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Neural Fuzzy Inference System Modelling with Different Input Vectors for Rainfall-Runoff Prediction

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ABSTRACT

A convenient and acceptable technique to develop mathematical models is through conceptual formulation and statistical development while integrating the effects of various variables on these physical processes. Overemphasizing on these techniques could result in increase in complexity of model which in turn influence the performance of the model. In this study, one conjunction model combining wavelet-neuro-fuzzy for runoff forecast is proposed and compared with simple neuro-fuzzy inference system. The inflow series to the conjunction model has been decomposed by wavelet transform. The performance of the conjunction model under the changed inflow parameters has been compared with the simple model. The results show that both the model performed well, however, increase in complexity of a model does not necessarily increase the performance of the model.

Keywords: *Runoff, Watershed, Hybrid Model, Wavelet, ANFIS etc.*

1. INTRODUCTION

Hydrologic processes, such as rainfall, runoff and sediment yield are complex in nature since they depend on various factors, e.g., initial soil moisture, land use, watershed geomorphology, evaporation, infiltration, distribution, and duration of the rainfall. The rainfall-runoff process is an extremely complex, dynamic, and nonlinear process, which is affected by many, often inter-related physical factors. The influence of these factors and many of their combinations in generating runoff is a complex physical process and is not clearly understood. Despite more than six decades of research floods and drought are still probably the most serious technical problem faced by the agriculture industry. Correct estimation and collection of runoff data are very expensive and difficult, which is essential for various purposes like maintenance of water bodies, nutrient flow, and pollution control programs. Accurate prediction of the hydrometerological events is of utmost importance for the proper management of natural resources. Over the years, several hydrological models ranging from empirical relationships to physically based models have been developed for the prediction of runoff and sediment yield. Physically based models are better because they consider the controlling physical processes, but at the same time, their data requirements are also high. Moreover, many of the deterministic rainfall-runoff models need a large amount of data for the calibration and validation purpose and are computationally extensive. As a result, the use of determininistic models of the rainfall-runoff process is viewed rather skeptically by researchers and the consequently has not become very popular (Grayson *et al*. 1992). Often, even in intensively monitored watersheds, all the required data are not available.

Therefore, there is a need to look for alternative methods for the prediction of runoff and sediment yield using readily available information e.g., rainfall and temperature. In recent years, Adaptive neuro-fuzzy inference system (ANFIS) has proved to be a better alternative for modeling complex and nonlinear processes (Nayak *et. al.*, 2004; Kumarsen et al., (2017). The wavelet transform is a strong mathematical tool that provides a time–frequency representation of an analyzed signal in the time domain (Dabuechies, 1990). In past years, wavelet transforms have become a useful method for analyzing such as variations, periodicities, trends in time series (Torrence and Compo, 1998; Smith et al., 1995; Coulibaly and Burn, 2004; Lu, 2002; Xingang et al., 2003; Yueqing et al., 2004; Partal and Ku¨c¸u¨k, 2006).

Wavelet-ANN models have been employed recently on some studies in hydrology and water resources successfully (Kim and Valdes, 2003; Wang and Ding, 2003; Anctil and Tape, 2004; Zhou et al., 2008; Kisi et al., 2012; Solgi et al., 2014). These studies show that wavelet transform fairly improves forecasting accuracy. Wavelet transform, which can produce a good local representation of the signal in both the time and frequency domains, provides considerable information about the structure of the physical process to be modeled. Discrete wavelet transform provide a decomposition of original time series. Sub-series decomposed by discrete wavelet transform from original time series provide detailed information about the data structure and its periodicity (Wang and Ding, 2003). The attribute of each sub-series is different. Wavelet components of original time series improve the ability of a forecasting model by giving useful information on various resolution levels (Kim and Valdes, 2003). Because of this, coupling wavelets with neuro-fuzzy can provide significant advantages.

One conjunction method wavelet-ANFIS for runoff forecast is proposed in this study. The conjunction method combines two methods, discrete wavelet transform with neuro-fuzzy inference system. The observed daily runoff is decomposed in subseries by using discrete wavelet transform and then appropriate sub-series are used as inputs to the neural network and neuro-fuzzy models for forecasting of daily precipitations. The conjunction model is then compared with ANFIS model.

