

Case Study

<https://doi.org/10.20546/ijcmas.2019.804.241>

Adaptive Neuro Fuzzy Inference System for Runoff Modelling– A Case Study

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ABSTRACT

Keywords

Triangular,
Trapezoidal,
Generalized bell
membership
function, ANFIS,
watershed, Basin

Article Info

Accepted:
15 March 2019
Available Online:
10 April 2019

Runoff simulation models were developed to predict runoff for basin of West Godavari district, Andhra Pradesh by utilizing adaptive neuro-fuzzy inference system (ANFIS). Combinations of variables like previous three day stage, previous two day stage, previous one day stage, previous three day run off, previous two day run off, previous one day runoff as input and present day runoff as output were explored. The performance of different ANFIS based models during training and testing periods were evaluated through correlation coefficient (r), coefficient of efficiency (CE) and root mean square error (RMSE). Results of different combination of input per membership function (MFs) were compared and it was depicted that ANFIS model with three MFs per input is having reasonable accuracy for triangular membership function with the values of r (0.991), CE (99.1%) and RMSE (529.93 m^3/s). ANFIS model with three MFs per input performed best among trapezoidal member function applied with r , CE and RMS E values 0.993, 99.0% and 468.40 m^3/s , respectively. ANFIS model with generalized bell membership function and one MF per input was selected as the best performing model with r (0.947), CE (96.8%) and RMSE (1265.56 m^3/s). Trapezoidal, 3 is the best simulation model among all ANFIS model.

Introduction

There are many things which are gifted by nature plays fundamental role for living beings. In which soil and water are the most important natural resource in the nature that must be conserved and maintained carefully for sustainable development of society. Scarcity of water, increasing rate of degraded land and increasing rate of population is putting pressure for judicious use of available land and water resources. Runoff and

sedimentation are the most important factors to accelerate above mentioned problems. Forecasting of runoff and sediment is desired for better planning and utilization of land and water resources in various fields such as water supply, flood control, soil and water conservation, irrigation, drainage, water quality etc (Lohani *et al.*, 2014).

Runoff estimation also plays a crucial role to transport sediment particle from one place to another place. There are many formulas and

models to estimate runoff rate, most discharge records are derived from converting the measured water levels (stages) to discharges by a functional relationship called as a rating curve. In the past years, machine learning approaches have been efficiently used for modeling nonlinear hydrologic systems.

Particularly, artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS) and support vector machine (SVM) have been recognized as effective tools for modeling difficult hydrologic systems (Kisi *et al.*, 2009; Chang, *et al.*, 2014; Akrami *et al.*, 2014; Kaltech, 2015; Gholami *et al.*, 2016; Singh *et al.*, 2016). Monfared (2016) adopted artificial nerve network technique (ANN) and phasic nerve (ANFIS) to simulate the suspended sediment for Shapour river, and found that both ANN and ANFIS are useful for predicting runoff and other useful parameters. Kisi, (2016) proposed a fuzzy c-means adaptive neuro-fuzzy embedded clustering (ANFIS-FCM) technique to predict suspended sediment concentration and model compared with artificial neural network (ANN).

ANFIS utilizes linguistic information from the fuzzy logic as well as 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 (Jang *et al.*, 1995; Loukas, 2001). Pahlavani *et al.*, (2017) estimated the flood hydrographs by an adaptive neuro-fuzzy inference system (ANFIS). Keeping in view the above facts, the present study has been undertaken with following objectives (a) Development of ANFIS based runoff simulation model using triangular, trapezoidal and generalized bell as membership function (b) Validation of developed models for training and testing period. (c) Performance evaluation of the selected model by statistical indices.

Materials and Methods

Study area and data acquisition

The present study was conducted for the basin of West Godavari district sharing the border with Khammam District to the west, East Godavari District to the East, Krishna District to the South. West Godavari District covers an area of 7742 Km². It has 7-10m elevation range over the district with beaches and belongs to Andhra Pradesh. The daily stage level and runoff for four months (1st June to 30th September) for the period from 1996 to 2010 of West Godavari sites were collected from Krishna and Godavari Basin Organization, Divisional Office of Central Water Commission, Hyderabad (Andhra Pradesh). The collected data, grouped into two sections (from 1996 to 2007 for training purpose and from 2008 to 2010 for the testing purpose), was explored in MATLAB software.

