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Discharge Modelling using Adaptive Neuro - Fuzzy Inference System

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Abstract

In this paper river stage discharge models using Adaptive Neuro- Fuzzy Inference System (ANFIS) and Linear Multiple Regression (MLR) methods have been developed. This paper also investigates the best model to forecast river discharge. From the literature it is clear that ANN models and Fuzzy logic models are quite applicable on river stage discharge modelling. Hence this present study carried out for hybrid ANFIS models. Ten ANFIS models were developed out of which best five ANFIS models are selected.

The developed models were trained, tested & validated on the data of Godavari river at Rajahmundry, Dhawalaishwaram Barrage site in Andhra Pradesh. Comparing observed data and the estimated data through developed ANFIS models, it has been proved that the developed ANFIS models predicted better results the traditional models, like MLR.

Key Words: *Adaptive Neuro- Fuzzy Inference System, Artificial Neural Network, fuzzy logic, training, testing, learning, Stage-Discharge.*

1. Introduction

Model based flood forecasting and warning systems are a cost effective means of reducing the damaging impacts of floods. By enabling early identification of flooding and timely protection or evacuation of potentially inundated area, it is possible to minimize the damages caused by flooding [20].

A large number of hydrological analyses require mapping and modeling of non-linear systems data. Traditionally such mapping is performed with the help of conceptual models or statistical tools such as regression and curve fitting. However, when the underlying physical laws are unknown or not precisely known, it is rather difficult to model the phenomenon adequately. Attempts have been made to develop a technique that does not require algorithm or rule development and thus reduces the complexity of the software. One such technique is known as neurocomputing, and the networks laid out with many parallel processing elements to do this neurocomputing are called artificial neural networks. Flood forecasting is vital for reducing the damage and loss of life caused by river flooding; flood warning-evacuation systems are the most realistic way to cope with large floods [27].

The present study was taken up in developing ANFIS models for the river discharge using the past river stage and discharge as inputs for specified lag time. ANN is the most widely accepted machine learning method and is widely used in various areas of water-related research such as rainfall-runoff modelling [7], [28] prediction of discharge [23]. Three layered feed forward ANNs have been shown to be a powerful tool for input-output mapping and have been widely used in water resources engineering problems [2].

ANNs were found to be very efficient in modelling stage-discharge relationship [3], [25]. Jain [26] used the ANN approach to establish an integrated stage-discharge-sediment concentration relation for two sites on the Mississipi River and showed that the ANN results were much closer to the observed values than the conventional technique. Nagy et al. [13] applied ANN technique to estimate the natural sediment discharge in rivers in terms of sediment concentration and addressed the importance of choosing an appropriate neural network structure and providing field data to that network for training purpose. ANN model perform better than the physically-based models for simulating sediment loads from different slopes and different rainfall intensities [11]. ANN approach gives better results compared to several commonly used formulas of sediment discharge [12], [19], [6], [10]. ANN and fuzzy models were found to be considerably better than conventional rating curve method [1]. Kisi [18] Rai and Mathur [22] investigated good application efficiency of ANNs in the sediment yield modeling and when compared with the conventional modeling techniques. Khadangi et al. [8] compared ANFIS with RBF models in daily stream flow forecasting and found that ANFIS give better results than RBF. The present study is aimed at developing a stage-discharge prediction model using ANFIS technique. The developed models were trained, tested and validated for the river system at Dhawalaishwaram barrage site (Rajahmundry) in Andhra Pradesh. In the study following objectives taken under consideration.

i. Development of river stage-discharge ANFIS models.

ii. Validation of the formulated models.

iii. Performance evaluation of the formulated models for the Godavari river system.

iv. Comparison of ANFIS and MLR models.

2. Adaptive - Neuro Fuzzy Inference System (ANFIS)

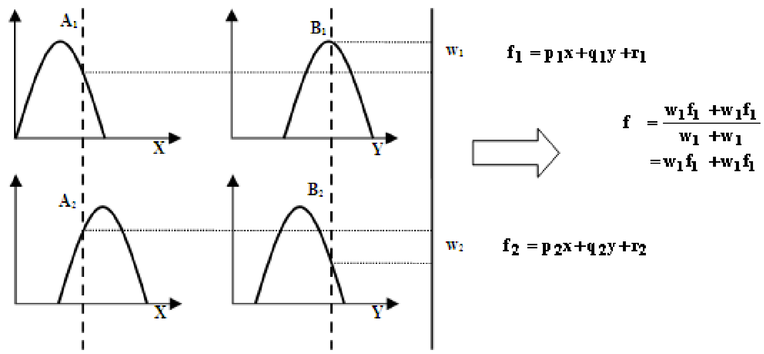
Neuro-fuzzy modeling is an approach where the fusion of neural networks and fuzzy logic find their strengths. These two techniques complement each other. The neuro-fuzzy approaches employ heuristic learning strategies derived from the domain of neural networks theory to support the development of a fuzzy system [4]. It is possible to completely map neural networks knowledge to fuzzy logic [9]. A marriage between neural networks and fuzzy logic techniques should help overcome the short comings of both techniques discussed at length by [15]. Neuro-fuzzy techniques can learn a system’s behavior from a sufficiently large data set and automatically generate fuzzy rules and fuzzy sets to a pre-specified accuracy level. Also, they are capable of generalization, thus overcoming the key disadvantages of the fuzzy logic-based approaches, viz., self-learning, inability to meet pre specified accuracy, and lack of generalization capability.

