International Journal of Earth Sciences and Engineering
ISSN 0974-5904, Volume 04, No 06 SPL, October 2011, pp 247-253


# Time Series Modeling in Water Resources Planning and Management

**Y. R. Satyaji Rao, B. Krishna, and P. C. Nayak**
*Deltaic Regional Centre, National Institute of Hydrology, Kakinada, Andhra Pradesh, India*

**ABSTRACT:** Most of the times continuous hydrological time series data availability is limited at the time of initiation of any new water resources project. In order to filling the missing gaps and prediction of future time series data, suitable and stable time series model is essentially required for successful water resources planning and management. Time series modelling procedures mostly fall within the framework of multivariate Auto Regressive Moving Average (ARMA) models. Traditionally, ARMA models have been widely used for water resources time-series modelling. However, these models do not attempt to represent the non-linear dynamics inherent in the hydrological process, and may not always perform well. Presently non-linear models such as neural networks are widely used for time series modelling. Artificial Intelligent (AI) techniques are extensively used for data driven modelling (DDM). This paper presents the potential of DDM in time series modeling, and presents case studies of their application to the monthly groundwater levels using Artificial Neural Networks (ANN) and daily stream flows using Wavelet Neural Networks (ANN) in Indian basins. The calibration and validation performance of these models (ANN and WNN) is evaluated with appropriate statistical indices. The results of monthly groundwater level and daily stream flow time series modelling indicated that the performances of ANN models are good for groundwater level modelling and WNN models are good at daily stream flow modelling. This is mainly due to the capability of wavelet to decompose a time series into multi levels of approximation and detail.

**KEY WORDS:** Time series, ANN, Wavelet, Stream flow, Groundwater levels, India

## INTRODUCTION

The application areas of time series analysis techniques are expanding with growing concerns about climate change and global warming. Most statistical analysis of hydrologic time series at the usual time scale encountered in water resources studies are based on these assumptions: the series in homogeneous, stationary, free from trends and shifts, non-periodic with no persistence. Time series modeling is mainly used to generate synthetic hydrologic records, to forecast hydrologic events, to detect trends and shifts in hydrologic records, and to fill in missing data and extend records. Time series modeling for either data generation or forecasting of hydrologic variables is an important step in the planning and operational analysis of water resources system. Machiwal and Jha (2006) have reviewed the present status of time series analysis of hydrologic data for water resources planning and management. They highlighted research needs in the filed of hydrology and climatology time series modeling which can serve as guidelines for both researchers and practicing water resources engineers or scientists. The climatological time series data is mainly precipitation, air and water temperature, Evapotraspiration etc. The hydrological time series data mainly stream flow, surface water quality, groundwater quality, groundwater levels etc.

Most of the time series modelling procedures fall within the framework of multivariate Auto Regressive Moving Average (ARMA) models. Traditionally, ARMA models have been widely used for modelling water resources time-series modelling (Maier *et al*., 1997). Time-series models are more practical than conceptual models because it is not essential to understand the internal structure of the physical processes that are taking place in the system being modelled. However, these models do not attempt to represent the nonlinear dynamics inherent in the hydrological process, and may not always perform well (Tokar *et al.*, 1999). Presently nonlinear models such as neural networks are widely used for time series modelling. Artificial Neural Networks (ANN) models were widely used to overcome many difficulties in time series modelling of hydrological variables (ASCE Task Committee, 2000a,b). However, it is also reported that ANN models are not very satisfactory in terms of precision because they consider only a few aspects of the behaviour of the time series (Wensheng, 2003). To raise the precision, a wavelet analysis has been used along with ANN. The advantage of the wavelet technique is that it provides a mathematical process for decomposing a signal into multiple levels of details and analysis. Wavelet analysis can effectively decompose signals into the main frequency components while also extracting local information of the time series. In recent years, wavelet theory has been introduced in the field of hydrology (Smith *et al*., 1998; Labat *et al*., 2000). Due to the similarity between wavelet decomposition and the single-hidden layer neural network, the idea of combining both wavelet and neural networks has resulted recently in formulation of the wavelet neural network, which has been used in various fields (Xiao *et al*., 2005).