2. METHODOLOGY

2.1 STUDY AREA: Vamsadhara Watershed

The area selected for the study is the Vamsadhara river basin situated in between well-known Mahanadi and Godavari river basins of South India. 74% of the total catchment area of Vamsadhara river basin falls in the state of Orissa and rest 26 % in Andhara Pradesh. The part of river basin up to gauge site Kashinagar, falling in the state of Orissa is taken as the study area in the present study. The total catchment area of Vamsadhara river basin, upstream to the point where the river joins the Bay of Bengal, is 10830 km^2 and is situated within the geographical coordinates of $18^0 15'$ to $19^0 55'$ north latitudes and $83^0 20'$ to $84^0 20'$ east longitudes.

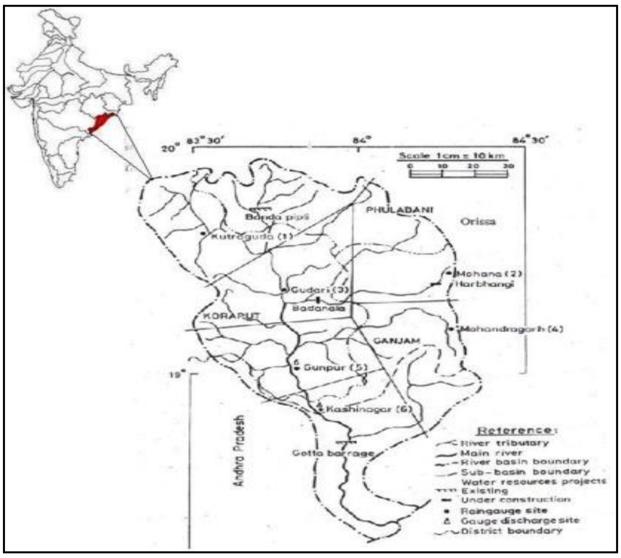

Fig.1 Topography map of Vamsadhara Watershed

The daily data of runoff of the active period of monsoon (July 1st to 30th September) for the years 1984-1989 and 1992-1995 (10 years) was used for the development of runoff forecasting model.

2.2 Adaptive Neuro Fuzzy Inference System (ANFIS)

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.,* 1997 and Loukas, 2001). ANFIS is the integration of neural networks and fuzzy logic and 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 for automatic fuzzy if-then rule generation and parameter optimization.
A conceptual ANFIS consists of five components: inputs and output database, a Fuzzy system generator, a Fuzzy Inference System (FIS), and an Adaptive Neural Network. The Sugeno- type Fuzzy Inference System, (Takagi and Sugeno, 1985)) which is the combination of a FIS and an Adaptive Neural Network was used in this study for rainfall-runoff modeling.

2.3 The Haar-á trous Wavelet Transform

From a time frequency perspective, each hydrological time series includes several frequency components, which satisfy various rules and constraints. Modeling of hydrological processes using the initial time series that is without or with zero resolution makes the internal mechanism difficult to understand. Resolution is the separation of data into different frequency components. The application of wavelet based multi-resolution analysis (MRA) therefore, can provide efficient tools for modeling hydrological processes. Wavelet transforms are of many forms and the choice depends on the object of the transform, meaning the information to be captured. To process the initial data Haar- á trous wavelet transform has been used in this study.

The number of resolution levels used in the wavelet decomposition must not be excessive or too few. Xu *et al.* (2001) recommended that the number of resolution levels is kept between three and five. In the present study, three resolution levels have been taken.

The original discrete time series $C_0(t)$ can be resolved by á trous decomposition algorithm (Wang and Ding, 2003) as,

$$C_r(t) = \sum_{\ell=-\infty}^{+\infty} h(\ell) C_{r-1}(t + 2^r \ell) \qquad (r = 1, 2, ...) \qquad ...(1)$$

$$W_r(t) = C_{r-1}(t) - C_r(t) \qquad (r = 1, 2, ...) \qquad ... (2)$$

Where,

$h(\ell)$ is the discrete low-pass filter.

