2012 International Conference on Computer Networks and Communication Systems (CNCS 2012)
IPCSIT vol.35(2012) © (2012) IACSIT Press, Singapore

Application of Soft computing techniques for Groundwater Level Forecasting

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Abstract. Soft computing is an innovative approach to construct computationally intelligent systems that are supposed to possess humanlike expertise within a specific domain, adapt themselves and learn to do better in changing environments and explain how they make decisions. The application of neural network and fuzzy logic techniques as modeling tools are growing in the field of hydrology. In the present study Artificial neural network (ANN), Mamdani fuzzy inference systems (MFIS) andAdaptive Neuro Fuzzy (ANFIS) was used to predict the groundwater levels of Thurinjapuram watershed, Tamilnadu. Antecedent rainfall and water levels are taken as inputs, and the future water level is an output. In this study, 25 years of water level data were analyzed. The analysis of the three models is performed by using the same input and outputvariables. The models are evaluated using three statistical performance criteria namely Mean Absolute Percentage Error, Root Mean Squared Error and Regression coefficient. For performance evaluation, the model predicted output was compared with the actual water level data. Simulation results reveal that ANFIS is an efficient and promising tool.

Keywords: Artificial neural networks, Fuzzy inference system, ANFIS, Back-propagation, MATLAB Simulation, Observation wells, Groundwater level.

1. Introduction

Soft computing is one of the latest approaches for the development of systems that possess computational intelligence (Zadeh, 1994). Soft computing attempts to integrate several different computing paradigms including artificial neural networks, fuzzy logic and genetic algorithms. On their own, each of these techniques appears to be extremely effective at handling dynamic, nonlinear and noisy data, especially when the underlying physical relationships are not fully understood. However, when utilized together, the strengths of each technique can be exploited in a synergistic manner for the development of low cost, hybrid systems. The use of soft computing in the field of hydrological forecasting is a relatively new area of research, although neural networks on their own have already been shown to be successful substitutes for rainfall-runoff models (N. Geethanjali, 2005, Karim Solaimani*, 2009*). Faster running fuzzy logic rule-based models can also be used in place of existing, physical models as demonstrated by Bârdossy & Disse (1993) in the modeling of infiltration processes. However, the integration of these different, soft computing technologies to produce a single, hybrid solution for the enhancement of operational river level and flood forecasting systems still remains to be investigated (R. K. Prasad,2007).

2. Study Area And Data

The Thurijapuram watershed covers geographical area of 151.38 sq. km and is located in between 12^{o}12’58” and 12^{o} 21’11” North latitudes and 78^{o}59’45” and 79o9’28” East longitudes (Fig. 1.) It is mainly

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situated in Thiruvannamalai district of Tamilnadu, India. Thurinjalar River, which is the major stream draining the area, so the drainage characteristics are very good. Bedrock is peninsular gneiss of Archean age. The Thurinjapuram area can be classified as ‘‘hard rock terrain’’. The predominant soil types in this river basin are Entiso, Inceptisols,Vertisol and Alfisols. The soil in this minor basin is observed to have good infiltration characteristics. Hence groundwater recharge is possible in this area.

The input data used for water level prediction are monthly Rainfall and Ground water (level in the observation well) data of Thurinjapuram watershed in Tamilnadu, India, and one month ahead groundwater level as output. For the present study monthly water level data for three observation wells (23112, 23141, and 23143) during 1985 to 2010 has been collected from Thiruvannamalai Groundwater subdivision. In the same period monthly Rainfall data were collected from Kilnatchipattu Raingauge station (Fig.2).