In this paper, an application of ANN model for groundwater level time series modeling in shallow coastal aquifer and Wavelet Neural Network (WNN) model for stream flow time series modelling of four west-flowing rivers in India is presented.

## GROUNDWATER LEVEL MODELING

### Study Area and Data

The study area forms a part of the river Godavari delta system in East Godavari District of Andhra Pradesh in India. Geographically the study area, Central Godavari Delta, is located between $16^0$25’ N to $16^0$55’ N longitude and $81^0$44’E to $82^0$15’ E latitude with its hydrological boundaries as the river Gowthami Godavari in the East, the river Vasistha Godavari in the west and the Bay of Bengal in the South. The total geographical area comprises of 825 sq km. The study area receives more than half of its annual rainfall during south-west monsoon (*i. e.* June to September), while a large portion of the rest occurs in the month of October and November. The normal average rainfall is 1142 mm. The canal releases, average aerial rainfall, groundwater levels for three observation wells (Kattunga, Munganda and Cheyyeru) for a period of 1981-89 have been considered.

### Neural network structure

The most popular ANN architecture in hydrological modelling is the multilayer perceptron (MLP) trained with a BP algorithm (ASCE 2000a,b). A multilayer perceptron network consists of an input layer, one or more hidden layers of computation nodes, and an output layer. The number of input and output nodes is determined by the nature of the actual input and output variables. The number of hidden nodes, however, depends on the complexity of the mathematical nature of the problem, and is determined by the modeller, often by trial and error. The input signal propagates through the network in a forward direction, layer by layer. Each hidden and output node processes its input by multiplying each of its input values by a weight, summing the product and then passing the sum through a nonlinear transfer function to produce a result. For the training process, where weights are selected, the neural network uses the gradient descent method to modify the randomly selected weights of the nodes in response to the errors between the actual output values and the target values. This process is referred to as training or learning. It stops when the errors are minimized or another stopping criterion is met. The BPNN can be expressed as

$$Y = f(\Sigma W X - \theta) \qquad (1)$$

where X is the input or hidden node value; Y is the output value of the hidden or output node; *f*() is the transfer function; $W$ is weights connecting the input to hidden, or hidden to output nodes; and $\theta$ is the bias (or threshold) for each node.

### Methods of network training

In the current investigation, the Levenberg-Marquardt (LM) method was used for training the given network. LM is a modification of the classic Newton algorithm for finding an optimum solution to a minimization problem. The algorithm uses the second-order derivatives of the function so that better convergence behaviour is observed. In the ordinary gradient descent method, only the first-order derivatives are evaluated and the parameter change information is contained solely in the direction along which the cost is minimized. In practice, LM is faster and finds better optima for a variety of problems than most other methods (Hagan & Menhaj, 1994).

The Levenberg-Marquardt algorithm is given by:

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

where, X contains the weights of the neural network, J is 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 the 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 the 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 it only when a step increases the error. Levenberg-Marquardt has large computational and memory requirements, and thus it can only be used in small networks (Maier & Dandy, 1998). However, it is faster and less easily trapped in local minima than other optimization algorithms (Toth *et al*., 2000).

### Selection of network architecture

Based on a physical knowledge of the problem and statistical analysis, different combinations of antecedent values of the time series were considered as input nodes. The output node is the time series data to be predicted in one step ahead. Time series data was standardized for zero mean and unit variation, and then normalized into the range [0 to 1]. The activation functions used for the hidden and output layer were logarithmic sigmoidal and pure linear function respectively. For deciding the optimal hidden neurons, a trial and error procedure was started with two hidden neurons initially, and the number of hidden neurons was increased up to 10 with a step size of 1 in each trial. For each set of hidden neurons, the network was trained in batch mode to minimize the mean square error at the output layer. To check for any over-fitting during training, a cross-validation was performed by keeping track of the efficiency of the fitted model. The training was stopped when there was no significant improvement in the efficiency, and the model was then tested for its generalization properties.