$C_r(t)$ and $W_r(t)$ (r = 1, 2 ….) are respectively sub time series of scale coefficient (background information) and wavelet coefficient (detail information) at r^{th} resolution level.

2.4 Activation Function

Sigmoid axon

Activation Function is given by $y = f(net) = \dfrac{1}{1+e^{-net}}$. ...(3)

2.5 Learning Rule

Levenberg-Marquardt

The Levenberg-Marquardt (LM) algorithm is one of the most appropriate higher-order adaptive algorithms known for minimizing the MSE of a neural network. It is a member of a class of learning algorithms called "pseudo second order methods". Standard gradient descent algorithms use only the local approximation of the slope of the performance surface (error versus weights) to determine the best direction to move the weights in order to lower the error. Second order methods use the Hessian or the matrix of second derivatives (the curvature instead of just the slope) of the performance surface to determine the weight update, while pseudo-second order methods approximate the Hessian. In particular, the LM utilizes the so called Gauss-Newton approximation that keeps the Jacobian matrix and discards second order derivatives of the error.

2.6 Development of Adaptive Neuro Fuzzy Inference System Based Runoff Prediction Models

The Adaptive neuro fuzzy inference system based models are designed to produce a continuous series of one day ahead runoff predictions based on hydrological and meteorological inputs.

2.6.1. Normalization of the Data

Each of the input and output variables ranges between a minimum value and a maximum value. These minimum and maximum values differ significantly from one variable to other. To avoid the network from giving more importance to some of the variables as compared with others, it is required to normalize them within a common range. In sigmoid activation function, the values of output variable range between zero and one.

If the values of any variable, say Z, are lying in the range between Z_{min} and Z_{max}, and it is desired to normalize these values, then the normalization is performed using equation 14 by which runoff data was normalized within range 0 to 1,

$$z_k = \frac{Z_k - Z_{\min}}{Z_{\max} - Z_{\min}} \qquad ... (4)$$

Where,

Z_k = value of the input or output variable (Z) in k^{th} input-output pair
z_k = normalized value of the input or output variable (z) in a k^{th} input-output pair
Z_{max} = maximum value of Z_k and Z_{min} = minimum value of Z_k
z_{max} = maximum value of z_k and z_{min} = minimum value of z_k

2.6.2 Identification of inputs to Models

One of the most important steps in developing a forecasting model is the selection of the input variables. Because these variables determine the structure of the network and also have an effect on the results of the model. The parameters that need to be selected in the input vector are the number of rainfall/runoff values for different intervals of time that can best represent the process by a neural network model. Determining the number of rainfall/runoff parameters involves finding the lags of rainfall/runoff that have a significant influence on the predicted flow. These influencing values corresponding to different lags can be very well established through statistical and hit and trial analysis of the data series.

2.6.2.1 Identification of Inputs to Models based on Raw Data Input

One quantitative technique is used to identify the best input combination for developing raw data based adaptive neuro fuzzy interface system based rainfall-runoff model for Vamsadhara watershed.

Gamma Test (GT)

GT is one of the non-linear modeling tools whereby an appropriate combination of input parameters can be investigated for modeling the output data as well as establishing a smooth model. GT estimates the minimum mean square errors which are obtainable in continuous non-linear models with unseen data. Suppose there is a set of data as the following:

$$((x_1,..., x_m), y) = (X, y) \qquad ... (5)$$

Where,

$X= (x_1….,..x_m)$ is the input vector in the output vector's areas of y and $C \in R^m$. If the relationship is established between the set members:

$$y = f (x_1….,..x_m) + r \qquad …(6)$$

in which r is a random variable. GT is an estimate of the output variance of a non-smooth model.

