RESEARCH ARTICLE OPEN ACCESS

Adaptive Neuro-Fuzzy Inference System For Rainfall-Runoff Modeling

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ABSTRACT
In this study an Adaptive Neuro-Fuzzy Inference System (ANFIS) was used for rainfall-runoff modeling for the Dharoi sub-basin, India. Different combinations of rainfall were considered as the inputs to the model, and runoff was considered as the output. Input space partitioning for model structure identification was done by grid partitioning. A hybrid learning algorithm consisting of back-propagation and least-squares estimation was used to train the model for runoff estimation. The optimal learning parameters were determined by trial and error using Triangular membership function. Root mean square error (RMSE) and correlation coefficient (r) were used for selecting the best performing model.

Keywords – Adaptive Neuro Fuzzy Inference System (ANFIS) modeling, Dharoi sub-basin, Rainfall-Runoff

I. INTRODUCTION

The hydrologic behavior of rainfall-runoff process is very complicated phenomenon which is controlled by large number of climatic and physiographic factors that vary with both the time and space. The relationship between rainfall and resulting runoff is quite complex and is influenced by factors relating the topography and climate. In recent years, artificial neural network (ANN), fuzzy logic, genetic algorithm and chaos theory have been widely applied in the sphere of hydrology and water resource. ANN have been recently accepted as an efficient alternative tool for modeling of complex hydrologic systems and widely used for prediction. Some specific applications of ANN to hydrology include modeling rainfall-runoff process. Fuzzy logic method was first developed to explain the human thinking and decision system by [1]. Several studies have been carried out using fuzzy logic in hydrology and water resources planning [2]. Adaptive neuro-fuzzy inference system (ANFIS) which is integration of neural networks and fuzzy logic has the potential to capture the benefits of both these fields in a single framework. ANFIS utilizes linguistic information from the fuzzy logic as well learning capability of an ANN. Adaptive neuro fuzzy inference system (ANFIS) is a fuzzy mapping algorithm that is based on Tagaki-Sugeno-Kang (TSK) fuzzy inference system [3] and [4]. ANFIS used for many applications such as, database management, system Design and planning/forecasting of the water resources [5].

II. NEURO-FUZZY MODEL

Neuro-fuzzy modeling refers to the way of applying various learning techniques developed in the neural network literature to fuzzy modeling or to a fuzzy inference system (FIS). The basic structure of a FIS consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database which defines the membership functions (MF) used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules to derive an output (see Fig. 1). FIS implements a nonlinear mapping from its input space to the output space. This mapping is accomplished by a number of fuzzy if-then rules, each of which describes the local behavior of the mapping. The parameters of the if-then rules (referred to as antecedents or premises in fuzzy modeling) define a fuzzy region of the input space, and the output parameters (also consequents in fuzzy modeling) specify the corresponding output. Hence, the efficiency of the FIS depends on the estimated parameters. However, the selection of the shape of the fuzzy set (described by the antecedents) corresponding to an input is not guided by any procedure [6]. But the ule structure of a FIS makes it possible to incorporate human expertise about the system being modeled directly into the modeling process to decide on the relevant inputs, number of

MFs for each input, etc. and the corresponding numerical data for parametestimation.

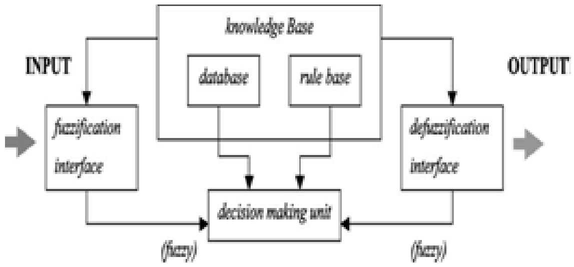

Fig. 1 Fuzzy Inference System with crisp

In the present study, the concept of the adaptive Network, which is a generalization of the common backpropagation neural network, is employed to tackle the parameter identification problem in a FIS.

