MULTISTEP LEAD TIME FORECASTING OF HYDROLOGIC TIME SERIES USING DAUBECHIES WAVELET – NEURAL NETWORK HYBRID MODEL

[1]Khandekar Sachin Dadu and [2]Paresh Chandra Deka

[1]Research Scholar, [2]Associate Prof. Department of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka, Surathkal, Mangalore- 575025, India.
E-mail: *khandekarsd@gmail.com, pareshdeka@yahoo.com,*

Abstract: *Accurate modeling of runoff is useful in urban and environmental planning, flood and water resources management. In this research, a hybrid model has been developed for Brahmaputra River flow forecasting based on wavelet and artificial neural network (ANN) methods. In this current study, discrete wavelet transform was linked to ANN naming Wavelet Artificial Neural Network (WANN) for flow forecasting. Ten year daily flow data from January 1990 to December 1999 of Pandu station on Brahmaputra River, which carries heavy flood in monsoon season in the North-East region of India, were used in the study. The observed flow data were decomposed (up to 7 level) to multiresolution time series via discrete wavelet transform using Daubechies wavelets of order 4 (db4) and 5 (db5). Then multiresolution time series data were fed as input to ANN to get the forecasted discharge values for lead times 2 day, 3 day, and 4 day. The root mean square error (RMSE), mean absolute error (MAE), mean relative error (MRE), BIAS, and scatter index (SI) were adopted to evaluate models performance. It was found that for almost all lead times WANN model has given better and consistent results compared to conventional ANN model. It was mainly because of multiresolution time series used as inputs. Also it was found that, in comparison with WANN model with db4 mother wavelet, db5 mother wavelet has given slightly better results for all lead times. Also, the effect of decomposition level on WANN models efficiency was studied.*

Keywords: *Wavelet transform, Neural network, Time series,Daubechies wavelet,Hybrid,Brahmaputra river.*

1. Introduction:

The hydrologic system is a highly complex non-linear system. Forecasting of hydrological time series can be done by using stochastic models like Auto regressive (AR), Auto regressive moving average (ARMA) and Auto regressive integrated moving average (ARIMA) etc. These models are basically time series models and have a limited ability to capture nonstationarities and nonlinearities.

Recently soft computing techniques such as artificial neural network (ANN), fuzzy logic (FL) and genetic algorithm (GA) has been gaining popularity since last decade due to its versatility in handling non linearity and somewhat extent to handle non stationary. Soft computing techniques offer an effective approach for handling large amounts of dynamic, non-linear and noisy data, especially when the underlying physical relationships are not fully understood (Nourani et al., 2011).

ANN is a mathematical model which mimics the function of human brain. It has the ability to identify the relationship from given patterns and solve large scale complex problems such as non-linear modeling pattern recognition, classification, association and control. Recently neural network models are successfully applied in rainfall-runoff modeling, runoff forecasting, evaporation estimation, precipitation forecasting, water quality modeling, ground water level forecasting, significant wave height forecasting and many others. Smith and Eli (1995), in their research demonstrated the ability of a three-layer artificial neural network to relate spatially and temporally varying rainfall excess to the runoff response of a simple synthetic watershed. Tokar et al. (2000) investigated application of ANN model for monthly and daily runoff prediction as a function of rainfall, snow water equivalent, and temperature in three basins with different climatic and physiographic characteristics and compared results with conceptual models and found that ANN results were better in all the cases. Jain and Chalisgaonkar (2000) used three layer feedforward ANN to model stage-discharge relation and compared the results with conventional curve-fitting approach and showed ANN was much superior. Raghuwanshi et al. (2006) developed ANN model with double hidden layer to model runoff and sediment yield and showed that ANN model with double hidden layer was superior to single hidden layer and linear regression models. Jothiprakash and Garg (2009) developed Multi-Layer Perceptron ANN model using the back propagation algorithm to estimate the volume of sediment retained in a reservoir using annual rainfall, annual inflow, and capacity of the reservoir as inputs and found that the ANN model has given better accuracy and less effort as compared to conventional regression analysis. The ASCE Task Committee (2000 II) reviews hydrologic applications of ANN.

In the last decade, Wavelet Transform (WT) has become a useful technique for analyzing variations, periodicities, and trends in time series. A wavelet transformation is a strong mathematical signal processing tool with the ability of analyzing both stationary as well as non stationary data, and to produce both time and frequency information with a higher resolution, which is not available from the traditional transformation (Fourier Transform and Short Time Fourier Transform). WT provides multi resolution analysis i.e. at low scales (high frequency) it gives better time resolution and poor frequency resolution and at high scales (low frequency) it gives better frequency resolution and poor time resolution. The lower scales (i.e. compressed wavelet) trace the abrupt change or high frequency of a signal and the higher scales (i.e. stretched wavelet) trace slowly progressing occurrences or low-frequency component of the signal. A non-stationary time series can be decomposed into certain number of stationary time series by WT. Then different single prediction methods are combined with wavelet transform to improve the prediction accuracy. In most of the hybrid models, WT is used as preprocessing technique. The wavelet-transformed data aid in improving the model performance by capturing helpful information on various resolution levels. Due the above mentioned advantages of WT, it has been found that the hybridization of wavelet transformation with other models like ANN, Fuzzy Logic (FL), ANFIS, linear models, etc., improved the results significantly than the single regular model (Deka and Prahlada, 2012).

