International Journal of Research and Development in Applied Science and Engineering (IJRDASE)

On the use of ANFIS for Ground Water Level Forecasting in an Alluvium Area

S. Sahay
sulabhsahai@gmail.com

Anurag Banoudha
iisc.anurag@gmail.com

Raghawendra Sharma
robie2007@gmail.com

Abstract- Accurate prediction of the ground water level is crucial for optimizing the management of water resources. In this direction use of Soft Computing Techniques is becoming increasingly important in the modeling and forecasting of hydrological and water resource processes. In this study applicability of an adaptive network-based fuzzy inference system (ANFIS) method was used to build a prediction model which can simulate the trend of the ground water level and provide an acceptable predictions upto three months ahead. To illustrate the applicability and capability of the ANFIS, a hydrograph station in block Sarojininagar, district Lucknow, India has been chosen as the study area as its ground water resources have been overexploited during the last twenty years and the ground water level has been decreasing steadily. Different models having different input variables are constructed and the best one is investigated. Further model efficiency is evaluated both for training and validating data sets. Also the best developed model is trained and tested by Artificial Neural Network (ANN) . The results of ANFIS and ANN models are compared and evaluated. The results demonstrate that the ANFIS can be applied successfully and provide high accuracy and reliability for ground water level prediction.

Keywords:- Soft computing techniques; Ground water level forecasting; ANN; ANFIS; model efficiency; water resource management

1. Introduction

Ground water is one of the major sources of supply for domestic, industrial and agricultural purposes. In some areas ground water is the only dependable source of supply, while in some other regions it is chosen because of its ready availability. Long term systematic measurements of water levels provide essential data needed to evaluate changes in resources over time, to develop ground water models and to forecast trends and design, implement and monitor the effectiveness of ground water management and protection programs.

In this direction several studies were carried out for forecasting the groundwater levels using conceptual/physical models that are not only laborious, but also have practical limitations, as many inter-related variables are involved. In the recent past, soft computing tools like artificial neural networks (ANNs) have been used increasingly in various fields of science and technology for prediction purposes.

Fuzzy logic method was first developed to explain the human thinking and decision system by Zadeh (1965). Several studies have been carried out using fuzzy logic in hydrology and water resources planning [Chang et. al., 2001; Ertunga et. al., 2001; Liong et. al., 2000; Mahabir et. al., 2000; Mitra et. al., 1998; Nayak et. al., 2004a]. Recently, Adaptive Neuro-fuzzy inference system (ANFIS), which consists of the ANN and fuzzy logic methods, have been used for many application such as, database management, system design and planning/forecasting of the water resources [Chen et. al., 2006; Chang et. al., 2006; Chang et. al., 2001; Da Silva et. al., 1999; Nayak et. al., 2004b; Firat et. al., 2006].

The main purpose of this study is to investigate the applicability and capability of ANFIS to develop ground water level forecasting models and to compare it with ANN in terms of performance criteria.

2. Adaptive Neural Fuzzy Inference System (ANFIS) methodology

2.1 Basic Theory

The fuzzy logic approach is based on the linguistic uncertain expression rather than numerical uncertainty. It is a soft computing technique that has been widely used in hydrological processes. Since Zadeh (1965) proposed the fuzzy logic approach to describe complicated systems, it has become popular and has been successfully used in various engineering problems, especially on control processes [Chen et. al., 2006; Chang et. al., 2006; Chang et. al., 2001; Liong et. al., 2000; Mahabir et. al., 2000; Nayak et. al., 2004a; Da Silva et. al., 1999; Firat et. al., 2006; Nayak et. al., 2004b; Şen, 2001]. Nonetheless, the main problem with this approach is that there is no systematic procedure for a design of fuzzy controller. Two methods, called as back propagation algorithm and hybrid-learning algorithm, provide learning of the ANFIS and construction of the rules, are used to determine the membership function of the input-output variables. A general structure of fuzzy system is given in Figure 1.

