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An Adaptive Neuro Fuzzy Approach for Groundwater Level Simulation – A Case Study of Lucknow District

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Abstract--**For management and planning of groundwater resources in any watershed basin, seasonal modelling of groundwater level fluctuation plays a very vital role. This particularly takes place in areas of rapid industrialization and urbanization, which leads to decline of water table and more groundwater extraction than recharge. In Indian context this is particularly seen in areas where there is decline in rainfall resulting in over-exploitation of groundwater. In this study, an Adaptive Neuro Fuzzy Inference System (ANFIS) model has been developed to predict the groundwater level fluctuations. The models were developed by employing rainfall and the past Ground Water Level (GWL) as input and the present GWL as output. The data for the modelling task have been used from Sarojini Nagar Block, district Lucknow, U.P, India, which is characterised by Ganga alluvium of Quaternary age. The performances of the developed AFIS model has been evaluated using Root Mean Square Error (RMSE). The result indicates that the models can successfully be used for prediction of GWL.**

Keywords: ANFIS, Groundwater level, GWL, RMSE

1 Introduction

For surface and ground water resources planning and management it is very important to go for seasonal modelling of water fluctuations in any watershed basin. This becomes all the more important in areas where there is increasing water demand due to urbanization and industrialization. It is also seen that there is marked variation the rainfall patterns and its quantity. Thus on seeing the above scenario it is felt that groundwater resources are becoming all the more important in order to cater to the increase in the demand of water. In Indian context, due to the changing rainfall patterns this groundwater exploitation has become inevitable.

Groundwater forecasting models are physical and system theoretical. On one hand physical models are complex, its complexity increases with the increase in the model parameters, on the other hand they are based on understanding the physical state of the system under consideration. However, system theoretical models are data based. They depend on the quality of data for its accuracy. There is no physical understanding of the process for the development of the model. These models have gained importance in the surface and subsurface hydrological field.

Here Adaptive Neural Fuzzy Inference System Techniques (ANFIS) approach has been applied to develop a model for forecasting ground water levels in Sarojini Nagar Block, district Lucknow, U.P., India, which is characterised by Ganga alluvium of Quaternary age. Irregular rainfall has often led to detrimental effects on the natural and human environment.

It is seen that excessive withdrawal of groundwater in areas of depleting groundwater resources has rsulted in lowering of groundwater table, thus resulting in undermining of water security in this region.

2 Literature Survey

There has been more recognition given to system theoretic models as compared to the physical driven models in case of surface and subsurface hydrology. The application of data driven models in the development of hydrological models are found in rainfall-runoff model [8], stream flow prediction [1][2][8], groundwater level forecasting [6][7][18]. Artificial Neural Network (ANN) is one such model which has been very successfully used [6] for the present study. Further there has been an increase in the use of Fuzzy Inference System (FIS). [3] made use of fuzzy logic and ANN for the development of water level prediction models. The techniques used were Radial Basis Function (RBF), Generalized Regression Neural Network (GRNN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS). [15] showed the importance of 6-month-ahead water level prediction model based on the precipitation forecasts from ECHAM 4.5 General Circulation Model Forced with Sea Surface Temperature forecasts. [16] illustrated the importance of soft computing techniques for precipitation estimation. It included data of Serbia for the period 1946-2012, which included 29 synoptic stations.

3 Available data and model structure

Here Mohanlalganj hydrograph station (W264150080572501), block Sarojininagar, district Lucknow, Uttar Pradesh, India has been chosen as a case study area. Ground water level data for this hydrograph station for the period 1981 to 2013 has been procured from Central Ground Water Board, Northern Region, Lucknow, an apex Central Government organisation which monitors ground water level of the whole of India through a network of hydrograph stations spread all over India four times a year i.e. January, May, August and November.

4 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.

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)

5 Methodology Used

The ANFIS architecture [5] consists of five layers [5]. In the first fuzzification layer crisp input values are fed, which then pass on to layers 2 and 3 (inference process) where rule application takes place. Next the output for each of the rules in layers 2 and 3 are calculated in layer 4 and finally summation of the output takes place in layer 5 to get the final output.

ANFIS uses hybrid learning algorithm, which uses the combination of least square estimate and gradient descent for determination of the optimum output of equivalent FIS parameters. This is done by minimizing the error between the input and output values. The parameters which are optimized are known as the premise and consequent parameters. The initial one determines the shape of the membership function and later on determines the final output values. ANFIS model has been developed using Sugeno FIS.

