International Journal of Advance Research in Science and Engineering
Volume No.07, Special Issue No.02, February 2018
www.ijarse.com
IJARSE
ISSN: 2319-8354

Improved Wavelet Neural Network Modeling of Daily Rainfall Forecast

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ABSTRACT

Rainfall is one of the most key parameter effective hydrologic processes in runoff prediction and water management. Hybrid data-driven models have become appropriate predictive patterns in various hydrological forecast scenarios. Especially, meteorology has witnessed that there is a need for a much better approach to handle weather-related parameters intelligently. The wavelet neural network (WNN) has been widely used for modeling different kinds of nonlinear systems including rainfall forecasting. Wavelet combines with Artificial Neural Networks (ANN) to solve different kinds of problems, especially efficient in rainfall prediction. In this paper, a model based on wavelet neural networks (WNN) decomposition is proposed as a learning tool to predict consecutive daily rainfalls on accounts of the preceding events of rainfall data. The WNN models with different transfer functions and different wavelets have been applied to daily rainfall data of Patna City, Bihar. The calibration and validation performance of the models is evaluated with appropriate statistical methods. The results of daily rainfall series modeling indicate that the performances of wavelet neural network models are more effective than the ANN models.

Keywords: Decomposition, Neural network, Rainfall, Training, Wavelet.

I. INTRODUCTION

Rainfall prediction is one of the challenge problems in hydrology due to meteorological and geographical factors with uncertainties. The sophisticated nature of rainfall behavior makes it difficult to assess. In light of this, several dynamical forcings are related to rainfall's periodicity − climatological, topographical factors, and others. Therefore, most conventional rainfall modelings usually take into account these factors [43, 44]. It is the dependence of these climatological and topographical factors in rainfall forecasting that affect the accuracy of the prediction. In this paper, accurate rainfall prediction based only on the collected historical data of rainfall is proposed. Among several rainfall forecasting techniques based on stochastic or deterministic methods and computational approaches, there has been an excess of evidence in literatures that artificial neural networks (ANNs) are increasingly used for hydrological modeling especially in rainfall prediction (45, Bustain. et al.2007). The ability of representing non-linear complex relation from a set of known input and output variables is the significant role of ANNs. Particularly, ANNs are non-linear modeling tools that do not require an explicit mathematical formulation of the physical relationship between variables. Among different kinds of ANNs, a feedforward backpropagation has gained much interest in weather forecasting [47]. While the significant progress has been made in wavelet analysis due to its capability of isolating the periodicity in a time series, wavelet transform can be applied for various problems, e.g., shortterm load forecasting [51], rainfall prediction [50]. Therefore, an application of wavelet decomposition with artificial neural network is proposed in this study for forecasting n-day daily rainfall. Overall performance efficiency of ANN predictions are summarized in terms of coefficient of determination, and root mean squared error. In the past decade, wavelet theory has been introduced to signal processing analysis. In recent years, the wavelet transform has been successfully applied to wave data analysis and other ocean engineering applications [28, 35, 20]. The time-frequency character of long-term climatic data is investigated using the continuous wavelet transform technique [26, 36, 27] and wavelet analysis of wind wave measurements obtained from a coastal observation tower [20]. [12] used wavelet denoising method in linear perturbation models (LPMs) and simple linear models (SLMs) for rainfall and runoff time series data. [40] used a new wavelet transform method for developing the synthetic generation of daily stream flow sequences. [41] used a combination of neural networks and wavelet methods to predict underground water levels. Venkataramana. et al. (2013) used wavelet neural network to prediction the monthly rainfall using minimum and maximum temperature. Dynamical Recurrent Neural Network (DRNN) on each resolution scale of the sunspot time series resulting from the wavelet decomposed series with the Temporal Recurrent Back propagation (TRBP) algorithm [6]. There are some appreciable studies of wavelet transform based neural network models [38, 2, 9, 21, 39]. The wavelet transform is also integrated with multiple linear regression [25, 22, 23] and support vector machine approach 24]. [1] compared the relative performance of the coupled wavelet-neural network models (WA–ANN) and regular artificial neural networks (ANN) for flow forecasting at lead times of 1 and 3 days for two different non-perennial rivers in semiarid watersheds of Cyprus. [24] investigated the performance of the wavelet regression (WR) technique in daily river stage forecasting and determined the WR model was improved combining two methods, discrete wavelet transform and a linear regression model. [33] developed a method for discrete wavelet decomposition and an improved wavelet modeling framework, WMF for short was proposed for hydrologic time series forecasting. By coupling the wavelet method with the traditional AR model, the Wavelet-Autoregressive model (WARM) is developed for annual rainfall prediction [50]. [31] used a conjunction model (wavelet-neuro-fuzzy) to forecast the Turkey daily precipitation. The observed daily precipitations are decomposed to some sub series by using Discrete Wavelet Transform (DWT) and then appropriate sub series are used as inputs to neuro-fuzzy models for forecasting of daily precipitations. Each of these studies showed that different black box models trained or calibrated with decomposed data resulted in higher accuracy than the single models that were calibrated with an undecomposed and noisy time series. In this paper, a Wavelet Neural Network (WNN) model, which is the combination of wavelet analysis and ANN, has been proposed for rainfall forecast Patna station, India. Using back propagation artificial neural network based on wavelet decomposition well simulated the change of annual runoff with annual average temperature and annual precipitation [52].Wavelet decomposition method is proposed to link to ANFIS and ANN models use the rainfall forecast [53]. Demonstrate wavelet- adaptive neuro-fuzzy inference system (WANFIS) with split data model and WANFIS-modified time series model have been used to forecast river water levels with one-day lead time.