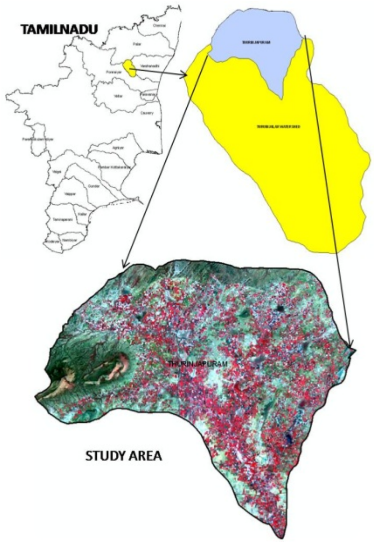

Fig. 1 Study area

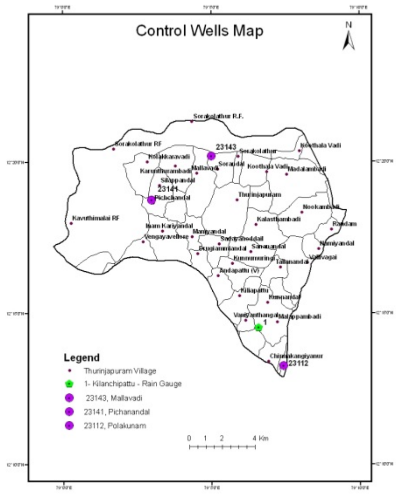

Fig. 2 Raingauge station and Wells location map

3. Theory And Methodology

In this paper different soft computing approaches such as Artificial Neural Network (ANN), Fuzzy Inference Systems (FIS) and Adaptive Neuro- Fuzzy Inference System (ANFIS) to Model the groundwater level prediction of a watershed. A simple model was developed by taking two parameter antecedent rainfall RF(k) and water levels WL(k) are taken as inputs, and the future water level WL(k+1) is an output using the representation

WL (k+1) = f{RF (k), WL (k)}.

The entire input data set is divided into three types.

Training: 1985 to 2000

Testing: 2001 to 2007

Validation: 2008 & 2009

All of the simulations were performed in MATLAB (version 7.6). For computational purposes, some MATLAB programming codes have been developed, but most of the times, fuzzy toolbox is used for modeling.

3.1. Artificial Neural Networks Model

An artificial neural network is a type of biologically inspired computational model, which is based loosely on the functioning of the human brain. It is more useful to think of a neural network as performing an input-output mapping via a series of simple processing nodes or neurons. (S. Alvisi,2005).

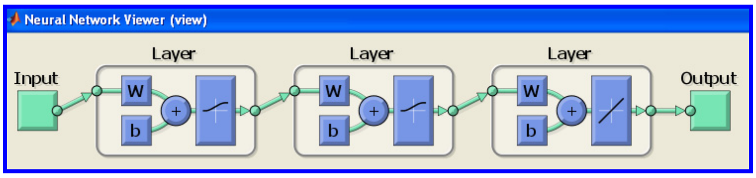

Fig.3 ANN structure for the groundwater level prediction model

In this study a feed-forward network with back-propagation algorithms was used to predict the groundwater level of a watershed. A number of 192 data were utilized during training session and 84 data were used during testing session. A suitable configuration has to be chosen for the best performance of the network. Out of the different configurations tested, two hidden layer with 12 and 20 hidden neurons produced the best result (Fig3). The log sigmoid function was employed as an activation function. Suitable numbers of epochs (2000 to 3000) have to be assigned to overcome the problem of over fitting and under fitting of data.

3.2. Fuzzy Logic Model

Mamdani's Fuzzy Inference method (MFIS) is the most commonly seen fuzzy methodology. The main idea of the Mamdani method is to describe the process states by linguistic variables and to use these variables as inputs to control rules. In FIS model, fuzzifier performs a mapping that transfers the input data into linguistic variables and the range of these data forms the fuzzy sets. It is an interface between the real world parameters and the fuzzy system and transforms the output set to crisp (non-fuzzy). The fuzzy inference engine uses the defined rules and it develops fuzzy outputs from the inputs. Defuzzifier maps the fuzzy output variables to the real world variables that can be used to control a real world application. The deffuzification process is a reverse of fuzzification (Gholam Abbas fallah-Ghalhary,2009).

In this paper Mamdani Fuzzy model (MFIS) was also conducted on the same data sets with the identical input and output variables. Two inputs and one output FIS were used to evaluate and classify the groundwater level in Thurinjapuram watershed. From MATLAB Fuzzy Logic Toolbox, fuzzy inference system is easily created. Based on Gaussian membership functions for inputs, the FIS has 3x3 = 9 rules. In the applied system: intersection, union, aggregation, implication and Defuzzification are considered MIN, MAX, SUM, PROD and CENTROID, respectively.