ANFIS is a well known artificial intelligence technique that has been used currently in hydrological processes. The ability of neural network to learn fuzzy structure from the inputoutput data sets in an interactive manner has encouraged many researchers to combine the ANN and the fuzzy logic effectively to organize network structure itself and to adapt theparameters of fuzzy system. Several well-known neuro-fuzzy modeling algorithms are available in the literature, such as fuzzy inference networks, fuzzy aggregation networks, neural network-driven fuzzy reasoning, fuzzy modeling networks, fuzzy associative memory systems etc [16], [24], [5]. Adaptive Neuro-fuzzy Inference System (ANFIS), proposed by Prof. J.S. Roger Jang 1993 [17], is based on the first-order Sugeno fuzzy model. The ANN paradigm used in a multiplayer feed-forward back-propagation network.

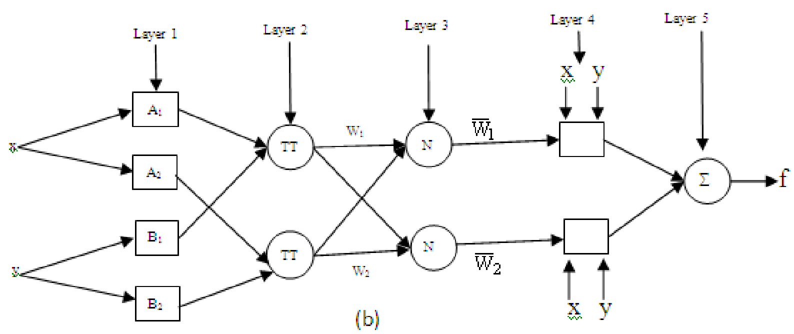
To understand the working of ANFIS in simple meaning, the fuzzy inference system with two fuzzy IFTHEN rules has been discussed here and can be expressed as follows For a first order Sugeno fuzzy model, a typical rule set with two fuzzy. IFTHEN rules can be expressed as

$$Rule1 : IF\ x\ is\ A_1\ and\ y\ is\ B_1\ THEN\ f_1 = p_1x+q_1y+r_1 \quad (1)$$

$$Rule2 : IF\ x\ is\ A_2\ and\ y\ is\ B_2\ THEN\ f_2 = p_2x+q_2y+r_2 \quad (2)$$



(a).



(b)

Figure 1.(a). Type – 3 Fuzzy Reasoning. (b)Equivalent ANFIS (type – 3 ANFIS).

Where, x and y are the crisp inputs . A_i and B_i are the linguistic labels (low, medium, high, etc.) characterized by convenient membership functions and p_i, q_i and r_i are the consequence parameters (i= 1 or 2). The corresponding equivalent ANFIS architecture can find in Figure 1. In the ANFIS, nodes in the same layer have similar functions as described below.

1)Layer 1 (Input nodes): Nodes of this layer generates membership grades of the crisp inputs which belong to each of convenient fuzzy sets by using the membership functions. The generated bell-shaped membership function given below has been used in this paper:

$$\mu_A(x) = \frac{1}{1+((x-c_i)a_i)^{2b_i}} \quad (3)$$

Where μ_A is the appropriate membership functions for A_i fuzzy set, a_i, b_i, c_i is the membership functions parameter set (premise parameters) that changes the shape of membership function from 1 to 0.

2) Layer 2 (Rule nodes): In this layer, the rule operator (AND/OR) is applied to get one output that represents the results of the antecedent for a fuzzy rule. The outputs of the second layer, called as firing strengths O_i^2 , are the products of the incoming signals obtaining from layer 1, named as w in below:

$$O_i^2 = w_i = \mu_A(x)\mu_B(y);\ i = 1,2 \tag{4}$$

3) Layer 3 (Average nodes): In this layer, the nodes calculate the ratio of the i^th^ rules firing strength to the sum of all rules firing strengths.

$$O_i^3 = w_i = \frac{w_i}{\sum_i w_i};\ i = 1,2 \tag{5}$$

4) Layer 4 (Consequent nodes): In this layer, the contribution of i^{th} rules towards the total output or the model output and/or the function calculated as follows:

$$O_i^4 = \overline{w}_i f_i = w_i(p_i x + q_i y + r);\ i = 1,2 \tag{6}$$

Where, $\overline{w_i}$ is the output of Layer 3 and p_i, q_i, r_i are the coefficients of linear combination in Sugeno inference system. These parameters of this layer are referred to as consequent parameters.

5) Layer 5 (Output nodes): This layer is called as the output notes. This layers single fixed node computes the fial output as the summation of all incoming signals.

$$O_i^5 = f(x,y) = \sum \overline{w}_i f_i(p_i x + q_i y + r);\ i = 1,2 \tag{7}$$

The learning algorithm for ANFIS is a hybrid algorithm,which is a combination between gradient descent and least-squares method for identifying nonlinear input parameters a_i, b_i, c_i and the linear output parameters respectively. The ANFIS modeling performed using the"subtractive fuzzy clustering" function as which can perform successfully even in less rules. Detailed information of ANFIS can be found in Jang 1993 [17].

3. Study Area

In the present study the river stage-discharge modeling has been studied for *Godavari* river basin. The hydrological data observation station selected is Dhawalaishwaram Barrage site at Rajahmundry in Andhra Pradesh, India, where the flood prone effect will be seen as the flow contribution of all major tributaries almost completed with heavy inflows (Figure 2).The hydrological data were collected from *Central Water Commission* (CWC), Govt. of India, Godavari circle at Hyderabad. The data consisted of river stage and discharge at Dhawalaishwaram Barrage site.