II. WAVELET ANALYSIS

The wavelet analysis is an advanced tool in signal processing that has attracted much attention since its theoretical development [16]. Its use has increased rapidly in communications, image processing and optical engineering applications as an alternative to the Fourier transform in preserving local, non-periodic and multiscaled phenomena. The difference between wavelets and Fourier transforms is that wavelets can provide the exact locality of any changes in the dynamical patterns of the sequence, whereas the Fourier transforms concentrate mainly on their frequency. Moreover, Fourier transform assume infinite length signals, whereas wavelet transforms can be applied to any kind and any size of time series, even when these sequences are not homogeneously sampled in time[3]. In general, wavelet transforms can be used to explore, denoise and smoothen time series which aid in forecasting and other empirical analysis. Wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. In wavelet analysis, the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end, the result will be a collection of time-frequency representations of the signal, all with different resolutions. Because of this collection of representations we can speak of a multiresolution analysis. By decomposing a time series into time-frequency-space, one is able to determine both the dominant modes of variability and how those modes vary in time. Wavelets have proven to be a powerful tool for the analysis and synthesis of data from long memory processes. Wavelets are strongly connected to such processes in that the same shapes repeat at different orders of magnitude. The ability of the wavelets to simultaneously localize a process in time and scale domain results in representing many dense matrices in a sparse form.

Discrete Wavelet Transform (DWT)

The basic aim of wavelet analysis is to determine the frequency (or scale) content of a signal and then it assess and determine the temporal variation of this frequency content. This property is in complete contrast to the Fourier analysis, which allows for the determination of the frequency content of a signal but fails to determine frequency-time dependence. Therefore, the wavelet transform is the tool of choice when signals are characterized by localized high frequency events or when signals are characterized by a large numbers of scale variable processes. Because of its localization properties in both time and scale, the wavelet transform allows for tracking the time evolution of processes at different scales in the signal.

The wavelet transform of a time series $f(t)$ is defined as

$$f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\varphi\left(\frac{t-b}{a}\right)dt \tag{1}$$

where φ (t) is the basic wavelet with effective length (*t*) that is usually much shorter than the target time series *f*(*t*). The variables '*a'* is the scale or dilation factor that determines the characteristic frequency so that its variation gives rise to a spectrum and '*b'* is the translation in time so that its variation represents the 'sliding' of the wavelet over *f*(*t*). The wavelet spectrum is thus customarily displayed in time-frequency domain. For low scales *i.e.* when $|a|<<1$, the wavelet function is highly concentrated (shrunken compressed) with frequency contents mostly in the higher frequency bands. Inversely, when $|a|>>1$, the wavelet is stretched and contains mostly low frequencies. For small scales, we obtain thus a more detailed view of the signal (also known as a "higher resolution") whereas for larger scales we obtain a more general view of the signal structure. The original signal $X(n)$ passes through two complementary filters (low pass and high pass filters) and emerges as two signals as Approximations (A) and Details (D). The approximations are the high-scale, low frequency components of the signal. The details are the low-scale, high frequency components. Normally, the low frequency content of the signal (approximation, A) is the most important part. It demonstrates the signal identity. The high-frequency component (detail, D) is nuance. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components.

Mother Wavelt

There are a number of basis functions that can be used as the mother wavelet for Wavelet Transformation. Since the mother wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting Wavelet Transform. Therefore, the details of the particular application should be taken into account and the appropriate mother wavelet should be chosen in order to use the Wavelet Transform effectively. The choice of the mother wavelet depends on the data to be analyzed. It should reflect the type of features present in the time series. Within each family of wavelets (such as the Daubechies family) are wavelet subclasses distinguished by the number of coefficients and by the level of iteration. Wavelets are classified within a family most often by the number of vanishing moments. This is an extra set of mathematical relationships for the coefficients that must be satisfied, and is directly related to the number of coefficients. For example, within the Coiflet wavelet family are Coiflets with two vanishing moments and Coiflets with three vanishing moments. Figure1 illustrates the several different wavelet families.

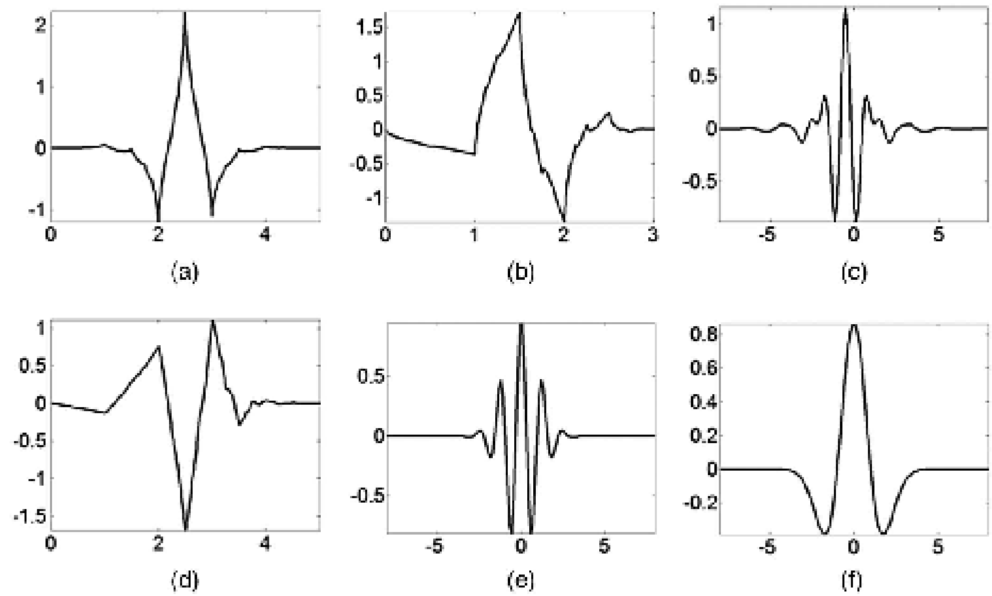

Figure 1. (a) Coif1 wavelet; (b) db2 wavelet; (c) Meyer wavelet; (d) Sym3 wavelet; (e) Morlet wavelet; (f) Mexican wavelet.

