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Groundwater Level Forecasting in a Shallow Aquifer Using Artificial Neural Network Approach

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Abstract. Forecasting the ground water level fluctuations is an important requirement for planning conjunctive use in any basin. This paper reports a research study that investigates the potential of artificial neural network technique in forecasting the groundwater level fluctuations in an unconfined coastal aquifer in India. The most appropriate set of input variables to the model are selected through a combination of domain knowledge and statistical analysis of the available data series. Several ANN models are developed that forecasts the water level of two observation wells. The results suggest that the model predictions are reasonably accurate as evaluated by various statistical indices. An input sensitivity analysis suggested that exclusion of antecedent values of the water level time series may not help the model to capture the recharge time for the aquifer and may result in poorer performance of the models. In general, the results suggest that the ANN models are able to forecast the water levels up to 4 months in advance reasonably well. Such forecasts may be useful in conjunctive use planning of groundwater and surface water in the coastal areas that help maintain the natural water table gradient to protect seawater intrusion or water logging condition.

Key words: neural networks, groundwater levels: forecasting

Introduction

Groundwater is one of the major sources of supply for domestic, industrial and agricultural purposes. In some areas groundwater is the only dependable source of supply, while in some other regions it is chosen because of its ready availability. In the coastal area such as Central Godavari Delta System in India, the phreatic surface is found at a shallow depth, generally 2 to 3 m below the ground surface. The shallow water table depths have significant impacts on crop growth, vegetation development and contaminant transport. Furthermore, depletion of groundwater supplies, conflicts between groundwater users and surface water users, potential for ground water contamination are concerns that will become increasingly important as further aquifer development takes place in any basin. The consequences of aquifer depletion can lead to local water rationing, excessive reductions in yields, wells going dry or producing erratic ground water quality changes, changes in flow patterns of ground water resulting for example in the inflow of poorer quality water and sea water intrusion in coastal areas. Below normal ground water recharge to creeks and steams during low flow periods could result in reduced supplies for surface water sources, and may prevent salmon from reaching spawning areas. So a constant monitoring of the groundwater levels is extremely important. The water levels if forecasted well in advance may help the administrators to plan better the groundwater utilization. Also, for an overall development of the basin, a continuous forecast of the ground water level is required to effectively use any simulation model for water management. In developed countries, water management planning usually, indeed almost always, proceeds through the use of one or more computer simulation models. These models, which may be very simple or highly complex, based on observed data or theoretical principles, stochastically or deterministically driven, provide a framework for decision-making that is endorsed by the community of water users and water regulators. Sometimes, a model is valued not so much for its accuracy of representation as for its utility in building social consensus. In the Indian context, the lack of strong predictive tools, or perhaps the lack of experienced users of those tools, may contribute to problems in data interpretation and failure to reach consensus about the need for key water management actions. Therefore it is extremely important to comprehend the spatial and temporal variations of the water level for the management of groundwater in the coastal areas.

To date, a wide variety of models have been developed and applied for groundwater table depth forecasting. These models can be categorized into empirical time series model and physical descriptive model. The empirical time series models have been widely used for water table depth modeling (e. g. Knotters and Van Walsum, 1997; Van Geer and Zuur, 1997; Bierkens, 1998). The major disadvantage of empirical approach is that they are not adequate for forecasting when the dynamical behavior of the hydrological system changes with time (Bierkens, 1998). Similarly, physics based model, in practice requires enormous data, in particular data pertaining to soil physical properties of the unsaturated zone (Knotters and Bierkens, 2000) that is generally difficult or expensive, to simulate water table fluctuation in developing countries like India. In a water table aquifer, relationship between precipitation, canal releases, and the groundwater level are likely nonlinear rather than linear, and the models that approximate the processes in linear form fail to represent the processes effectively. Owing to the difficulties associated with non-linear model structure identification and parameter estimation, very few truly non-linear empirical models such as stochastic differential equation and threshold autoregressive self-extracting open-loop models have been reported for shallow water table modeling (Bierkens, 1998; Knotters and Bierkens, 2000). In recent years, artificial neural networks (ANNs) have been used for forecasting in many areas of science and engineering. ANNs have been proven to be effective in modeling virtually any nonlinear function to an arbitrary degree of accuracy. The main advantage of this approach over traditional methods is that it does not require the complex nature of the underlying process under consideration to be explicitly described in mathematical form. This makes ANN an attractive tool for modeling water table fluctuations.