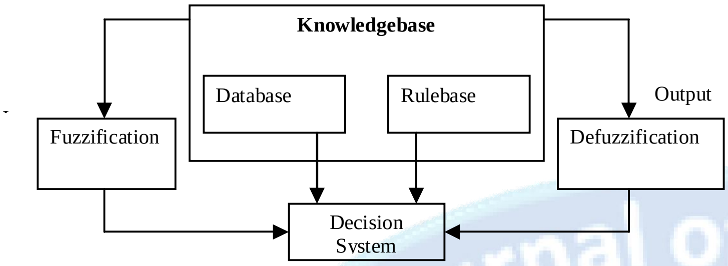

Fig.1. A General Fuzzy System

2.2 ANFIS Architecture

ANFIS has been shown to be powerful in modeling numerous processes such as wind speed time series and real-time reservoir operation [Chen et. al., 2006; Chang et. al., 2006; Fırat et. al., 2006]. The ANFIS architecture consists of five layers (Figure 3). Here the circles denote a fixed node whereas squares denote an adaptive node. For simplicity it is assumed that the examined FIS has two inputs and one output. For a first order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as

Rule 1: *IF x is* A_1 *and y is* B_1 *THEN* $f_1 = p_1 * x + q_1 * y + r_1$

Rule 2: *IF x is* A_2 *and y is* B_2 *THEN* $f_2 = p_2 * x + q_2 * y + r_2$

where, x and y are the crisp inputs to the node i , A_i and B_i are the linguistic labels (low, medium, high, etc.) characterized by convenient membership functions and p_i , q_i and r_i are the consequence parameters ($i = 1$ *or* 2) .

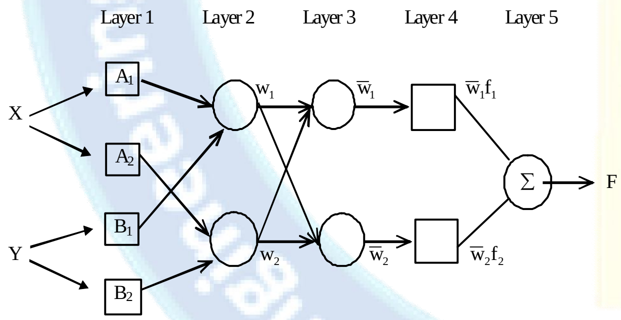

Fig. 2.

The model is briefly presented step by step in the following way;

Input nodes (Layer 1): Each node in this layer generates membership grades of the crisp inputs which belong to each of convenient fuzzy sets by using the membership functions. Each node's output Oi^1 is calculated by:

$$O_i^1 = \mu_{A_i}(x) \text{ for i= 1,2 ; } O_i^1 = \mu_{B_{i-2}}(y) \text{ for i= 3,4} \qquad (1)$$

Where μ_{Ai} and μ_{Bi} are the appropriate membership functions for A_i and B_i fuzzy sets, respectively.

Rule nodes (Layer 2): In this layer, the AND/OR operator is applied to get one output that represents the results of the antecedent for a fuzzy rule, that is, firing strength. It means the degrees by which the antecedent part of the rule is satisfied and it indicates the shape of the output function for that rule. The outputs of the second layer, called as firing strengths O_i^2 are the products of the corresponding degrees obtaining from layer 1, named as w given below.

$$O_i^2(x) = w_i = \mu_{A_i}(x)\,\mu_{B_i}(y), \text{ i=1,2} \qquad (3)$$

Average nodes (Layer 3): Main target is to compute the ratio of firing strength of each ith rule to the sum of all rules' firing strength. Thus the firing strength in this layer is normalized as;

$$O_i^3 = \overline{w_i} = \frac{w_i}{\sum w_i} \text{ i=1,2} \qquad (4)$$

Consequent nodes (Layer 4): The contribution of ith rule's towards the total output or the model output and/or the function defined is calculated in Equation (5);

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}\left(p_i x + q_i x + r_i\right) \text{ i=1,2} \qquad (5)$$

Where, w_i is the ith node's output from the previous layer (i.e., demonstrated in the third layer). {p_i ,q_i , r_i } is the parameter set in the consequence function and also the coefficients of linear combination in Sugeno inference system.