An adaptive network is a multi layered feed forward structure whose overall output behavior is determined by the value of a collection of modifiable parameters. More specifically, the configuration of an adaptive network is composed of a set of nodes connected through directional links, where each node is a process unit that performs a static node function on its incoming signal to generate a single node output. The node function is a parameterized function with modifiable parameters. It may be noted that links in an adaptive network only indicate the flow direction of signals between nodes and no weights are associated with these links. Readers are referred to [7] for more details on adaptive networks. [8] introduced a novel 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 MFs from the stipulated input–output pairs. This procedure of developing a FIS using the framework of adaptive neural networks is called an adaptive neuro fuzzy inference system (ANFIS).

1.1. ANFIS architecture

The general structure of the ANFIS is presented in Fig. 2. Selection of the FIS is the major concern when designing an ANFIS to model a specific target system. Various types of FIS are reported in

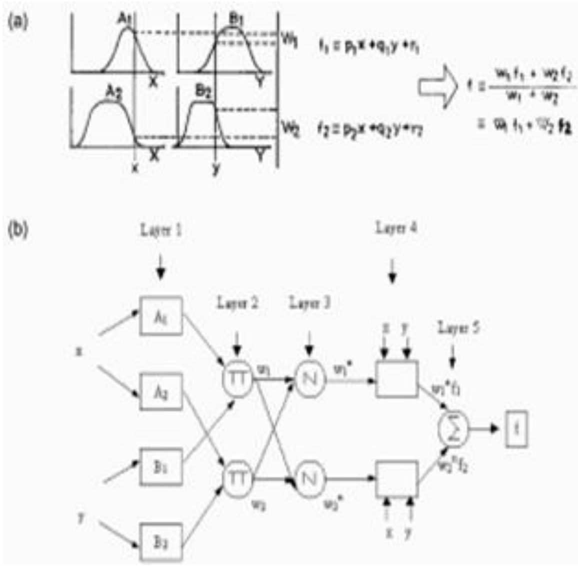

Fig. 2 (a) Fuzzy Inference System (b) Equivalent ANFIS

the literature and each are characterized by their consequent parameters only. The current study uses the Sugeno fuzzy model since the consequent part of this FIS is a linear equation and the parameters can be estimated by a simple least squares error method.

For instance, consider that the FIS has two inputs x and y and one output z: For the 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

$$=p_1x + q_1y + r \tag{1}$$

Rule 2: If x is A_2 and y is B_2; then f_2

$$= p_2x + q_2y + r \tag{2}$$

Where A_1, A_2 and B_1, B_2 are the MFs for inputs x and y; respectively; p1; q1; r1 and p2; q2; r2 are the parameters of the output function. Fig. 2(a) illustrates the fuzzy reasoning mechanism for this Sugeno model to derive an output function (f) from a given input vector [x, y].

The corresponding equivalent ANFIS architecture is presented in Fig. 2(b), where nodes of the same layer have similar functions. The functioning of the ANFIS is as follows:

Layer 1: Each node in this layer generates membership grades of an input variable. The node output OP_i^1 is defined by:

$$OP_i^1 = \mu_{Ai}(x) \text{ for } i = 1, 2 \text{ or} \tag{3}$$

$$OP_i^1 = \mu_{Bi-2}(y) \text{ for } i = 3, 4 \tag{4}$$

where x (or y) is the input to the node; Ai (or B_{i-2}) is a fuzzy set associated with this node, characterized by the shape of the MFs in this node and can be any appropriate functions that are continuous and piecewise differentiable such as Gaussian, generalized bell shaped, trapezoidal shaped and triangular shaped functions. Assuming a generalized bell function as the MF, the output OP_i^1 can be computed as,

$$OP_i^1 = \pi_{Ai} = \frac{1}{1+(\frac{x-c_i}{a_i})^{2bi}} \quad (5)$$

Where $\{ai; bi; ci\}$ is the parameter set that changes the shapes of the MF with maximum equal to 1 and minimum equal to 0.