A few applications of ANN approach in aquifer system modeling have been recently reported in the literature (e. g. Rizzo and Dougherty, 1994; Rajanithan *et al*., 1995; Moeshed and Kaluarchchi, 1998; Coulibaly *et al*., 2001, etc.). A comprehensive review of applications of ANN to hydrology can be found in the report of ASCE task committee (ASCE, 2000a,b), where they have discussed the merits and shortcomings of the ANN approach. This paper investigates the prediction of water table depth using artificial neural networks (ANN). The applicability of the method is demonstrated by modeling the groundwater levels of Central Godavari Delta System in India.

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 (Figure 1). Geographically the study area, Central Godavari Delta, is located between 16°25′ N to 16°55′ N latitude and 81°44′E to 82°15′ E longitude with its hydrological boundaries as the river Gowthami

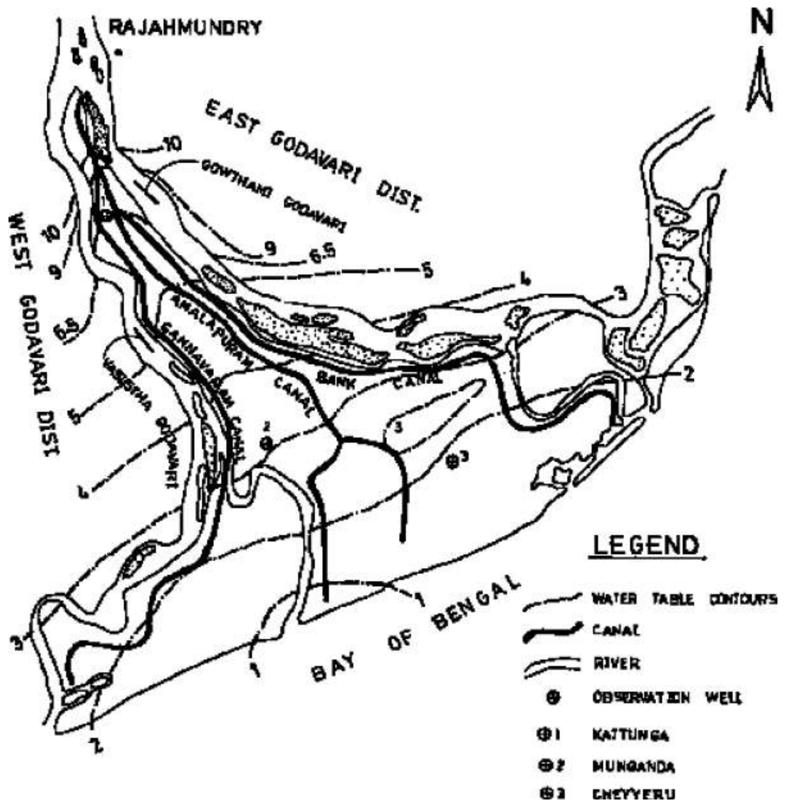

Figure 1. The average water table contours above MSL for the month of October for the year 1980 to 1990.

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. Study area consists of rich alluvial plains formed by river Godavari and has a very gentle land slope of about 1 m per kilometer. The groundwater is under water table condition. Texturally, a major part of the study area consists of sandy loams and sandy clay loams. The entire area is under the command of the Godavari Central Canal system and the canal system remains operational for 11 months during the year with a closure for one month for maintenance purposes. As an efficient canal irrigation system is available in the study area, the groundwater utilization for irrigation purpose is very limited.