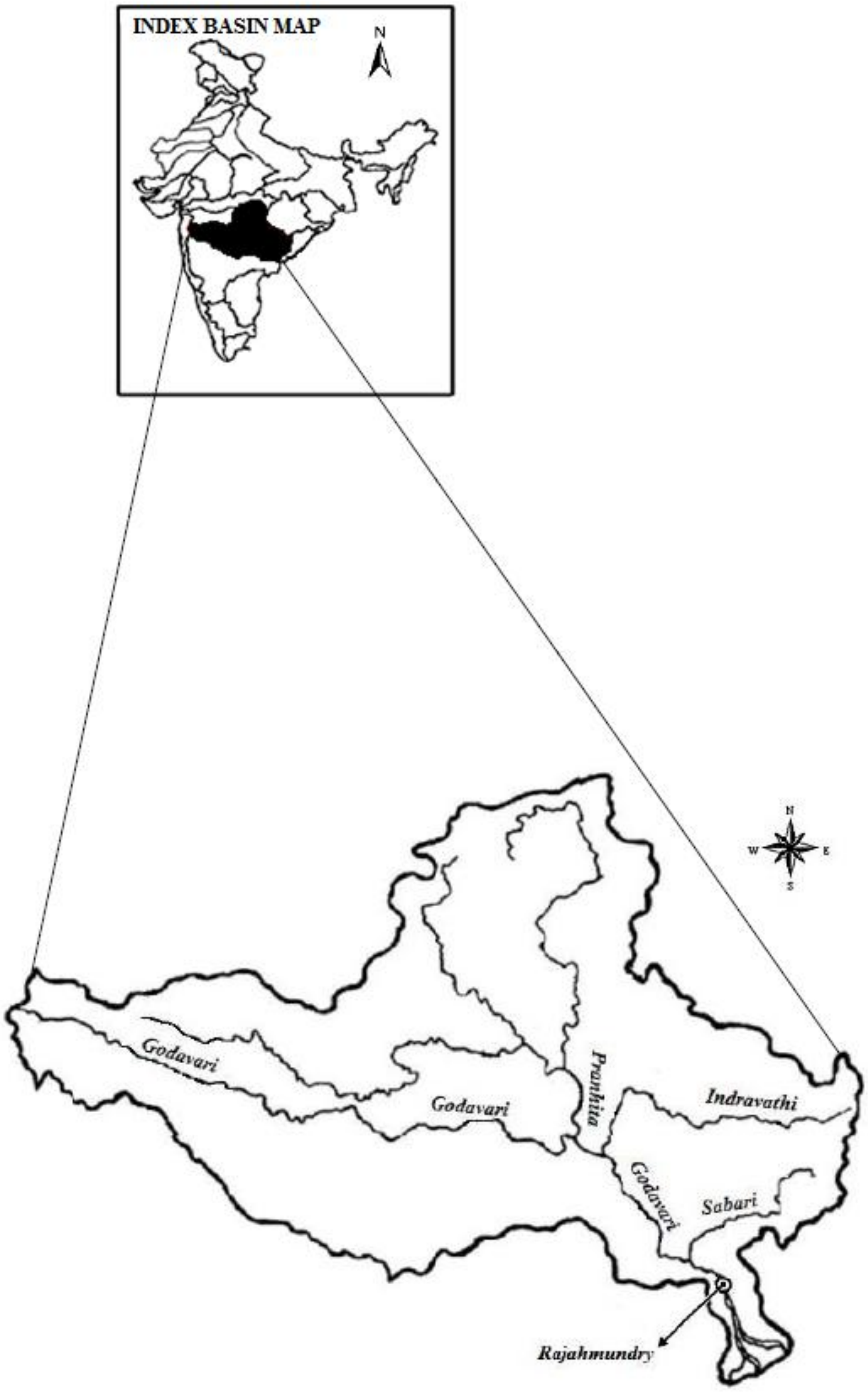


Figure 2. Hydrological Study Location Dhawalaishwaram Barrage Site Rajahmundry, Andhra Pradesh, India

4. Methodology

Matlab used for modelling ANFIS to solve real-world forecasting, classification and function approximation problems.

5. Performance evaluation criteria

The statistical and hydrological evaluation criteria used in the present study are Mean Absolute Deviation (MAD), Root Mean Square Error (RMSE), Correlation Coefficient (R) and Coefficient of Efficiency (CE) or Coefficient of Determination (R^2).

5.1. Mean Absolute Deviation (MAD)

It is a measure of mean absolute deviation of the observed value from the estimated values. It has a unit and not a normalized criterion. It is expressed as,

$$MAD = \frac{\sum_{j=1}^{n} \left| Y_j - \hat{Y}_j \right|}{n}$$

Where, Y and $\hat{Y}$ are the observed and estimated values respectively and 'n' is the number of observations.

5.2. Root Mean Square Error (RMSE)

It yields the residual error in terms of the mean square error expressed as

$$RMSE = \sqrt{\frac{residualvariance}{n}} = \left(\sum_{j=1}^{n} (Y_j - \hat{Y}_j)^2 / n \right)^{1/2}$$

5.3. Correlation Coefficient (R)

The correlation coefficient a concept from statistics is a measure of how well trends in the predicted values follow trends in past actual values. It is a measure of how well the predicted values from a forecast model fit with the real-life data.It is expressed as

$$R = \frac{\sum_{j=1}^{n} \left\{ \left(Y_j - \overline{Y}\right)\left(\hat{Y}_j - \overline{\hat{Y}}\right) \right\}}{\left\{ \sum_{j=1}^{n} \left(Y_j - \overline{Y}\right)^2 \sum_{j=1}^{n} \left(\hat{Y}_j - \overline{\hat{Y}}\right)^2 \right\}^{1/2}}$$

Where, $\overline{Y}$ and $\overline{\hat{Y}}$ are mean of observed and estimated values.