The Daubechies and Morlet wavelet transforms are the commonly used mother wavelets. Daubechies wavelets exhibit good trade-off between parsimony and information richness, produce identical events across the observed time series, and appear in so many different fashions that most prediction models are unable to recognize them well [7]. Daubechies wave lets are complex functions, i.e., they include both amplitude and phase information. For time series with steps, one would choose a boxcar-like mother wavelet function such as the Haar wavelet (db1).Morlet wavelets, on the other hand, have a more consistent response to similar events but have the weakness of generating many more inputs than the Daubechies wavelets for the prediction models. For more smoothly varying time series, one would choose a smoother mother wavelet function such as the Morlet wavelet. In this study, first the wavelet function is derived from the family of Daubechies wavelets with order 5 (db5) used for the selection of best architectures of ANN and MLR. Thus, input data were decomposed using Daubechies wavelet function (mother wavelets) and sub–time series components [time series of 2-month mode (D1),4-month mode (D2), 8-month mode (D3), and approximation mode (A3) were obtained for the calibration and validation period]. Second, the input for the selected architectures was taken from the decomposed series by nine different kinds of wavelet transforms, i.e., Haar wavelet; Daubechies Reverse biorthogonal , Biorthogonal Symlets and Coiflets; and irregular wavelets.

Method of Network Training

Levenberg-Marquardt method (LM) was used for training of the given network. It is a modification of the classic Newton algorithm for finding an optimum solution to a minimization problem. In practice, LM is faster and finds better optima for a variety of problems than most other methods. The method also takes advantage of the internal recurrence to dynamically incorporate past experience in the training process [14].

The Levenberg-Marquardt Algorithm (LMA) is given by

$$X_{k+1} = X_k - (J^T J + \mu I)^{-1} J^t e \quad (2)$$

where, X is the weights of neural network, J are the Jacobian matrix of the performance criteria to be minimized, 'μ' is a learning rate that controls the learning process and 'e' is residual error vector. If scalar μ is very large, the above expression approximates gradient descent with a small step size, while if it is very small; the above expression becomes Gauss-Newton method using the approximate Hessian matrix. The Gauss-Newton method is faster and more accurate near an error minimum. Hence we decrease μ after each successful step and increase only when a step increases the error. LMA has great computational and memory requirements, and thus it can only be used in small networks. It is faster and less easily trapped in local minima than other optimization algorithms.

III. PERFORMANCE CRITERIA

The performance of various models during calibration and validation were evaluated by using the statistical indices: the Root Mean Squared Error (RMSE) and Coefficient of Efficiency (COE).

IV. STUDY AREA

Patna, capital of Bihar state is situated on the bank of river Ganga with Latitude 25^0 $37'$ and longitude 85^0 $10'$ and has a mean elevation of 49.68m above the MSL. Patna and its upland is sandwiched between the high Himalayan ranges in the far north and the high tracts of Chhotanagpur in the south. Due to its location with relation to latitude and other features, Patna has a humid subtropical climate with hot summers from late March to early June, the monsoon season from late June to late October and a mild winter from November to February. Highest temperature ever recorded is 46.6^0C (in 1966) lowest ever is 2.3^0C (in 2003) and highest daily rainfall was 250.8 mm (in 1987). Patna has a temperate climate, suitable for urban living. Patna is a linear city and is about 30 Km long from east to west and 5-7 Km from north to south. The city is situated between the river Ganga in the north, river Punpun in the south and river Sone in the west as shown in figure 2.

V. DEVELOPMENT OF WAVELET NEURAL NETWORK MODEL

The original time series was decomposed into Details and Approximations to certain number of sub-time series $\{D_1, D_2 \ldots D_p, A_p\}$ by wavelet transform algorithm. These play different role in the original time series and the behavior of each sub-time series is distinct [38]. So the contribution to original time series varies from each successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components, tested using different scales from 1 to 10 with different sliding window amplitudes. In this context, dealing with a very irregular signal shape, an irregular wavelet, the Daubechies wavelet of order 5 (DB5), has been used at level 3. Consequently, D_1, D_2, D_3 were detail time series, and A_3 was the approximation time series.

An ANN was constructed in which the sub-series $\{D_1, D_2, D_3, A_3\}$ at time t are input of ANN and the original time series at $t + T$ time are output of ANN, where T is the length of time to forecast. The input nodes for the WNN are the decomposed subsets of antecedent values of the rainfall are presented in Table 1. The Wavelet Neural Network model (WNN) was formed in which the weights are learned with Feed forward neural network with Back Propagation algorithm. The number of hidden neurons for BPNN was determined by trial and error procedure.