As stated earlier, the major focus of the current study is to investigate the potential of ANN approach in modeling water table fluctuation. 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; see Figure 1) were collected.

Artificial Neural Networks

The artificial neural networks are massively parallel distributed processing and computing technique inspired by biological neuron processing. ANN models have been widely applied in various fields of science and technology involving time series forecasting, pattern recognition and process control. There are multitudes of network types available for ANN applications and its choice depends on the nature of the problem and data availability. The multi layer perception (MLP) trained with the back propagation algorithm is perhaps the most popular network for hydrologic modeling (ASCE 2000a,b). In this type of network, the artificial neurons, or processing units, are arranged in a layered configuration containing an input layer, usually one "hidden" layer, and an output layer. Units in the input layer introduce normalized or filtered values of each input into the network. Units in the hidden and output layers are connected to all of the units in the preceding layer. Each connection carries a weighting factor. The weighted sum of all inputs to a processing unit is calculated and compared to a threshold value. That activation signal then is passed through a mathematical transfer function to create an output signal that is sent to processing units in the next layer. Training an ANN is a mathematical exercise that optimizes all of the ANN's weights and threshold values, using some fraction of the available data. Optimization routines can be used to determine the ideal number of units in the hidden layer and the nature of their transfer functions. ANNs "learn" by example; as long as the input dataset contains a wide range of the types of patterns that the ANN will be asked to predict, the model is likely to find those patterns and successfully use them in its predictions. The basic concepts about the MLP and its application, have been introduced in numerous hydrological papers, are not reproduced in the body of this paper, more details about MLP can be seen from Hornik, *et al* (1989).

Present study employed a standard back propagation algorithm for training, and the number of hidden neurons is optimized by a trial and error procedure.

ANN Model Development

The goal of an ANN model is to generalize a relationship of the form of:

$$Y^m = f(X^n) \tag{1}$$

where X^n is an n-dimensional input vector consisting of variables $x_1, \ldots, x_i, \ldots, x_n$; Y^m *is an* m-dimensional output vector consisting of the resulting variables of interest $y_1, \ldots, y_i, \ldots, y_m$. In groundwater depth modeling values of x_i may include rainfall, canal releases, and water level values at different antecedent time lags and the value of y_i is generally the water table depth for a subsequent period or at a different special location. However, how many antecedent values of rainfall, canal release and/or water level values should be included in the vector X^n is not known *a priori*. The input vector identification is generally done through a trial and error procedure. In the current study, instead of relying completely on trail and error procedure, a model driven approach (Sudheer *et al.*, 2002) in combination with domain knowledge have been explored for general guidance in the number of inputs selected. This helps the model formulation process to be more objective and the ANN modeling process to be easier.

Model Structure Identification

INPUT VECTOR SELECTION

One of the most important steps in the model development process is the determination of significant input variables. Usually, not all of the potential input variables will be equally informative since some may be correlated, noisy or have no significant relationship with the output variable being modeled (Maier and Dandy, 2000). Generally some degree of *a priori* knowledge is used to specify the initial set of candidate inputs (*e.g.* Campolo *et al.*, 1999; Thirumalaiah and Deo, 2000). Although *a priori* identification is widely used in many applications and is necessary to define a candidate set of inputs, it is dependent on an expert's knowledge, and hence, is very subjective and case dependent. When the relationship to be modeled is not well understood, then an analytical technique, such as cross-correlation, is often employed (*e.g.* Sajikumar and Thandaveswara, 1999; Luk *et al.*, 2000; Silverman and Dracup, 2000; Coulibaly *et al.*, 2000, 2001; Sudheer *et al.*, 2002). The major disadvantage associated with using cross-correlation is that it is only able to detect linear dependence between two variables. Therefore, cross-correlation is unable to capture any nonlinear dependence that may exist between the inputs and the output, and may possibly result in the omission of important inputs that are related to the output in a nonlinear fashion. Intuitively, the preferred approach for determining appropriate inputs and lags of inputs, involves a combination of *a priori* knowledge and analytical approaches (Maier and Dandy, 1997).