5.4. Coefficient of Efficiency (R^2)

Based on the standardization of residual variance with initial variance, the Coefficient of Efficiency can be used to compare the relative performance of the two approaches effectively [14]. It is expressed as:

$$R^2 = 1 - \frac{residual\,variance}{initial\,variance}$$

$$= 1 - \frac{\sum_{j=1}^{n} (Y_j - \hat{Y}_j)^2}{\sum_{j=1}^{n} (Y_j - \bar{Y})^2}$$

The Coefficient of Efficiency is also commonly known as the Coefficient of Determination which may be written in a number of ways and represents the fraction of variance that is explained by regression. The closer this ratio is to unity, the better is the regression relation. It is possible to get a negative R-square for equations that do not contain a constant term. If R-square is defined as the proportion of variance explained by the fit, and if the fit is actually worse than just fitting a horizontal line, then R-square is negative. In this case, R-square cannot be interpreted as the square of a correlation.

While judging the acceptability of a model through above evolution criteria, the ability of each model must be properly understood. The mean absolute deviation and root mean square error are dimensional criteria reproducing an absolute error. The criteria can compare the performance of two models when the same data are used for their development. The correlation coefficient represents the degree of correlation between the observed and estimated values. Coefficient of efficiency compares the residual and initial variance and could vary depending upon the initial variance of observed data [21].

6. Models using ANFIS

The models are developed with river stage / river flow level (H) as input and river discharge (Q) as output for a major hydrological location on Godavari river at Rajahmundry (Dhawalaishwaram Barrage site) in Andhra Pradesh, India (Table 1).

Table 1. Model Development of Various ANFIS River Stage-Discharge Models.

Model	Output	Input Variables
ANFIS – 1	Q_t	H_t
ANFIS – 2	Q_t	H_t, H_{t-1}
ANFIS – 3	Q_t	H_t, Qt-1
ANFIS – 4	Q_t	H_t, H_{t-1}, Q_{t-1}
ANFIS – 5	Q_t	H_t, H_{t-1}, H_{t-2}
ANFIS – 6	Q_t	H_t, H_{t-1}, H_{t-2}, Q_{t-1}
ANFIS – 7	Q_t	H_t, H_{t-1}, H_{t-2}, Q_{t-1}, Q_{t-2}
ANFIS – 8	Q_t	H_t, H_{t-1}, H_{t-2}, H_{t-3}
ANFIS – 9	Q_t	H_t, H_{t-1}, Q_{t-1}, Q_{t-2}
ANFIS – 10	Q_t	H_t, H_{t-1}, Q_{t-1}, Q_{t-2}, Q_{t-3}

Note: *Q = Discharge, H= River Stage*

On the basis of correlation coefficient (R) and coefficient of efficiency (R^2) ten models were selected for the training, testing and validation. The output discharge Q_t at time step t was mapped with river stage H_t with specified lag time i.e. H_{t-1}, H_{t-2}, H_{t-3} etc. and the previous discharge i.e. Q_{t-1}, Q_{t-2}, Q_{t-3} etc. Each model is trained tested and validated using the input data of the Godavari river. Five best models out of all the developed models were selected to represent the river-stage-discharge modeling of the study location with a view to predict and forecast the real time situation with a single parameter utilization possible.

Table 2. Best Stage-Discharge ANFIS Models for Dhawalaishwaram Barrage Site, Godavari River.

S. No.	Best Model	R	R²
1	ANFIS – 1	0.700	0.490
2	ANFIS – 2	0.726	0.530
3	**ANFIS – 3**	**0.922**	**0.850**
4	**ANFIS – 4**	**0.925**	**0.860**
5	ANFIS – 5	0.652	0.425
6	**ANFIS – 6**	**0.926**	**0.860**
7	**ANFIS – 7**	**0.929**	**0.863**
8	ANFIS – 8	0.606	0.367
9	**ANFIS – 9**	**0.930**	**0.864**
10	**ANFIS – 10**	**0.930**	**0.863**

The table 2 gives the tabulation of performance of the different models. The performance indicators in throughout the study are Correlation Coefficient(R), Coefficient of Efficiency (R^2) and Root Mean Square Error (RMSE). Based on the Correlation Coefficient and Coefficient of Efficiency five models (i.e. models ANFIS-4, ANFIS-6, ANFIS- 7, ANFIS-9 and ANFIS-10) are selected out of the ten models (table 3). Comparing R and R^2 of these models the model ANFIS-9 may be treated as the best model.

Table 3. Representative Best Stage-Discharge ANFIS Models for Dhawalaishwaram Barrage Site, Godavari River .

S. No.	Best Model	RMSE	R	R²
1	ANFIS – 4	50422.80	0.925	0.860
2	ANFIS – 6	50259.78	0.926	0.860
3	ANFIS – 7	49349.07	0.929	0.863
4	ANFIS – 9	49056.98	0.930	0.864
5	ANFIS – 10	49339.74	0.930	0.863

For the selected best five models a comparative study has been done with graphical representation of observed and predicted data. For the same scattered plots are also presented.

Figures from 3 to 7 present the details of the observed and estimated discharges time versus discharge and their corresponding scatter plots for the best fit ANFIS models to represent the stage-discharge modeling of the river Godavari.

Out of all the presented figures, Figure 6 (i.e. ANFIS-9) clearly give the information of the best fit modeling for the study location with Coefficient of Efficiency values 0.864.