Output nodes (Layer 5): This layer is called as the output notes in which the single note computes the overall output by summing all the incoming signals and is the last step of the ANFIS. Hence, each rule's fuzzy results are transformed into a crisp output in this layer by defuzzification process, as;

$$f(x,y) = \frac{w_1(x,y)\,f_1(x,y) + w_2(x,y)\,f_2(x,y)}{w_1(x,y) + w_2(x,y)} = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2}$$

(6)

$$O_i^5 = f(x,y) = \sum_i \overline{w_i} f_i = \overline{w_i} f_1 + \overline{w_i} f_2 = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (7)$$

3. Study area and data description

Sarojininagar hydrograph station in district Lucknow, Uttar Pradesh has been chosen as the study area. The data records consists of ground water level data (recorded four times a year) between the period 1986 - 2008 are procured from Central Ground Water Board and rainfall and surface data (temperature, relative humidity, etc.) are procured from IMD, Pune. The plot of time series record of water level and rainfall data for the period 1986 to 2008 is shown in fig. 3.

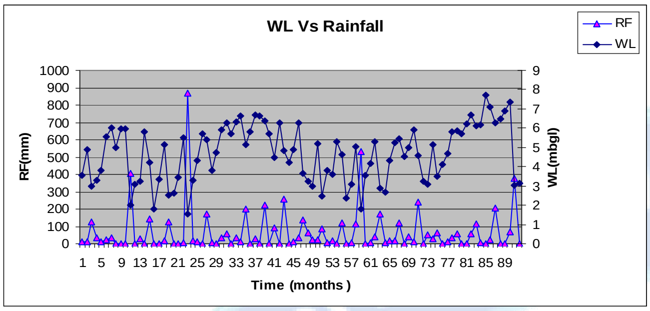

Figure 3

4. Input Variables and Model Structure

In this study, those two terms are used synonymously. Different combinations of Water level (WL), Rainfall (RF), Temperature(T) and Relative Humidity(RH) has been used as input variables, keeping the number of input variables to three. Also to make the training data cover all the characteristic of the problem in order to get effective forecasting model, the data has been further subdivided into three sub models based on the principles of Cross Validation. Here the structure of forecasting model is depicted in table-1, cross validated data sets in table-2 and data selection for optimum water level prediction in table-3

Table – 1 Structure of Forecasting model both for ANN and ANFIS

Model	Input Variables	Output Variable
M1	WL(t-3), WL(t-2), WL(t-1)	WL(t)
M2	WL(t-2), WL(t-1), RF(t)	WL(t)
M3	WL(t-1), RF(t), RH(t)	WL(t)
M4	WL(t-1), T(t), RH(t)	WL(t)
M5	WL(t-1), T(t), RF(t)	WL(t)

where, WL(t, t-1, t-2, t-3) is the water level at time periods (t), (t-1), (t-2) and (t-3) RF = Rainfall; RH = Relative Humidity; T = Temperature; WL = Water Level

Table – 2 Cross Validation of data for selection of training / testing datasets.

Cross Validated Data	Data Period	Number of data
CV1	1986 - 1993	30
CV2	1994 – 2001	30
CV3	2002 - 2008	29

Table – 3 Data Selection for optimum water level prediction

Main Models	Sub - models	Cross Validation data		
		CV1	CV2	CV3
M1 to M5	MD1	Testing	Training	Training
	MD2	Training	Testing	Training
	MD3	Training	Training	Testing

where Training = TRG, Testing = TST

5. Performance Measuring Criteria

The performance of ANFIS models using training and testing data are evaluated and compared using Correlation Coefficient (r), Efficiency (E) and Root Mean Square Error (RMSE)

5.1 Correlation Coefficient (r)

It provides information on the strength of linear relationship between the observed and the computed values. The value r close to 1.0 indicates good model performance and can be calculated using the following formula,

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

5.2 Root Mean Square Error (RMSE) :-

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.