The current study has been designed to forecast the groundwater level at Munganda and Cheyyeru observation wells with Kattunga observation well as reference (datum point) well which is located upstream of the study area. The average water table contours above mean sea level for the month of October during the period of 1980 to 1990 is shown in Figure 1. From Figure 1 it is observed that subsurface flow takes place from the rivers to basin aquifer and the water table gradient is sloping towards the Bay of Bengal. Therefore it appears that the water level of Kattunga observation well has some significant influence in the water table levels at Munganda and Cheyyeru observation wells. The influencing lags are established through statistical analysis from the available data series.

A cross correlation analysis is performed between the water level records of Kattunga and Munganda wells. The analysis shows that the water level at Munganda well at any time period has a significant correlation with the water level at Kattunga well at lag of 1 time step (month). A similar analysis between Kattunga and Cheyyeru wells reveal that the significant relationship exists between the data at 1, 2 and 4 lag time steps. From Figure 1, it is also observed that there exists a gradient from Munganda and Cheyyeru wells implying inclusion of Munganda water levels in the input vector to the model that predicts the water levels at Cheyyeru. A cross correlation analysis suggested including water level of Munganda at previous time step in this case. A further statistical analysis of the time series of water levels at Munganda and Cheyyeru suggests that both the time series is autoregressive and according to Sudheer *et al.* (2002) values at significant lags are also included in the input vector. Apart from water levels of different wells, exogenous variables such as rainfall and canal releases are also included in the input vector as per the procedure suggested by Sudheer *et al.* (2002). The identified input vector for both the wells is presented in Table I.

Table I. Variables in the input vector to ANN models

	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)

Hidden Neurons Optimization

In order to ensure good generalization ability by an ANN model, a number of empirical relationships between the number of training samples and the number of connection weights have been suggested in the literature (Maier and Dandy, 2000). However, network geometry is generally highly problem dependent and these guidelines do not ensure optimal network geometry, where optimality is defined as the smallest network that adequately captures the relationships in the training data (principle of parsimony). In addition, there is quite a high variability in the number of hidden nodes suggested by the various rules. While research is being conducted in this direction by the scientists working in ANNs, it may be noted that traditionally, optimal network geometries have been found by trial and error (Maier and Dandy, 2000). Consequently, in the current application the number of hidden neurons in the network, which is responsible for capturing the dynamic and complex relationship between various input and output variables, was identified by various trials.

The trial and error procedure 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. In order to check 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. The parsimonious structure that resulted in minimum error and maximum efficiency during training as well as testing was selected as the final form of the ANN model.

Internal Parameters of the Model

A sigmoid function is used as the activation function in both hidden and output layers. As the sigmoid transfer function has been used in the model, the input-output data have been scaled appropriately to fall within the function limits. A standard back propagation algorithm (Rumelhart *et al.*, 1986) has been employed to estimate the network parameters. Note that in a standard steepest descent (backpropagation), the learning rate is held constant throughout training. The performance of the algorithm is very sensitive to the proper setting of the learning rate. If the learning rate is set too high, the algorithm may oscillate and become unstable. If the learning rate is too small, the algorithm will take too long to converge. It is not practical to determine the optimal setting for the learning rate before training, and, in fact, the optimal learning rate changes during the training process, as the algorithm moves across the performance surface. The performance of the steepest descent algorithm can be improved if we allow the learning rate to change during the training process. An adaptive learning rate will attempt to keep the learning step size as large as possible while keeping learning stable. The learning rate is made responsive to the complexity of the local error surface. Accordingly an adaptive learning and momentum rate have been employed in the current study.