Wavelet theory (Mallat, 1989) is first developed in the end of 1980s of last century. Now days, it has been applied in many fields, such as signal process, image compression, voice code, pattern recognition, hydrology, earthquake investigation, ocean engineering and many other non-linear science fields. The researches and applications of wavelet analysis have already begun in hydrology and water resources. The document (Li, 1997) points out the potential applications of wavelet analysis to hydrology and water resources. Li et al. (1999) probed longtime interval forecast of hydrological time series with combining neural network models based on wavelet transform. The multitime scale characteristics of hydrological variable have been studied by Wang et al. (2002). Cannas et al. (2005) studied the river-flow forecasting one month ahead with Neural Networks and Wavelet Analysis using monthly runoff data for the Tirso Basin, Italy, and tests showed that neural networks trained with pre-processed data showed better performance. Zhou et al. (2008) developed wavelet predictor-corrector model for simulation and prediction of monthly discharge time series. Adamowski (2008) developed a short term river flood forecasting (1, 2 and 6 days ahead) method based on wavelet and cross-wavelet analysis. Partal and Cigizoglu (2008) estimated and forecasted daily suspended sediment using wavelet neural networks. Nourani V. et al. (2009) linked wavelet analysis to the ANN for developing rainfall-runoff model in Lingvanchai watershed at Tabriz, Iran. For this purpose the main time series of rainfall and runoff, were decomposed to some multi-frequency time series by wavelet theory, then these time series were imposed as input to ANN to predict the runoff discharge 1 day ahead. In this research the authors examined not only the sensitivity of the pre-processing to the wavelet type and decomposition level but also the effect of number of inputs were evaluated. Kisi (2009) developed neurowavelet model for forecasting daily intermittent streamflow 1 day ahead. Nourani et al. (2009) developed neural-wavelet model for prediction of precipitation in Ligvanchai watershed at Tabriz, Iran. Adamowski and Sun (2010) coupled discrete wavelet transform with ANN for flow forecasting in two different non-perennial rivers in semi-arid watershed at lead times of 1 and 3 days. It was found that in both the cases coupled wavelet-neural networks model were more accurate than the single ANN model. Rajaee et al. (2011) hybridized wavelet analysis with ANN (WANN) to predict 1 day ahead daily suspended load (*S*) in the Iowa River gauging station in United States and compared results with single ANN, multilinear regression (MLR), and sediment rating curve (SRC) models. The results showed that WANN model performed better than the other model. Wang W. et al. (2011) developed wavelet transform method for synthetic generation of daily streamflow sequences. Maheswaran and Khosa (2012) presented a comparative evaluation of different wavelet types when employed for hydrologic time series forecasting. Deka and Prahlada (2012) examined wavelet neural network approach for significant wave height forecasting. Khandekar and Deka (2012) developed wavelet-neural network hybrid model for Brahmaputra River flow forecasting using db4, COIFLET-2 and SYMHLET-4 as mother wavelet and showed that db4 wavelet has given better results. Ramana et al. (2013) applied wavelet and ANN model to predict monthly precipitation of Darjeeling rain gauge station and showed that the performances of wavelet neural network models are more effective than ANN models.

In this study, it proposed to forecast 2 day, 3 day and 4 day ahead discharge values using daily Brahmaputra River flow data at Pandu station by combining discrete wavelet transform and artificial neural network techniques (WANN) using Daubechies wavelets of order 4 (db4) and 5 (db5) as mother wavelets. The main objectives of the present study are:

1. To investigate the potential and applicability of hybrid model by combining discrete Daubechies Wavelet - Artificial Neural Network (WANN) for Brahmaputra River flow forecasting.
2. To study the effect of higher order Daubechies mother wavelets on model efficiency.
3. To investigate the influence of different decomposition levels for various lead times on the model performance.

2. Wavelet transformation basics:

Signals whose frequency content does not change with time are called stationary signals. In stationary signals it is not necessary to know at what times frequency components exists, since all frequency components exists at all times. Mathematical transformations (viz. Fourier transform (FT), Short Time Fourier transform (STFT), Wavelet Transform (WT), etc.) are applied to time domain signals (raw signals) to obtain further information from that signal that is not readily available in the raw signals. FT of a signal in time domain gives information about how much of each frequency exists in the raw signal without giving the information about time (Misiti et al. 2010). So FT is not suitable for non-stationary data. On the other hand, STFT provides a measure of time and frequency resolutions, but the use of a fixed window size at all times and for all frequencies is a limitation of this method. The wavelet representation addresses the above limitation, by adaptively partitioning the time-frequency plane, using a range of window sizes. WT provides multi resolution analysis i.e. at low scales (high frequency) it gives better time resolution and at high scales (low frequency) it gives better frequency resolution. The wavelet transform breaks the signal into its wavelets (small wave) which are scaled and shifted versions of the original wavelet so called mother wavelet.

2.1 Discrete wavelet transform (DWT):

The Continuous Wavelet Transform (CWT) of a signal *x(t)* is given by the Eq. 1.

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t).\psi^{*}\left(\frac{t-b}{a}\right).dt \qquad (1)$$

In the above equation, the transformed signal is a function of two variables, *a* and *b*, the scale and translation factor, respectively, of the function $\psi(t)$. * corresponds to complex conjugate (Mallat, 1989). $\psi(t)$ is the transforming function, and is called the mother wavelet, which is defined mathematically as

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \qquad (2)$$

The term translation is related to the location of the window, as the window is shifted through the signal. This term, obviously, corresponds to time information in the transform domain. The scale parameter is defined as 1/frequency. Low frequencies (high scales) correspond to a global information of a signal (that is usually spans the entire signals), whereas high frequencies (low scales) correspond to a detailed information of a hidden pattern in the signal (that usually lasts a relatively short time). The CWT is computed by changing the scale of the analysis window, shifting the window in time, multiplying by the signal, and integrating over all times.

Calculating the wavelet coefficients at every possible scale is a fair amount of work, and it generates a lot of data. CWT produces N^2 coefficients from a data set of length *N*. Hence redundant information is locked up within the coefficients, which may or may not be a desirable property (Rajaee T. et al., 2011). If one chooses scales and positions based on the powers of two (dyadic scales and positions) then the analysis will be much more efficient as well as accurate. This transform is called discrete wavelet, and has the form as

$$\psi_{m,n}(t) = \frac{1}{\sqrt{a_o^m}} \psi\left(\frac{t - nb_o a_o^m}{a_o^m}\right) \qquad (3)$$

where *m* and *n* are integers that control the wavelet dilation and translation, respectively; b_o is the location parameter and must be greater than zero; a_o is a specified fixed dilation step greater 1. From this equation, it can be seen that the translation step $nb_oa_o^m$ depends upon the dilation, a_o^m. The most common and simplest choice for parameters a_o and b_o are 2 and 1 (time steps), respectively. This power of two logarithmic scaling of the translations and dilations is known as the dyadic grid arrangement (Mallat, 1989) and is defined as

$$\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n) \qquad (4)$$

For discrete time series x_t, where x_t occurs at discrete time *t*, the discrete wavelet transform becomes

$$W_{m,n} = 2^{-m/2}\sum_{i=0}^{N-1}\psi(2^{-m}t - n)x_t \qquad (5)$$

where $W_{m,n}$ = wavelet coefficient for the discrete wavelet of scale $a = 2^m$ and location $b = 2^m n$. Eq. (5) considers a finite time series, x_t, $t = 0, 1, 2, \ldots, N - 1$, and *N* is an integer power of 2: $N = 2^M$; *n* is time translation parameter. This gives the range of *m* and *n* as, respectively, $0 < n < 2^{M-m} - 1$ and $1 < m < M$.

DWT operates two sets of function viewed as high-pass and low-pass filters. The original time series are passed through high-pass and low-pass filters and down sampled by two (i.e throwing away every second data point) (Deka and Prahalada, 2012). After passing the signal through high pass and low pass filters, detailed (D_1, D_2,…., D_n, which are high frequency components of the original signal) and approximation coefficients (A_1, A_2,….A_n, which are low frequency components of the original signal), respectively, are obtained.