3.3. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) Model

The ANFIS architecture consists of fuzzification layer, inferences process, defuzzification layer, and summation as final output layer. The process flows from layer 1 to layer 5. It is started by giving a number of sets of crisp values as input to be fuzzifiedin layer 1, passing through inference process in layer 2 and 3 where rules applied, calculating output for each corresponding rules in layer 4 and then in layer 5 all outputs from layer 4 are summed up to get one final output. The main objective of the ANFIS is to determine the optimum values of the equivalent fuzzy inference system parameters by applying a learning algorithm using input-output data sets. The parameter optimization is done in such a way during training session that the error between the target and the actual output is minimized. Parameters are optimized by hybrid algorithm which combination of least square estimate and gradient descent method. The parameters to be optimized in ANFIS are the premise parameters which describe the shape of the membership functions, and the consequent parameters which describe the overall output of the system. The optimum parameters obtained are then used in testing session to calculate the prediction.

The Sugeno type Fuzzy Inference System is used to construct the ANFIS model. The hybrid ANFIS model with 3 subsets of membership functions of Gaussian shape for input and linear output membership function gives the best results. The 150 epochs were given to train the model. The Gaussian membership function of each input was tuned using the hybrid method consisting of back propagation for the parameters associated with the input membership function and the least square estimation for the parameters associated with the output membership functions. The computations of the membership function parameters are facilitated by a gradient vector which provides a measure of how well the FIS system is modeling the input/output data.

4. Performance Evaluation Of The Model

The Root Mean Squared Error (RMSE), the Mean Absolute Percentage Error (MAPE) and Regression coefficient (R^2) are used in order to assess the effectiveness of this model and its ability to make precise predictions. The RMSE calculated by

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \quad (1)$$

Also, the MAPE and R^2 are calculated by

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|x_i - y_i|}{x_i} \times 100 \quad (2)$$

$$R^2 = 1 - \frac{\sum(x_i - y_i)^2}{\sum x_i^2 - \frac{\sum y_i^2}{n}} \quad (3)$$

Where, x_i = observed ground water levels, $\bar{x}$ = mean of x_i, y_i = predicted ground water levels, $\bar{y}$ = mean of y_i and n = the number of data set used for evaluation

5. Result And Discussion

The same data under the same conditions was applied to the three methods discussed above. The results obtained were compared with one another and target output. Finally, the performance of the methods was discussed. All of the simulations were performed in MATLAB (version 7.6).

	Training			Testing			Validation		
Models	**RMSE**	**MAPE %**	**R²**	**RMSE**	**MAPE %**	**R²**	**RMSE**	**MAPE %**	**R²**
Well no.23112									
MFIS	1.59	17	0.73	0.88	10	0.88	0.77	10.62	0.92
ANN	0.9	8	0.88	0.84	8	0.86	0.33	3.43	0.97
ANFIS	0.53	5	0.96	0.23	3	0.99	0	0.24	0.99
Well no.23141									
MFIS	1.07	19	0.81	0.59	15	0.94	0.98	18.30	0.85
ANN	0.64	11.4	0.93	0.47	7	0.96	0.34	4.11	0.98
ANFIS	0.59	9.7	0.94	0.14	3	0.99	0.06	0.50	0.99
Well no.23143									
MFIS	1.6	18	0.79	1.13	13	0.85	0.89	11.94	0.92
ANN	1.57	15	0.82	0.82	7	0.91	0.31	6.48	0.98
ANFIS	0.61	6	0.96	0.57	5	0.96	0.13	0.68	0.99

Table 2. Model Evaluation

From the above table it is clear that the RMSE values using ANFIS were lower than those using ANN and MFIS. In general a MAPE of 10% is considered very good, a MAPE in the range 20% - 30% or even higher is quite common. In this investigation it is observed that the MAPE values obtained from MFIS is less than 20 %, ANN is less than 15 % and the same from ANFIS model is lesser than 10 %. R^2 value for ANFIS model is very much close to unity when compare to other models. This shows that the best learning method is ANFIS among the others. The observation reveals that ANFIS model found to be good for the prediction of groundwater level of Thurinjapuram watershed.

6. Forecasting of Groundwater Level of The Study Area

To forecast the groundwater level using ANFIS model the input data (rainfall and water level) is derived by using linear regression method.To forecast the future groundwater level of Thurinjapuram watershed, predicted values of factors (rainfall and water level) are plugged in the ANFIS model.