Adaptive neuro-fuzzy inference system (ANFIS)

Black box mapping algorithm like adaptive network based neuro-fuzzy inference system (ANFIS) utilizes fuzzy mapping algorithm based on Tagaki-Sugeno-Kang (TSK) fuzzy inference system (Loukas, 2001 and Jang *et al.*, 1997). Adaptive neuro-fuzzy inference system, integrated the benefits of the both neural networks (i.e. optimization capability, learning capability) and fuzzy logic (i.e. IF-THEN rule base for ease of incorporating expert knowledge) makes it possible to utilize the benefits of both ANN and fuzzy logic in the single framework. ANFIS utilizes linguistic information from the fuzzy logic and learning capability of an ANN for automatic fuzzy if-then rule base generation and parameter optimization. ANFIS consists of five components: input (s), a fuzzy system generator, a fuzzy inference system (FIS), an

adaptive neural network and an output. The Sugeno- type fuzzy inference system (Takagi and Sugeno, 1985) combining an adaptive neural network and FIS was used in this study for stage-runoff simulation.

ANFIS architecture

The ANFIS is a fuzzy sugeno model put in the framework of adaptive systems to facilitate learning and adaptation (Jang, 1993). A first-order sugeno model, a common rule set with two fuzzy if-then rules is as follows;

Rule 1: If x_1 is A_1 and x_2 is B_1 , then $f_1 = a_1 x_1 + b_1 x_2 + c_1$.

Rule 2: If x_1 is A_2 and x_2 is B_2 , then $f_2 = a_2 x_1 + b_2 x_2 + c_2$.

where, x_1 and x_2 are the crisp inputs to the node and A_1, B_1, A_2, B_2 are fuzzy sets, a_i, b_i and c_i ($i = 1, 2$) are the first-order polynomial linear function coefficients. It is possible to assign different weight to each rule base on the structure of the system.

Where, weights w_1 and w_2 are assigned to rules 1 and 2, respectively. Weighted average is calculated as,

$$f = \text{weighted average} = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \dots (1)$$

The ANFIS consists of five layers (Jang, 1993). The five layers of model are as follows;

Layer 1

Each node output in this layer is fuzzified by membership grades of a fuzzy set corresponding to each input. Fuzzification means using the membership to compute each term's degree of validity at a specific point of

the process. The membership function for this fuzzy set can be triangular, trapezoidal, generalized bell and gaussian membership functions. $O_{j,i}$ is the output of the i^{th} node in layer j .

$$O_{1,i} = \mu_{A_i}(x_1) \quad i = 1, 2 \quad \dots (2) \text{ or}$$

$$O_{1,i} = \mu_{B_{i-2}}(x_2) \quad i = 3, 4 \quad \dots (3)$$

where, x_1 and x_2 is the input to node i ($i = 1, 2$ for x_1 and $i = 3, 4$ for x_2) and A_i (or B_{i-2}) is a fuzzy label. The membership functions for A and B can be any membership functions parameterized appropriately; for instance:

$$\mu_A(x_1) = \frac{1}{1 + \left[\left(\frac{x_1 - c_i}{a_i} \right)^2 \right]^{b_i}} \quad (4)$$

where $\{a_i, b_i, c_i\}$ are the parameters on which bell shaped function depends, thus exhibiting various forms of membership functions on linguistic label A_i . Parameters in this layer are referred to as foundation parameters.

The outputs of this layer are the membership values of the premise part. In present study triangular shaped, generalized bell shaped and trapezoidal type membership functions were used.

Layer 2

In this layer, the AND/OR operator is applied to get one output that represents the firing strength of a rule, which performs fuzzy, AND operation. Each node in this layer, labeled TT is a stable node which multiplies incoming signals and sends the product out.

$$O_{2,i} = W_i = \mu_{A_i}(x_1) \mu_{B_i}(x_2) \quad i = 1, 2 \quad \dots (5)$$

Layer 3

Each node in this layer is a fixed node labeled N. The i^{th} node calculates the ratio of the i^{th}

rule's firing strength to the sum of all rules' firing strength.

$$O_{3,i} = \bar{W}_i = \frac{W_i}{\sum_{k=1}^n W_{k_i}} \quad i = 1, 2 \dots (6)$$

Layer 4

Each node output in this layer is the normalized value of each fuzzy rule. The nodes in this layer are adaptive. Here \bar{W}_i is the output of layer 3, and $\{a_i, b_i, c_i\}$ is the parameter set. Parameters of this layer are referred to as consequence or output parameters and can be expressed as,

$$O_{4,i} = \bar{W}_i f_i = \bar{W}_i (a_i x_1 + b_i x_2 + c_i) \quad i = 1, 2 \dots (7)$$

Layer 5

The single node in this layer is the overall output of the system, which is the summation of all coming signals.

$$Y = \sum_1^2 \bar{W}_i f_i = \frac{\sum_1^2 W_i f_i}{\sum_1^2 W_i} \quad \dots (8)$$

In this way the input vector was fed through the network layer by layer.