3. Artificial neural network:

Neural network are inter connected group of artificial neurons, that can be used as computational model for information processing based on connectionist approach to computation. These are non–linear statistical data modeling tools, which can be used as model to develop a good relationship between input and output. Mathematically, an ANN can be treated as universal approximators having an ability to learn from examples without the need of explicit physics. In most of the hydrologic time series modeling three layer-feedforward type of artificial neural network is used (Tayfur, 2006), which is shown in **Fig. 1**. In a feedforward ANN, the input quantities are fed into the input layer neurons that, in turn, pass them on to the hidden layer neurons after multiplication by connection weights. A hidden layer neuron adds up the weighted input received from each input neuron and associates it with a bias. The result is then passed on through a transfer function to produce an output. In the present

ISSN 2229-5518

study, backpropagation algorithm with Lavenberg-Marquardt (LM) learning function and Tangent Sigmoid as transfer function were used. The ANN model implementation was carried out in MATLAB routine. The ANN was trained using LM technique because it is more powerful and faster than the conventional gradient descent technique (Kisi, 2009).

4. Case study:

The study area is located in the international river Brahmaputra main stream within India. Pandu station is selected for the study. The Brahmaputra River which originates in Tibet region in China is the fourth largest river in the world in terms of average discharge at mouth, with a flow of 19,830 cumec (Goswami, 1985). The hydrologic regime of the river responds to the seasonal rhythm of the monsoons and to the freeze-thaw cycle of the Himalayan snow. The discharge is highly fluctuating in nature. Discharge per unit drainage area in the Brahmaputra Basin River is among the highest of major rivers of the world. The basin lies between latitudes $24^0 13'$ and $31^0 30'9$ North and longitudes 82^0 and $96^0 49'$ East. The catchment area upto Pandu station is 500,000 km^2. The location of the Pandu discharge gauging stations is shown in the **Fig. 2**.

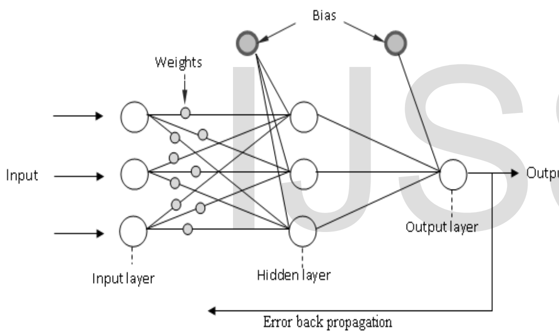

Fig.1 Basic ANN model structure

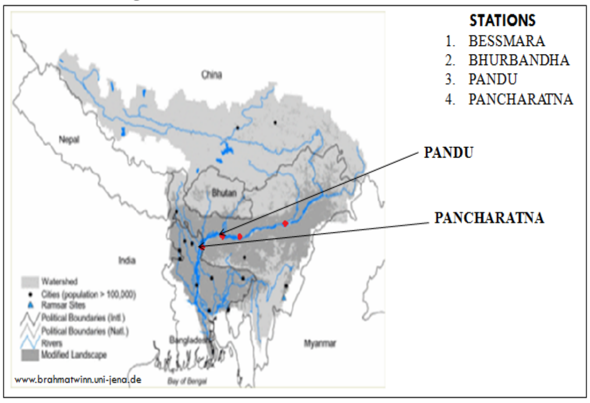

Fig. 2. Location of the gauging site

Ten year daily flow data from January 1990 to December 1999 of Pandu station were used in the study. First seven years (70 %) and last three years (30 %) data were used for training and testing, respectively. The main advantage of using first 70 % data as training data is that the values of maximum and minimum discharge, Q_{max} and Q_{min}, respectively, for testing data lies in the range of training data set. Hence there may not be extrapolation difficulties in estimation of high and low discharge values. **Table 1** depicts the statistical parameters of the river flow data. In the table Q_{mean}, Q_{max}, Q_{min}, S_d and C_x denotes the mean, maximum, minimum, standard deviation and skewness, respectively. The time series data before going through the network are usually normalized between 0 and 1 (Nourani et al., 2009). So the time series flow data is normalized by dividing the discharge value by the maximum one.

Table 1: Statistical analysis for training, testing, and all data sets

Data set	Q_{mean} (m^3/s)	Q_{max} (m^3/s)	Q_{min} (m^3/s)	S_d (m^3/s)	C_x
Training	17802	58200	3008	10509	0.51
Testing	19387	54100	5567	10672	0.70
All	18258	58200	3008	10580	0.56

5. Efficiency criteria:

Following measures of evaluation have been used to compare the performance of models.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Q_{obs} - Q_{com}\right| \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(Q_{obs} - Q_{com}\right)^2}{N}} \quad (7)$$

$$MRE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|Q_{obs} - Q_{com}\right|}{Q_{obs}} \times 100 \quad (8)$$

$$B = \frac{\sum_{i=1}^{N} Q_{comp}}{\sum_{i=1}^{N} Q_{obs}} \quad (9)$$

$$SI = \frac{RMSE}{\sum_{i=1}^{N} \bar{Q}_{obs}} \quad (10)$$

where *RMSE*, *MAE*, *MRE*, *B*, *SI*, *N*, Q_{obs}, Q_{com}, and $\bar{Q}_{obs}$ are root-mean squared error (*RMSE*), mean absolute error (*MAE*), mean relative error (*MRE*), bias (*B*), scatter index (*SI*), number of observations, observed data, computed values, mean of observed data, respectively. The *RMSE* provide a good measure of goodness of fit at high flows, whereas *MAE* measures a more balanced perspective of the goodness of the fit at moderate flows (Karunanithi et al. 1994). Models with low *RMSE* are treated as best models. The BIAS (*B*) provides a good measure of whether the model is overestimating (B>1) or underestimating (B<1) compared to observed values. *B* = 1 indicates non-biased model performance. Scatter index is scalable measure of model precision. The

ISSN 2229-5518

model becomes more precise as the *SI* reaches zero (Salvatore et al. 2012).

6. Model development:

In this study, ANN and WANN models has been developed using daily time series flow data. Flows up to previous four time steps were taken as input variables. To predict 2, 3 and 4 day ahead flow values the input combinations employed were i) Q_t, $Q_{(t-1)}$, ii) Q_t, $Q_{(t-1)}$, $Q_{(t-2)}$, and iii) Q_t, $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$, respectively. Where Q_t is current day discharge value and $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$ are one day, 2 day and 3 day past discharge value. The input and output scenarios are same for both ANN and WANN models.