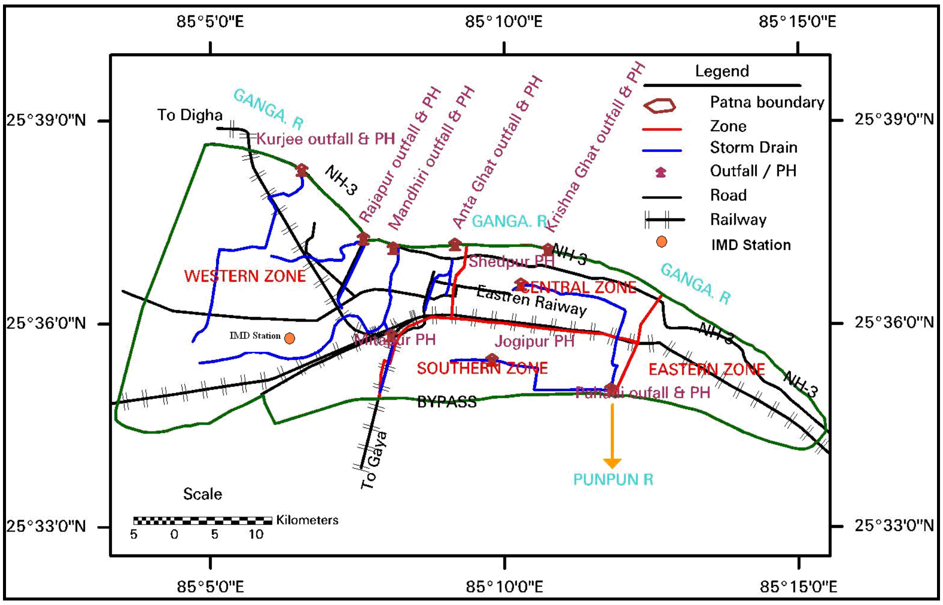

Figure 2. Study area and location of IMD station of Patna.

Table 1. Model Inputs

Model 1	X (t) = f (x [t-1])
Model 2	X (t) = f (x [t-1], x [t-2])
Model 3	X (t) = f (x [t-1], x [t-2], x [t-3])
Model 4	X (t) = f (x [t-1], x [t-2], x [t-3], x [t-4])
Model 5	X (t) = f (x [t-1], x [t-2], x [t-3], x [t-4], x [t-5])
Model 6	X (t) = f (x [t-1], x [t-2], x [t-3], x [t-4], x [t-5] x [t-6])
Model 7	X (t) = f (x [t-1], x [t-2], x [t-3], x [t-4], x [t-5] x [t-6] x [t-7])

VI. RESULTS AND DISCUSSION

To forecast the rainfall at Patna gauging station of IMD Patna (Figure 2), the daily rainfall data of 29 years from 1975 to 2004 was used. The first twenty years (1975-95) data were used for training of the model, and the remaining nine years (1995-2004) data were used for validation. The model inputs (Table 1) were decomposed by wavelets and decomposed sub-series were taken as input to ANN. ANN was trained using back propagation with LM algorithm. A standard MLP with a tangent sigmoidal, logarithmic sigmoidal and linear transfer function for the hidden layer and linear transfer function for the output layer were used in the analysis. The optimal number of hidden neurons was determined as three by trial and error procedure. The performance of tangent sigmoidal, logarithmic sigmoidal and linear transfer function for input the hidden layer and linear transfer function for the output layer models estimated to forecast the rainfall was presented in table2.

Table 2. Model performance.

Wavelet-db5	Tangent sigmoid		Logarithmic sigmoid		Linear	
	RMSE	%COE	RMSE	%COE	RMSE	%COE
Model-1	8.70	48.87	8.70	48.87	8.31	53.31
Model-2	4.95	83.45	4.95	83.40	5.46	79.88
Model-3	4.26	87.76	4.49	86.35	4.87	83.97
Model-4	3.69	90.81	4.04	88.96	4.05	88.91
Model-5	3.57	91.40	3.57	91.40	3.78	90.37
Model-6	**3.02**	**93.85**	**3.14**	**93.32**	**3.17**	**93.24**
Model-7	4.43	86.77	3.23	92.96	3.02	93.84

From Table 2, it is found that low RMSE values (3.02mm to 8.70mm) and coefficient of efficiency (48.87% to 93.85%) for WNN models with input hidden layer transfer function and it was the found the tangent sigmoidal function is optimum when compared with logarithmic sigmoidal and linear transfer function and same as shown in figure 3. It is further analyzed data with optimum input hidden layer transfer function and linear transfer function output layer with different mother wavelet used to forecast the daily rainfall. It has been observed that coiflet5 WNN model estimated the peak values of rainfall to a reasonable accuracy (peak rainfall in the data series is 205.4 mm) from table 3. Further, it is observed that the coiflet5 WNN model having two antecedent values of the rainfall time series estimated minimum RMSE (1.63mm) and coefficient of efficiency (>98%) during the validation period. The model 6 of WNN was selected as the best-fit model to forecast the rainfall one-day in advance.

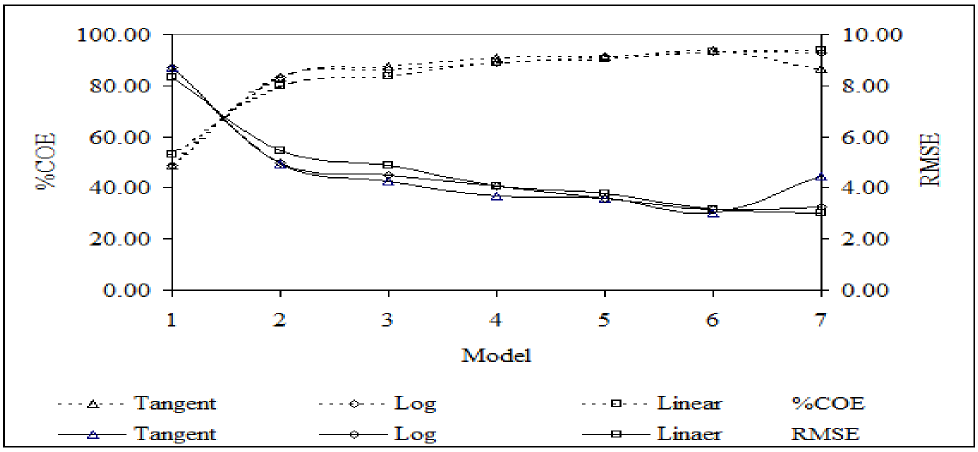

Figure 3. WNN model performance with with input hidden layer transfer function.