As stated earlier, the major focus of the current study is being to investigate the potential of ANN approach in modeling water table fluctuation in the study area. The monthly averages of rainfall, canal releases and groundwater level were collected from the State Government. The data of all these parameters was available during the years 1981 to 1989. The canal releases data was available for Amlapuram main canal at Mukamalla Lock. The water table levels for 3 observation wells (Kattunga, Munganda and Cheyyeru) were collected. Present study employed a standard back propagation algorithm for training, and the number of hidden neurons is optimized by a trial and error procedure. Standard statistical procedure is followed to find out input vectors to the ANN model. The identified input vector for both the wells is presented in Table 1. The goodness of fit statistics considered are the root mean square error (RMSE) between the computed and observed runoff, coefficient of correlation (CORR), average absolute relative error (AARE) and percentage error in deepest level estimation (%EDLF).

**Table 1 Variables in the input vector to ANN**

| Munganda observation well | | Cheyyeru observation well |
|---|---|---|
| Rain | R(t−1), R(t−2), R(t−3), R(t−4) | R(t−1), R(t−4) |
| Release | Q(t−1) | Q(t−1), Q(t−3) |
| Kattunga | W(t−1) | W(t−1), W(t−2), W(t−4) |
| Munganda | W(t−1), W(t−2) | W(t−1), W(t−2) |
| Cheyyeru | | W(t−1) |

**RESULTS**

The statistical adequacies of the developed models for 1-month ahead forecasts for Munganda and Cheyyeru observation wells are summarized in Table 2. It is observed from Table 2 that the model performance is good, and forecasted the water levels with reasonable accuracy in terms of all the statistical indices during calibration and validation period. The correlation statistics that evaluates the linear correlation between the observed and the computed water table is consistent during calibration as well as validation period. The RMSE statistic, which is a measure of residual variance that shows the global goodness of fit between the computed and observed water levels, is very good as is evidenced by a low RMSE value (<0.4 m) during both training and validation. The AARE, which is a measure of accuracy that is less sensitive for the outlying values than the RMSE, is good in forecasting water levels during calibration and validation period. The %EDLF statistic is a measure of the percentage error in estimating deepest water level in data series, and the model predictions of deepest level is good as the estimation error is less than 10% (<0.5m). Figure 1 shows the predicted water level plots during validation period for Munganda and Cheyyeru observation well. In general, the results indicate the potential of neural computing techniques in forecasting the water levels at Munganda and Cheyyeru observation well one month in advance. While one-month ahead forecasts are good enough for water management in the aquifer, forecasts at higher lead-time are required for efficient planning of conjunctive use.

**Table 2 Performance indices for 1 month lead forecast models**

| Statistical Indices | Munganda Observation Well | | Cheyyeru Observation Well | |
|---|---|---|---|---|
| | Calibration | Validation | Calibration | Validation |
| CORR | 0.9416 | 0.8656 | 0.8636 | 0.7851 |
| RMSE | 0.2099 | 0.3747 | 0.218 | 0.3246 |
| AARE | 7.427 | 15.078 | 9.663 | 22.82 |
| %EDLF | -0.83 | -9.32 | -7.68 | -9.76 |

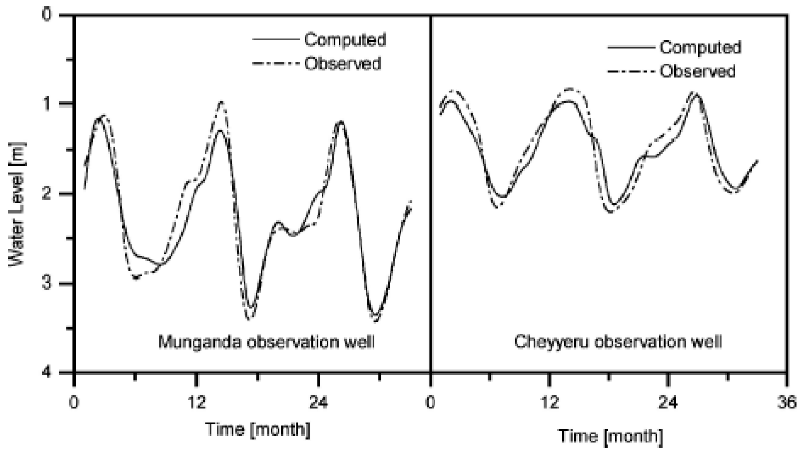


Figure 1. Plots of observed and computed water levels during validation period for Munganda and Cheyyeru observation well for 1 month lead forecast

**Stream Flow Modeling**

A Wavelet Neural Network (WNN) model, which is the combination of wavelet analysis and ANN, has been applied for stream flow time series modelling of four west-flowing rivers in India: the Kollur, Seethanadi, Varahi and Gowrihole rivers.