6.1. ANN model:

At the first stage, a multilayer perceptron (MLP) feed forward backpropagation ANN models without data pre-processing were developed to forecast river discharge. Each MLP was trained with 1–20 hidden neurons in the hidden layer with Levenberg–Marquardt back propagation as the training algorithm with tansig activation function to optimize the parameters which were sufficient to produce results. In this study, ANN models have been developed for lead times 2, 3, and 4 day and the best model (with low *RMSE*) for various lead times are shown in **Table 2.**

6.2. Wavelet Artificial Neural Network (WANN) Model:

In the second stage, WANN model using db4 and db5 [which are represented as WANN(db4) and WANN(db5), respectively] mother wavelets, were developed. The schematic diagram of WANN model is shown in **Fig. 3. Figure 4** shows db4 and db5 wavelets. For any Daubechies wavelet of order *N*, the support width is equal to 2*N* – 1 (Misiti, M. et al. 2010). Hence, for db4 and db5 wavelets support widths are 7 and 9, respectively, as shown in **Fig. 4.** As all hydrological data are observed at discrete time interval, in all WANN models, discrete wavelet transform (DWT) was used for processing of time series data in the form of approximations and details at different levels so that gross and small features of a signal can be separated (Deka and Prahalada, 2012). These coefficients of details and approximations were used as input to ANN component of the hybrid model to obtain predicted output. For decomposition Mallat algorithm (Mallat 1989) was used. The output signals were kept as original series without decomposition.

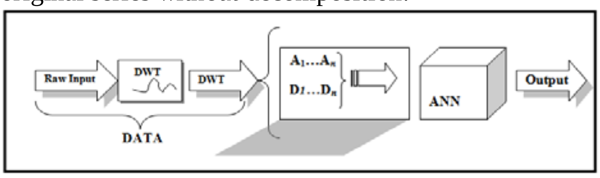

Fig. 3. Schematic diagram of the proposed WANN model

A multilayer perceptron (MLP) feedforward backpropagation ANN was trained with 2 to 15 neurons in hidden layer using Levenberg-Marquardt training algorithm with tansig as activation function. Fourteen models, each for 2day, 3 day and 4 day lead times, were developed using the Daubechies function of order 4 and 5 and multiresolution level ranging from 1 to 7 for each order of the function ($db_i l_j$, i = 4, 5 and j = 1,2,..,7). In which *db* refers to the Daubechies function, *i* is the order of the function, *l* is the resolution and *j* is the level of resolution. For a model with *j* resolution levels there are *j+1* decomposed time series (one approximation A_j and *j* detailed i.e. D_1, D_2, ….., D_j). The output layer has only one neuron which is the discharge value for the given lead time.

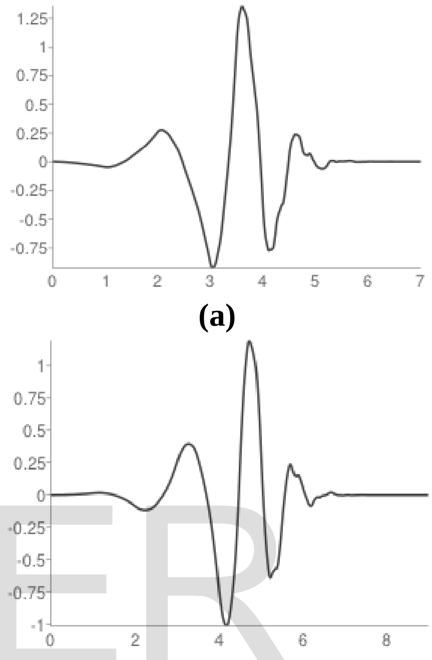

Fig. 4. (a) db4, (b) db5 wavelet function

7. Results and discussion:

Ten year daily flow data from January 1990 to December 1999 of Pandu station on Brahmaputra River in the North-East region of India were used for model application. The proposed WANN model with db4 and db5 mother wavelets was compared with conventional ANN model. The results of WANN models with db4 and db5 are also compared. Also the effect of decomposition level on model efficiency was studied. Models were tested for various lead times of 2, 3 and 4 day.

At the first stage, a multilayer perceptron (MLP) feed forward backpropagation ANN model without data pre-processing was developed to forecast river discharge. Each MLP was trained with 1–20 hidden neurons in the hidden layer with Levenberg–Marquardt back propagation as the training algorithm with tansig activation function to optimize the parameters. In this study, ANN models have been developed for various lead times for different input scenarios as mentioned earlier and the best model (with low RMSE) results for various lead times in training and testing period are shown in **Table 2.**

It can be seen from **Table 2** that for ANN model in training and testing period the values of root mean squared error (RMSE), mean absolute error (MAE), mean relative error (MRE), BIAS (B) and scatter index (SI) changes with respect lead time forecast. The RMSE increases from 1636.55 cumec and 1636.18 cumec for 2 day lead time to 2743.17 cumec and 2727.18 cumec for 4 day lead time, for training and testing periods, respectively. Also MAE values increases from 974.65 to 1773.4 cumec for training period and from 993.00 to 1792.17 cumec for testing period, for 2 day and 4 day lead times, respectively. Also MRE values increases from 5.67 % to 10.09 % for training period and from 4.50 % to 8.28 % for testing period, for 2 day and 4 day lead times, respectively. The SI increases from 0.092 and 0.084 for 2 day lead time to 0.154 and 0.140 for 4 day lead time, for training and testing periods, respectively. While BIAS values are very close to 1 for both training and testing period. The model efficiency is decreasing with increase in lead time. This may be due to significant fluctuations of the data around mean values such as high standard deviation **(Table 1)**. **Table 2** also shows optimum ANN structure (e.g. for 3 day lead time, the meaning of 3-11-1 is that, 3 neurons in input layer, 11 neurons in hidden layer and 1 neuron in output layer).

In the second stage, WANN models with db4 and db5 as mother wavelet, which are denoted as WANN(db4) and WANN(db5), respectively, for lead time of 2, 3 and 4 day were developed by combining wavelet transform and artificial neural network. In all the WANN models, discrete wavelet transform (DWT) was used for processing of time series data in the form of approximations and details at different levels so that gross and small features of a signal can be separated. These coefficients of details and approximations were used as input to ANN component of the hybrid model to obtain predicted output. In the present study, the time series data were decomposed up to 7^{th} level. Similar to ANN models, a multilayer perceptron (MLP) feedforward ANN was trained with 2 to 15 hidden neurons using Levenberg-Marquardt training algorithm with tansig as activation function. After applying the WANN models to forecast Brahmaputra River flow, the performances of models were evaluated using RMSE, MAE, MRE, BIAS, and SI statistics for training and testing periods. The statistical performance measurements of the results of daily river flow forecasting for training and testing sets of 2, 3, and 4 days ahead forecasting models are shown in **Table 3 through 5**, respectively.