According to N[i,k], Gamma Test includes a list of $k(1 \leq k \leq p)$ the k^{th} neighbour for each vector X_i ($1 \leq i \leq M$). Delta function calculates the mean squared distance of the k^{th} neighbour.

$$\delta_M(k) = \frac{1}{M}\sum_{i=1}^{M}\left|X_{N[i,k]} - X_i\right|^2 \qquad …(7)$$

Where $|X_{N[i,k]} - X_i|$ indicates the Euclidean distance and its corresponding Gamma function:

$$\gamma_M(k) = \frac{1}{2M}\sum_{i=1}^{M}(y_{N[i,k]} - y_i)^2 \qquad …(8)$$

Where $y_{N[i,k]}$ is the value of y corresponding to the k^{th} neighbor of X_i in the Equation 18. In order to calculate Γ, the linear regression is fitted from p spot to values of δ_M (k) & Y_M (k).

$$Y= A\delta + \Gamma \qquad ...(9)$$

The intercept of this line δ=0 indicates the Γ value and $Y_M(k)$ is equal to the errors variance. Provided that n is the number of the input variables, the combination of 2^n-1 would be among them. Reviewing all these combinations takes a lot of time. GT can identify the most effective variable in modeling and the best combination of the input variables.

2.6.2.2 Identification of Inputs to Models based on Wavelet Data Input

For developing wavelet decomposed data based adaptive neuro-fuzzy interface system based rainfall-runoff model for Vamsadhara watershed, Wavelet transforms analysis is employed to preprocess the observed data to be inputted to a traditional Adaptive neuro fuzzy interface system (ANFIS). For developing wavelet decomposed data based ANFIS (adaptive neuro fuzzy interface system) rainfall-runoff model for Vamsadhara watershed, runoff of the current day is considered to be a function of rainfall and runoff of previous days and rainfall of current day.

Daily rainfall and runoff data of monsoon season (1^{st} June to 30^{th} September) of seven years for Vamsadhara watershed were used for training of ANFIS model, while the two years data were used for its testing and one year data was used for cross validation of the model.

2.7 Statistical Indices for Performance Evaluation

The visual observations and quantitative evaluation of developed models were performed to judge the goodness of fit between measured and predicted values. The visual observation based on the graphical comparison between measured and predicted values is one of the simplest methods for the performance assessment of a model. Since the visual observations comparison may have a personal bias, it is not a very accurate decision making process. Therefore, following statistical and hydrological indices were also used for testing the goodness of fit for the quantitative comparison of the observed and predicted values.

2.7.1 Statistical Evaluation Criteria

(i) *Mean square error (MSE)*

The mean square error (MSE) is determined to measure the prediction accuracy. It always produces positive values by squaring the errors. The MSE is zero for perfect fit and increased values indicate higher discrepancies between predicted and observed values (Wilks, 1995). The Mean Square Error between observed and predicted values is determined by the following equation:

$$\text{MSE} = \frac{\sum_{j=1}^{n}(Y_j - Y_{ej})^2}{n} \qquad …(10)$$

Where =observed values and Y_{ej} = predicted values and

n= number of observations

(ii) *Correlation coefficient (CC)*

The correlation coefficient (CC) is an indicator of the degree of closeness between observed and predicted values. If observed and predicted values are completely independent, the CC will be zero (Mutreja, 1992). The correlation coefficient is estimated by the following equation:

$$CC = \frac{\sum_{j=1}^{n}\left\{\left(Y_j - \bar{Y}\right)\left(Y_{ej} - \bar{Y}_{ej}\right)\right\}}{\sum_{j=1}^{n}\left(Y_j - \bar{Y}\right)^2 \sum_{j=1}^{n}\left(Y_{ej} - \bar{Y}_{ej}\right)^2} \times 100\% \qquad \ldots(11)$$

Where, $\bar{Y}$ =mean of observed values, $\bar{Y}_{ej}$ = mean of predicted values, Y_j =observed values, Y_{ej} = predicted values and

n = number of observations

(iii) Nash-Sutcliffe efficiency (NSE)

The Nash-Sutcliffe efficiency (NSE) is a normalized statistic that determines the relative magnitude of the residual variance (“noise”) compared to the measured data variance (“information”) Nash and Sutcliffe, 1970). NSE indicates how well the plot of observed versus simulated data fits the 1:1 line. NSE is computed as given in equation 12

$$NSE = \left[\frac{\sum_{j=1}^{n}\left(Y_j - Y_{ej}\right)^2}{\sum_{j=1}^{n}\left(Y_j - \bar{Y}\right)^2}\right] \qquad \ldots(12)$$

Where, Y_j =observed values, Y_{ej} = predicted values, $\bar{Y}$ =mean of observed values and n = number of observations.