Model Training and Evaluation

The data are used for training the network after standardization (subtracting monthly mean and dividing it by standard deviation of the corresponding month) to remove the cyclicity or periodicity present in the data. The variables are scaled to a limit between 0 and 1 as the activation function warrants. The total available data has been divided into two sets, calibration and validation set: the model is trained using data for 6 years (1981–1986) and validated on the rest of the data (1987–1989).

The final structure of the ANN model for Munganda observation well is: 8 input neurons, 3 hidden neurons and 1 output neuron and for Cheyyeru observation well is: 10 input neurons, 2 hidden neurons and 1 output neuron. The resulting water level plots from the model are analyzed statistically using various indices employed for performance analysis of models. 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).

Results and Discussions

The statistical adequacies of the developed models for 1-month ahead forecasts for Munganda and Cheyyeru observation wells are summarized in Table II. It is observed from Table II that the model performance is good, and the models have 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

Table II. Performance indices for 1 month lead forecast models

	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

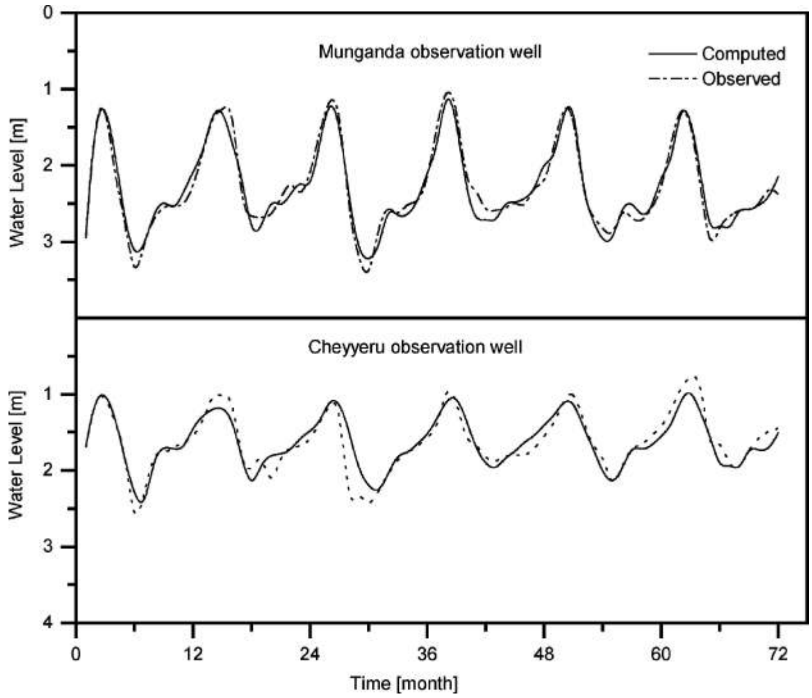

Figure 2. Plots of observed and computed water levels during calibration period for Munganda and Cheyyeru observation well for 1 month lead forecast.

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). Figures 2 and 3 shows the predicted water level plots during calibration and validation period. 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 a 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. Consequently, 5 different ANN models are developed to forecast water levels at 2-, 3-, 4-, 5- and 6- months in advance. It may be noted that the input to all these models are kept as the same as presented in Table I. The performance of these models in terms of RMSE and AARE statistics along the prediction time horizon is summarized in Table III. It is observed from the table that the variation in RMSE statistics lies between a minimum of 0.2 m to a maximum of 0.6 m. However it seems that the AARE index is nonlinearly varying along the prediction time horizon in this analysis. It is also to be noted that the performance of any model may be good for smaller lead times, but may become worse as the lead time increases.

