Nature Environment and Pollution Technology An International Quarterly Scientific Journal	Vol. 8	No. 3	pp. 429-436	2009

Original Research Paper

Prediction of Groundwater Levels Using Different Artificial Neural Network Architectures for Tirupati Mandal

P. Sujatha and G. N. Pradeep Kumar
Department of Civil Engineering, Govt. Polytechnic for Women, Kadapa-516 002, A.P., India
Department of Civil Engineering, S.V. University, Tirupati-517 507, A. P., India

Key Words:
Neural Network
Groundwater level forecasting
Evapotranspiration
Tirupati mandal

ABSTRACT

Performance of four types of functionally different artificial neural network (ANN) models, namely Feed forward neural network, Elman type recurrent neural network, Input delay neural network and Radial basis function network was examined in order to identify an efficient ANN architecture that can simulate the water table fluctuations using a relatively short length of groundwater level records. Due to inherent advantages, Levenberg Marquardt algorithm (trainlm) has been used in the present study. The town Tirupati, located in Chittoor district of the drought-prone Rayalaseema region of Andhra Pradesh having resident population of over 3.0 lakhs and pilgrims of over 50,000 per day was chosen as the study area as its groundwater levels showed a rapid decline in the last decade due to overexploitation for the domestic, agricultural and industrial needs. Accurate prediction of groundwater levels will help the administrators to plan better the groundwater resources. Results show that accurate predictions can be achieved with Feed Forward Neural Network trained with training algorithm Levenberg-Marquardt with the available shorter length data.

INTRODUCTION

Artificial Neural Network (ANN) technique has recently attracted considerable attention in all branches of engineering and science. ANN offers the distinctive ability to learn complex nonlinear relationships without requiring the mechanistic knowledge about the underlying systems. Ability to learn a complex nonlinear relationship with limited prior knowledge of the system structure and performing inferences for an unknown combination of input variables are some of its advantages. Therefore, it has a great potential in areas such as hydrological systems where complex, dynamic and highly nonlinear mechanisms are the norm. ANNs are used for rainfall-runoff modelling, precipitation forecasting, stream flow prediction, groundwater modelling, water quality modelling, water management, reservoir operations and other hydrologic applications (ASCE 2000a, b, Coulibaly et al. 2001a, b, c, Ioannis et al. 2004, Nayak et al. 2005). In this study, an attempt has been made to compare the performance of four types of functionally different ANN models that can best simulate the groundwater levels.

Groundwater is one of the most valuable natural resources possessed by many developing countries, as it is reliable in dry seasons or droughts, cheaper to develop, requires little treatment, can be tapped where it is needed and is less affected by catastrophic events. In the more arid areas, where rainfall is low and less predictable, groundwater may be the only source of supply for all types of activities. Without pro-active management and protection, there is a serious risk of deterioration on an increasingly widespread basis. Under the pressure of the need to rapidly develop new water supplies, there is rarely adequate attention to, and investment in, the maintenance, protection and longerterm sustainability of groundwater. In this context, a reliable water supply planning policy necessitates accurately acceptable predictions of groundwater level fluctuations. This generally requires a longer data of water table depth measurements, which are usually unavailable. Therefore, a common approach is to use empirical time series models as described by Box & Jenkins (1976) and Hipel & McLeod (1994) to generate a longer time series of water table depths. Unfortunately, a major disadvantage of empirical models is that they are not adequate for making predictions when the dynamical behaviour of the hydrological system changes with respect to time (Bierkens 1998). In general, relationships between the precipitation, the nearby surface water and the groundwater are nonlinear. However, owing to the difficulties of identifying nonlinear model structure and estimating the associated parameters, only very few nonlinear empirical models, such as stochastic differential equation and threshold autoregressive self-exciting open-loop models, have been recently proposed for shallow water table modelling (Bierkens 1998, Knotters & De Gooijer 1999). Alternatively, one can resort to physical models (Belmans et al. 1983, Feddes et al. 1988). But, in practice, the data requirements to simulate water table fluctuation are enormous and generally difficult. Hence, it is not affordable for developing countries. Therefore, a dynamical predictive model that can cope with the persistent trend and time-varying behaviour of the aquifer system is very desirable for improved water resources management and reliable water supply planning.