NSE ranges between $-\infty$ and 1.0 (1 inclusive), with NSE = 1 being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values <0.0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance.

(iv) Percent bias (PBIAS)

Percent bias (PBIAS) measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. The optimal value of PBIAS is 0, with low-magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias (Gupta et al., 1999).PBIAS is calculated with the equation:

$$PBAIS = \left[\frac{\sum_{j=1}^{n}\left(Y_j - Y_{ej}\right)*100}{\sum_{j=1}^{n}\left(Y_j\right)}\right]\% \qquad \ldots(13)$$

Where, Y_j =observed values Y_{ej} = predicted values.

n = number of observations and PBIAS is the deviation of data being evaluated, expressed as a percentage.

(v) RMSE-observations standard deviation ratio (RSR)

RMSE-observations standard deviation ratio (RSR), was developed.RSR standardizes RMSE using the observations standard deviation, and it combines both an error index and the additional information recommended by Legates and McCabe (1999). RSR is calculated as the ratio of the RMSE and standard deviation of measured data, as shown in equation

$$RSR = \left[\frac{\sqrt{\sum_{j=1}^{n}\left(Y_j - Y_{ej}\right)^2}}{\sqrt{\sum_{j=1}^{n}\left(Y_j - \bar{Y}\right)^2}}\right] \qquad \ldots(14)$$

Where, Y_j =observed values Y_{ej} = predicted values. $\bar{Y}$ =mean of observed values, n = number of observations.

RSR incorporates the benefits of error index statistics and includes a scaling/normalization factor so that the resulting statistic and reported values can apply to various constituents. RSR varies from the optimal value of 0, which indicates zero RMSE or residual variation and therefore perfect model simulation, to a large positive value. The lower the RSR, the lower the RMSE, and the better the model simulation performance.

3. RESULTS AND DISCUSSION

3.1 Input Vectors to Develop RANFIS Model

Gamma test (GT) was used to identify the best input combination for developing raw data based Adaptive neuro fuzzy interface system (RANFIS) rainfall-runoff model for Vamsadhara watershed.

The best input combination for runoff prediction was identified by the Gamma test In order to predict runoff different combinations of corresponding input and output status are shown in Table 1.

Table 1: Different Input Scenarios for Runoff Prediction for Vamsadhara Watershed

Sl. No.	Model Input	Model Output
1.	R_{ij}, $R_{i(j-1)}$, $Q_{i(j-1)}$	Q_{ij}
2.	R_{ij}, $R_{i(j-1)}$, $Q_{i(j-1)}$, $Q_{i(j-2)}$,	Q_{ij}
3.	R_{ij}, $R_{i(j-1)}$, $Q_{i(j-1)}$, $R_{i(j-2)}$, $Q_{i(j-2)}$,	Q_{ij}
4.	R_{ij}, $R_{i(j-1)}$, $Q_{i(j-1)}$, $R_{i(j-2)}$, $Q_{i(j-2)}$, $Q_{i(j-3)}$,	Q_{ij}
5.	R_{ij}, $R_{i(j-1)}$, $Q_{i(j-1)}$, $R_{i(j-2)}$, $Q_{i(j-2)}$, $R_{i(j-3)}$, $Q_{i(j-3)}$	Q_{ij}

According to the principals of the GT, the combination with the minimum gamma value and the minimum RMSE would be the best combination for modeling. The results obtained from Gamma test are shown in Table 2 for Vamsadhara watershed. Small amounts of gamma value showed that the data with the provided combination has the possibility to achieve better results in modeling. The low standard error is also a reason for this proof. Low amount of V ratio shows that complexity of modeling is lower regarding the input combination and better responses would be expected.