The two major phases for applying the ANFIS for applications are the structure identification phase and the parameter identification phase. The structure identification phase involves finding an appropriate number of fuzzy rules and fuzzy sets and a proper partition feature space. The parameter identification phase involves the adjustment of the suitable and consequence parameters of the system.

Formulation of training and testing data

Stage and runoff represented by H_{ij} and Q_{ij} of i^{th} year and j^{th} day, respectively. For training and testing of the ANFIS, the required daily

stage time series H_{ij} for $i = 1$ to M year index and for $j = 1$ to N day index was available, where M is the total number of years and N is the total number of days in the monsoon season in the data set of i^{th} year. Similarly the required daily runoff time series Q_{ij} , $i = 1$ to M and $j = 1$ to N , was also available. It was observed that, $N = 122$ days (i.e., 1st June to 30th September) in a year and $M = 15$ years (1996-2010) for the 0 into two sets: a set of training data for model development, and a set of testing data for validation (testing) of developed model.

Performance evaluation

Correlation coefficient

The correlation coefficient was determined using following equation,

$$CC = \frac{\sum_{j=1}^n \{(Y_j - \bar{Y})(Y_{ej} - \bar{Y}_{ej})\}}{\sum_{j=1}^n (Y_j - \bar{Y})^2 \sum_{j=1}^n (Y_{ej} - \bar{Y}_{ej})^2} \times 100 \quad (9)$$

Which, Y_j is the desired values, \bar{Y} is the mean of desired values, Y_{ej} is the observed values, n is the number of observations and \bar{Y}_{ej} is the mean of observed values

The correlation coefficient measures the statistical correlation between the observed and predicted values. The value of correlation coefficient closer to one means better model.

Root mean square error (RMSE)

Root mean square error is the most commonly used for assessment of numeric prediction. The root mean square error has been calculated with the help of following equation,

$$RMSE = \sqrt{(1/n) (\sum_{i=1}^n (Y_{ej} - Y_j)^2)} \quad \dots (10)$$

The value of root mean square error closer to zero indicates better fit and increased values indicate higher disagreement between predicted and observed values (Wilks, 1995).

Coefficient of efficiency (CE)

The coefficient of efficiency is computed using equation as reported by Luchetta *et al.*, (2003). The value ranges from $-\infty$ to 1.

$$CE = \left[1 - \frac{\sum_{i=1}^n (Y_{ej} - Y_j)^2}{\sum_{i=1}^n (Y_{ej} - \bar{Y}_{ej})^2} \right] \times 100\% \quad \dots (11)$$

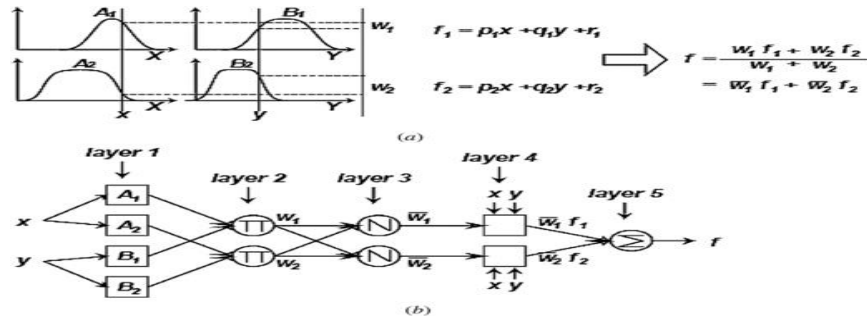
Results and Discussion

This section of study represented the findings of the ANFIS based runoff simulation models. ANFIS based runoff models were developed using input space partitioning for the model structure identification which was done by grid partition method and hybrid learning algorithm to train the models. Triangular, Trapezoidal, Generalized Bell and with one, two, three and four membership functions per input were used for training of the models. Models were iterated for various combinations of epochs (50, 100, 200) for all three membership functions to reach the best performing model.