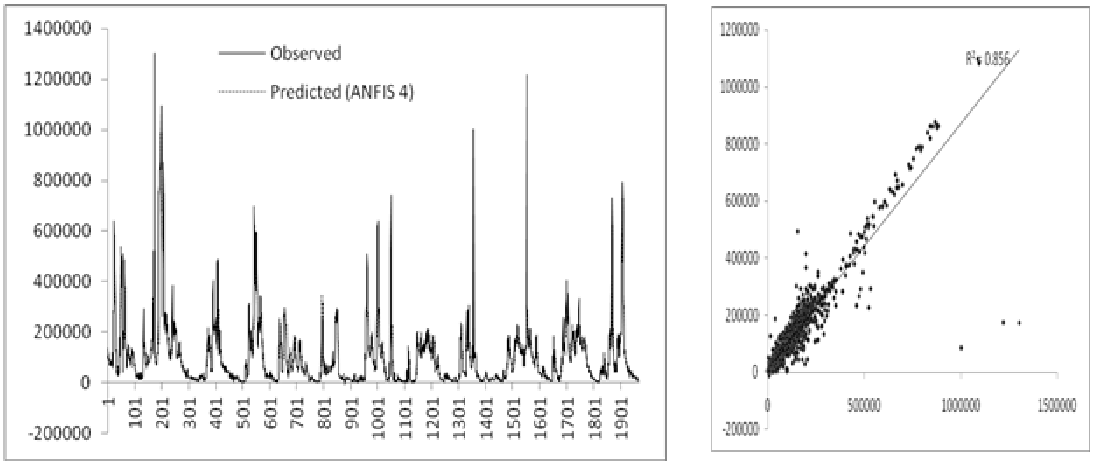


Figure 3. Comparative Plots of Observed and Predicted Flows and their Corresponding Scatter Plots for Dhawalaishwaram Barrage Site, ANFIS – 4.

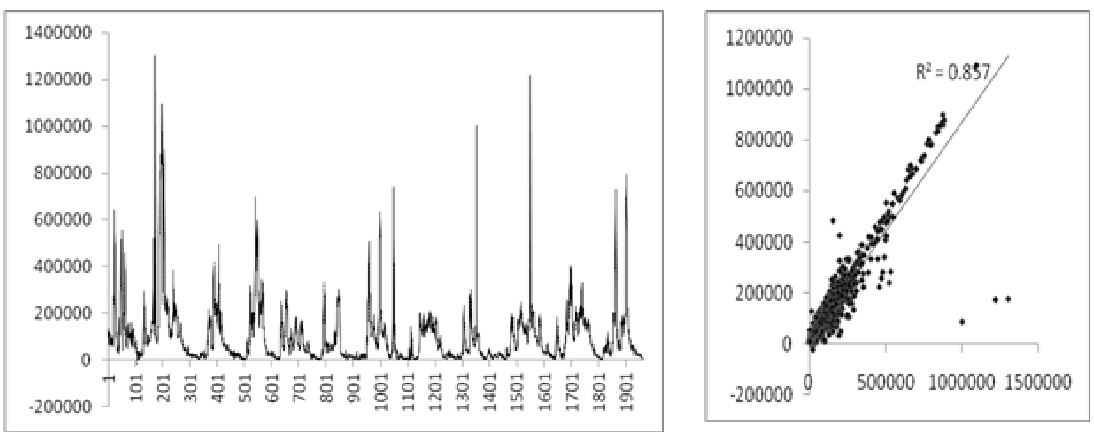


Figure 4. Comparative Plots of Observed and Predicted Flows and their Corresponding Scatter Plots for Dhawalaishwaram Barrage Site, ANFIS – 6.

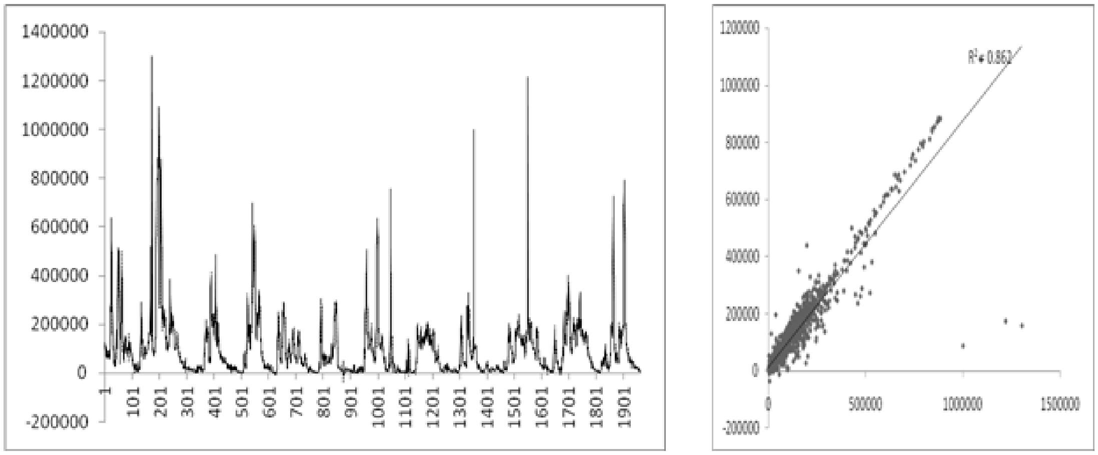


Figure 5. Comparative Plots of Observed and Predicted Flows and their Corresponding Scatter Plots for Dhawalaishwaram Barrage Site, ANFIS – 7.