MATERIALS AND METHODS

In its most general form, an ANN is a machine that is designated to model the way in which the brain performs a particular task. The network is implemented using electronic components or simulated in software on a digital computer. To achieve good performance, ANNs employ a massive interconnection of neurons. The manner in which the computation performed at one layer is passed to the next layer is called network architecture. Feed forward neural network, Elman type recurrent neural network, Input delay neural network and Radial basis function network are some of the widely used ANN architectures.

A feed forward neural network consists of an input layer, one or more hidden layers and an output layer. Fig. 1a shows a typical feed forward network with one hidden layer consisting of five nodes, an input layer with four nodes and an output layer with one node. In this network input variable values are fed through neurons into the input layer. The hidden layer neuron collects each input value, multiplies it by a connection weight, sums up such weighted inputs together, attaches a bias value and passes on the result through a non-linear function to the output layer. Standard sigmoidal function is employed by a Feed forward neural network. The resulting value is fired out through output neuron. The main advantage of feed forward neural networks is that they are easy to handle, and can approximate any input/output map (Hornik et al. 1989), but they train slowly.

Elman network is a two-layer network with feedback from the first layer output to the first layer input and allows both to detect and generate time-varying patterns. Fig. 1b shows a typical Elman type recurrent neural network consisting of an input layer with five nodes, a hidden layer with five nodes, a context layer with five units, and an output layer with one node. Each input unit is connected to every hidden unit. There are one-by-one downward connections between the hidden nodes and the context units leading to an equal number of hidden and context units. The recurrent connections allow the hidden units to recycle the information over multiple time steps and thereby to discover temporal information contained in the sequential input and relevant to the target function. Thus, the Elman network has an inherent dynamic memory provided by the context units in its recurrent connections. The output of the network depends on the connection weights, current input signal and on the previous states of the network.

Input delay neural network consists of a memory structure and a nonlinear associator (Fig. 1c). Memory structure is a time delay line while the associator is conventional feed forward network with one hidden layer and one output layer. It holds onto the relevant past information and the associator uses the memory to predict future events.

Radial basis function networks are nonlinear hybrid networks containing a single hidden layer of computation nodes. These networks have a static Gaussian function as the nonlinearity for the hidden layer processing elements. Fig. 1d shows the network consisting of a hidden layer of ***R*** nodes, ***r*** inputs and one output. Net input to the hidden layer is the vector distance between its weight vector ***w*** and the input vector ***p***, multiplied by the bias ***b***. Success of these networks is to find suitable centres for the Gaussian functions. The advantage of this network is that it finds the input to output map using local approximators. While developing an architecture, an algorithm plays an important role. Traingd, Traingdm, Traingda, Traingdx, Trainrp, Traincgf, Traincgp, Traincgb, Trainscg, Trainbgf, Trainoss, Trainlm, Trainbr and Trainr are the often used algorithms in the model development. In the present study, due to inherent advantages, Levenberg-Marquardt (Trainlm) algorithm is used.

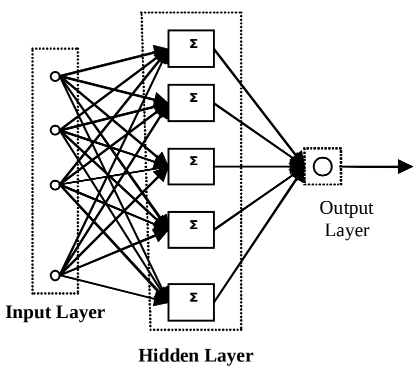

Fig. 1a: Feed forward neural network.