As it clear from the results of **Table 3** that, for the training set of data of 2 day ahead forecasting models, model M12 (db5*l*5) with the Daubechies wavelet of 5^{th} order and 5 level of decomposition have the best performance with lowest RMSE (720.43 cumec), MAE (455.51 cumec), second lowest MRE (2.97 %), and SI (0.041) and BIAS equal to1.00. On the other hand, for testing data set of 2 day ahead, same model i.e. M12 (db5*l*5) has lowest RMSE (774.72 cumec), MAE (470.21 cumec), SI (0.039), second lowest MRE (2.21 %), and BIAS equal to 0.999. From **Table 4** it is clear that, for the training set of data of 3 day ahead forecasting models, M26 (db5*l*5) model has low RMSE (727.98 cumec), MAE (446.72 cumec), MRE (2.58 %), SI (0.041) and BIAS equal to 0.999. On the other hand, for testing set, model M27 (db5*l*6) has lowest RMSE (784.13 cumec), MAE (470.08 cumec), SI (0.040), and third lowest MRE (2.26 %) and BIAS equal to 0.999. For training data set of 4 days ahead forecasting models (**Table 5**), model M41 (db5*l*6) has lowest RMSE (907.57 cumec), SI (0.051), and BIAS equal to 1.001, while M42 (db5*l*7) has lowest MAE (546.53 cumec) and MRE (3.23 %). On the other hand, for testing data set, M40 (db5*l*5) model has lowest RMSE (911.97 cumec), MAE (557.09 cumec), MRE (2.68 %), SI (0.046) and BIAS equal to 1.000.

It can be seen from **Table 3 through 5** that for all the WANN models the values of RMSE, MAE, MRE, BIAS and SI changes with respect lead time forecast. This decrease in model efficiency with increase in lead time may due to increase in uncertainty. Time series and scatter plots are shown in **Fig. 5** and **Fig. 6**, respectively, for 4 day lead time showing comparison between ANN and WANN(db5).

In comparison with regular ANN model all WANN models has given better results for all lead times. The WANN model was found more accurate because wavelet transform decompose the non-stationary time series data into several stationary approximation and detailed time series. In hybrid WANN model, wavelet transform takes care of non-stationarity while ANN handles non-linearity. In the flow time series, approximation coefficient denotes deterministic component (such as trend) whereas detailed coefficients denotes the stochastic component and noise. The decomposed stationary time series can exhibit the fine structures of flow time series, reduce the interference between the deterministic components and the stochastic components, and increase the stability of the data variation. Therefore, the prediction accuracy is improved.

In the present study, the results obtained by WANN models using db4 and db5 as mother wavelets are also compared. In comparison with WANN(db4), WANN(db5) model has given better results. In almost all the signals, high frequency exists only for short duration, while low frequency spans over almost entire length of the signal. The wavelets having wider support are capable of capturing low frequencies which spans over almost entire length of the signal. On the other hand, wavelets having smaller support are capable of capturing high frequencies. As mentioned earlier, db4 and db5 wavelets have support widths of 7 and 9, respectively. In short, the db5 wavelet has a reasonable support and also has good time-frequency localization property and these together enable the model to capture both the underlying trend as well as the short term variablities in the time series better than the db4 wavelet based forecast model.

This study also aims at investigating the effect of decomposition level on WANN model efficiency. In the WANN models, the results obtained for different lead times had undergone different decomposition levels starting from 1 to 7. In all lead time analysis,

Table 2: Values of statistical parameters for ANN models for various lead times

Lead time (day)	Training period					Testing period					Optimum ANN structure
	RMSE	MAE	MRE	BIAS	S.I.	RMSE	MAE	MRE	BIAS	SI	
2	1636.55	974.65	5.67	1.001	0.092	1636.18	993.00	4.50	0.993	0.084	2-8-1
3	2262.62	1389.6	7.67	0.999	0.127	2254.51	1423.98	6.39	0.991	0.116	3-11-1
4	2743.17	1773.4	10.09	1.002	0.154	2727.18	1792.17	8.28	0.988	0.140	4-19-1

Table 3: Values of statistical parameters for WANN models
Lead time: 2 day

Model type	Daubechies order and decomposition level	Training period					Testing period					Optimum ANN structure
		RMSE	MAE	MRE	BIAS	S.I.	RMSE	MAE	MRE	BIAS	SI	
M1	db4/1	1469.43	870.12	4.75	1.000	0.082	1553.88	925.33	4.12	0.992	0.080	4-2-1
M2	db4/2	1054.99	647.89	3.80	1.000	0.059	1150.42	660.90	3.03	0.992	0.059	6-2-1
M3	db4/3	807.45	529.92	3.66	1.000	0.045	871.39	549.15	2.76	0.994	0.045	8-2-1
M4	db4/4	727.89	507.51	3.97	1.002	0.041	842.58	568.61	3.17	0.988	0.043	10-2-1
M5	db4/5	723.54	488.40	3.59	1.001	0.040	779.20	509.81	2.63	0.999	0.041	12-2-1
M6	db4/6	722.81	491.05	3.64	1.000	0.040	794.83	524.36	2.74	0.998	0.041	14-2-1
M7	db4/7	717.38	483.57	3.59	1.001	0.040	805.61	536.13	2.91	0.997	0.041	16-2-1
M8	db5/1	1478.73	868.50	4.88	1.000	0.083	1521.88	899.95	3.98	0.992	0.078	4-2-1
M9	db5/2	1126.53	701.75	4.78	1.001	0.063	1105.43	667.74	3.15	0.995	0.057	6-2-1
M10	db5/3	816.09	527.68	3.48	0.999	0.046	873.91	534.26	2.63	0.995	0.045	8-2-1
M11	db5/4	741.49	461.91	**2.97**	1.000	0.041	824.55	477.71	**2.21**	0.997	0.042	10-2-1
M12	db5/5	**720.43**	**455.51**	3.23	**1.000**	0.041	**774.72**	**470.21**	2.33	**0.999**	**0.039**	12-2-1
M13	db5/6	739.58	480.16	3.26	1.001	0.041	801.52	475.64	2.27	0.998	0.041	14-2-1
M14	db5/7	739.38	468.72	3.09	0.999	0.041	807.13	473.05	2.24	0.998	0.041	16-2-1

