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Groundwater Level Simulation Using ANFIS Technique

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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 these modeling tools are growing in the field of hydrology. In the present study Adaptive Neuro Fuzzy Inference System (ANFIS) has been used to develop prediction model for groundwater levels of Sarojininagar Block of Lucknow district. Antecedent rainfall, temperature and water levels are taken as inputs, and the future water level is an output. In this study, 27 years of water level data were analyzed. The analysis of the models is performed by using different combinations of input variables and output variables. The models are evaluated using RMSE as performance criteria. For performance evaluation, the model predicted output was compared with the actual water level data. MATLAB simulation results reveal that ANFIS is an efficient and promising tool.
Keywords: ANFIS, MATLAB Simulation, Soft Computing, Groundwater level.

1. Introduction

Groundwater always has been as one important resource to supply drinking and agriculture water especially in arid and semi-arid region. These resources commonly have a high quality, usually do not need chemical treatment, and commonly are free of pathogenic factors. All these reasons make groundwater an important and reliable resource in supplying consumption needs of different users. The physical interaction between the hydrological variables (such as rainfall, evapotranspiration) with ground water is highly nonlinear, stochastic, and complex.

Thus, to exploit and manage groundwater, models are needed to predict groundwater level fluctuations. Nowadays, because of developing and progressing of computer, using mathematical models for groundwater level forecasting has a significant development. A big problem that user and suppliers of these models are faced now is the needs of these models to to be able to correlate the input data with output data. A common non-linear method for ground water problems is ANFIS. It is a new improved tool and a data-driven modeling approach for determining the behavior of imprecisely defined complex dynamical systems . The ANFIS model has human-like expertise within a specific domain it adapt itself and learns to do better in changing environments.

2. Literature Survey

In recent years, the system theoretic models have gained recognition in the field of surface as well as subsurface hydrology. The application of the data driven models to hydrological models can be found in: for rainfall-runoff model [18], stream flow prediction [1][2][8], groundwater level forecasting [6][7][18]. Among the data driven models, artificial neural network (ANN) model has been successfully applied to a wide variety of hydrologic problems [6]. The application of a more promising data driven technique, the fuzzy inference system (FIS), has recently been increasing in hydrology. [3] predicted water level using fuzzy logic and ANN. Further, in recent years many advancements of ANN, which includes, Radial Basis Function (RBF), Generalized Regression Neural Network (GRNN) And Adaptive Neuro-Fuzzy Inference Systems (ANFIS) has been adapted to hydrologic problems.

In case of groundwater literature only few studies have been carried out using the above data driven models [3][4][7][11][9]. [4] developed a adaptive neuro-fuzzy inference system (ANFIS) and artificial neural networks (ANN) model based on Levenberg-Marquardt (LM) for forecasting daily groundwater level fluctuation (GLF).It was found that the algorithms produced no significant differences in prediction results. Overall, the results suggest that the soft computing algorithms can predict daily groundwater level with high accuracy using time lag as inputs networks. In [8], the seasonal ground water levels are predicted using the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Radial Basis Function (RBF) based on previous seasonal rainfall and ground water levels. The study is carried out in Malattar sub-watershed, located in Vellore district, Tamilnadu, India. The results show that both the models are able to predict the seasonal ground water levels with sufficient accuracy.

3. Study Area and Data

The data used for Groundwater Level prediction model development consists of water level data of Mohanlalganj hydrograph station (W264150080572501), block Sarojininagar, district Lucknow, Uttar Pradesh, India for the period 1981 to 2013 and mean monthly temperature and monthly rainfall data for the same period.

A. Model Inputs

Different permutations and combinations of Water level (WL), Rainfall (RF) and Temperature(T) has been used as input variables, keeping the number of input variables to three to make four model MI, MII, MIII and MIV as shown in ***table 1.*** In all these models the output variable has been kept fixed to one with water level as the variable parameter.

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Table 1: Structure of Forecasting model both for ANFIS

Model	Input Variables	Output Variable
MI	WL(t-1), WL(t), T(t), RF(t)	WL(t)
MII	WL(t-1), WL(t), RF(t)	WL(t)
MIII	WL(t-1), WL(t), T(t)	WL(t)
MIV	WL(t-2), WL(t-1), WL(t)	WL(t)

B. Theory and Methodology

The ANFIS architecture [5] 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 the fuzzifying 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[5][6] 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 [15]. The Sugeno type Fuzzy Inference System is used to construct the ANFIS model. The hybrid ANFIS model with membership functions of Gaussian shape for input and linear output membership function gives the best results. The 100 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.