Table.1 Performances of different ANFIS runoff simulation

Model Architecture	Testing		
	RMSE (m ³ /sec)	r	CE (%)
Triangular, 1	2641.52	0.87	86.4
Triangular, 2	1230.65	0.954	97.2
Triangular, 3	529.93	0.991	99.1
Triangular, 4	1965.59	0.946	96.2
Trapezoidal, 1	1934.10	0.926	93.8
Trapezoidal, 2	1092.80	0.984	99.2
Trapezoidal, 3	468.40	0.993	99.0
Trapezoidal, 4	625.56	0.988	99.5
Generalized bell, 1	1265.56	0.947	96.8
Generalized bell, 2	5249.26	0.765	83.3
Generalized bell, 3	6269.13	0.685	76.3
Generalized bell, 4	4812.32	0.826	89.7

Fig.1 ANFIS architecture



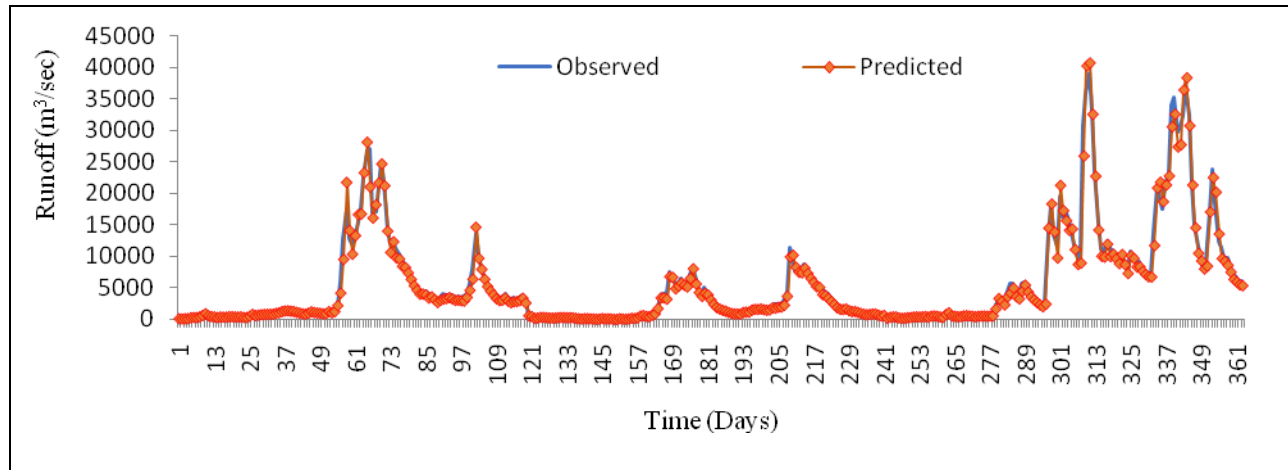


Fig. 2 Line diagram of ANFIS (Trapezoidal-3) model for runoff simulation for testing period

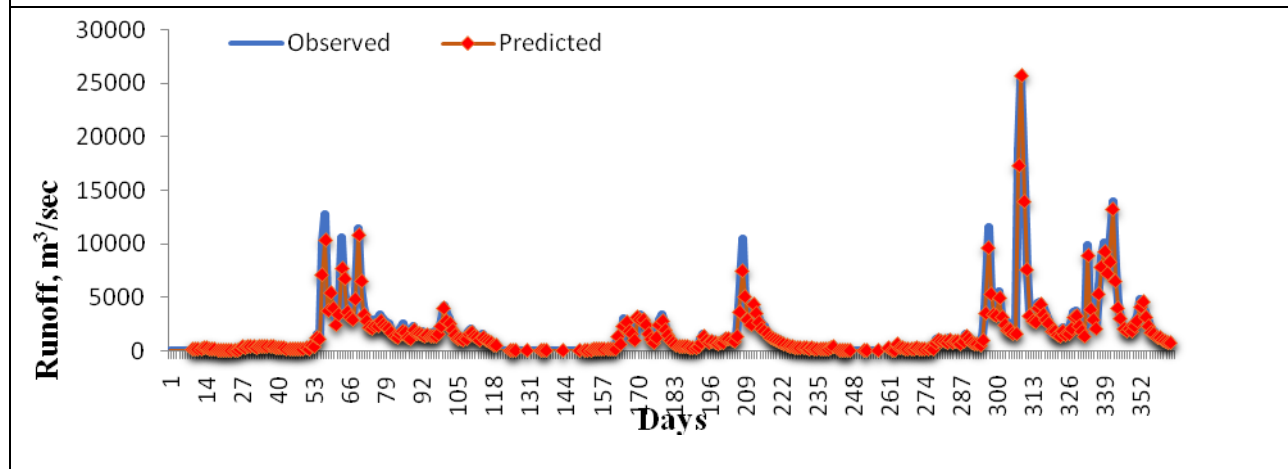


Fig. 3 Line diagram of ANFIS (Traingular, 3) model for runoff simulation for testing period