Layer 2: Every node in this layer multiplies the incoming signals, denoted as $\prod$, and the output OP_i^2 that represents the firing strength of a rule is computes as,

$$OP_I^2 = w_i = \mu_{Ai}(x)\ \mu_{Bi}(y), \quad i = 1, 2. \quad (6)$$

Layer 3: The *i*th node of this layer, labeled as *N*, computes the normalized firing strengths as,

$$OP_i^3 = \overline{w}_i = \frac{wi}{w1+w2}, \ i = 1, 2 \quad (7)$$

Layer 4: Node *i* in this layer compute the contribution of the *i*th rule towards the model output, with the following node functions:

$$OP_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \quad (8)$$

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

Layer 5: The single node in this layer computes the overall output of the ANFIS as:

$$OP_i^5 = \text{Overall output} = \sum_i \overline{w}_i f_i = \frac{\sum_i Wifi}{\sum_i Wi} \quad (9)$$

III. STUDY AREA AND DATA

Area selected for the present study is the Dharoi sub basin which is the part of Sabarmati river basin. Study area is the Dharoi sub basin which is designated by line in Sabarmati river basin map. The area covering upper sub-basin and the catchment of the main river up to Dharoi dam is designated as Dharoi sub-basin. Constructed in 1978, the Dharoi dam is located about 165 km upstream Ahmadabad in village Dharoi of Mehsana district. This covers drainage area of the main river up to Dharoi dam.

In this study, long term monthly Rainfall and Runoff data are derived for Dharoi sub basin which is the part of Sabarmati river basin. Catchment area of the sub basin is 5,540 sq.km, out of which about 2,640 sq.km lies in Gujarat state.

The area covering upper sub-basin and the catchment of the main river up to Dharoi Dam is designated as Dharoi sub-basin. The Dharoi dam is constructed in 1978 and is located about 165 kms upstream Ahmedabad in village Dharoi of Mehsana district.

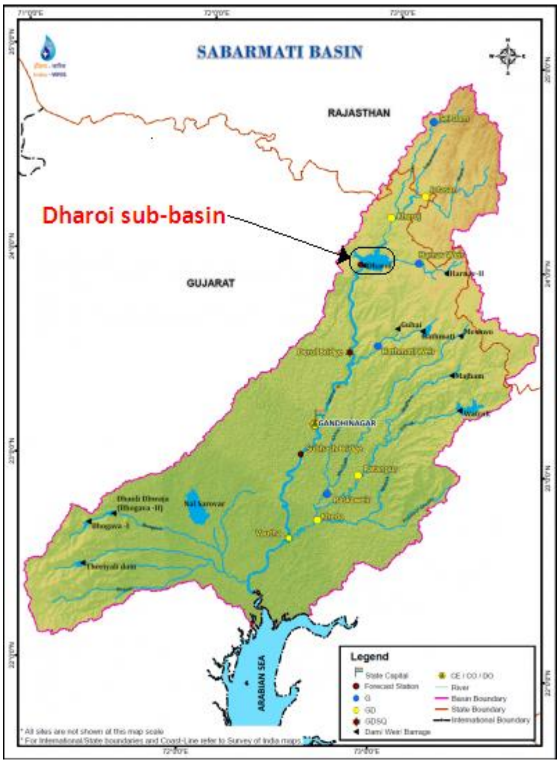

Fig. 3 Dharoi sub-basin in Sabarmati Basin

In Dharoi sub basin there are six Rain gauge stations existed but among them Hadad Rain gauge station's data is selected for the year 1968 to 2010 (42 years). Rainfall data are considered from June to October for each year so total 217 monthly data sets are used.

IV. MODEL DEVELOPMENT AND TESTING

There are no fixed rules for developing an ANFIS, even though a general framework can be followed based on previous successful applications in engineering. The selection of proper input and output data posses the prime importance and needs to be selected carefully. Here the Rainfall-Runoff model was developed using the Rainfall data as input and Runoff data as output.