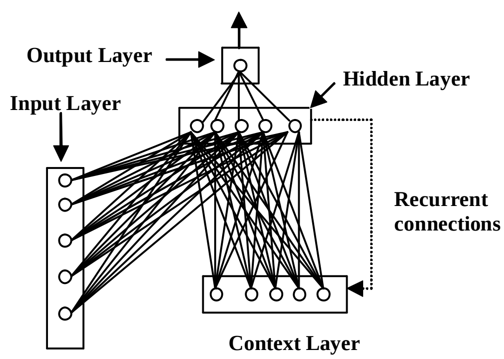

Fig.1b. Elman type recurrent neural network.

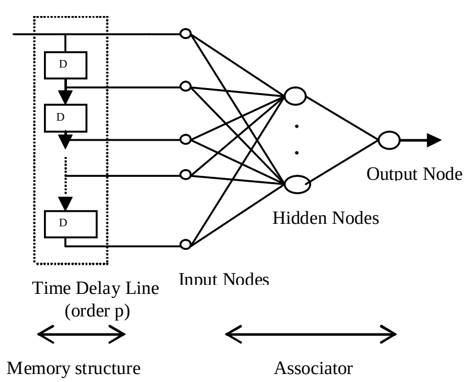

Fig.1c. Input delay neural network with *p* memory order.

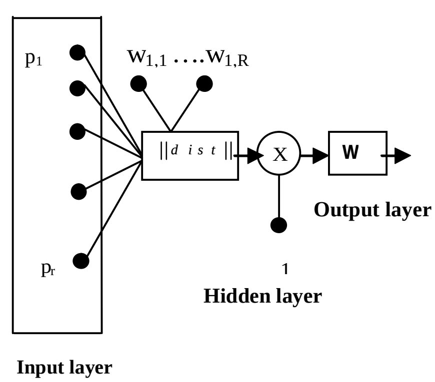

Fig.1d. Radial basis function network.

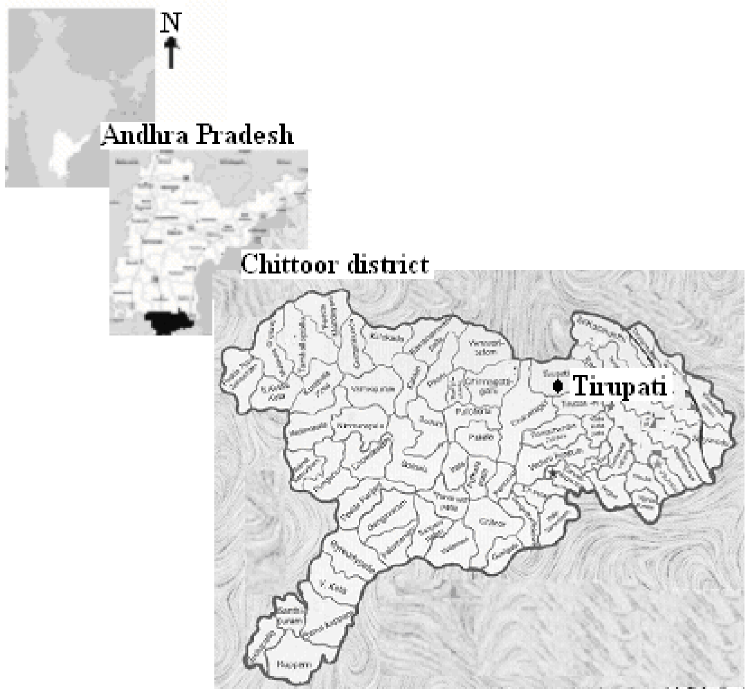

Fig.2: Location of the study area.

STUDY AREA AND DATA

All the four architectures are tested with data taken from observation wells located in Tirupati. Fig. 2 shows the area of the study. Tirupati is world renowned pilgrim centre, connected to various parts of the globe through railways, roadways and airways. It has a static population of more than 3.0 lakhs in an area of 110 km^2, in addition to a daily pilgrimage of 50,000 to 60,000. This figure touches to 1.0 lakh during summer vacation and Brahmotshavams. The climate of Tirupati, on the whole, is dry. December to February is dry and cool. March to May is summer followed by the southwest monsoon from June to September. October to November is the post monsoon retreating period. The annual mean rainfall is 700 mm, whereas the annual temperature ranges from 18°C to 42°C. Geologically, Tirupati region is covered by granites and dyke rocks of Archean age overlain by recent alluvium deposits of 10-25 m thick. Most of the hill streams originating from the Sapthagiri hills to the north of the city exhibit a dendritic pattern. All the streams are ephemeral.