Table 4: Values of statistical parameters for WANN models
Lead time: 3 day

Model type	Daubechies order and decomposition level	Training period					Testing period					Optimum ANN structure
		RMSE	MAE	MRE	BIAS	S.I.	RMSE	MAE	MRE	BIAS	SI	
M15	db4/1	2034.75	1247.3	6.79	1.001	0.114	2167.35	1372.66	6.09	0.989	0.111	6-2-1
M16	db4/2	1314.27	845.16	5.18	1.001	0.074	1260.99	808.31	3.80	0.994	0.065	9-2-1
M17	db4/3	890.09	573.58	3.49	1.000	0.050	952.42	577.72	2.71	0.998	0.049	12-2-1
M18	db4/4	860.35	559.78	3.60	0.999	0.048	937.84	552.77	2.66	0.997	0.048	15-2-1
M19	db4/5	872.36	573.29	3.71	1.001	0.049	925.38	557.69	2.71	0.998	0.047	18-2-1
M20	db4/6	855.84	549.61	3.41	1.000	0.048	928.20	548.72	2.55	0.998	0.048	21-2-1
M21	db4/7	854.76	547.20	3.42	0.999	0.048	950.72	548.10	2.59	0.997	0.049	24-2-1
M22	db5/1	2031.40	1226.8	6.55	0.998	0.114	2109.51	1312.74	5.75	0.990	0.108	6-3-1
M23	db5/2	1113.05	731.44	4.44	1.001	0.062	1137.23	736.44	3.46	0.995	0.058	9-3-1
M24	db5/3	756.94	463.44	2.56	0.999	0.042	848.19	514.54	2.43	1.000	0.044	12-3-1
M25	db5/4	729.57	452.10	2.62	0.999	0.041	791.78	474.78	2.24	0.999	0.041	15-3-1
M26	db5/5	**727.98**	**446.72**	**2.58**	0.999	**0.041**	787.11	472.75	**2.22**	0.999	0.040	18-3-1
M27	db5/6	735.84	452.62	2.67	0.999	0.041	**784.13**	**470.08**	2.26	0.999	**0.040**	21-3-1
M28	db5/7	783.60	527.88	3.85	1.001	0.044	824.68	516.47	2.58	0.997	0.042	24-3-1

Table 5: Values of statistical parameters for WANN models
Lead time: 4 day

Model type	Daubechies order and decomposition level	Training period					Testing period					Optimum ANN structure
		RMSE	MAE	MRE	BIAS	S.I.	RMSE	MAE	MRE	BIAS	SI	
M29	db4/1	2622.39	1712.6	10.41	1.009	0.147	2660.76	1764.44	7.95	0.988	0.136	8-2-1
M30	db4/2	1684.13	1037.4	5.99	0.999	0.094	1705.27	1062.52	4.92	0.989	0.087	12-2-1
M31	db4/3	1048.64	685.48	4.36	1.002	0.059	1075.87	661.02	3.22	0.997	0.055	16-2-1
M32	db4/4	987.43	618.57	3.73	1.001	0.055	1029.18	608.59	2.82	0.998	0.053	20-2-1
M33	db4/5	984.67	637.70	4.05	0.999	0.055	1003.16	626.22	3.04	0.9980	0.051	24-2-1
M34	db4/6	990.65	647.20	4.20	1.002	0.055	1034.08	655.49	3.14	1.000	0.053	28-2-1
M35	db4/7	1000.96	635.14	3.98	1.001	0.056	1054.22	623.69	2.99	0.997	0.054	32-2-1
M36	db5/1	2596.07	1619.8	9.27	1.003	0.146	2586.61	1659.72	7.41	0.987	0.133	8-2-1
M37	db5/2	1640.08	1014.8	5.79	1.001	0.092	1661.74	1029.26	4.73	0.992	0.085	12-2-1
M38	db5/3	980.04	619.74	3.96	1.001	0.055	999.23	621.25	3.11	0.997	0.051	16-2-1
M39	db5/4	935.45	605.48	4.17	1.006	0.052	938.45	587.69	2.85	1.000	0.048	20-2-1
M40	db5/5	914.17	567.40	3.65	1.001	0.051	**911.97**	**557.09**	**2.68**	**1.000**	**0.046**	**24-2-1**
M41	db5/6	**907.57**	558.07	3.55	1.001	0.051	942.25	569.61	2.71	0.999	0.048	28-2-1
M42	db5/7	918.04	**546.53**	**3.23**	0.999	0.051	978.32	587.81	2.76	0.996	0.050	32-2-1

Note: RMSE and MAE are in cumec unit. MRE is in %.

there was an increasing trend in the model performance from low decomposition levels towards higher one. At the stage where optimum value (low RMSE) is reached, the performance started to decline (see **Table 3 through Table 5**). The result corresponding to optimum value in testing period was considered to be the optimum decomposition level as illustrated in **Fig.** 7, and it was considered as the best model among the WANN models. In testing period, the study of **Table 3 through Table 5** depicts that, for 2, 3 and 4 day lead times the optimum level of decomposition was found to be the 5th, 6th, and 5th, respectively.