**Wavelet analysis**

Wavelet analysis involves the decomposition 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, it can be called a multi-resolution 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 a time and scale domain results in representation of many dense matrices in a sparse form.

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

$$f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-b}{a}\right)dt \qquad (3)$$

where $\psi(t)$ is the basic wavelet with effective length ($t$) that is usually much shorter than the target time series $f(t)$; $a$ 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 the time-frequency domain. For low scales, i.e. when $|a| << 1$, the wavelet function is very concentrated (shrunk, compressed) with frequency content 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 "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: 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. 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.

**Method of combining the Wavelet analysis with ANN**

The decomposed details (D) and approximation (A) are used as inputs to the neural network structure as shown in Fig. 2. Here, $i$ is the level of decomposition varying from 1 to $I$, $j$ is the number of antecedent values varying from 0 to $J$, and $N$ is the length of the time series. To obtain the optimal weights (parameters) of the neural network structure, the LM algorithm is used to train the network. The output node represents the original value at one step ahead.

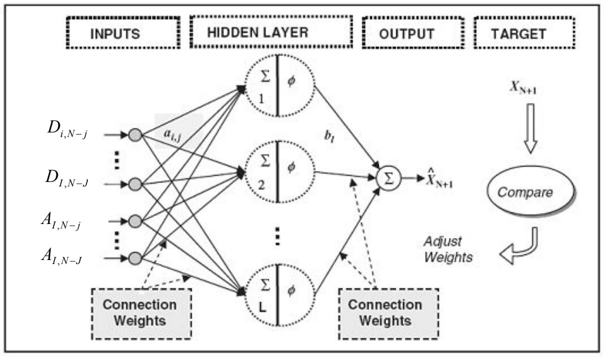


Figure 2. Wavelet based Multilayer Perceptron Neural network structure.

**Study area and data**

The Western Ghats form a range of mountains in peninsular India running approximately parallel to the west coast and are home to the largest tracts of moist tropical forest in India. The study area, is between latitudes 12°N to 14°N and longitude 74°E to 76°E. The basins and gauging stations considered for this study are: Kollur at Jadkal (108 $km^2$), Sitanadi at Kokkarne (343 $km^2$), Varahi at Dasanakante (135 $km^2$) and Gowrihole at Sarve Bridge (126 $km^2$). These stream gauges are maintained by the Water Resources Development Organization (WRDO), Govt. of Karnataka. The annual rainfall is as high as 4000 mm; the basins are characterized by steep gradients and good forest cover. The bulk of the rainfall occurs during the monsoon season (June–September), which accounts for about 80% of the annual total. The daily stream flow data for Kollur, Sitanadi, Varahi and Gowrihole basins for period of 1981–2002 (22 years), 1973–98 (26 years), 1978–2003 (26 years), and 1979–2003 (25 years), respectively, are considered for the study. Due to geographical conditions the measurement of daily rainfall and other climatic variables is difficult in densely forested basins and the availability of historical data is very limited.

**RESULTS**

The daily stream flow data of four west-flowing river basins namely Kollur, Sithanadi, Varahi and Gowrihole for the total period of 1981–2002 (22 years), 1973–1998 (26 years), 1978–2003 (26 years), and 1979–2003 (25 years) respectively is used for time series modelling. The daily stream flow data of these four basins for the period of 1981–1995 (15 years), 1973–1990 (18 years), 1978–1995 (18 years), and 1979–1995 (17 years) are used for calibration and for periods of 1996–2002 (7 years), 1991–1998 (8 years), 1996–2003 (8 years) and 1996–2003 (8 years) are used for validation period, respectively. The model inputs for each WNN model are indicated in Table 3.