6 Model Performance Evaluation

The RMSE is a measure of general model performance. It can be interpreted with ease because it has the same units as the parameters estimated. The RMSE is the variation of an observed and an 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

7 ANFIS Model Development

Parameter Used

ANFIS is a sensible incorporation of the merits of FIS and ANN [3]. The main element of FIS is the identification of the rule base.

The main issue is the non existence of any technology of converting the human knowledge into rule base and also is is required to fine tune the membership functions so as to reduce the performance error. Thus when generating a FIS using ANFIS, it is important to select proper parameters which includes each antecedent variable's MFs. For better refinement and learning process selection of proper parameters is very important. This includes the step size determination. In the current work subtractive clustering has been applied for FIS refinement. The ANFIS is simulated using the MATLAB Fuzzy Logic Toolbox.

Table 2 and Table 3 gives the parameters used for ANFIS training and rule extraction methods respectively. The initial and the final membership function curves for the input variables for the best fit model based on performance criteria are shown in figure 1. The summary results of the model parameters are given in Table 4.

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'

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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

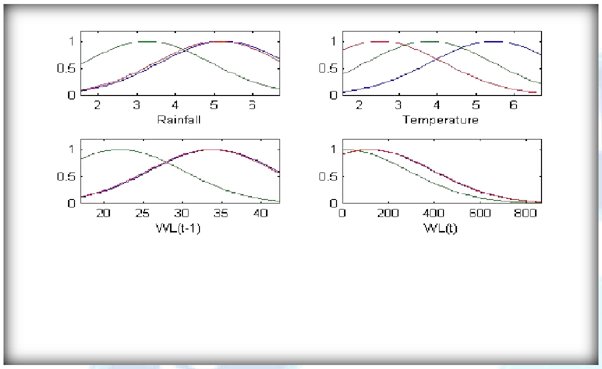

Fig. 1. Initial Membership Function Curves used for input variables

8 Results and Discussions

Here the ANFIS model has been trained and tested using ANFIS methodology and their performance for the best prediction model M-IV for clustering radius r=0.90 have been determined and comparing done using separate training and testing datasets. Their corresponding range of values for all the four models are summarized in *table 5*. The comparative plot of all the four models M-I to M-IV is plotted below in *fig. 2*.

Table 5 RMSE Val. Range during training and testing phase for different clustering radius

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

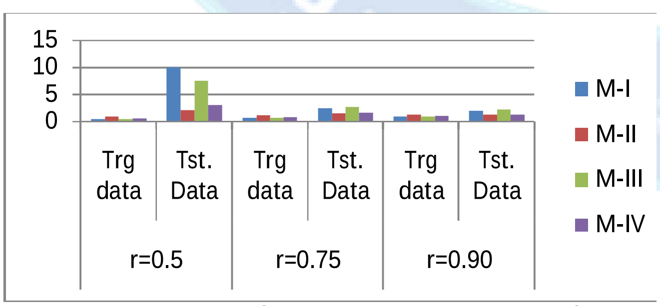

Fig. 2. Graphical plot of Comparative RMSE values for different models

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.

From the above discussion it can now be clearly inferred that determination of proper clustering radius plays a very important role in better model development and thus leading to reduction in RMSE values for training and testing datasets. Thus it can be said that for small number datasets ANFIS seems to perform 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 & 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.

9 Conclusion

Here the performance of ANFIS models for prediction of groundwater levels in block Sarojininagar, district Lucknow, Uttar Pradesh, India has been analysed. The modelling work has been done using split-sample validation. The model has been validated based on RMSE criteria. The results show that ANFIS has been able to perform well in the development of the prediction model. It can be seen that for modelling the seasonal rainfall, temperature and groundwater process, ANFIS can be a better alternative to other techniques. 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.

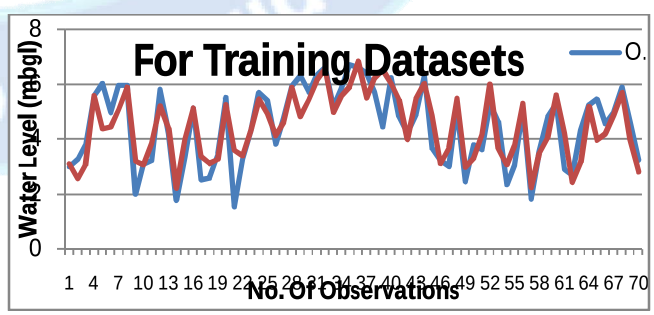

Fig. 3. Comparative plot of Observed versus Predicted Water Level for Training Datasets