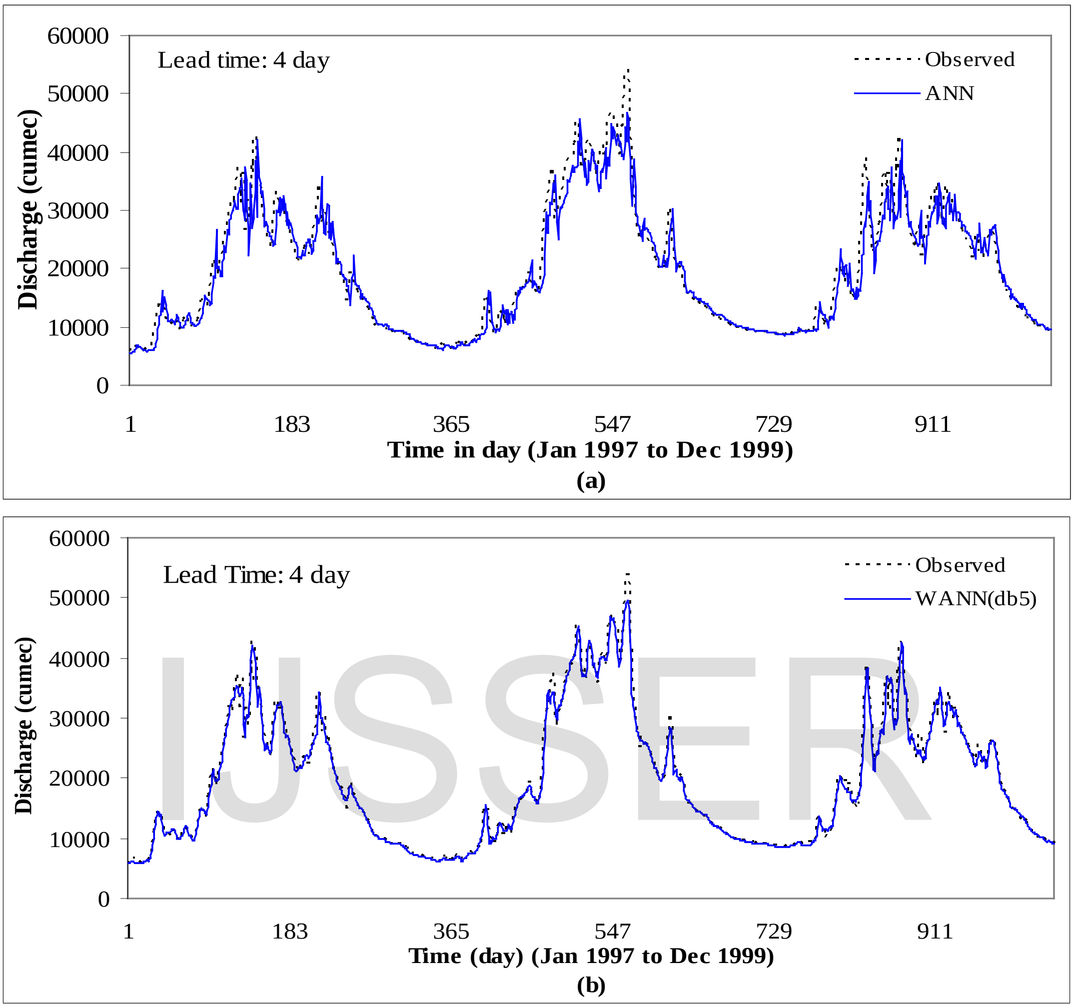

Fig. 5. Time series comparison between (a) observed and ANN, (b) observed and WANN(db5), for lead time 4 day during testing period

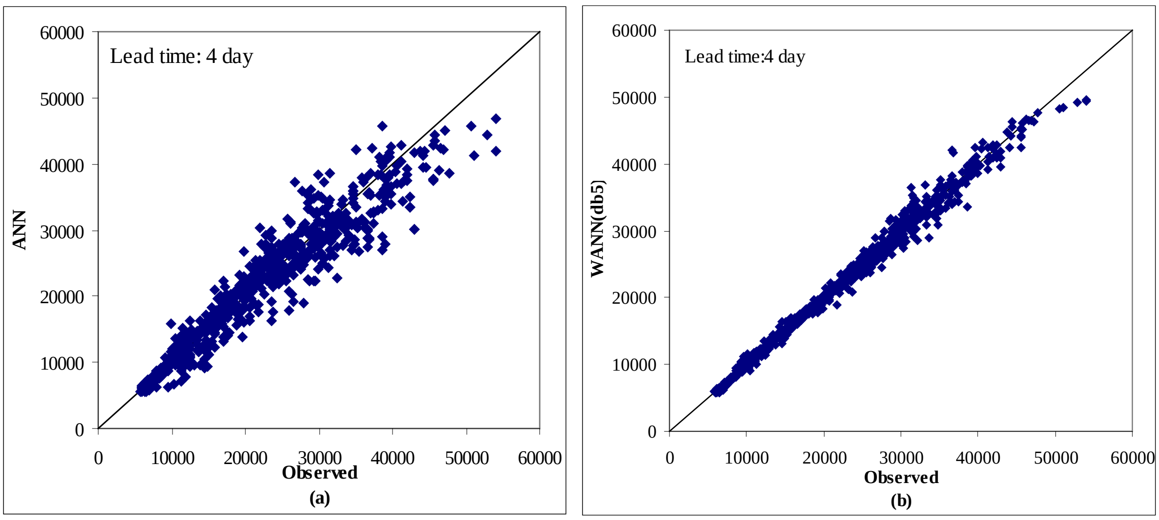

Fig. 6. Scatter plot (a) observed and ANN, (b) observed and WANN(db5), for lead time 4 day during testing period

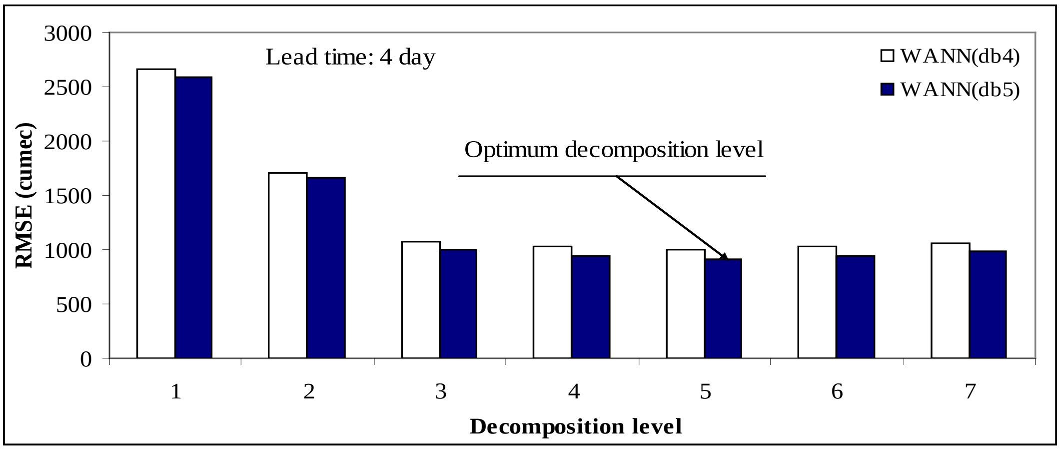

Fig. 7. Effect of decomposition level on RMSE (lead time: 4 day)

Based on the results, it was noticed that the number of decomposition levels had considerable impact on the results. Since the random parts of original time series were mainly in the first resolution level, obviously the prediction errors were also mainly in the first resolution level. Thus, the errors were not increased proportionately with the resolution number. Also, with increase in decomposition level the number of neurons in the input layer also increased, hence ANN was exposed to large number of weights attached with higher input nodes during training. Hence, the higher adaptability was achieved for input– output mapping.

8. Conclusions:

In this study, a hybrid model of wavelet and ANN (WANN) has been developed using Daubechies wavelets of order 4 (db4) and 5 (db5) as mother wavelets to forecast flow at Pandu station located on Brahmaputra River located in North-East region of India for lead times 2, 3, and 4 day. The discrete wavelet transform was used for decomposing the non-stationary time series flow data into stationary time series. These decomposed stationary time series were fed as input to ANN to give the predicted output.

The accuracy of WANN models has been investigated for river flow forecasting. The WANN model results were compare with conventional ANN model. The accuracy of WANN models with db4 and db5 wavelets was found to be much better than ANN model for all lead times.

In the present study, for WANN models with db4 and db5 mother wavelets, the models efficiency increased with decomposition level up to a certain optimum level, there after it was decreased. For WANN models the 5th and 6th level was found to be the optimum level of decomposition.