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

5.3 Efficiency (E)

The efficiency (E) is one of the widely employed statistics to evaluate model performance. An efficiency of 1 (E=1) corresponds to a perfect match.

$$E = \frac{E_1 - E_2}{E_1} \quad E_1 = \sum_{i=1}^{n}\left(x_i - \overline{x_i}\right)^2 \quad E_2 = \sum_{i=1}^{n}(y_i - x_i)^2$$

where x_i = observed ground water level

$\overline{x_i}$ = mean of x_i

y_i = predicted ground water level

$\overline{y_i}$ = mean of y_i

n = number of data sets used for evaluation

6. ANFIS Model Development

In this study firstly, the five models having various input variables are trained and tested by ANFIS method using MATLAB R2012a software and the performances of the ground water level forecasting models are compared and evaluated based on training and testing performances. The models generate Fuzzy Inference System structure from data using subtractive clustering. Gaussian membership function has been used as the input membership function and linear membership function for the output function. Here separate sets of input and output data has been used as input arguments. Subtractive clustering has been used as the rule extraction method to determine the number of rules and antecedent membership function and least square estimation to determine each rule's consequent equation. The hybrid learning algorithm, which is the combination of least square estimation and back propagation gradient descent has been applied. The best fit model structure is determined according to criteria of performance evaluation. The performance indices of all the ANFIS models are given in tables 4, 5, and 6 for correlation coefficient, Efficiency and RMSE respectively and their comparative graphs are shown in Fig. 4, 5 and 6. The membership function curves for M1, M2, M3, M4 and M5 models are given in Fig. 7, 8, 9, 10 and 11 respectively.

Table 4

Models	M1	M2	M3	M4	M5
MD1_TRG	0.69	0.77	0.81	0.78	0.86
MD1_TST	0.36	0.66	0.77	0.68	0.81
MD2_TRG	0.47	0.79	0.8	0.76	0.8
MD2_TST	0.003	0.65	0.77	0.74	0.66
MD3_TRG	0.63	0.73	0.81	0.76	0.81
MD3_TST	0.69	0.85	0.77	0.72	0.75

Table 5

Models	M1	M2	M3	M4	M5
MD1_TRG	0.48	0.6	0.65	0.6	0.74
MD1_TST	0.04	0.39	0.57	0.45	0.65
MD2_TRG	0.08	0.63	0.65	0.58	0.65
MD2_TST	0	0.41	0.59	0.53	0.57
MD3_TRG	0.39	0.53	0.65	0.56	0.66
MD3_TST	0.4	0.71	0.55	0.48	0.55

Table 6

Models	M1	M2	M3	M4	M5
MD1_TRG	1.02	0.9	0.82	0.88	0.71
MD1_TST	1.16	1.1	0.91	1.04	0.82
MD2_TRG	1.09	0.9	0.87	0.94	0.86
MD2_TST	1.04	1.05	0.88	0.95	0.89
MD3_TRG	1.07	0.96	0.83	0.92	0.82
MD3_TST	1.06	0.76	0.92	0.99	0.92