The pace of urban development and the rapid increase in population of Tirupati town, which started in the 1980s, has led to the depletion of surface and groundwater resources. The large number of visitors with their additional demands for water has further aggravated the problem of water scarcity. Available surface water resources from the Kalyani dam and Telugu ganga is not adequate to cope up with the needs. Further, due to successive failure of monsoons, water supply from borewells has become an important resource. Heavy dependence on groundwater has resulted in increasing numbers of wells and boreholes necessitating the administrators to predict the groundwater levels reliably with the available data of shorter length to plan for the demands of the future. Hence, four

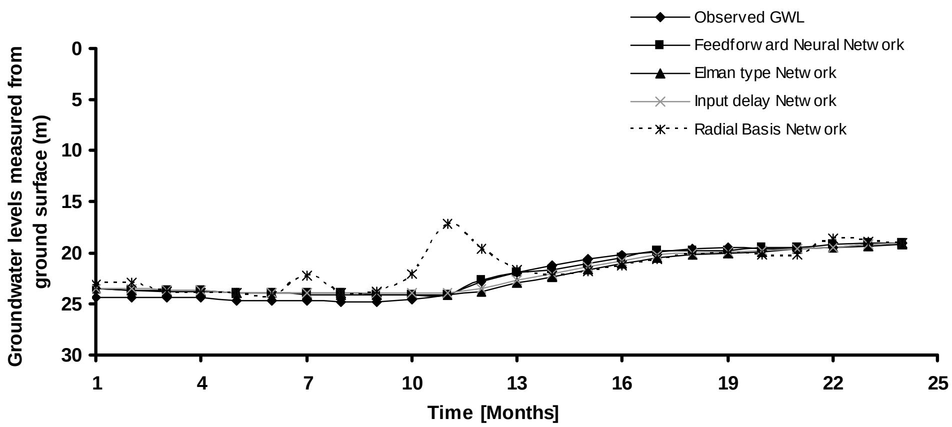

Fig. 3: Observed groundwater levels and groundwater levels computed by different network architectures during testing.

different types of neural network architectures are examined to determine the network that is best suitable to predict the water table fluctuations for the observation wells located in Tirupati.

MODEL DEVELOPMENT

Input variable selection: In order to develop a suitable neural network for predicting the groundwater levels, appropriate assignment of past values of inputs to input nodes is required. Basically, the crucial process of developing a predictive model is to identify the input variables among the available variables for each output variable. Generally, sensitivity analysis is carried out to assess the relative significance of each input variable. A glance at the past work (Coulibaly et al. 2001a, Ioannis et al. 2004, Nayak et al. 2005) indicates that past precipitation data, minimum, maximum and mean temperatures, stream flow and groundwater level data alone were considered as inputs. In the present study, precipitation and past groundwater levels for the period 1999 to 2006, along with evapotranspiration data were selected as input variables. Evapotranspiration data were included as input variables to improve the model performance. FAO Penman-Monteith method was used for the estimation of evapotranspiration. Identified input variables for the observation wells located in Tirupati are R(t-1), R(t-2), GWL(t-1), GWL(t-2) and ET(t-1) where R is rainfall data and GWL is groundwater levels and ET is evapotranspiration, t-1 and t-2 are data pertaining to 1 and 2 lag time steps respectively. Data used for training the network are normalized to remove the cyclicity. Variables were scaled between –1 and 1. Number of hidden neurons in the proposed network was determined by several trails. It was started with two hidden neurons initially and the number of hidden neurons was increased up to 20 with a step size of one in each trial. Learning rate and momentum factors were so selected that they are responsive to the complexity of the local error surface. For each set of hidden neurons, network was trained with different architectures in batch mode to minimize the mean square error at the output layer. Training was stopped when there was no significant improvement in the efficiency, and then model was tested for its generalization properties. Optimum number of hidden neurons was found to be 5. A tansigmoidal function was used as the activation function in both hidden and output layers for Feed forward network, Elman type recurrent network and Input delay

Table 1: R^2, AARE and RMSE for the observation well in Tirupati.