Figure 4 shows the observed and modeled graph for WNN model 6 during calibration and validation respectively. It is found that values modeled from WNN model properly matched with the observed values. It is evident that the performance of WNN model 6 to forecasting the rainfall.

Table 3. Performance of the different mother wavelet used to forecast the daily rainfall

Wavelet	Tangent sigmoid transfer function													
	Calibration							Validation						
Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
RMSE														
haar	9.39	7.88	6.83	6.85	6.56	6.59	6.19	9.54	9.63	7.64	7.50	8.31	**7.73**	8.20
db5	7.73	4.24	3.67	3.31	3.00	2.65	2.48	8.70	4.95	4.26	3.69	3.57	**3.02**	4.43
rbio1.5	9.22	6.10	5.88	5.15	4.95	4.40	4.40	8.93	7.02	6.31	5.95	5.83	**6.94**	7.03
bior2.4	8.35	5.22	5.13	4.03	3.75	3.40	3.27	9.11	5.10	4.98	4.97	4.44	**4.03**	4.15
bior4.4	8.46	4.99	4.44	3.73	3.48	3.10	2.91	8.56	5.32	4.37	4.38	3.87	**3.55**	4.09
sym4	8.31	4.90	4.12	3.52	3.23	2.66	2.85	8.99	5.72	4.51	4.12	4.20	**3.04**	3.35
sym8	8.47	4.56	3.65	2.50	2.29	1.84	1.76	8.35	5.53	4.00	3.24	2.59	**2.16**	2.70
coif3	8.15	4.45	3.71	2.81	2.51	2.13	2.03	9.39	5.78	3.88	3.59	2.84	**2.73**	3.02
coif5	8.02	4.21	3.26	2.30	2.27	1.58	1.44	8.11	4.47	3.56	3.05	2.62	***1.63***	1.79
%COE														
haar	43.80	60.39	70.29	70.08	72.57	72.31	75.57	38.43	37.36	60.59	62.00	53.34	**59.68**	54.57
db5	61.90	88.56	91.42	93.00	94.25	95.54	96.08	48.87	83.45	87.76	90.81	91.40	**93.85**	86.77
rbio1.5	45.83	76.30	77.97	83.13	84.40	87.66	87.65	46.04	66.69	73.13	76.05	77.04	**67.49**	66.62
bior2.4	55.60	82.63	83.23	89.67	91.06	92.62	93.20	43.82	82.42	83.21	83.28	86.68	**89.02**	88.38
bior4.4	54.38	84.17	87.42	91.12	92.27	93.87	94.59	50.44	80.90	87.07	87.02	89.88	**91.50**	88.72
sym4	55.96	84.73	89.21	92.12	93.36	95.51	94.83	45.40	77.88	86.24	88.54	88.07	**93.74**	92.40
sym8	54.26	86.75	91.52	96.02	96.66	97.85	98.02	52.85	79.31	89.16	92.93	95.47	**96.86**	95.08
coif3	57.73	87.36	91.22	94.96	95.97	97.10	97.37	40.34	77.45	89.85	91.30	94.55	**94.95**	93.86
coif5	59.03	88.69	93.25	96.64	96.72	98.40	98.67	55.51	86.52	91.43	93.70	95.38	***98.21***	97.83

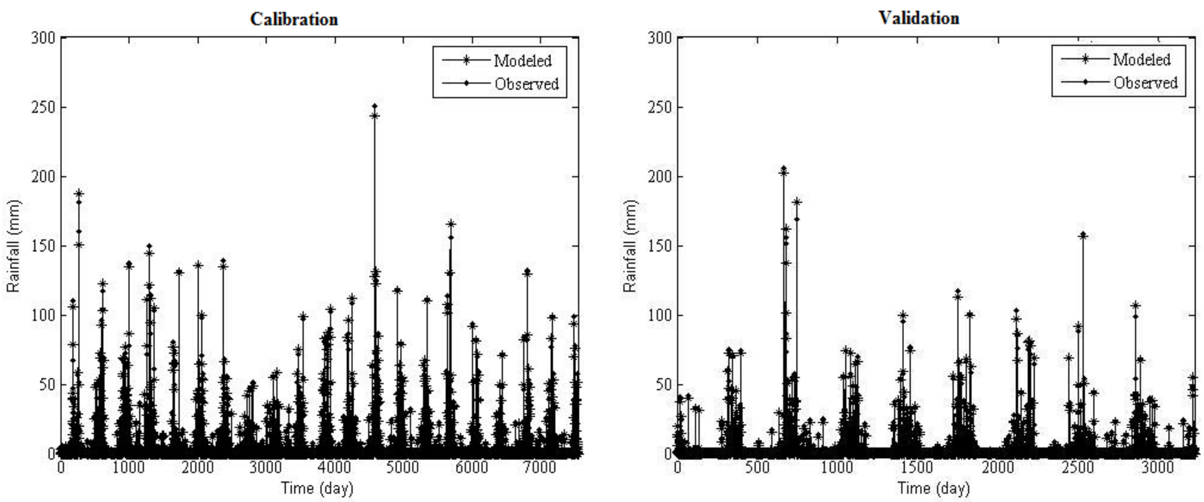

Figure 4. WNN model 6 during calibration and validation

The distribution of error along the magnitude of rainfall computed by WNN model 6 during the validation period has been presented in Figure 5. it was observed that the estimation of peak rainfall error is minimum. Figure 6 shows the scatter plot between the observed and modeled rainfall by WNN model 6. It was observed that the rainfall forecasted by WNN model 6 were very much close to the 45 degrees line. From this analysis, it was worth to mention that the performance of WNN model 6 is the best model in forecasting the rainfall in one-day advance.