C. Model Performance Evaluation

The RMSE is a measure of general model performance. It is the most easily interpreted statistic, since it has the same units as the parameters estimated. The RMSE is thus the difference, on average, of an observed data and the estimated data. RMSE evaluates the residual between measured and forecasted ground water level. It is given by

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

Where, xi = observed ground water levels, x = mean of xi , yi = predicted ground water levels, and n = the number of data set used for evaluation

D. Model Parameters Used

The parameters used in the model for training ANFIS are given in Table 2 and the rule extraction method used are given in Table 3. The initial and the final membership function curves for the input variables for the best fit model based on performance criteria are shown in fig 1. Tables 4 summerizes the results of types and values of model parameters used for training ANFIS.

Table 2: Model Parameters for ANFIS Training

Rule extraction method	Input MF type	Input partitioning	Output MF Type	Number of output MFs	Training algorithm	Training epoch number	Initial step size
Parameters used	Gaussian membership (‘gaussmf’)	variable	Linear	one	Hybrid learning	10	0.01

Table 3: Rule extraction method for training ANFIS

Rule Extraction Method	And method	Or method	Defuzzy method	Implication method	Aggregation method
Type	‘prod’	‘probor’	‘wtever’	‘prod’	‘max’

Table 4: Parameter values obtained in ANFIS training

No. of nodes	**No. of linear parameters**	**No. of non-linear parameters**	**Total no. of prameters**	**No. of training data pairs**	**No. of testing data pairs**	**No. of fuzzy rules**
1311	646	1216	1862	40	23	38

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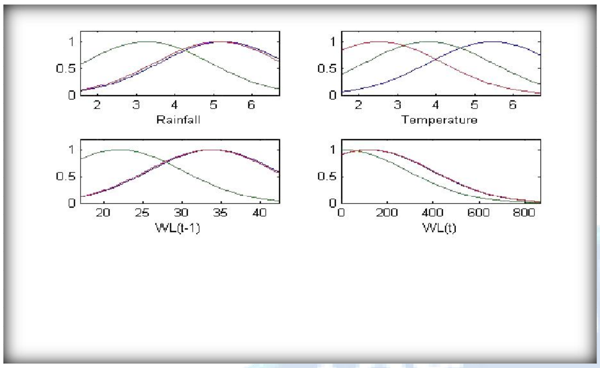

Fig. 1. Initial Membership Function Curves used for input variables

4. Result and Discussion

Using the proposed methodology, for the case study mentioned above as related to real world data sets, it was found that ANFIS was able to develop best predictive model M-IV, having only water level input variables and water level as output variable as compared to other three models. This is clearly evident from the comparative table and graph given in Table 5 and Fig. 2 below. This was followed by M-I, M-II and in the last by M-III model based on RMSE values. M-I model has all the three input variable, viz. water level, rainfall and temperature, M-II model has water level and rainfall as input variables and the least developed model, M-III has water level and temperature as input variables. Hence, it was seen from the case study that the models that are developed using only water level, as input variables (M-IV model) perform very well as far as their prediction efficiency is concerned.

Table 5: Range of RMSE Val. during training and testing phase for different clustering radius for all the four models

Model	RMSE VALUE					
	r=0.5		r=0.75		r=0.90	
	Trg data	Tst. Data	Trg data	Tst. Data	Trg data	Tst. Data
M-I	0.41	10	0.64	2.46	***0.85***	***1.88***
M-II	0.92	2.12	1.1	1.47	1.17	1.21
M-III	0.47	7.47	0.69	2.7	0.87	2.24
M-IV	0.61	3.01	0.78	1.53	1	1.18

