ANN and Fuzzy Logic Models for the Prediction of groundwater level of a watershed

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Abstract- Computational Intelligence techniques have been proposed as an efficient tool for modeling and forecasting in recent years and in various applications. Groundwater is a highly valuable resource. Measurement and analysis of groundwater level is needed for maintaining groundwater availability. It is therefore necessary to implement mechanisms and systems that can be employed to predict the groundwater level. The primary objective of this paper is to compare the efficiency of two computational intelligence techniques in groundwater level prediction of a watershed. The techniques under comparison are Artificial Neural Networks (ANNs) and Fuzzy Logic (FL). A three-layer feed-forward ANN was developed using the sigmoid function and the back propagation algorithm. The FL model was developed employing the Gaussian fuzzy membership functions for the input and output variables. The fuzzy rules were inferred from the measured data. In this study it was observed that ANNs perform significantly better than FLs. This performance is measured against the generalization ability of the two techniques in groundwater level prediction of a watershed.

Keywords- Artificial Neural Networks, Fuzzy logic, Mamdani fuzzy inference systems, Groundwater level, MATLAB, Observation wells.

I. INTRODUCTION

Obtaining a mathematical model for a complex system is complex and time consuming as it often requires some assumptions such as defining an operating point and doing linearization about that point and ignoring some system parameters, etc. This fact has recently led the researchers to exploit the AI techniques using neural and fuzzy tools in modeling complex systems utilizing solely the input output data sets.

Artificial Neural Networks and Fuzzy Logic have been increasingly in use in many engineering fields since their introduction as mathematical aids by McCulloch and Pitts in 1943, and Zadeh in 1965 respectively. Being branches of Artificial Intelligence, both emulate the human way of using past experiences, adapting itself accordingly and generalizing. While the former has the capability of learning by means of parallel connected units, called neurons, which process inputs in accordance with their adaptable weights usually in a recursive manner for approximation; the latter can handle imperfect information through linguistic variables, which are arguments of their corresponding membership functions. After the introduction of back-propagation algorithm for training multi-layer networks Artificial Neural Networks have found many applications in numerous inter-disciplinary areas .On the other hand, FL made a great advance in the mid 1970s with some successful results of laboratory experiments by Mamdani and Assilian[1]. In 1985, Takagi and Sugeno proposed a new rule-based modeling technique using FL. Operating with linguistic expressions; fuzzy logic can use the experiences of a human expert and also compensate for inadequate and uncertain knowledge about the system. On the other hand, ANNs have proven superior learning and generalizing capabilities even on completely unknown systems that can only be described by its input-output characteristics [2].

A common nonlinear method for groundwater problems is the artificial neural network (ANN). Many kinds of algorithms for training the network have been developed for groundwater level forecasting. A significant advantage of the ANN approach in system modeling is that one need not have a well-defined physical relationship for systematically converting an input to an output. There have been various papers considering the application of ANN techniques in water resource problems. In the groundwater domain, ANN has been used for groundwater management [3] . Several papers have reported the use of ANN for groundwater level forecasting [4,5]. Gautam et al. (2004) reported that the groundwater table change before and after a bridge pier construction could be well analyzed by ANN. Many previous researchers have pointed out that ANN as non-linear model is a powerful tool to estimate a fluctuation of groundwater level with considering hydrological variables as inputs. A detailed theory and application of ANN in hydrology can be found in Govindaraju (2000a, b) [6,7,8].

The application of a more promising soft computing technique, the fuzzy inference system (FIS), has recently been increasing in hydrology. Lu and Lo (2002) used self-organizing maps (SOM) and fuzzy theory for diagnosing reservoir water quality. Tayfur et al. (2003) developed fuzzy logic algorithms for estimating sediment loads from bare soil surface. Wong et al. (2003) predicted volume of rainfall using SOM, BPNN (Back propagation neural networks), and fuzzy rule systems. Alvisi et al. (2006) predicted water level using fuzzy logic and ANN [9,10,11,12].

In the present work two different models have been developed using two different soft computing techniques namely, ANN, and Fuzzy for groundwater level prediction of a watershed.