Model~	Training			Testing		
	R^2	AARE	RMSE	R^2	AARE	RMSE
Feed Forward Neural Network with trainlm	0.998	1.180469	0.24585	0.966	3.378442	1.271485
Elman Type Recurrent Neural Network	0.998	1.187832	0.259775	0.935	4.340135	1.342292
Input Delay Neural Network	0.998	1.162424	0.259749	0.947	3.924771	1.322815
Radial Basis Function Network	1.000	0.049615	0.02626	0.697	6.99177	2.336718

network except for Radial basis function network. Predicted groundwater level is treated as output variable. Therefore, the proposed model has 5 input nodes with a single input layer, five hidden nodes with a single hidden layer and one output node in the output layer for all the networks studied.

PERFORMANCE OF THE MODEL

Using the error estimating functions, such as Correlation Coefficient (R^2), Average Absolute Relative Error (AARE) and Root Mean Square Error (RMSE), the effectiveness of each network is tested.

$$\text{Correlation Coefficient } R^2 = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\left[\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2\right]^{1/2}} \qquad ...(1)$$

$$\text{Average Absolute Relative Error AARE} = \frac{1}{n}\sum_{t=1}^{n}\left|RE_{(t)}\right| \qquad ...(2)$$

Relative error in forecasting $GWL_{(t)}$ can be computed as:

$$RE_{(t)} = \left(\frac{x_i - y_i}{x_i}\right)x100 \qquad ...(3)$$

$$\text{Root Mean Square Error RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i-y_i)^2}{n}} \qquad ...(4)$$

Where x_i is the observed groundwater level for ith month, y_i is the forecasted groundwater level, $(x_i-\bar{x})$ is deviation of observed groundwater level from its mean, $(y_i-\bar{y})$ is deviation of forecasted groundwater level from its mean and n is the number of observations.

RESULTS AND DISCUSSION

Once the architecture of the model was optimized (i.e., 5 input nodes, 5 hidden nodes and 1 output node), the selected inputs R(t-1), R(t-2), GWL(t-1), GWL(t-2) and ET(t-1) were fed into the MATLAB 7.0 environment with Feed forward network, Elman type recurrent network, Input delay network and Radial basis network for the proposed model. For training the model, data pertaining to the period between 1999 and 2004 (360 readings) were used. Model was tested using data pertaining to the period between 2005 and 2006 (120 readings). Efficiencies of the models were then tested using R^2, AARE and RMSE, and the values are listed in Table 1.

During training, it is observed that the correlation coefficient R^2 values were 0.998 for Feed forward network, Elman type recurrent network, Input delay network and 1.000 for Radial Basis function network. The AARE values were computed as 1.180469 for Feed forward network, 1.187832 for Elman type recurrent network, 1.162424 for Input delay network, and 0.049615 for Radial basis function network. The RMSE were computed as 0.24585m for Feed forward network, 0.259775m for Elman type recurrent network, 0.259749m for Input delay network and 0.02626m for Radial basis function network. The values of R^2 suggest that all the four models were able to train the network effectively. The lower values of AARE and RMSE also indicate that all the four models were able to forecast the groundwater levels efficiently during training.

During testing, R^2 was 0.966 for Feed forward network, 0.935 for Elman type recurrent network, 0.947 for Input delay network, and 0.697 for Radial basis function network. Similarly, AARE values were determined for all the four networks as 3.378442, 4.340135, 3.924771 and 6.99177 respectively. RMSE values were computed as 1.271485m, 1.342292m, 1.322815m and 2.336718m respectively. Values of R^2, AARE and RMSE suggest that Feed forward network showed the best performance in simulating the observed groundwater levels among the networks studied. The next best performance was observed by Input delay network followed by Elman type recurrent network. In contrast, Radial basis function network was unable to predict the groundwater levels efficiently during the testing period. This suggests that the Radial basis networks may not be suitable for water table modelling based on short length calibration data. Radial basis networks are very sensitive to the presence of noise in the data and this could be the reason for this network to perform poorly in predicting the groundwater levels. These observations suggest that Feed forward network trained with training algorithm 'Levenberg-Marquardt' showed best performance in predicting the groundwater levels with data of relatively shorter period for the observation wells located in Tirupati.