Table 2: Gamma Test Results for Vamsadhara Watershed

Sl. No.	Model Input	T	SE	V RATIO
1.	R_{ij}, $R_{i(j-1)}$, $Q_{i(j-1)}$	0.058907	0.00630	0.2356
2.	R_{ij}, $R_{i(j-1)}$, $Q_{i(j-1)}$, $Q_{i(j-2)}$,	0.05607	0.0055	0.22428
3.	R_{ij}, $R_{i(j-1)}$, $Q_{i(j-1)}$, $R_{i(j-2)}$, $Q_{i(j-2)}$,	0.05368	0.00345	0.2147
4.	R_{ij}, $R_{i(j-1)}$, $Q_{i(j-1)}$, $R_{i(j-2)}$, $Q_{i(j-2)}$, $Q_{i(j-3)}$,	0.06546	0.00590	0.26185
5.	R_{ij}, $R_{i(j-1)}$, $Q_{i(j-1)}$, $R_{i(j-2)}$, $Q_{i(j-2)}$, $R_{i(j-3)}$, $Q_{i(j-3)}$	0.06084	0.00357	0.24338

Based on the results of Gamma test, it is observed that 2 day lag of rainfall-runoff with a combination of R_{ij}, $R_{i(j-1)}$, $Q_{i(j-1)}$, $R_{i(j-2)}$, $Q_{i(j-2)}$, is the best combination from the input variables. The runoff was predicted using RANFIS model for Vamsadhara watershed using the best combination of input variables.

For developing wavelet decomposed data based adaptive neuro fuzzy interface system based rainfall-runoff model for Vamsadhara watershed, Wavelet transforms analysis is employed to preprocess the observed data to be inputted to a traditional Adaptive neuro fuzzy interface system (ANFIS). For developing wavelet decomposed data based ANFIS (adaptive neuro fuzzy interface system) rainfall-runoff model for Vamsadhara watershed, runoff of the current day is considered to be a function of rainfall and runoff of previous days and rainfall of current day.

3.1 Adaptive Neuro-Fuzzy Inference System Based Runoff Prediction Model

One hybrid model combining the application of artificial neural network and fuzzy logic technique of data characterization based on two different type of data sets i.e. raw data with appropriate time lag and wavelet decomposed data and named as Raw data based ANFIS (RANFIS) model and Wavelet data based ANFIS (WANFIS) model for runoff prediction, has been developed, evaluated and compared for Vamsadhara watershed.

3.1.1. Development of models

For RANFIS models daily raw data of rainfall for the current and the previous two days as well as raw runoff flow data for the previous two days have been inputted after normalization for each watershed. In order to have homogeneous input numbers, For WANFIS model, daily data of rainfall for the current and the previous day as well as daily resolved (three resolution level) runoff flow data for the previous day have been considered for the development of the model. Runoff of the current day was considered as the output in all the models. Levenberg-Marquardt learning rule was used to train the network with sigmoid axon transfer function for the runoff flow prediction models. The optimal learning parameters were used with Gaussian membership function and TSK fuzzy model (Table 3). In order to choose better model among developed models to mean square error and correlation coefficient were set as the primary parameters.

Table 3: Models Topology used in the Study for Vamsadhara Watershed

Topology	Learning Algorithm	Transfer Function	Learning Rule	Fuzzy Model	Membership Function	Membership Function per Input
RANFIS	FFBP	Sigmoid axon	Levenberg-Marquardt	TSK	Gaussian	2
WANFIS	FFBP	Sigmoidaxon	Levenberg-Marquardt	TSK	Gaussian	2

4.4.2 Performance Evaluation of the Developed Model

The visual observations and quantitative evaluation of the developed model are performed to judge the goodness of fit between observed and predicted values. The developed model has been verified for its performance considering the rainfall and runoff data of monsoon season.

4.4.2.1 Visual observations evaluation

For assessing the suitability of the model, the predicted runoff flow was compared visually with the observed runoff. The visual observation based on the graphical comparison between the observed and the predicted values is one of the simplest methods for the performance assessment of a model. The prediction performance of the model was evaluated by comparing ordinates of observed and predicted runoff hydrographs. The observed and predicted values of runoff for selected monsoon season during the training and testing period for best RANFIS and WANFIS models with selected networks are depicted in Fig.2 to Fig.7 for Vamsadhara watershed. There is a fairly good agreement between the predicted and the observed runoff, and overall shape of the plot of predicted runoff is similar to that of the observed runoff. Therefore, the visual observations performance during the training has been found satisfactory.