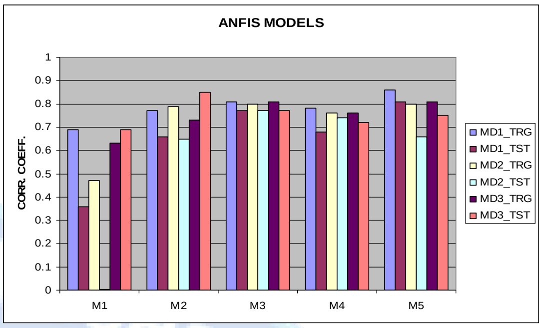

Figure 4

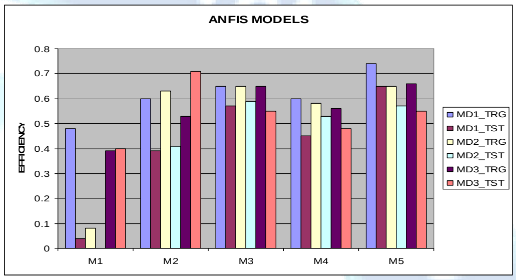

Figure 5

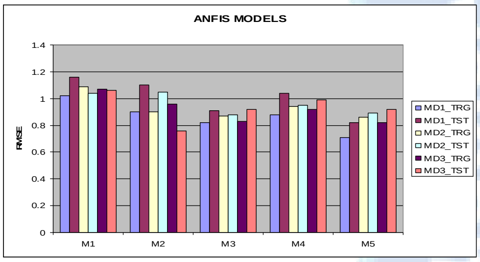

Figure 6

Comparing the results of all the five models using the performance criteria, it is seen that the best developed model for ground water level forecasting is the M3 model with input variables as groundwater level, rainfall and relative humidity. Using the cross validated data for M3 model, it is seen that M3 MD1 is the best predictive model, with MD1 being the best cross validated data wherein the training data covers all the characteristic of the problem in order to get effective forecasting model. This M3 model is very close to M5 model on the basis of performance indices. The input variables for M5 models are groundwater level, rainfall and temperature. It appears that both the M3 and M5 models are generally accurate and the values of RMSE are small enough and corr. coeff. and efficiency values close to unity as compared to other models. The prediction versus observed value curves for M3 MD1 and M5 MD1 models are shown in fig. 12 and fig. 13 respectively. These models are followed by M4, M2 and M1 in decreasing order of best fit model developed. From the above tables 4, 5 and 6, it is seen that Model M3 MD1 has E, Corr. Coeff. and RMSE values both for training and testing datasets as (0.65, 0.57), (0.81, 0.77) and (0.82, 0.91) respectively. The least developed model in terms of model efficiency is the M1 model with all the three input variables as ground water levels only with E, Corr. Coeff. and RMSE values both for training and testing datasets as (0.48, 0.04), (0.69, 0.36) and (0.1.02, 1.16) respectively. The results of ANFIS models demonstrate that ANFIS can be applied accurately to establish accurate and reliable ground water level forecasting.

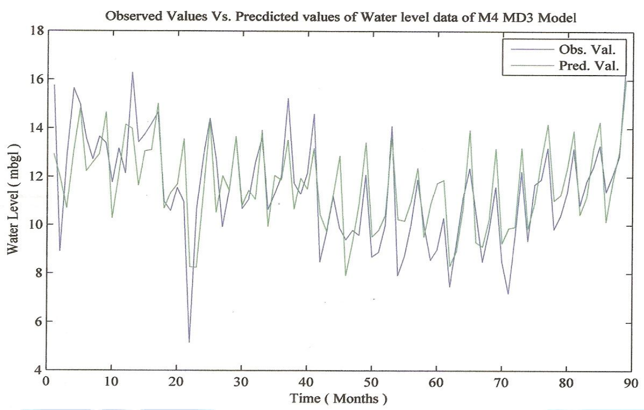

Figure 12

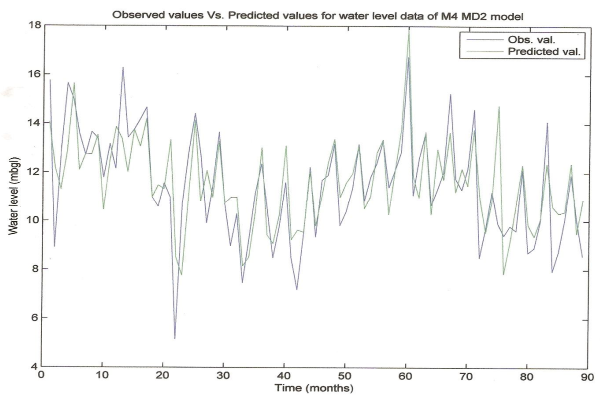

Figure 13

7. ANN Model Development

7.1 Basic ANN Theory

An ANN can be defined as a system or mathematical model consisting of many nonlinear artificial neurons running in parallel which can be generated as one or multiple layered. In this study, Feed Forward Neural Network (FFNN) method has been used for forecasting of ground water level. A FFNN consists of at least three layers, input, output and hidden layer. The number of hidden layers and neurons in hidden layer are determined by trial and error method. The strength of connection between the two layers is determined by the weights W_{ij} . The schematic diagram of a FFNN is shown in Fig. 11