II. ARTIFICIAL NEURAL NETWORK (ANN)

ANN based methods are data analysis methods and algorithms loosely based on nervous systems of humans and animals. Zhang et al has explained that there is the class of cells in the human brain behave as functional units called dendrites as a receiver of information, cell body as a processor of information, axon as a carrier of the processed information to other neurons, synapse as a junction between axon end and dendrites of the other neurons. Similarly artificial neural network consists of a large number of simple processing units linked by weighted connections.

The feed-forward neural network was used in this work as one kind of ANN, it was the first and arguably simplest type of ANN devised. It has been applied successfully in many different problems since the advent of error back-propagation learning algorithm.

A feed-forward network consists of an input layer, one or more hidden layers of computation nodes and an output layer. In this network, the information moves in only one direction, forward from the input nodes, through the hidden nodes and to the output nodes. There are no cycles or loops in the network. Fig1 below, Shows a typical feedback networks with four input nodes, one hidden layer with six nodes and one output

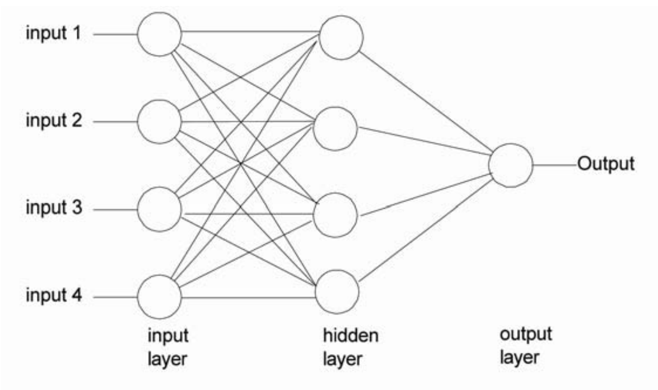


Figure 1. Typical feed forward neural network

III. FUZZY LOGIC (FL)

The most common method to deal with the uncertainties was probability theory, until 1965, when Zadeh introduced the fuzzy set theory. Fuzzy logic is an effective tool for handling the ambiguity and uncertainty of the real world systems. The Fuzzy Rule-Based (FRB) systems or Fuzzy Inference Systems (FIS) originate from fuzzy logic and generally, the fuzzy set theory. Fuzzy Inference System (FIS) can be particularly suited to models that relationship between variables in environments that are either ill-defined or very complex.

Mamdani's Fuzzy Inference method (MFIS) is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Mamdani et al. (1975) as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Lotfi Zadeh's 1973 paper on fuzzy algorithms for complex systems and decision processes.

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 (Fig.2), 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.

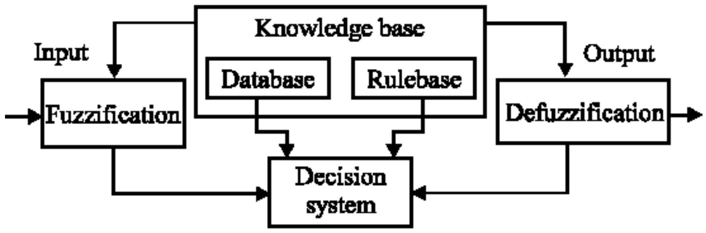


Figure 2. Fuzzy Inference System

The Knowledge Base in FIS model, includes the information given by the expert in the form of linguistic variables (fuzzy if-then rules), composed of two components, the first is Data Base that contains the linguistic term sets considered in the linguistic rules and the input-output membership functions defining the semantics of the linguistic label. The second component is a Rule Base that comprised of a collection of linguistic rules that are joined by the operator . A wide description of FIS can be found in Ross (2004).