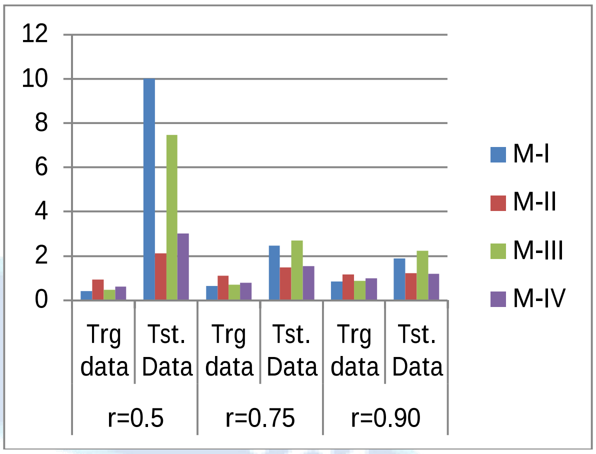

Fig. 2. Graphical plot of Comparative RMSE values for different models

Further from the perusal of the data given in Table 5 it is also evident that the model performance has improved during testing phase as we go on increasing the clustering radius from 0.50 to 0.90 for all the models, whereas during the training phase the trend is just the reverse. This clearly demonstrated that clustering radius has an adverse effect on the performance of the ANFIS during training phase and vise-versa for testing phase. This can be confirmed from the Fig.2 given above.

Thus, it is clear that proper selection of influential radius which affects the cluster results directly in ANFIS using substractive clustering rule extraction method , has resulted in reduction of RMSE both for training and testing data sets. Hence, it is seen that for small size training data, ANFIS has performed well.

In order to depict how well ANFIS model has performed, a comparative plot of observed water level versus predicted water level, both for training and testing datasets using ANFIS technique has been shown in Fig. 3 and Fig. 4. From the graph it is seen that ANFIS model line almost closely follows the observed water level line, although the matching is better for training datasets.

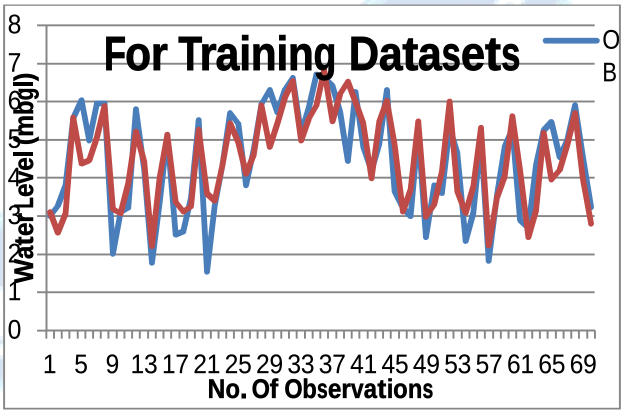

Fig. 3. Comparative plot of Observed versus Predicted Water Level for Training Datasets

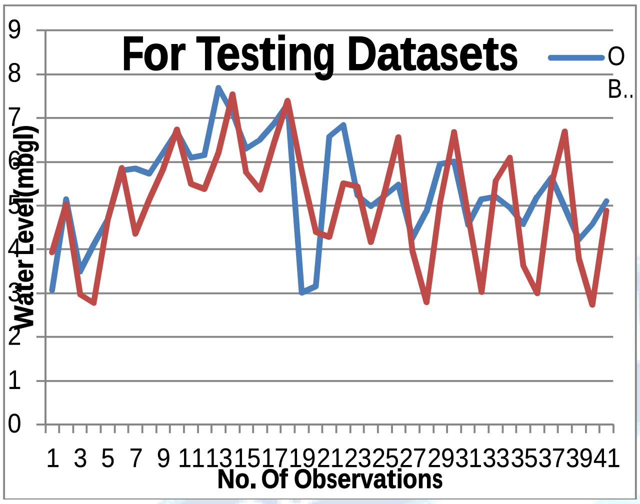

Fig. 4. Comparative plot of Observed versus Predicted Water Level for Testing Datasets

5. Conclusion

In this study the performance of ANFIS models for prediction of groundwater levels in block Sarojininagar, district Lucknow, Uttar Pradesh, India has been analysed. The modeling exercise is carried out based on split-sample validation. The performance of the model is carried out based on performance measures such as root mean square error. It is observed that the performance of the ANFIS is quite satisfactory providing close or sometime superior performance in terms of the performance measures used in this study. It is envisaged that ANFIS model can be a better alternate for modeling the seasonal rainfall, temperature and groundwater process. Further it was seen that clustering radius has a great influence on the performance of the model. Increasing the clustering radius from 0.5 to 0.90, the model performance improved for testing datasets. The number of epochs too had an influence on the model performance. For training the ANFIS model, the number of epochs was kept at 100.

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