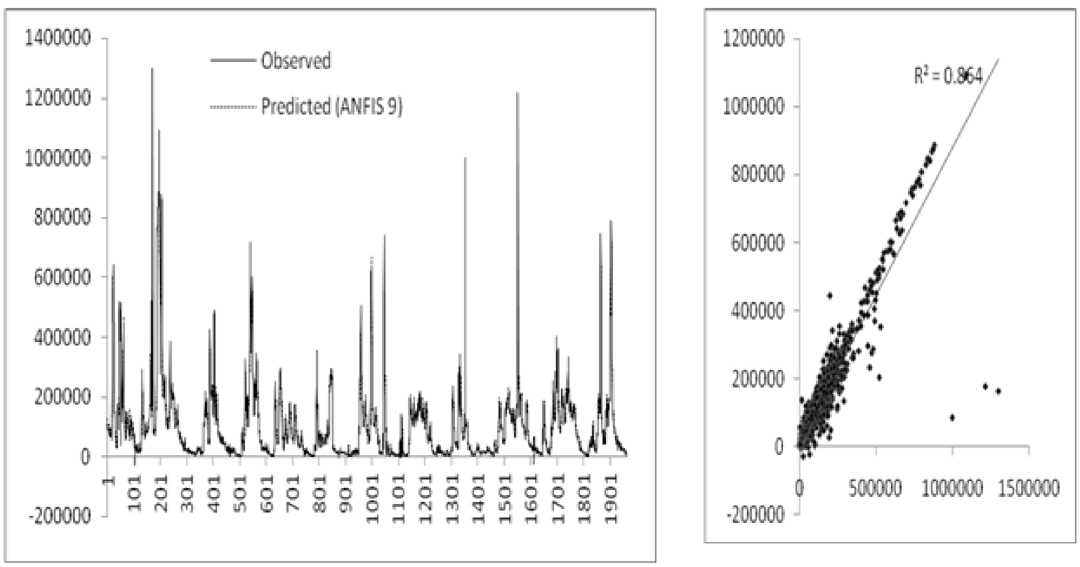


Figure 6. Comparative Plots of Observed and Predicted Flows and their Corresponding Scatter Plots for Dhawalaishwaram Barrage Site, ANFIS – 9.

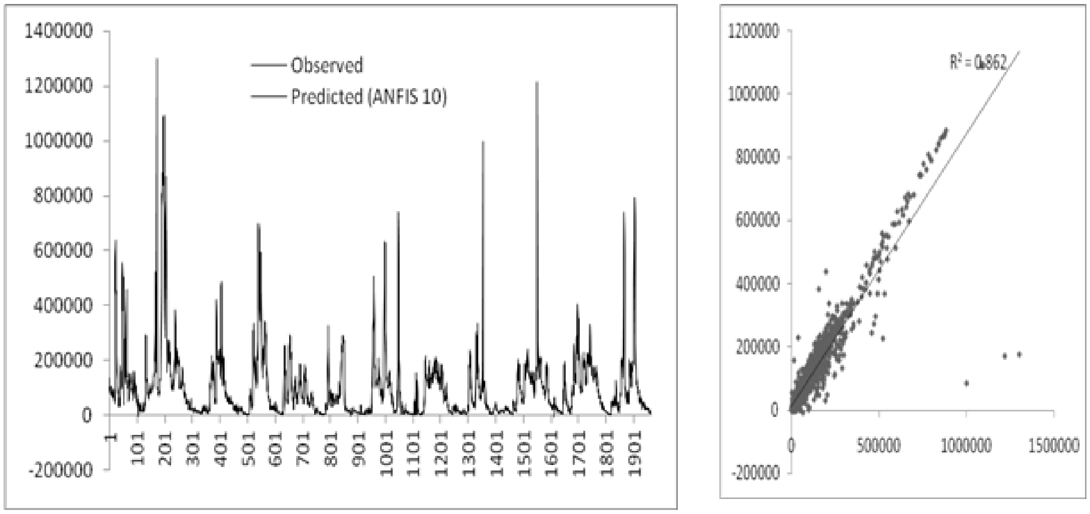


Figure 7. Comparative Plots of Observed and Predicted Flows and their Corresponding Scatter Plots for Dhawalaishwaram Barrage Site, ANFIS – 10.

7. Models using Multiple Linear Regression

In developing Multiple Linear Regression (MLR) models, the River Discharge at time t, (Q_t), can be regressed against the River Stage and River Discharge in the past. The MLR models can be represented as follows

$$Q_t = \beta_0 + \beta_1 H_t + \beta_2 H_{t-1} + \beta_3 H_{t-2} + \beta_4 H_{t-3} + \beta_5 Q_{t-1} + \beta_6 Q_{t-2} + \beta_7 Q_{t-3}$$

Where β_i's represent the regression coefficients to be determined; H_i's represent the River Stage; Q_i's represent the Discharge; and t = index representing time.

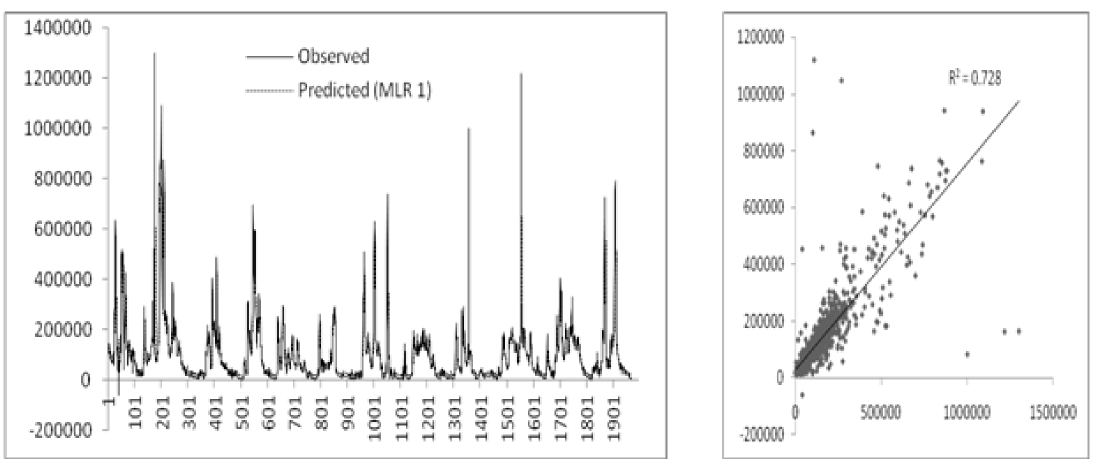


Figure 8. Comparative Plots of Observed and Predicted Flows and their Corresponding Scatter Plots for Dhawalaishwaram Barrage Site, MLR – 1.