Table III. The RMSE indices during calibration and validation period at different lead time forecasts

	Munganda observation well		Cheyyeru observation well	
Lead time	Calibration	Validation	Calibration	Validation
		RMSE		
1	0.2099	0.3747	0.218	0.3246
2	0.2775	0.5106	0.207	0.4566
3	0.2512	0.5825	0.258	0.488
4	0.293	0.589	0.2777	0.4743
5	0.3668	0.5179	0.2461	0.5559
6	0.4153	0.5664	0.2602	0.5074
		AARE		
1	7.427	15.078	9.663	22.82
2	11.206	23.292	9.628	32.2955
3	11.9	27.238	8.043	37.7
4	13.6	26.694	14.55	36.103
5	14.5229	25	12.58	39.409
6	16.508	22.771	13.53	37.127

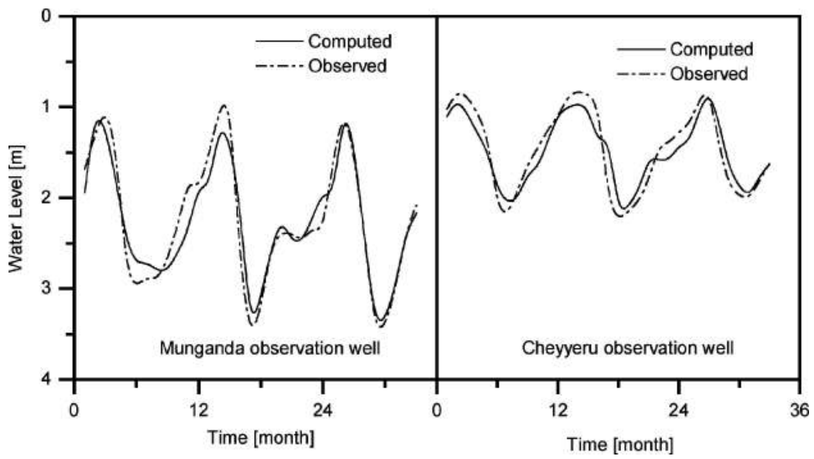

Figure 3. Plots of observed and computed water levels during validation period for Munganda and Cheyyeru observation well for 1 month lead forecast.

As the global evaluation measures employed so far do not reveal any information about the magnitude of errors, the prediction error, which is the difference between the observed and predicted water levels, is used for assessment of the model developed and is presented in Figures 4 and 5 respectively for Munganda and Cheyyeru. Note that in these figures a positive sign indicates underestimation

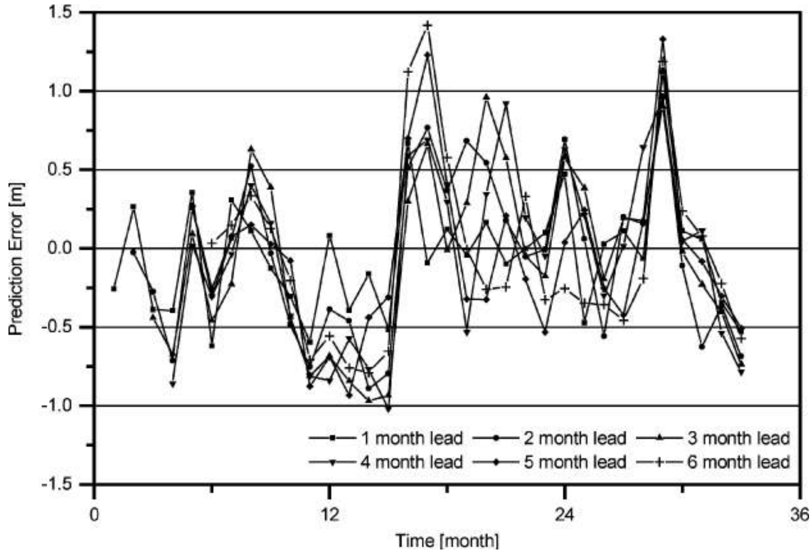

Figure 4. The direct error plot during validation period for Munganda observation well.