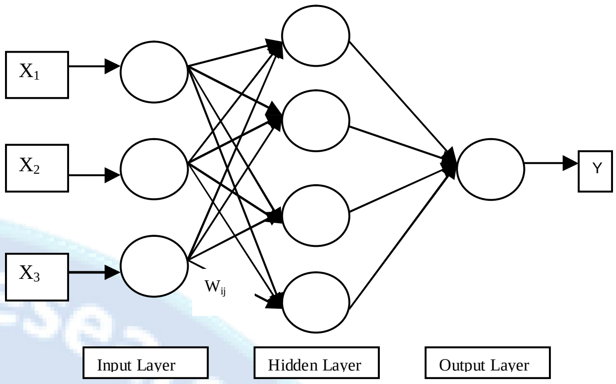

Fig 14

Each neuron in a layer receives weighted inputs from a previous layer and transmits its output to neurons in the next layer. The summation of weighted input signals is calculated by Eq. (1) and is transferred by a nonlinear activation function given in Eq. (2). The responses of network are compared with the observation results and the network error is calculated with equation (3)

$$Y_{net} = \sum_{i=1}^{N} X_i . w_i + w_0 \qquad (8)$$

$$Y_{out} = f(y_{net}) = \frac{1}{1+e^{-Y_{net}}} \qquad (9)$$

$$J_r = \frac{1}{2} . \sum_{i=1}^{k} (Y_{obs} - Y_{out})^2 \qquad (10)$$

Y_{out} is the response of neural network system, f (Y_{net}) is the nonlinear activation function, Y_{net} is the summation of weighted inputs, X_i is the neuron input, w_i is weight coefficient of each neuron input, w_0 is bias, J_r is the error between observed value and network result, Y_{obs} is the observation output value

7.2 ANN Model development

Here same five models M1, M2, M3 M4 and M5 as used in ANFIS model development has been used for Feed Forward Neural Network (FFNN) model development with Back Propagation learning algorithm. Here the summation of the input signals is transferred to next layer using sigmoid activation function. The faster learning of the network has been achieved by selecting optimum learning rate and momentum, both found by trial and error. For better performance of the network, the number of hidden layers has been kept to minimum, i.e one and the number of neurons in this layer has been varied. In the training and testing of the ANN models, the same data set is used and performences of the models is evaluated using the above mentioned criteria. The performance indices viz. correlation coefficient, efficiency and RMSE, of all the ANN models are given in tables 7, 8, and 9 and their comparative graphs are shown in Fig. 15, 16 and 17.

Table 7

Models	**M1**	**M2**	**M3**	**M4**	**M5**

MD1_TRG	0.71	0.77	0.83	0.81	0.79
MD1_TST	0.31	0.74	0.75	0.71	0.74
MD2_TRG	0.61	0.84	0.85	0.73	0.75
MD2_TST	0.62	0.77	0.77	0.75	0.64
MD3_TRG	0.6	0.78	0.78	0.8	0.74
MD3_TST	0.58	0.84	0.73	0.68	0.71

Table 8

Models	**M1**	**M2**	**M3**	**M4**	**M5**
MD1_TRG	0.43	0.46	0.55	0.65	0.46
MD1_TST	0	0.21	0.27	0.49	0.25
MD2_TRG	0.25	0.67	0.7	0.34	0.42
MD2_TST	0.35	0.57	0.55	0.37	0.24
MD3_TRG	0.19	0.59	0.61	0.62	0.49
MD3_TST	0.15	0.65	0.47	0.27	0.43

Table 9

Models	**M1**	**M2**	**M3**	**M4**	**M5**
MD1_TRG	1.06	1.06	0.98	1.23	1.07
MD1_TST	1.19	1.25	1.15	1.25	1.31
MD2_TRG	1.23	0.85	0.8	1.17	1.12
MD2_TST	1.07	0.89	0.9	1.09	1.21
MD3_TRG	1.33	0.97	0.94	0.92	1.06
MD3_TST	1.01	0.91	0.9	1.02	0.89