Thus, developed model may be regarded as satisfactory on the basis of the visual observations evaluation

4.4.2.2 Quantitative evaluation

The quantitative evaluation of the model was performed by applying different statistical indices, viz. mean square error (MSE), correlation coefficient (CC), Nash-Sutcliffe efficiency (NSE), Percent bias (PBIAS), and RMSE-observations standard deviation ratio (RSR). Quantitative performance evaluation of the developed model for training, cross validation, and testing are shown in Table 4 and Table 5. Further RANFIS model is compared with WANFIS model to find out the performance of the best model in between both the models. Table 6 shows the comparision of both models.

Table 4: Quantitative Performance of the RANFIS Models during Training, Cross Validation and Testing for Vamsadhara Watershed

Performance Indices	CV	TESTING	TRAINING
MSE	0.0012	0.0029	0.0028
CC (%)	91	87.89	86.14
NSE	0.839718	0.7706	0.785367
PBAIS	4.955531	-1.389	8.633278
RSR	0.400352	0.4789	0.380768

Table 5: Quantitative Performance of the WANFIS Models during Training, Cross Validation and Testing for Vamsadhara Watershed

Performance Indices	CV	TESTING	TRAINING
MSE	0.0018	0.0042	0.0018
CC (%)	89	85.95	89.03
NSE	0.77149	0.673487	0.88231
PBAIS	4.040263	-14.2806	3.030355
RSR	0.478027	0.571413	0.388038

Table 6: Comparative Performance of Best RANFIS and WANFIS Model for Vamsadhara Watershed

Performance Indices	RANFIS	WANFIS
MSE	0.0029	0.0042
CC (%)	87.89	85.95
NSE	0.7706	0.673487
PBAIS	-1.389	-14.2806
RSR	0.4789	0.571413

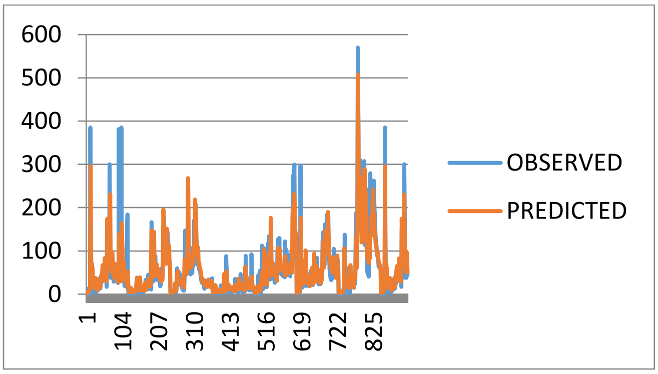

Fig. 2 Observed and Predicted daily Runoff for WANFIS, during Training Period of Vamsadhara Watershed

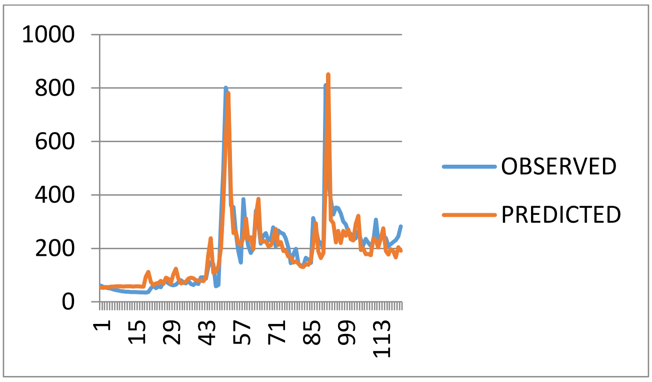

Fig. 4 Observed and Predicted Daily Runoff for WANFIS, during Cross Validation Period of Vamsadhara Watershed