IV. DESCRIPTION OF STUDY AREA

The Thurinjapuram 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 79^{o}9’28” East longitudes (Fig. 3.) It is mainly situated in Thiruvannamalai district of Tamilnadu, India. It is mainly located in Thurinjapuram block (in India, a block is a group of villages, an administrative sub-division of a taluk.) and partially falls into two other blocks (Chengam and Thiruvannamalai). Thurinjalar is one of the major tributaries of Ponnaiyar Major River originating from Kavuttimalai reserve forest in Chengam Taluk of Tiruvannamalai district. It flows in south-southeast direction of the basin crossing Thurinjapuram, Kilpennathur and Tiruvannamalai blocks and confluences with Ponnaiyar river near Thirukkoilur after flowing a distance of about 44 kms. Thurinjalar River, which is the major stream draining the area, exhibits only sporadic flow during the rainy season. 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 climate is semi-arid. May is the hottest month with a maximum temperature of up to 41° C and December is the coolest month with a maximum of 21.6° C. The climate of the area is characterized by four distinct seasons, namely southwest monsoon (Jun –Sep), northeast monsoon (Oct – Dec), winter season (Jan – Feb) and hot summer season (Mar - May). Hydro meteorological data were collected from Kilnatchipattu weather station maintained by State Ground & Surface Water Resources Data Centre, W.R.O, and P.W.D. The economy of the Thurinjapuram sub watershed depends mainly on agriculture. Data from three observation wells which have been monitored on a monthly basis by the Department of Groundwater are available in the Thiruvannamalai Groundwater subdivision.

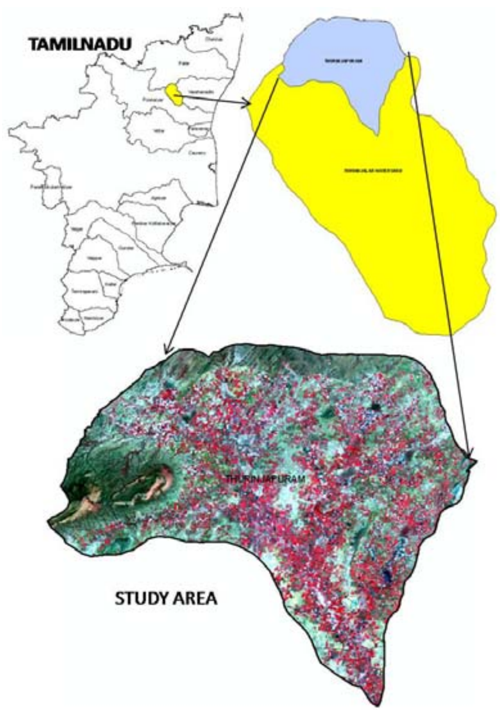


Figure 3. Study area

A. Data

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, 23142, and 23143) during 1985 to 2008 has been collected from Thiruvannamalai Groundwater subdivision. In the same period monthly Rainfall data were collected from Kilnatchipattu Raingauge station.

V. EVALUATION OF MODELS

The developed ANN and FL models were calibrated and tested with monthly rainfall and water level data to predict one month ahead groundwater level and comparison of the models is presented here. In this research MATLAB software of version 7.0 was selected to evaluate and classify the groundwater level.

A. ANN Model Training and Testing

For predicting groundwater level, the three-layer feed forward ANN model had 2 neurons in the input layer, 12 and 20 neurons in the hidden layers, and 1 neuron in the output layer. Antecedent rainfall and water levels were taken as inputs, and the future water level was the target output. For the number of neurons in the hidden layer, a trial-and-error procedure was used. The log sigmoid function was employed as an activation function and the supervised training algorithm of back propagation was employed for training the network. Before training and testing, all the external input and output data were normalized. For training the network, 192 sets of data were used. And for testing 84 data sets were used. The training was accomplished with a 0.6 learning rate and momentum factor was set to be 0.9. Number of training epochs given were 2000 to 3000 early stopping methods was applied, and error goal was set to be 0.001.

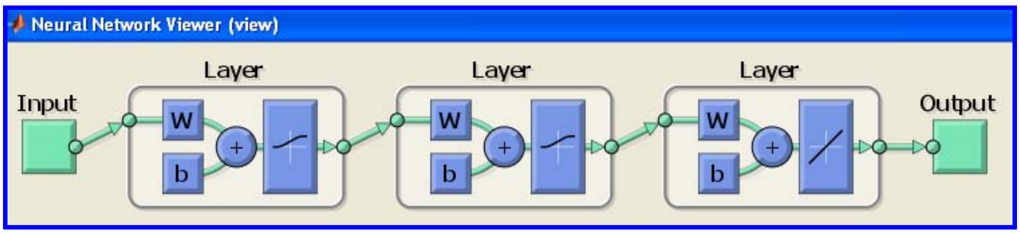


Figure 4. ANN model

B. *Fuzzy Model Training and Testing*

The generation of a fuzzy forecast model can be based both on expert's knowledge and historical data. 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. 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.