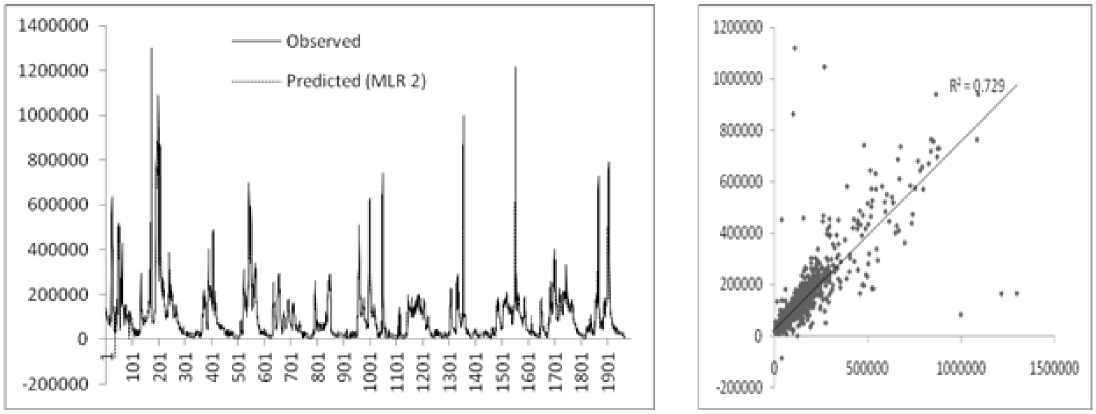


Figure 9. Comparative Plots of Observed and Predicted Flows and their Corresponding Scatter Plots for Dhawalaishwaram Barrage Site, MLR – 2.

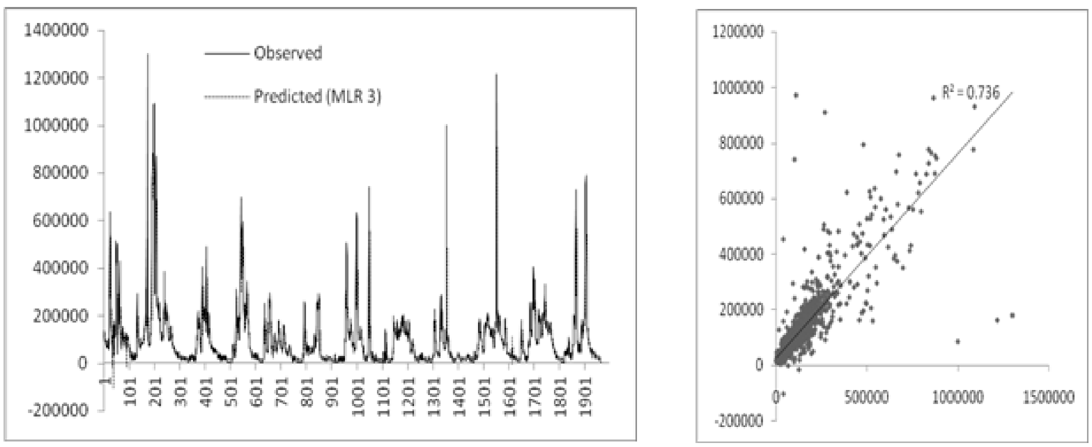


Figure 10. Comparative Plots of Observed and Predicted Flows and their Corresponding Scatter Plots for Dhawalaishwaram Barrage Site, MLR – 3.

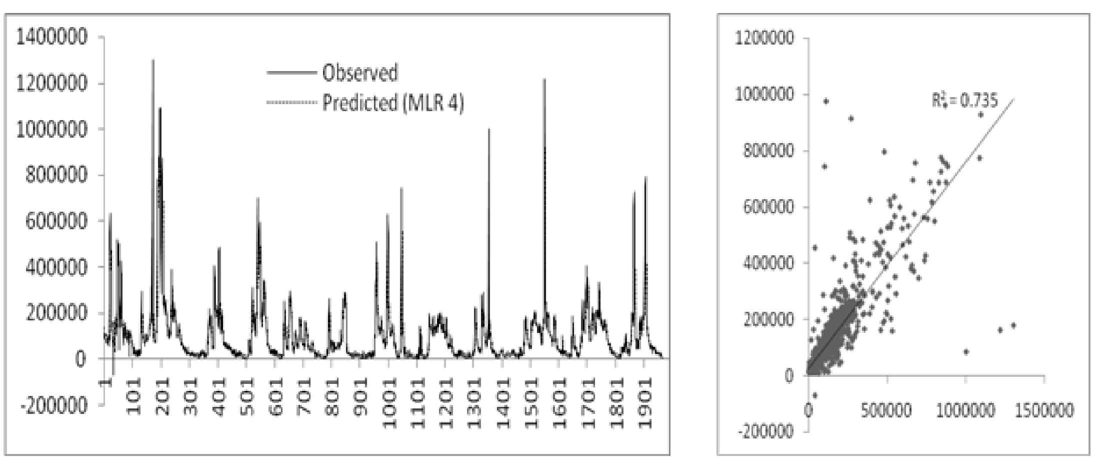


Figure 11. Comparative Plots of Observed and Predicted Flows and their Corresponding Scatter Plots for Dhawalaishwaram Barrage Site, MLR – 4.