Here, in the current study, Rainfall-Runoff datasets were firstly divided in the different ratio of training and testing data i.e. 80-20%, 70-30% and 60-40% that means the 80% datasets were used for training the model and remaining 20% dataset were taken for its validation purpose. The runoff model was developed for each of the three rain gauge station namely Hadad, Khedbrhama and Dharoi in, Dharoi sub-basin. The best model for the each of the three stations has been selected by means of model evaluation parameters.

The results obtained for all three stations then evaluated by means of the model evaluation parameters selected for the current study given below:

Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q(i) - \widehat{Q}\ (i))^2}{n}}$$

Correlation coefficient:

$$r = \frac{\sum_{i=1}^{n}(Q\ (i) - \bar{Q})(\hat{Q}(i) - \tilde{Q})}{\sqrt{\sum_{i=1}^{n}(Q\ (i) - \bar{Q})^2 \sum_{i=1}^{n}(\hat{Q}(i) - \tilde{Q})^2}}$$

Where $\widehat{Q}$ (i) is the n estimated runoff value, Q(i) is the n observes runoff value, $\overline{Q}$ is the mean of the observed runoff values, and $\tilde{Q}$ is the mean of the estimated runoff values.

V. RESULTS AND DISCUSSION

The models were developed using 7 numbers of membership functions of type *triangular* with 7 If-then rules for all different sets of training and testing dataset for each rain gauge station in ANFIS.

After obtaining the results the best model for the stations was selected and highlighted by means of the evaluation parameters that are *RMSE* and r values given in table-1.

Table-1: ANFIS results for different stations

Hadad				
Ratio %	**Training**		**Testing**	
	RMSE	**r**	**RMSE**	**r**
80-20	1.249	0.999	0.853	0.999
70-30	1.319	0.999	0.808	0.999
60-40	1.395	0.999	0.845	0.999
Khedbrhama				
Ratio %	**Training**		**Testing**	
	RMSE	**r**	**RMSE**	**r**
80-20	1.365	0.999	0.841	0.999
70-30	1.367	0.999	1.015	0.999
60-40	1.457	0.999	0.988	0.999
Dharoi				
Ratio %	**Training**		**Testing**	
	RMSE	**r**	**RMSE**	**r**
80-20	1.259	0.999	1.023	0.999
70-30	1.659	0.999	1.123	0.999
60-40	1.367	0.999	1.110	0.999

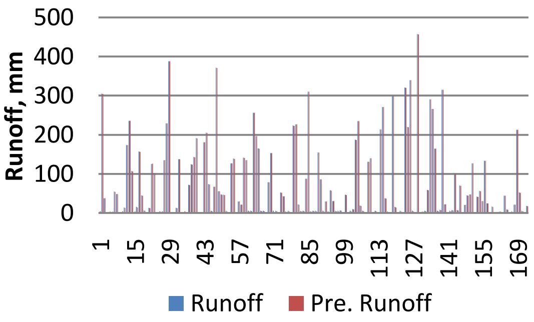

Fig. 4 Comparison of observed runoff vs predicted runoff for the station hadad training

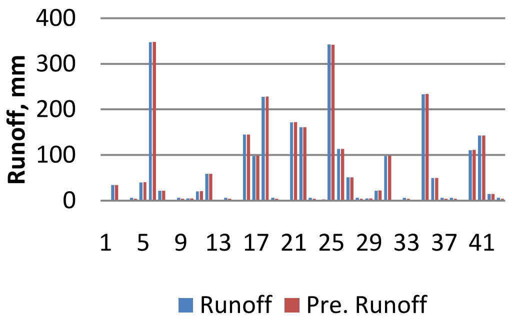

Fig. 5 Comparison of observed runoff vs predicted runoff for the station hadad testing

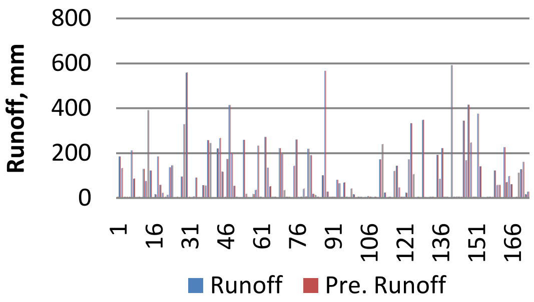

Fig. 6 Comparison of observed runoff vs. predicted runoff for the station khedbrhama training