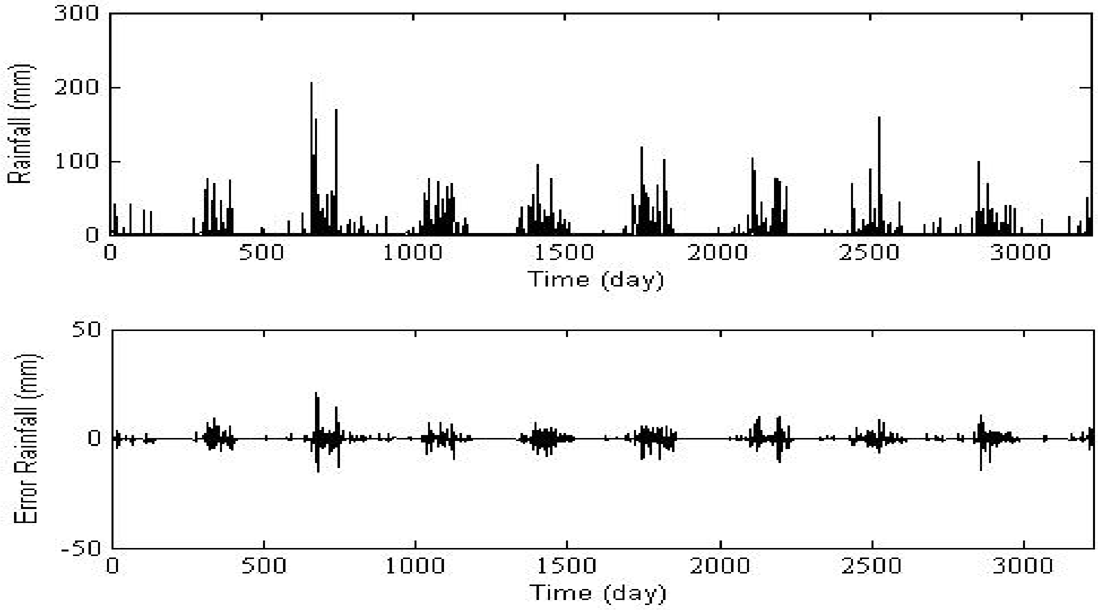

Figure 4. Distribution of error WNN model 6 during the validation period.

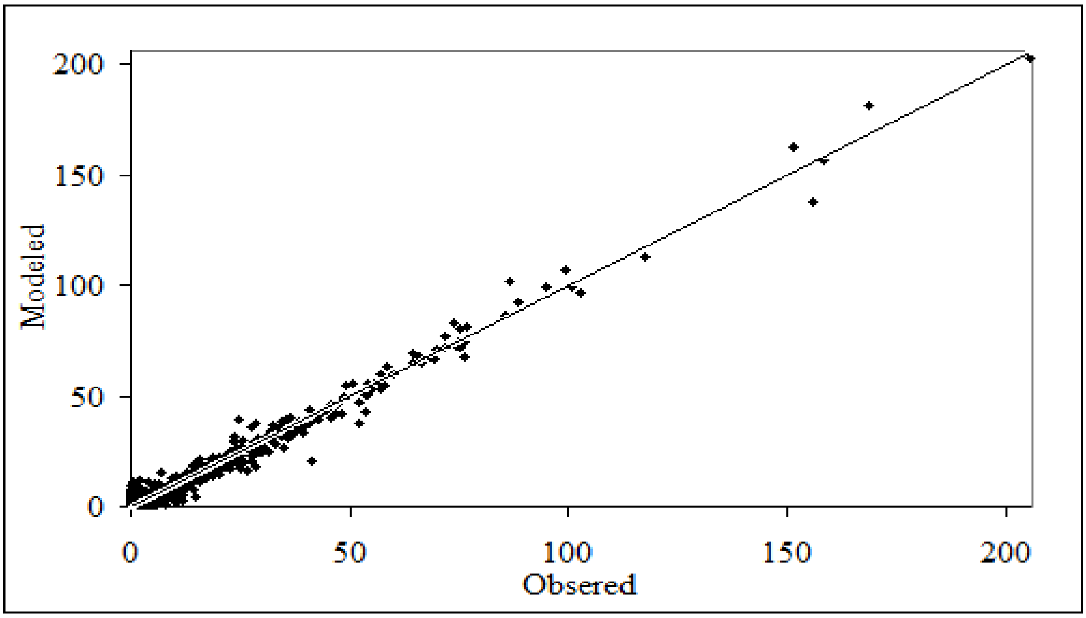

Figure 5. Scatter plot between the observed and modeled rainfall by WNN model 6

VII. CONCLUSIONS

Daily rainfall data obtained from IMD, Patna rain gauge station been analyzed using wavelet-transform based artificial neural network. The proposed model is a combination of wavelet analysis and artificial neural network. Wavelet decomposes the time series into multilevel of details and it can adopt multiresolution analysis and effectively diagnose the main frequency component of the signal and abstract local information of the time series. The proposed WNN model with different input hidden transfer function and linear transfer function for out hidden layer has been applied to daily rainfall of Patna rain gauge station and finds the optimal input hidden layer transfer function. The time series data of rainfall was decomposed into sub series by DWT. Appropriate sub-series of the variable used as inputs to the ANN model and original time series of the variable as output. Model parameters are calibrated using 44 years of data and rest of the data is used for model validation. Data analysis was with optimal input hidden layer transfer function with different mother wavelets, it was found that efficiency index is more than 98% for coiflet 5 WNN model 6. It may be noted that hydrological data used in the WNN model has been decomposed in details and approximation, which may lead to better capturing the rainfall processes. The study only used data from one rain gauge station and further studies using more rain gauges data from various areas may be required to strengthen these conclusions.