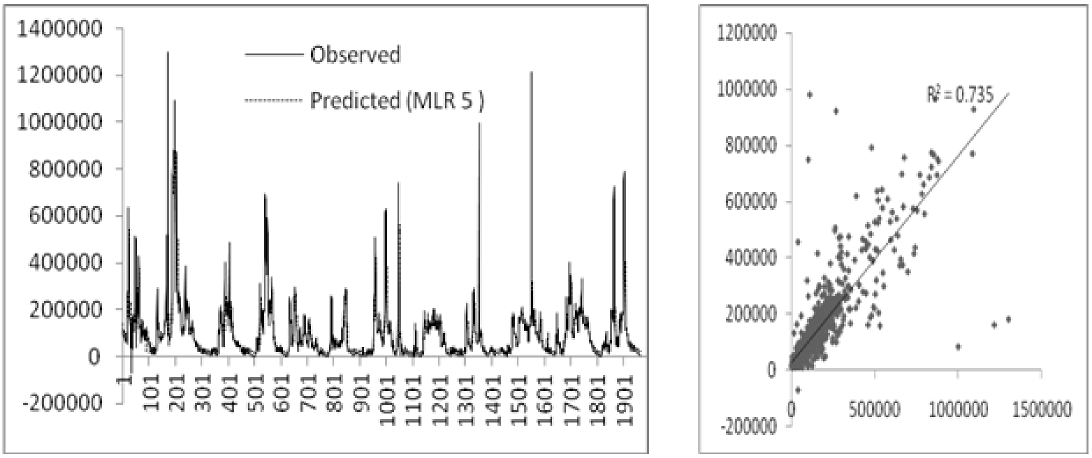


Fig. 12. Comparative Plots of Observed and Predicted Flows and their Corresponding Scatter Plots for Dhawalaishwaram Barrage Site,MLR – 5.

The developed regression models description is as follows

Model – MLR-1

$Q_t = 5468.10 + 632.871H_t + 0.847Q_{t-1}$

Model – MLR-2

$Q_t = 6448.59 + 2988.57H_t – 2426.495H_{t-1} + 0.849Q_{t-1}$

Model – MLR-3

$Q_t = 7152.94 + 3645.588H_t – 970.85H_{t-1} – 2159.02H_{t-2} + 0.849Q_{t-1}$

Model – MLR-4

$Q_t = 5129.522 + 3176.236H_t - 2678.169H_{t-1} + 0.702Q_{t-1} + 0.151Q_{t-2}$

Model – MLR-5

$Q_t = 5502.061 + 3165.77H_t - 2659.148H_{t-1} + 0.726Q_{t-1} + 0.810Q_{t-2} - 0.039Q_{t-3}$

The graphical representations along with corresponding scattered plots of developed MLR models are shown in figures 8 to12.

8. Comparison of Results of Five Developed Best Stage-Discharge ANFIS Models with MLR Models

The table 4 gives comparison of performance of the best five ANFIS models with Multiple Linear Regression (MLR) models. The performance indicators throughout the study are Mean Absolute Deviation (MAD) Correlation Coefficient(R), Coefficient of Efficiency (R^2) and Root Mean Square Error (RMSE). In the table FIL the Correlation Coefficient of ANFIS models varies from 92.5% to high as 92.8% , whereas Correlation Coefficient for MLR models varies 85.4% to as high as 85.8%. Coefficient of Efficiency for ANFIS models varies from 85.6% to as high as 86.4%, while the same for the MLR models varies from 72.9% to as high as 73.6%. Mean absolute deviation for the ANFIS models varies from 157621.16 to as high as 158062.02, whereas that for the MLR models varies from 26694.78 to as high as the 27407.36. Root mean square error for the five best ANFIS models varies from 27064.17 to as high as 28821.87, whereas that for the MLR models varies from 68385.07 to as high as 694522.48.

Table 4. Comparison of Five Best Stage-Discharge ANFIS Models with MLR Models for Dhawalaishwaram Barrage Site, Godavari River.

S. No.	Model	RMSE	R	R^2	MAD
1	ANFIS – 4	50422.80	0.925	0.857	18278.34
2	ANFIS – 6	50259.78	0.926	0.858	18231.78
3	ANFIS – 7	49349.07	0.929	0.863	17660.07
4	ANFIS – 9	49056.98	0.930	0.864	17151.98
5	ANFIS – 10	49339.74	0.930	0.863	17597.92
6	MLR – 1	69311.67	0.854	0.729	26765.64
7	MLR – 2	69262.87	0.854	0.729	26812.58
8	MLR – 3	68389.06	0.858	0.736	27341.82
9	MLR – 4	68534.89	0.857	0.735	27264.21
10	MLR – 5	68480.18	0.858	0.736	27260.64

By the comparison made in table 4 it is clear that performance of ANFIS models is better than MLR models for River Stage-Discharge.

9. Conclusions

In the present study ANFIS methodology was adopted to model the flow behaviour of the river system. The performance of the methodology was also evaluated to suggest readily available and accurate methodology for the simulation and forecasting of the problem. ANFIS have shown better applicable performance and accuracy level for better system approach. The study suggests that ANFIS methodology is highly successful in the simulation and forecasting of the stage-discharge process.

The statistical evolution criteria used in the development of ANFIS modelling was Correlation Coefficient (R), Coefficient of Efficiency (R^2). The results of the study have been found much closer to the observed process and the study shows the successful development of reliable relationship between the stage and discharge of river flow.

The results obtained by ANFIS models are compared to multiple linear regression models. The comparison reveals that the ANFIS models give better accuracy in prediction of discharge than the MLR models.

The study has investigated only one application of the ANFIS approach in the hydrological modeling. ANFIS methodology can also be successfully applied in the modeling of runoff, inflow forecasting, ground water fluctuation, evapotranspiration, sediment transportation etc.

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