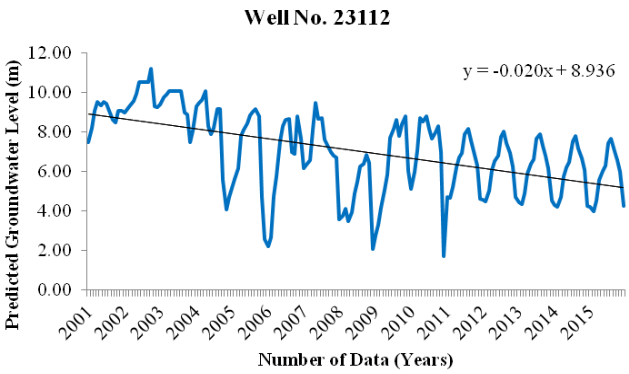

Fig.9Forecasting of Groundwater level for all the well No.23112

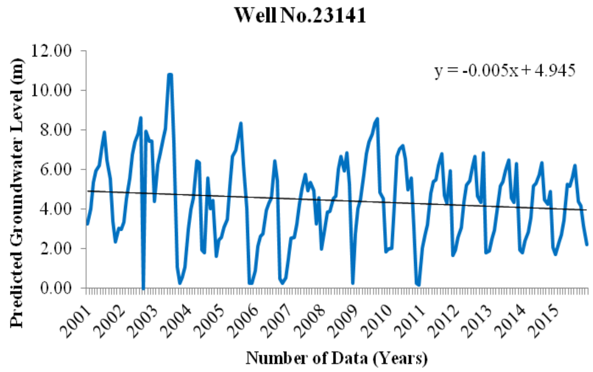

Fig.10Forecasting of Groundwater level for all the well No.23141

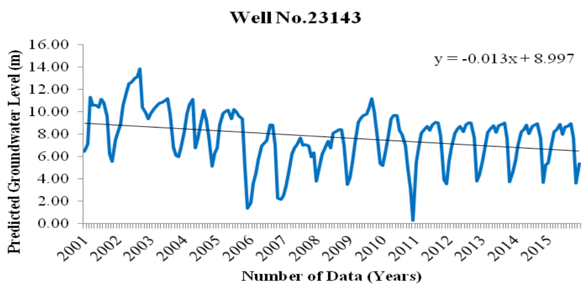

Fig.11Forecasting of Groundwater level for all the well No.23143

The model show an average annual decrease in groundwater level of three wells of Thurinjapuram watershed in the next 6 years (Fig.8 to 11).The result forecasts the groundwater level in well number 23141 is not that much changing with time but in well number 23112 and 23143 the level is decreasing with time.

This shows the potentiality of the aquifers is different for the different parts of the hard rock basin. Well no. 23141 will not be affected more but for other wells abstraction should be reduced. The study indicates, controlled pumping could sustain the groundwater level but over exploitation of aquifer will cause aquifer mining in the moderate to poor zone. This observation draws attention to take care of each area in particular due to their difference in aquifer characteristics with different groundwater management strategy.

7. Conclusion

In the present study Artificial neural network (ANN), Mamdani fuzzy inference systems (MFIS) andAdaptive Neuro Fuzzy (ANFIS) was used to predict the groundwater levels of Thurinjapuram watershed, Tamilnadu. From the comparison of the model, It may be noted that a trial and error procedure has to be performed for ANN model to develop the best network structure, while such a procedure is not required in developing an ANFIS model. Moreover, in the current study, the ANFIS model was trained by using just 150 epochs, while the ANN model took 2000 to 3000 epochs. the learning duration of ANFIS is very short than neural network case. It implies that ANFIS reaches to the target faster than neural network. When a more sophisticated system with a huge data is imagined, the use of ANFIS instead of neural network would be more useful to overcome faster the complexity of the problem.

Fuzzy logic method seems to be the worst in contrast to others. If more membership variables and more rules had been used, a better result would have been available. The restriction of fuzzy rules and fuzzy sets is due to the ANFIS constraint. The aim was to choose the same FIS in both Fuzzy and in ANFIS methods to be able to compare with one another. When the above discussions are all considered, it can be said that ANFIS is better system for the prediction of groundwater level of a watershed than neural networks and fuzzy methods lonely.

8. Acknowledgement

The First author gratefully acknowledges the support given by DST Govt. of India, New Delhi, under Women Scientist Scheme.

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