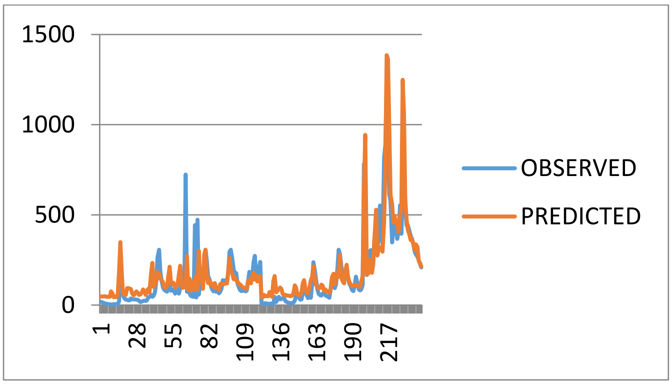

Fig. 3 Observed and Predicted Daily Runoff for WANFIS during Testing Period of Vamsadhara Watershed

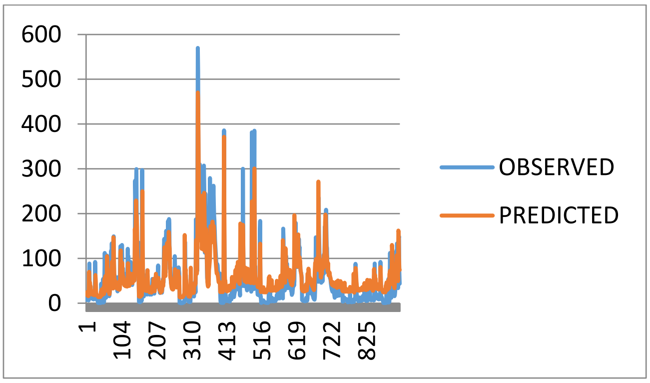

Fig. 5 Observed and Predicted Daily Runoff for RANFIS during Training Period of Vamsadhara Watershed

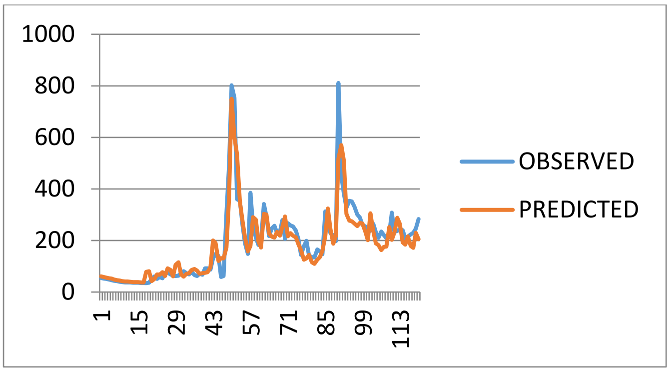

Fig. 6 Observed and Predicted Daily Runoff for RANFIS during Cross Validation Period of Vamsadhara Watershed

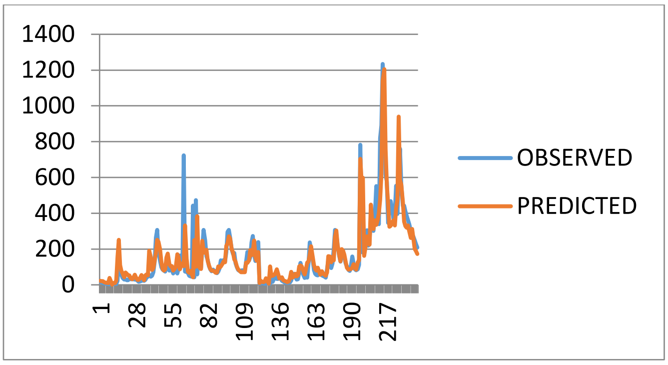

Fig. 7 Observed and Predicted Daily Runoff for RANFIS during Testing Period of Vamsadhara Watershed

4. CONCLUSIONS

Based on the results it can be concluded that for Vamsadhara watershed both RANFIS Model and WANFIS Model were found suitable. On comparison among these two models RANFIS Model performed better than WANFIS Model on the basis of High correlation coefficient and low Mean square error values. It is clear from the above revelations that decomposition of raw data with the help of wavelet technique does not always helps increasing the accuracy of prediction.

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