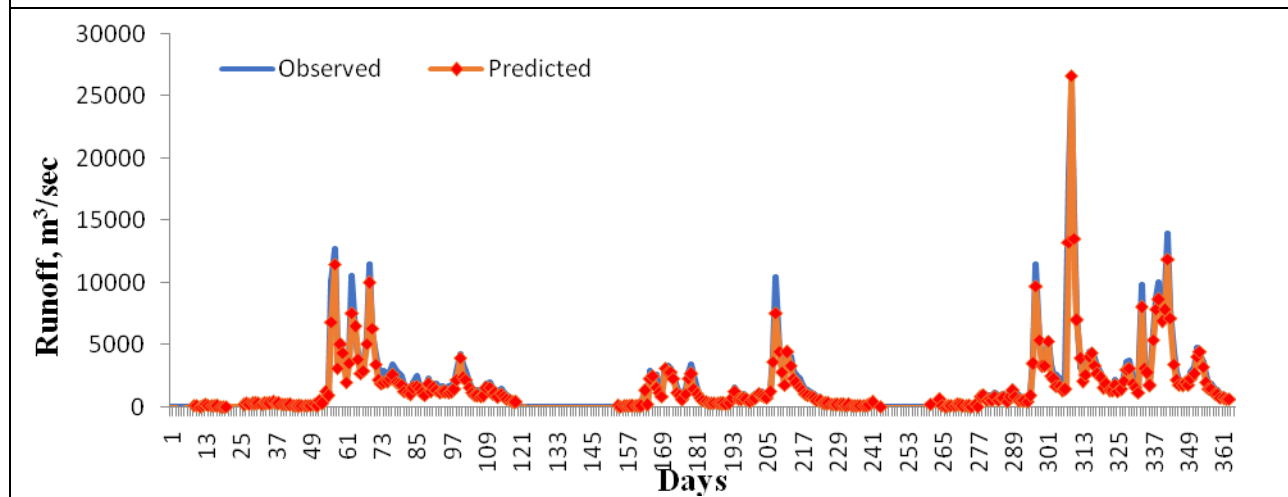


Fig.4 Line diagram of ANFIS (Generalized bell, 1) model for runoff simulation for testing period

ANFIS model using Triangular membership function with three MFs per input has given the best goodness of fit when model was iterated for the 200 epochs and the desired value obtain by the model is very close to the observed runoff with the values of statistical indices i.e. r (0.991), CE (99.1%) and RMSE (529.93 m³/s) as presented in Table 1. In the case of trapezoidal member function with three MFs per input performed better than other trapezoidal member function based ANFIS model and r , CE and RMSE values are 0.993, 99.0% and 468.40 m³/s, respectively. Generalized bell membership function based ANFIS model with one MF per input produced the result with good accuracy with the values of r , CE and RMSE, 0.947, 96.8 and 1265.56 m³/s. Trapezoidal, 3 is the best simulation model among all ANFIS model. Bisht *et al.*, (2011) established the stage-discharge relation for Dhawalaishwaram Barrage site at Rajahmundry in Andhra Pradesh, India and showed the values of r and RMSE was 0.93 and 49056.98 m³/s respectively. The performance of runoff simulation model was better than the study by Bisht *et al.*, (2011), due to hydrological, geological and geometrical dissimilarity.

The performance of the models was also evaluated by graphical representation using the line diagram. ANFIS model with triangular and generalized bell activation function showed some fluctuation in estimated values as depicted in Figure 2, 3 and 4. It can be easily noticed from line diagram the ANFIS (trapezoidal, 3) model has the very close relation between observed and predicted values as shown in Figure 1.

It is concluded in the present study that the relationship of stage with runoff was developed for West Godavari district. Correlation coefficient (r), coefficient of efficiency (CE) and root mean square error

(RMSE) are reasonable good estimator for performance evaluation of different ANFIS based models during training and testing periods for the runoff simulation. It was revealed that by increasing the MFs per input, it is not necessary to get more accurate model. Performance of Trapezoidal ANFIS based model with three MFs per input is better than all other membership functions followed by triangular with three MFs per input and Generalized bell with one MFs per input. Trapezoidal, 3 may be used for ANFIS simulation model for runoff.

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How to cite this article:

Ashish Kumar and Tripathi, V.K. 2019. Adaptive Neuro Fuzzy Inference System for Runoff Modelling– A Case Study. *Int.J.Curr.Microbiol.App.Sci*. 8(04): 2054-2061. doi: <https://doi.org/10.20546/ijcmas.2019.804.241>