Comparing the results of all the five models, it is seen that the prediction accuracy of M3 model is the best with input variable as water level, rainfall and relative humidity. Here the FFNN model has been developed with one hidden layer with four neurons. The training parameters of the FFNN model such as learning rate (0.5), momentum (0.7) and epochs (1000) were selected by trial and error method during training. Also using the cross validation of the dataset we see that MD2 sub model has given the best forecasting performance. Thus it is see that M3 MD2 is the best prediction model.

From the above tables it is seen that for the best developed model i.e. M3 MD2 has RMSE, Corr. Coeff. And E values for both the training and testing set as (0.80, 0.90), (0.85, 0.77) and (0.70, 0.55) respectively. The least developed model is the M1 model with all the three input variables as water levels only.

8. Comparison of ANFIS and ANN Models

From the analysis of all the models developed using ANFIS and ANN techniques, it was found that in both the cases the best developed model was found to be M3 with water level, rainfall and humidity as input variables and the least developed forecasting model was M1 with water level as the only input variables. However from the analytical study of the ANFIS and ANN models as given in tables 4,5,6 and 7,8,9 respectively depicting the performance indices viz. correlation coefficient, efficiency and RMSE, it is seen that ANFIS has outperformed ANN in case of prediction accuracy. The RMSE value for M3 MD1 model using ANFIS and ANN techniques, both for training and testing datasets are (0.82, 0.91) and (0.98, 1.15) respectively. During testing, the corr. coeff. value for M3 MD1 ANFIS and ANN models are 0.77 and 0.75, where as efficiency values are 0.57 and 0.27. The evaluation of M3 model based on the performance criteria are shown in Table 10 and Figures 18, 19 and 20 with respect to Correlation coefficient, Efficiency and RMSE respectively.

Table 10

M3	**ANN**			**ANFIS**		
Model	**RMSE**	**Corr. Coeff.**	**E**	**RMSE**	**Corr. Coeff.**	**E**
MD1_TRG	0.98	0.83	0.55	0.82	0.81	0.65
MD1_TST	1.15	0.75	0.27	0.91	0.77	0.57
MD2_TRG	0.8	0.85	0.7	0.87	0.8	0.65
MD2_TST	0.9	0.77	0.55	0.88	0.77	0.59
MD3_TRG	0.94	0.78	0.61	0.83	0.81	0.65
MD3_TST	0.9	0.73	0.47	0.92	0.77	0.55