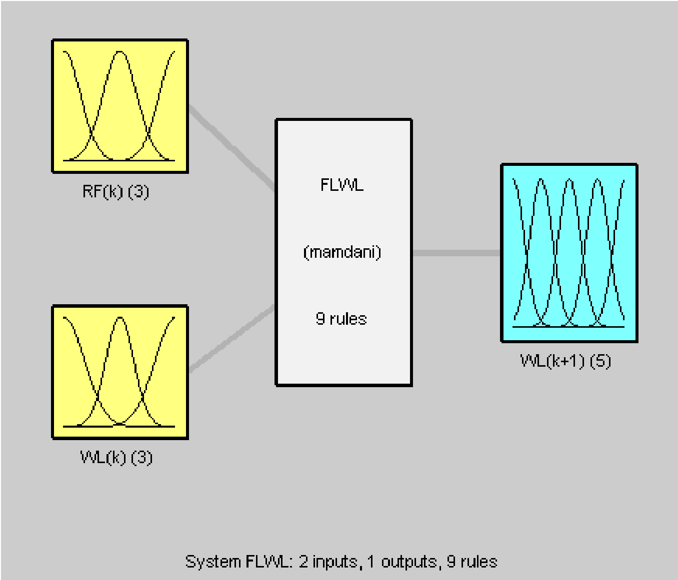


Figure 5. MFIS model

VI. COMPARISON CRITERIA

In order to objectively evaluate the model performance, the most commonly employed error measures, such as the root-mean-square error RMSE and regression coefficient R^2 were computed and are summarized in Table 1. The RMSE and R^2 are defined as

A. *Root mean-squared error*

RMSE is frequently used measure of differences between values predicted by a model or estimator and the values actually observed from the thing being modeled or estimated. It is just the square root of the mean square error as shown in equation given below:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(x_t - y_t)^2}{n}}$$

B. *Regression coefficient*

R^2 assesses the goodness of fit by indicating the deviation of the estimates values from the line of the best fit or the regression line.The value of R^2 is between zero and unity. A value close to unity indicates a satisfactory result, while a low value implies an inadequate result.

$$R^2 = 1 - \frac{\sum(x_t - y_t)^2}{\sum x_t^2 - \frac{\sum y_t^2}{n}}$$

Assuming that the actual output is x_i , expected output is y_i . n the number of observations