**Table 3 Model inputs for WNN model.**

| | |
|---|---|
| Model I | Q(t)=f (x[t-1]) |
| Model II | Q(t)=f (x[t-1], x[t-2]) |
| Model III | Q(t)=f (x[t-1], x[t-2], x[t-3]) |
| Model IV | Q(t)=f (x[t-1], x[t-2], x[t-3], x[t-4]) |
| Model V | Q(t)=f (x[t-1], x[t-2], x[t-3], x[t-4], x[t-5]) |

Q(t) is daily runoff; f(x( )) is decomposed series of runoff

A total of five sub models were developed for each basin and these models were calibrated and tested for daily runoff series. The performances of these models in terms of global statistical tests (RMSE, R and %E) are given in Table 4. Similarly, five ANN models have been developed for four basins for the same data in which WNN models are developed. The performances of the ANN models in terms of global statistics are shown in Table 4.

Table 4 reveals that the RMSE is much better (2.8 to 21.57 $m^3$/s) for WNN models as compared to ANN (7.00 to 48.48 $m^3$/s) models in all four basins during the validation period. From Table 3, it was also observed that among different antecedent values of the time series models (WNN), the model marked with bold shows lowest RMSE (2.8 to 16.75 $m^3$/s), high correlation coefficient (0.9876 to 0.9950) and highest efficiency (97.53 to 98.99%) during the validation period in all four basins. Therefore, the WNN model (bold in Table 4) is selected as the best-fit model as compared to the ANN model to forecast the stream flows in the rivers.

**CONCLUSIONS**

This paper has reported on an application of ANN models for monthly groundwater level time series modelling and wavelet neural network (WNN and ANN) models for daily stream flow modelling. The comparison revealed that the WNN model exhibits better performance in modelling daily stream flow time series data than ANN. This is mainly due to the capability of wavelets to decompose the time series into multi-levels of approximation and detail. The models developed for groundwater level forecasting and daily stream flow modelling would be useful for water resources planning in the coastal areas and Western Ghats where the continuous measured hydrological data is limited.

**Acknowledgements**

Authors are thankful to Dr Bhishmkumar, Scientist “F” and Coordinator, DRC, Kakinada and Dr R. D. Singh, Director, NIH, Roorkee, for their encouragement to submit the paper.

**Table 4 Performance of WNN and ANN models during calibration and validation**

| Station | Model | | Calibration: RMSE | Calibration: R | Calibration: E (%) | Validation: RMSE | Validation: R | Validation: E (%) |
|---|---|---|---|---|---|---|---|---|
| Jadkal | WNN | I | 11.36 | 0.9527 | 90.76 | 12.08 | 0.9703 | 94.14 |
| | | II | 5.69 | 0.9883 | 97.68 | 7.01 | 0.9907 | 98.03 |
| | | III | 5.07 | 0.9907 | 98.16 | 6.80 | 0.9908 | 98.14 |
| | | IV | **4.37** | **0.9931** | **98.63** | **6.12** | **0.9925** | **98.49** |
| | | V | 3.82 | 0.9947 | 98.95 | 8.48 | 0.9859 | 97.11 |
| Jadkal | ANN | I | 14.39 | 0.9230 | 85.20 | 30.70 | 0.7893 | 62.12 |
| | | II | 13.93 | 0.9280 | 86.13 | 16.69 | 0.9492 | 88.80 |
| | | III | **13.75** | **0.9300** | **86.49** | **15.90** | **0.9522** | **89.83** |
| | | IV | 13.37 | 0.9339 | 87.22 | 16.71 | 0.9446 | 88.78 |
| Kokkarne | WNN | I | 20.16 | 0.9804 | 96.12 | 21.57 | 0.9794 | 95.91 |
| | | II | 17.71 | 0.9849 | 97.00 | 19.65 | 0.9830 | 96.61 |
| | | III | 13.27 | 0.9915 | 98.32 | 17.09 | 0.9873 | 97.43 |
| | | IV | **12.20** | **0.9928** | **98.57** | **16.75** | **0.9876** | **97.53** |
| Kokkarne | ANN | I | 43.67 | 0.9044 | 81.80 | 46.25 | 0.9015 | 81.19 |
| | | II | 44.06 | 0.9026 | 81.48 | 46.25 | 0.9012 | 81.19 |
| | | III | **44.22** | **0.9019** | **81.34** | **46.36** | **0.9009** | **81.10** |
| | | IV | 41.54 | 0.9140 | 83.54 | 48.48 | 0.8915 | 79.33 |
| Dasanakatte | WNN | I | 11.67 | 0.9510 | 90.45 | 7.30 | 0.9655 | 93.22 |
| | | II | 6.39 | 0.9857 | 97.17 | 3.33 | 0.9933 | 98.59 |
| | | III | 5.47 | 0.9896 | 97.93 | 3.45 | 0.9924 | 98.48 |
| | | IV | **4.72** | **0.9922** | **98.45** | **2.80** | **0.9950** | **98.99** |
| | | V | 4.47 | 0.9930 | 98.61 | 3.06 | 0.9914 | 98.81 |
| Dasanakatte | ANN | I | 16.16 | 0.9054 | 81.98 | 7.72 | 0.9614 | 92.40 |
| | | II | 15.21 | 0.9167 | 84.04 | 7.00 | 0.9684 | 93.76 |
| | | III | 14.96 | 0.9195 | 84.56 | 7.07 | 0.9680 | 93.64 |
| | | IV | **14.93** | **0.9199** | **84.62** | **7.02** | **0.9682** | **93.73** |
| | | V | 14.98 | 0.9193 | 84.52 | 7.07 | 0.9678 | 93.64 |
| Sarve Bridge | WNN | I | 10.04 | 0.9285 | 86.22 | 11.10 | 0.9536 | 90.94 |
| | | II | 5.55 | 0.9787 | 95.78 | 6.84 | 0.9833 | 96.55 |
| | | III | **4.55** | **0.9857** | **97.17** | **5.05** | **0.9905** | **98.12** |
| | | IV | 4.06 | 0.9886 | 97.74 | 6.29 | 0.9859 | 97.09 |
| Sarve Bridge | ANN | I | 13.02 | 0.8767 | 76.86 | 18.61 | 0.8658 | 74.50 |
| | | II | 12.92 | 0.8786 | 77.20 | 17.88 | 0.8860 | 76.48 |
| | | III | **13.02** | **0.8766** | **76.84** | **16.48** | **0.9031** | **80.00** |
| | | IV | 13.13 | 0.8744 | 76.46 | 19.10 | 0.8623 | 73.14 |