REFERENCES

[1] Adamowski, J. & Sun, K. (2010). 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(1-2): 85-91*.

[2] Anctil F, Tape D. G. (2004). An exploration of artificial neural network rainfall-runoff forecasting combined with wavelet decomposition. *J. Environ. Eng. Sci., 3: 121-128*.

[3] Antonios, A. and Constantine, E. V. (2003) "Wavelet Exploratory Analysis of the FTSE ALL SHARE Index," Preprint submitted to Economics Letters University of Durham, Durham.

[4] ASCE Task Committee, 2000(a) "Artificial Neural Networks in hydrology-I: Preliminary Concepts," Journal of Hydrolo- gic Engineering, Vol. 5, No. 2, pp. 115-123.

[5] ASCE Task Committee, 2000(b) "Artificial Neural Networks in Hydrology-II: Hydrologic Applications," *Journal of Hydrologic Engineering*, Vol. 5, No. 2, pp. 124- 137.

[6] Aussem, A. and Murtagh, F. (1997) "Combining Neural Network Forecasts on Wavelet Transformed Series," *Connection Science, Vol. 9, No. 1, pp. 113-121*.

[7] Benaouda, D., Murtagh, F,. Starck, J. L. and Renaud, O. (2006) "Wavelet-Based Nonlinear Multiscale Decomposition M- odel for Electricity Load Forecasting," *Neurocomputing, Vol. 70, No. 1-3, pp. 139-154*.

[8] Bhakar, S. R., R. V. Singh, Neeraj, C., and A.K. Bansal, (2006) "Stochastic modeling of monthly rainfall at kota region" *ARPN Journal of Engineering and Applied Sciences, Vol.1, No. 3, October, 36-44.*

[9] Cannas, B., Fanni, A., See, L. & Sias, G. (2006). Data preprocessing for river flow forecasting using neural networks: Wavelet transforms and data partitioning. Physics and Chemistry of the Earth, PartsA/B/C, 31(18): 1164-1171.

[10] Carlson, R.F., A.J.A. MacCormick, and D.G. Watts. (1970). Application of linear models to four annual streamflowseries, *Water Resour. Res., 6,4, pp 1070-1078*

[11] Chinchorkar, S. S., G. R. Patel and F. G. Sayyad. (2012). "Development of monsoon model for long range forecast rainfall explored for Anand (Gujarat-India) *International Journal of Water Resources and Environmental Engineering Vol. 4(11), pp. 322-326.*

[12] Chou, C. (2011) " A Threshold Based Wavelet Denoising Method for Hydrological Data

[13] Modelling" *Water Resources Management, 25:1809–1830*

[14] Coulibaly, P., Anctil, F., Rasmussen, P.and Bobee, B. (2000) "A Recurrent Neural Networks Approach Using Indices of Low-Frequency Climatic Variability to Forecast Regional Annual Runoff," *Hydrological Processes, Vol. 14, No. 15, pp. 2755-2777.*

[15] Dawson, D.W. & Wilby, R. (2001). Hydrological modeling using artificial neural networks. prog. Phys. Geogr 25(1), 80– 108.

[16] Grossmann, A. and Morlet, J. (1984) "Decomposition of Hardy Functions into Square Integrable Wavelets of Constant shape," *SIAM Journal on Mathematical Analysis, Vol. 15, No. 4, pp. 723-736.*

[17] Hagan, M.T. & Menhaj, M.B. (1994). Training feed forward networks with Marquardt algorithm. IEEE Transactions on Neural Networks 5, 989-993.

[18] Hettiarachchi, P., Hall, M.J. & Minns, A.W. (2005). The extrapolation of artificial neural networks for the modeling of rainfall-runoff relationships. *Journal of Hydroinformatics 7(4), 291–296*

[19] Hsu, K. L., Gupta, H. V., and Sorooshian, S. (1995). ''Artificial neural network modeling of rainfall-runoff process.'' *Water Resour. Res., 31(10), 2517–2530.*

[20] Huang, M.C. (2004). Wave parameters and functions in wavelet analysis, Ocean Engineering 31:1, pp 111-125

[21] Kisi, O. (2008). Stream flow forecasting using neuro-wavelet technique. Hydrological Processes, 22(20): 4142-4152.

[22] Kisi, O. (2009). Neural networks and wavelet conjunction model for intermittent stream flow forecasting. Journal of Hydrologic Engineering, 14(8): 773-782.

[23] Kisi, O (2010). Wavelet regression model for short-term stream flow forecasting. J. Hydrol., 389: 344-353.

[24] Kisi (2011) "Wavelet Regression Model as an Alternative to Neural Networks for River Stage Forecasting" *Water Resources Management, 25(2), 579-600*

[25] Kucuk, M., Agiralioğlu, N. (2006). Wavelet regression technique for stream flow prediction. *J. Appl. Stat., 33(9): 943-960.*

[26] Lau, K.M., H.Y. Weng. (1995). Climate signal detection using wavelet transform: how to make a time seriessing, Bull. Amer. Meteor. Soc. 76, pp 2391-2402

[27] Mallat, S. (1998). A wavelet tour of signal processing, San Diego, CA: Academic Press.