WANN model with db5 wavelet has given slightly better results compared to WANN model with db4 wavelet for all lead times. This was due the fact that, db5 wavelet has a reasonable support and also has good time-frequency localization property.

Acknowledgement:

The authors greatly acknowledged the support provided by Water Resource Department, Govt. of Assam, India, for providing the necessary data for the analysis.

Reference:

[1] Adamowski J., F. “Development of short- term river flood forecasting method for snowmelt driven floods based on wavelet and cross-wavelet analysis.” Journal of Hydrology, 353, 247-266, 2008.

[2] Adamowski, J., and Sun, K. “Development of a coupled wavelet transform and neural network method for flow forecasting of non-perennial rivers in semi-arid watersheds.” Journal of Hydrology, 390, 85-91, 2010.

[3] ASCE Task Committee. “Artificial neural networks in hydrology II: Hydrologic application.” J. Hydrologic Engg., 5(2), April, 124-137, 2000b.

[4] Cannas, B., Fanni, A., Sias, G., Tronchi, S., Zedda, M. K.. “River flow forecasting using Neural Networks and Wavelet Analysis.” EUG (2005), European Geosciences Union, Vienna, Ausrtia, vol.7, 24-29, 2005.

[5] Dawson, C., W., and Wilby, R., L.. “Hydrological modelling using artificial neural network.” Progress in Physical Geography, 25, 1 (2001), 80-108, 2001.

[6] Deka, P. C., and Prahlada, R. “Discrete wavelet neural network approach in significant wave height forecasting for multistep lead time.” Ocean Engineering, 43, 32-42, 2012.

[7] Goswami, D. C.. “Brahmaputra River, Assam India: Physiographic, basin denudation and channel aggradation”. Water Resources Research, 21, 959-978, 1985.

[8] Jain, S. K., and Chalisgaonkar, D. “Setting up stage-discharge relations using ANN.” ASCE J. Hydrologic Engg., 5(4), October, 428-433, 2000.

[9] Jothiprakash, V., and Garg, V. “Reservoir Sedimentation Estimation Using Artificial Neural Network.” ASCE J. of Hydrologic Engineering, 14 (9), 1035-1040, 2009.

[10] Karunanithi, N., Grenney, W. J., Whitley, D., Bovee, K. "Neural networks for river flow prediction" J. of computing in Civil Engineering, 8(2), 201-220, 1994.

[11] Khandekar, S. D., and Deka, P. C. "Wavelet-neural network conjunction model in flow forecasting of sub-Himalayan river Brahmaputra." Int. J. of Civil Engg. and Technology, 3 (2), 415-425, 2012.

[12] Kisi, O. "Neural Networks and Wavelet Conjunction Model for Intermittent Stream flow Forecasting." Journal of Hydrologic Engineering, 14(8), 773–782, 2009.

[13] Li, X., Ding, J, Li, H. "Wavelet analysis and its potential application to hydrology and water resources." J. Sichuan Union University (Engineering science); vol. 1(4), 49-52, 1997.

[14] Li, X., Ding, J., Li, H. "Combing neural network models based on wavelet transform." J. of Hydraulic, vol.2, 1-4, 1999.

[15] Maheswaran, R. and Khosa, R. "Comparative study of different wavelets for hydrologic forecasting." Computers and Geosciences, 46, 284-295, 2012.

[16] Mallat, S., G. "A theory for multiresolution signal decomposition: The wavelet representation." IEEE Trans. Pattern Anal. Mach. Intell., 11(7), 674-693, 1989.

[17] Misiti, M., Misiti, Y., Oppenheim, G., and Poggi, J. Wavelet toolbox: For use with MATLAB, The MathWorks, Natic,Mass, 2010.

[18] Nourani, V., Komasi, M., Mano, A. "A Multivariate ANN–Wavelet Approach for Rainfall-Runoff Modeling." Water Resources Manage, 23, 2877-2894, 2009.

[19] Nourani, V., Alami, T. M., Aminfar, M. H. "A combined neural-wavelet model for prediction of Ligvanchai watershed precipitation." Elsevier, Engineering Applications of Artificial Intelligence, 22, 466–472, 2009.

[20] Nourani, V., Kisi,O., Komasi, M. "Two hybrid artificial intelligence approaches for modeling rainfall – runoff process." Journal of Hydrology, 402, 41-49, 2011.

[21] Partal, T., and Kisi, O. "Wavelet and neuro-fuzzy conjunction model for precipitation forecasting." J. of Hydrology, 342, 199-212, 2007.

[22] Partal, T., and Cigizoglu, H., K. "Estimation and forecasting of daily suspended sediment data using wavelet-neural networks." J. of Hydrology, 358, 317-331, 2008.

[23] Raghuwanshi, N. S., Singh, R., and Reddy, L. S. "Runoff and Sediment Yield Modeling Using Artificial Neural Networks: Upper Siwane River, India." ASCE J. Hydrologic Engg., 11(1), January, 71-79, 2006.

[24] Rajaee, T., Nourani, V., Kermani, M. Z., Kisi, O. "River suspended sediment load prediction: Application of ANN and wavelet conjunction model." ASCE J. Hydrologic Engg., 16(8), August, 613-627, 2011.

[25] Ramana, R. V., Krishna, B., Kumar, S. R., Pandey, N.G. "Monthly rainfall prediction using wavelet neural network analysis." Water Resources Manage, 27, 3697-3711, 2013.

[26] Salvatore, C. P., Adamowski, J., and Oron, G. "Forecasting urban water demand via wavelet denoising and neural network models. Case study: City of Syracuse, Italy." Water Resource Manage, 26, 3539-3558, 2012.

[27] Smith, J., and Eli, R. N. "Neural-network models of rainfall-runoff process." ASCE J. of Water Resources Planning and Management, November/December, 121(6), 499-508, 1995.

[28] Tayfur, G., and Singh, V. P. "ANN and Fuzzy logic models for simulation event based rainfall runoff." ASCE J. Hydraulic Engg., 132 (12), 1321-1330, 2006.

[29] Tokar, A. S., and Markus, M. "Precipitation-runoff modeling using artificial neural networks and conceptual models." ASCE J. Hydrologic Engg., 5 (2), April, 156-161, 2000.

[30] Wang, W., Ding, J., Xiang, H. "The multi-time scale analysis of hydrological time series with wavelet transform." J. of Sichuan university, 35(4),14-17, 2002.

[31] Wang, W., Hu, S., Li, Y. "Wavelet transform method for synthetic generation of daily streamflow." Water Resources Management, 25:41-57, 2011.

[32] Zhou, H.C., Peng, Y., Liang, G-H. "The research of monthly discharge predictor corrector model based on wavelet decomposition." Water Resources Management, 22; 217-227, 2008.