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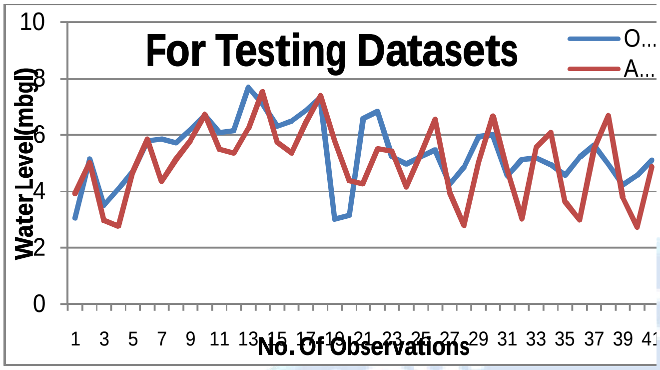

Fig. 4. Comparative plot of Observed versus Predicted Water Level for Testing Datasets

References:

[1] ASCE: Task Committee on Application of Artificial Neural Networks in Hydrology. I: Preliminary Concepts, J. Hydrol. Eng., 5(2), 115–123, 2000.

[2] ASCE: Task Committee on Application of Artificial Neural Networks in Hydrology. II: Hydrologic Applications, J. Hydrol. Eng., 5(2), 124–137, 2000

[3] Alvisi, .S., G. Mascellani., M. Franchini., and A. Bardossy., (2006). Water level forecasting through fuzzy logic and Artificial Neural Network approaches, Journal of Hydrology and Earth System Sciences 10, 1-17. 3

[4] Azhar K., Affandi and Kunio Watanabe (2007), Daily groundwater level fluctuation forecasting using soft computing technique, Nature and Science, 5(2).1-10. 4

[5] Jang, J.S.R., (1993). ANFIS: Adaptive network based fuzzy inference system, IEEE Trans. On System, Man, and Cybernetics 23(3), 665-685.8

[6] Maier.H.R.,G.C.Dandy.,(2000).Neural networks for the prediction and forecasting of water resources variables:.Environmental Modeling & Software15(1), 101-124 9

[7] Nayak, P.C., K.P.Sudheer., D.M. Rangan., K.S. Ramasastri., (2004). A neuro-fuzzy computing technique for modeling hydrological time series, Journal of Hydrology 291 (1, 2), 52-66. 10

[8] Amutha R and Porchelvan P, (2011), “SEASONAL PREDICTION OF GROUNDWATER LEVELS USING ANFIS AND RADIAL BASIS NEURAL NETWORK”, International Journal of Geology, Earth and Environmental Sciences, Vol. 1 (1), pp.98-108 13

[9] Uruya Weesakul, et. al., (2010), “Application of Soft Computing Techniques for Analysis of Groundwater Table Fluctuation in Bangkok Area and Its Vicinity”, International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies. Volume 1 No.1. eISSN: 1906-9642 16

[10] P. Abbasi Maedeh, et. al., (2013), “ Application of Artificial Neural Network to Predict Total Dissolved Solids Variations in Groundwater of Tehran Plain, Iran”, International Journal of Environment and Sustainability, Vol. 2 No. 1, pp. 10-20 17

[11] Sanjeev Kumar, et. al., (2013), “Neural network Model for Prediction of Groundwater Level in Metropolitan Considering Rainfall-Runoff as parameter”, International Journal of Soft Computing and Engineering (IJSCE), Volume-3, Issue-3. 18

“Fuzzy Logic Toolbox”, MATLAB version R2013a.

[12] CHEN, D.W. AND ZHANG, J.P., (2005), “Time series prediction based on ensemble ANFIS”, Proceedings of the fourth International Conference on Machine Learning and Cybernatics, IEEE, pp 3552-3556.

[13] CHIU, S., (1994), “Fuzzy Model Identification based on cluster estimation”, Journal of Intelligent and Fuzzy Systems, 2 (3), pp 267–278.

[14] Naser Almanaseer, et al. (2014), “Improving Groundwater Predictions Utilizing Seasonal Precipitation Forecasts from General Circulation Models Forced with Sea Surface Temperature Forecasts”, Journal Of Hydrologic Engineering © ASCE, pp. 87-98.

[15] ShahaboddinShamshirband, Member, IEEE, et al. (2015) March, “Soft-Computing Methodologies for Precipitation Estimation: A Case Study”, IEEE Journal Of Selected Topics In Applied Earth Observations And Remote Sensing, Vol. 8, No. 3.