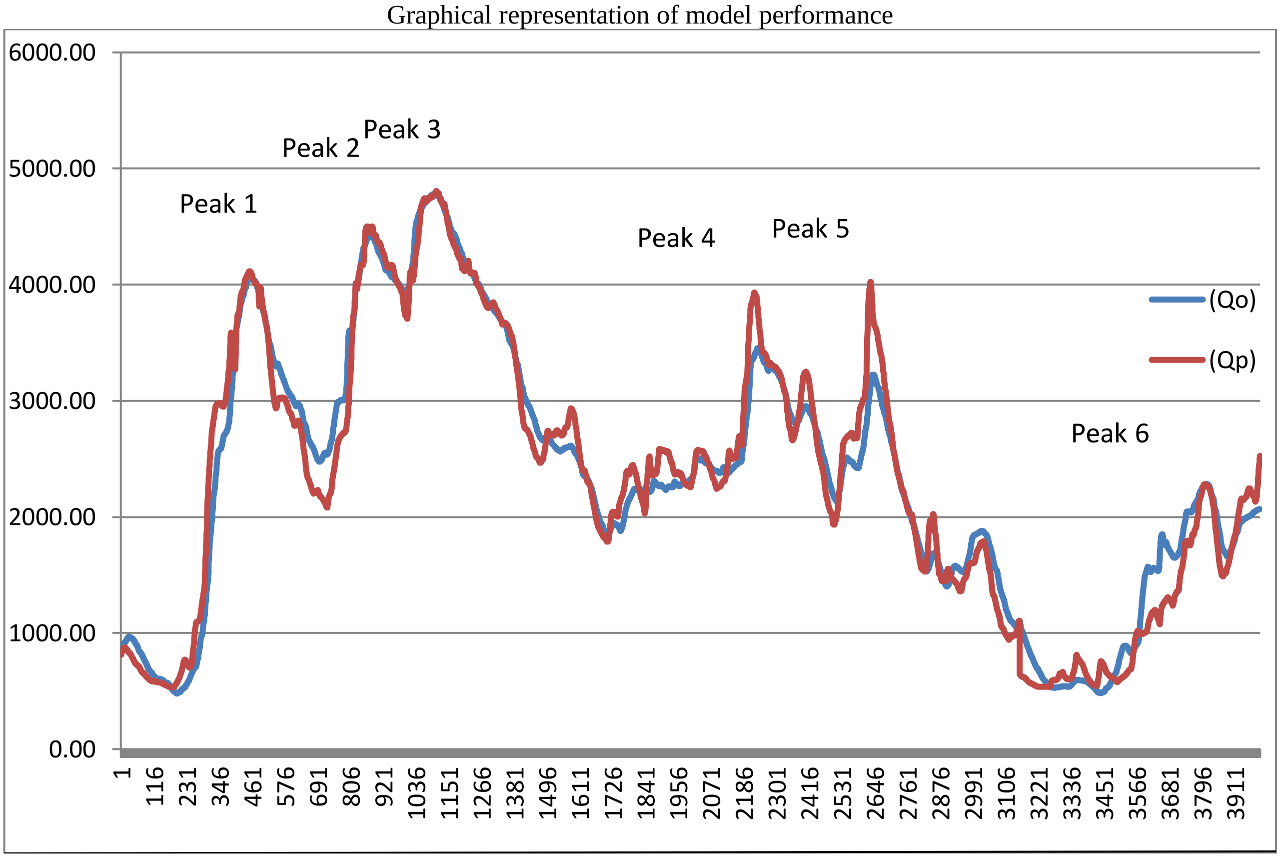


Configuration of the ANFIS model

Graphical representation of model performance



Q_o = Observed output discharge. Q_P = Predicted output discharge.

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Determination of Discharge difference and Difference of time between 6 peak discharges:-From the graph the Discharge difference and Time lag between the Observed and Predicted discharge is found out as shown in chart below,

No. of peak	1	2	3	4	5	6
Discharge difference ($Q_0 \sim Q_p$)(m^3/sec.)	22	14	62	95	121	38
Difference of time ($T_o \sim T_p$) (Hours.).	1	3	2	6	5	2

8. SUGGESTION

In the present study ANFIS model has been developed for multiple inflow, single outflow problem. The forecasting model can be used to predict common downstream flow using multiple upstream flows. Flow prediction with different forecast lead time can be obtained using the model. The result obtained show that the predicted output discharge matches the observed discharge closely.

9. CONCLUSION

ANFIS has been found to be very useful tool for flood discharge prediction of multiple inflow, single outflow river system.

10.REFERENCES

1. *Stmatios. V. Karlalopulos "Understanding Neural Network and Fuzzy logic".*
2. *Timothy J. Ross "Fuzzy logic with Engineering application"*
3. *S. Rajasekharan and Vijayalakshmi Pai, "Neural nrtworks, Fuzzy logic and Genetic algorithm".*
4. *Thirumalaiah. K and Deo M.C. "Hydrological forecasting using neural networks".*
5. *Chau K.W. and Lee J.H.W. "A micro-computer model for flood prediction with applications".*
6. *Jang J.S.R "ANFIS".*
7. *Takagi . T ,and Sugeno. M "Fuzzy identification of systems and its applications to modeling and control".*
8. *Tilmant A , Vanclooster. M, Duckslein .L. and Persoons. E "Comparison of fuzzy and Non-fuzzy optimal reservoir operating policies."*
9. *Zedah L and Kacprzyk J.eds "Fuzzy logic for the management of uncertainty "*
10. *Subramaniya .K.(1997) "Engineering Hydrology".*
11. *Kalyanmoy Deb, a text book on "Optimization for engineering design."*
12. *M.Ganesh "Fuzzy sets and Fuzzy Logic."*