Fig. 3 shows the forecasted groundwater levels and observed groundwater levels during testing period. It is clear that groundwater levels computed by the models Feed forward network, Elman type recurrent network and Input delay network are in good agreement with those of the observed groundwater levels. However, deviation is noticed in the values of groundwater levels computed by Radial basis function network with the observed groundwater levels.

CONCLUSION

In countries like India where vast area depends largely on groundwater resources, non-availability of groundwater level records for sufficient period has been the main hindrance in developing a model for prediction of realistic groundwater levels. In this paper an attempt was made for more realistic prediction of groundwater levels with the data of shorter period for the observation wells located in Tirupati, Chittoor district using ANN. Four different network architectures namely Feed forward network, Elman type recurrent network, Input delay network and Radial basis function network were studied to detect the more efficient network architecture. The results suggested that Feed forward network trained with training algorithm 'Levenberg-Marquardt' was effective in predicting the monthly groundwater levels. Predicted results using a neural network are in good agreement with values of observed groundwater levels and represent the dynamic characteristics of the given system very well.

REFERENCES

ASCE 2000a. Artificial Neural Networks in hydrology. I: Preliminary Concepts. J. Hydrologic Engineering, ASCE, 5(2): 115-123.

ASCE 2000b. Artificial Neural Networks in hydrology. II. Hydrologic applications, J. Hydrologic Engineering, ASCE, 5(2): 124-137.

Belmans, C., Wesseling, J. G. and Feddes, R.A. 1983. Simulation of water balance of a cropped soil: SWATRE, J. Hydrol., 63: 271-286.

Bierkens, M.F.P. 1998. Modeling water table fluctuations by means of a stochastic differential equation. Water Resource Res., 34(10): 2485-2499.

Box, G.E.P. and Jenkins, G.M. 1976. Time Series Analysis: Forecasting and Control, Holden-Day, Boca Raton, Fla.

Coulibaly, P., Anctil, F., Aravena, R., Bobee, B. 2001a. Artificial neural network modeling of water table depth fluctuations. Water Resources Res., 37(4): 885-896.

Coulibaly, P., Anctil, F. and Bobee, B. 2001b. Multivariate reservoir inflow forecasting using temporal neural networks. J. Hydrol. Eng., 9-10: 367-376.

Coulibaly, P., Bobee, B. and Anctil, F. 2001c. Improving extreme hydrologic events forecasting using a new criterion for artificial neural network selection. Hydrol. Process., 15: 1533-1536.

Feddes, R.A., Kabat, P., Van Bakel, P. J. T., Bronswijk, J. J. B. and Halbertsma, J. 1998. Modeling soil water dynamics in the unsaturated zone-State of the art. J. Hydrol., 100: 69-111.

Hipel, K.W. and McLeod, A.I. 1994. Time Series Modeling of Water Resources and Environmental Systems, Dev. Water Sci., Vol. 45, Elsevier Sci., New York.

Hornik, K., Stinchcombe, M. and White, M. 1989. Multilayer feed forward networks are universal approximators. Neural Networks, 2: 359-366.

Ioannis, N., Daliakopoulos, Paulin Coulibaly and Ioannis K. Tsanis 2004. Groundwater level forecasting using artificial neural network. Journal of Hydrology, 309: 229-240.

Knotters, M. and De Gooijer, J. G. 1999. TARSO modeling of water table depths. Water Resources Res., 35(3): 695-705.

Nayak, Purna C., Satyaji Rao Y.R. and Sudheer, K.P. 2005. Groundwater level forecasting in a shallow aquifer using artificial neural network approach. J. Water Resources Management, 20: 77-90.