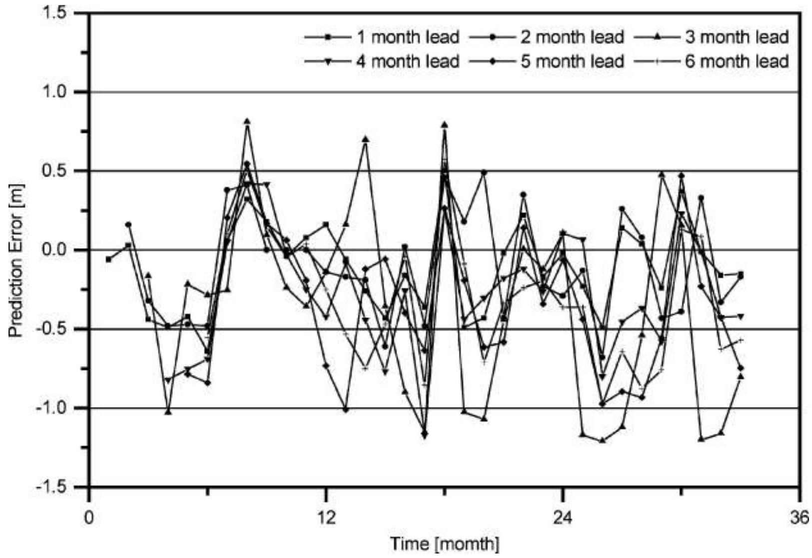

Figure 5. The direct error plot during validation period for Cheyyeru observation well.

and a negative sign indicates overestimation by the models. This error plot helps evaluating whether the model is predicting the rising levels badly or the falling levels badly. It is observed from Figure 4 that the prediction error for the whole range of water levels is within ± 1 m. Also, note that the errors are clustered around the monsoon season data in the case of Munganda. The Cheyyeru observation well is located nearer to the seashore and fluctuation is very less compared to Munganda observation well as can be evidenced by a smaller prediction error of $\pm$ 0.5 m. It is worth mentioning that ANN models were able to forecast the water levels up to 4 month ahead with less then ± 1 m prediction error for Munganda observation well. For the case of 5- and 6-month lead forecasts, the performance is good except for 3 months during the monsoon (see Figure 4). From Figure 5 it may also be observed that ANN model predictions for Cheyyeru observation well are not good beyond 2 month ahead. The prediction error is found to deteriorate after 2-month lead forecast. This may be plausibly due to backwater effect into the drains and the water logged area near the observation well, which are not considered in the present analysis, and reasons for these phenomena need to be explored further.

A further analysis was performed by using the forecasted water levels at Munganda observation well as input to the model for Cheyyeru well along with all other observed values of variables to forecast the water level in Cheyyeru observation well. The results indicate that the model predictions do not get significantly affected implying the noise tolerance potential of the ANN model for Cheyyeru.

An analysis that evaluates the input sensitivity to model predictions was carried out by developing two models: one using only rainfall as input to the model, and the other using a combination of rainfall and canal releases only as input to the model. The results were found to be not encouraging and may be because the recharge time for water to reach the groundwater is quite higher compared to the lag period considered in the model.

Summary and Conclusions

In this paper, the potential of neural computing techniques for forecasting groundwater levels is investigated by developing ANN models for a shallow aquifer of Central Godavari Delta System in India. Different ANN models were developed that forecasts the water level at two observation wells up to 6 months in advance. The inputs to the models were identified using a combined approach that uses the domain knowledge and statistical analysis of the data series. The results from ANN model in general indicate that ANN is an effective tool for monthly groundwater levels forecasting. The performance evaluation criteria namely the RMSE, the coefficient of correlation, and the AARE are found to be very good and consistent for groundwater levels forecasted 1-month in advance. Furthermore, the prediction error, which indicates the magnitude of error for both large and moderate water table fluctuations, is within the reasonable limit. Although good results are obtained for Munganda observation well up to 4 months ahead forecasts, the model performance is found to deteriorate after 2 month lead forecast for Cheyyeru observation well.

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