[28] Massel, S.R. (2001). Wavelet analysis for processing of ocean surface wave records, Ocean Engineering 28, pp 957-987

[29] Matalas, N.C., and J.R. Wallis. (1971) "Statistical properties of multivariate fractional noise process", *Water Resour.Res., 7, pp 1460-1468*

[30] Moustris, K. P. and Ioanna K. Larissi (2011) "Precipitation Forecast Using Artificial Neural Networks in Specific Regions of Greece" *Water Resour Management, 25:1979–1993*

[31] Partal, T. & Kisi, O. (2007). Wavelet and neuro-fuzzy conjunction model for precipitation forecasting. *Journal of Hydrology. 342, 199-212.*

[32] Rumelhart, D. E., Hinton G. E. and Williams, R. J. (1986) "Learning Representations by Back-Propagating Errors," *Nature, Vol. 323, No. 9, pp. 533-536*

[33] Sang, Y (2013) "Improved wavelet modeling framework for hydrologic time series forecasting" *Water resources management, DOI 10.1007/s11269-013-0316-1*

[34] Tantanee, S., Patamatammakul, S., Oki, T., Sriboonlue, V. & Prempree, T. (2006). Coupled wavelet-autoregressive model for annual rainfall prediction. *Journal of Environmental hydrology 13(18), 1-8.*

[35] Teisseire, L.M., M.G. Delafoy, D.A. Jordan, R.W. Miksad, and D.C. Weggel. (2002). "Measurement of the instantaneous characteristics of natural response modes of a spar platform subjected to irregular wave loading", *International Journal of Offshore and Polar Engineering 12:1, pp 16-24*

[36] Torrence, C., and G.P. Compo. (1997). A practical guide to wavelet analysis, Bull. Amer. *Meteor. Soc. 79:1, pp 61-78*

[37] Valencia, D.R., and J.C. Schaake, Jr. (1973). Disaggregation processes in stochastic hydrology, *Water Resour. Res.9:3, pp 580-585*

[38] Wang, D. and Ding, J. (2003) "Wavelet Network Model and Its Application to the Prediction of Hydrology," *Nature and Science, Vol. 1, No. 1, pp. 67-71.*

[39] Wang, W., Jin, J. & Li, Y. (2009). Prediction of inflow at Three Gorges dam in Yangtze River with wavelet network model. *Water Resources Management, 23(13): 2791-2803.*

[40] Wang, W., S,H. and Y, Li.(2011) "Wavelet Transform Method for Synthetic Generation of Daily Stream flow" *Water Resources Management (2011) 25: 41-57*

[41] Wu, D. J., Wang, J and Teng, Y. (2004) "Prediction of Under-ground Water Levels Using Wavelet Decompositions and Transforms," *Journal of Hydro-Engineering, Vol. 5, pp. 34-39.*

[42] Yevjevich, V. (1972). Stochastic processes in hydrology, Water Resources Publications, Colorado.

[43] N. Q. Hung, M. S. Babel, S. Weesakul, and N. K. Tripathi, "An artificial neural network model for rainfall forecasting in Bangkok, Thailand," *Hydrology and Earth System Science, vol. 5, pp. 183-218, 2008.*

[44] S. Lee, S. Cho, and P. M. Wong, "Rainfall prediction using artificial neural networks," *Journal of Geographic Informaiton and Decision Analysis, vol. 2, pp. 233-242, 1998.*

[45] M. Nayebi, D. Khalili, S. Amin, and Sh. Zand-Parsa, "Daily stream flow prediction capability of artificial neural networks as influenced by minimum air temperature data," *Biosystems Engineering, vol. 95(4), pp. 557-567, 2006.*

[46] R. Bustami, N. Bessaih, C. Bong, and S. Suhaili, "Artificial neural network for precipitation and water level predictions of bedup river," *IAENG International Journal of Computer Science, vol. 34:2, 2007*.

[47] R. VanRullen, "The power of the feed-forward sweep," *Advances in Cognitive Psychology,* vol. 3, no. 1-2, pp. 167-176, 2007.

[48] R. Venkata Ramana , B. Krishna, S.R. Kumar, N. G. Pandey (2013) Monthly Rainfall Prediction using Wavelet Neural Network analysis *Journal of Water Resources Management. 27: 3697–3711(DOI 10.1007/s11269-013-0374-4).*

[49] S. Tantanee, S. Patamakul, T. Oki, V. Sriboonlue, and T. Prempree, "Downscaled rainfall prediction model (DRPM) using a unit disaggregation curve (UDC)," *Hydrol. Earth Sys. Sci. Discuss., vol. 2, pp. 543-568, 2005.*

[50] Y. Bi, J. Zhao, and D. Zhang, "Power load forecasting algorithm based on wavelet packet analysis," *International Conference on Power System Technology, vol. 1, issue 21-24, pp. 987-990, November 2004*.

[51] Xu. J, Chen. Y, Li. W, Nie. O, Song. C and Wei. C (2014). Integrating Wavelet Analysis and BPANN to Simulate the Annual Runoff with Regional Climate Change: A Case Study of Yarkand River, Northwest China*, journal of water Resources Management, Volume 28, Issue 9, pp 2523-2537.*

[52] Akrami. S. A, Nourani. V and Hakim. S.J.S (2014) Development of Nonlinear Model Based on Wavelet-ANFIS for Rainfall Forecasting at Klang Gates Dam. *Journal of water Resources Management. DOI 10.1007/s11269-014-0651-x, Online ISSN 1573-1650.*

[53] Sehgal. V, Sahay. R. R, and Chatterjee. C (2014).Effect of Utilization of Discrete Wavelet Components on Flood Forecasting Performance of Wavelet Based ANFIS Models. *Journal of water Resources Management. Volume 28, Issue 6, pp 1733-1749.*