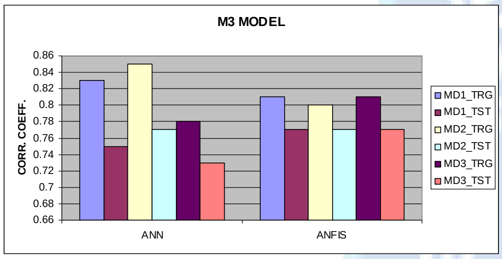

Figure 18

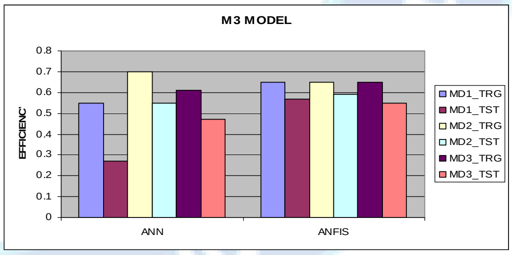

Figure 19

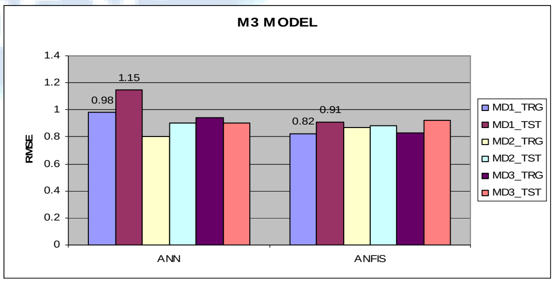

Figure 20

9. Conclusion

In this study, an ANFIS model is used to predict ground water level fluctuation in Mohanlalganj hydrograph station, district Lucknow based on historical records. Data for the period 1986 to 2008 has been used for training and testing in developing the forecasting model. The results indicate that ANFIS can give more accurate prediction as compared to ANN models. This demonstrates its distinct capability and advantage in identifying hydrological time series comprising non linear characteristics. M3 was found to be the best developed prediction model with water level, rainfall and relative humidity as input variables and M1 was the least efficient model in terms of prediction accuracy with water level as the only input variable. Thus it is seen that for prediction of water level, only water level aas input variable is not sufficient for better model development, instead more interrelated parameters like rainfall, relative humidity and temperature along with water level as input parameters produce better models with more prediction accuracy.

References:

[1]. Artificial Neural Networks – A Neural Network Tutorial

[2]. Ahmad S., Simonic S.P., "An artificial neural network model for generating hydrograph from hydro-meteorological parameters", Journal of hydrology315(2005) 236 – 251.

[3]. Chang, F.J., Chang, Y.T., : Adaptive neuro-fuzzy inference system for prediction of water level in reservoir, Advances in Water Resources, 29(2006) 1-10.

[4]. Coulibaly, P., Anctil F., et. al., "Artificial Neural Network modelling of water table depth fluctuations"., Water Resources Research, vol.37, No. 4, pages 885-896, April, 2001.

[5]. Coppola E., Poulton M., et.al. "Application of Artificial Neural Networks to complex groundwater Management Problems". Natural Resources Research, vol.12, No. 4, 303 – 320, Dec., 2003. SPRINGER

[6]. Coppola E., Poulton M., et.al. "Artificial Neural network approach for predicting transient water levels in a multilayered groundwater system under variable state pumping and climatic conditions", Journal Hydrologic engineering, Vol.8, Issue 6, pp.348-360, Nov.-Dec. 2003.

[7]. Govindraju, R.S.," Artificial Neural Networks in Hydrology II – Hydrologic applications", J. Hydrologic Engineering, Vol.5, issue 2, pp. 124-137 (April 2000). The ASCE Task Committee report on application of ANN in Hydrology.

[8]. Govindraju, R.S., "Book on Artificial Neural Networks in Hydrology", Water Science and Technology Library, vol. 36

[9]. Jang, J.S. R., Sun, C.T., et al,: Neuro-Fuzzy and Soft Computing, PrinticeHall., ISBN 0-13-261066-3, 607s., United States of America, 1997.

[10]. Jang, J.S. R., Sun, C.T.,: Neuro-Fuzzy Modeling and control, Proceedings of IEEE, 1995.

[11]. Jang, J.S.R., ANFIS:Adaptive- network based fuzzy inference systems, IEEE Trans. On systems, Man and Cybernatics, 23(03):665-685, May, 1993.

[12]. Nayak, P.C., Sudheer, K.P., el al.,: Fuzzy computing based rainfall-runoff model for real time flood forecasting, Hydrol. Process., 17, 3749-3762, 2004a.

[13]. Sen Z: Fuzzy Logic and Foundation, ISBN 9758509233, Bilge Kultur Sanat Publisher, Istanbul, 172 pp., 2001

[14]. "Use of ANN and Fuzzy logic for integrated water management : Review of applications", Project report, Delft 2000, Hydroinformatics.

[15]. Watanabe K., Weesakul U., "Hydrological Monitoring System Based on the ANN: Application to the ground water management".

[16]. Zadeh, L.A.,: Fuzzy Sets, Information and Control, 8(3), 338-353, 1965.

[17]. Zhang, G.P.: Time Series Forecasting using Hybrid ARIMA and neural network model, Neurocomputing, 50, 159-175, 2003.

[18]. Zhang, G., Patuwo, B.E., Hu, M.Y., 1998. Forecasting with artificial neural networks: the state of the art. Int. J. Forecasting 14, 35–62.