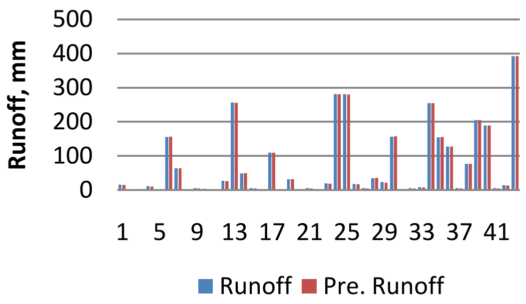

Fig. 7 Comparison of observed runoff vs. predicted runoff for the station khedbrhama testing

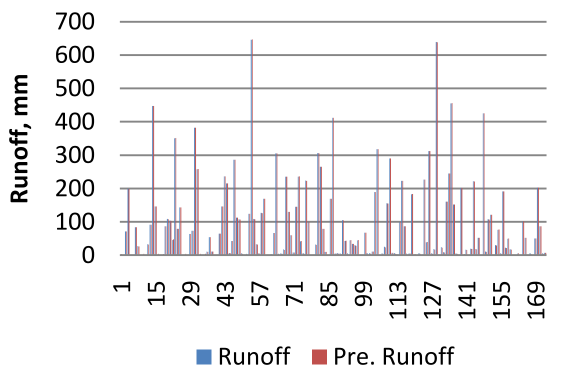

Fig. 8 Comparison of observed runoff vs. predicted runoff for the station dharoi training

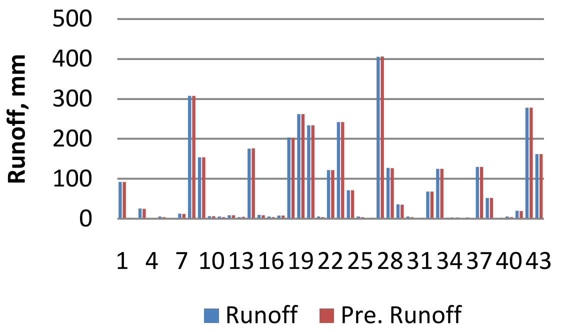

Fig. 9 Comparison of observed runoff vs. predicted runoff for the station dharoi testing

Here, the results shows (table-1) that the ratio for training and testing data of 60-40% and 70-30% gives the better results for the RMSE and r values but when looking to the ratio of 80-20%, it gives the best results for the current study and gives the best model of Rainfall-Runoff for all the three rain gauge stations namely Hadad, Khedbrhama and Dharoi. Also the estimated runoff values shows the very little variation as compared to the observed runoff values.

Also, the comparison of the observed runoff vs. predicted runoff was shown for all the stations namely hadad (fig. 4 & 5), khedbrhama (fig. 6 & 7) and dharoi (fig. 8 & 9).

VI. SUMMARY AND COCLUSION

Here, one can conclude that the Rainfall-Runoff model for the Hadad, Khedbrhama and Dharoi rain gauge stations is 7 triangular type membership functions with the input and output training and testing ratio of 80-20% which gives the *RMSE* and *r* values as 1.249, 0.999 training and 0.853, 0.999 testing for Hadad rain gauge station, 1.365, 0.999 training and 0.841, 0.999 testing for Khedbrhama rain gauge station and 1.259, 0.999 training and 1.023, 0.999 testing for Dharoi rain gauge station.

Also the ratio of 60-40% and 70-30% training and testing gives the reasonably much accurate results and one can use these models in absence of the best model for the prediction of runoff in Dharoi sub-basin for the future prediction of runoff.

Summary states that the ANFIS tool provides the betterment of the Rainfall-Runoff modeling in comparison of the other tools as ANN, Fuzzy logic etc. And one can used this tool for such hydrological modeling say rainfall-runoff, rainfall prediction, evapotranspiration etc. for the future prediction.

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