## REFERENCES


[1] ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000a), Artificial neural networks in hydrology I: Preliminary concepts, *J. Hydrol. Engg.*, ASCE, 5 (2), 115-123.

[2] ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000b), Artificial neural networks in hydrology II: Hydrologic applications, *J. Hydrol. Engg.*, ASCE, 5 (2), 124-137.

[3] Hagan, M. T. and Menhaj, M. B. (1994), Training feed forward networks with Marquardt algorithm. *IEEE Trans. Neural Networks,* 5, 989–993.

[4] Labat, D., Ababou, R., and Mangin, A. (2000), Rainfall–runoff relations for karstic springs: Part II. Continuous wavelet and discrete orthogonal multiresolution analyses. *J. Hydrol.,* 238, 149–178.

[5] Machiwal, D., and Jha, K.M. (2006), Time Series Analysis of Hydrologic data for water resources planning and Management: A Review. *Journal of Hydrol. Hydromech*, 54, 3:237-257.

[6] Maier, H. R. and Dandy, G. C. (1998), Understanding the behaviour and optimising the performance of back-propagation neural networks: an empirical study. *Environ. Modelling and Software,* 13, 179–191.

[7] Smith, L. C., Turcotte, D. and Isacks, B. L. (1998), Stream flow characterization and feature detection using a discrete wavelet transform. *Hydrol. Processes,* 12, 233–249.

[8] Tokar, A. S. and Johnson, P. A. (1999), Rainfall runoff modelling using artificial neural network. *J. Hydrologic Engng ASCE* 4(3), 232–239.

[9] Toth, E., Brath, A. and Montanari, A. (2000), Comparison of short-term rainfall prediction models for real-time flood forecasting. *J. Hydrol.* 239, 132–147.

[10] Wensheng, W. and Jing, D. (2003), Wavelet network model and its application to the prediction of hydrology. *Nature & Science,* 1(1), 67–71.

[11] Xiao, F., Gao, X., Cao, C. and Zhang, J. (2005), Short-term prediction on parameter-varying systems by multiwavelets neural network. *Lecture Notes in Computer Science (LNCS)* no. 3611, 139–146. Springer-Verlag, Berlin, Germany.