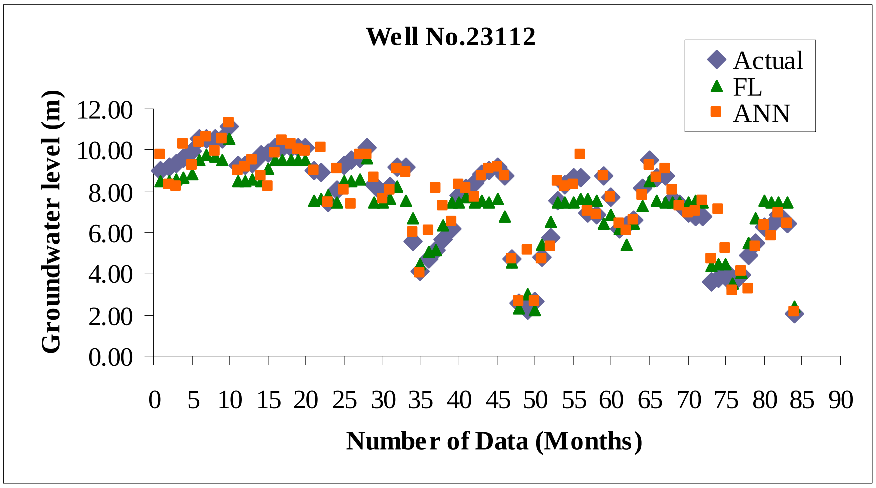
VII. RESULTS AND DISCUSSIONS

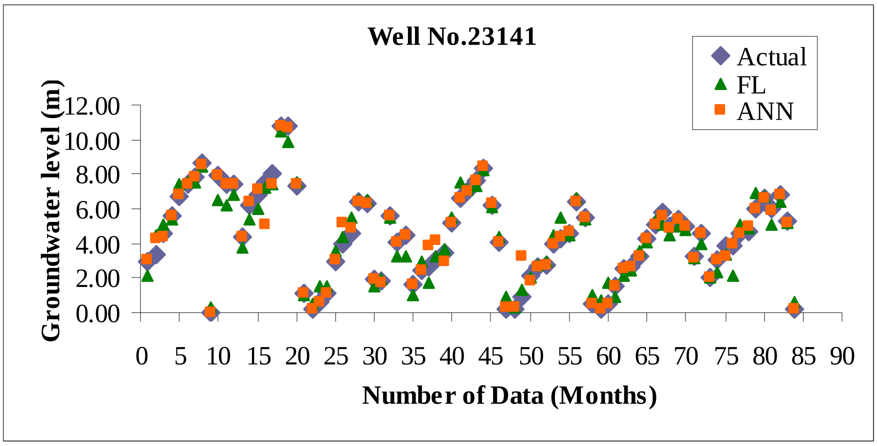
The same training and testing data sets were used to train and test both models to extract more solid conclusions from the comparison results. Accuracy of the two models was evaluated using R^2 and RMSE between the measured and predicted values.

TABLE I. RMSE AND R^2 GOODNESS OF FIT CRITERIONS FOR THE ANN AND MFIS MODELS

Well. No	Method	RMSE	R^2
23112	ANN	0.84	0.86
	MFIS	0.88	0.88
23141	ANN	0.47	0.96
	MFIS	0.59	0.94
23143	ANN	0.82	0.91
	MFIS	1.13	0.85

Analysis of data in randomized sets clearly showed that ANN model is best fit for predicting the groundwater level in terms of statistical significance as well is given in Table (1).





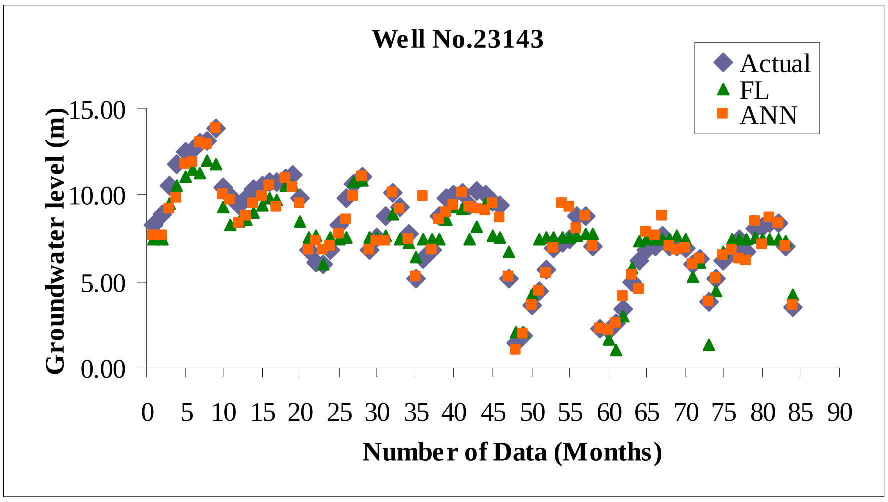


Figure 6. Actual data versus the corresponding ANN and MFIS -predicted output data

Further, the data were analyzed separately for each independent well point to have a clear comparison of the mean observed and estimated water levels for the two models. The scatter plot of the measured against predicted water level for the two models is given in Fig. 6. As this figure showed that ANN model predicted with high accuracy, which this point demonstrate applicability and performance of ANN for prediction of groundwater level.

VIII. CONCLUSIONS

In this study, a better forecasting model using ANN and MFIS has been developed for predicting monthly groundwater level fluctuations in the Thurinjapuram watershed, Tamilnadu, India. The ANN method presented in this paper shows a good potential to model complex, nonlinear and multivariate problems. The model-predicted water level data are given in Fig. 6, from which it is seen that the ANN model satisfactorily predicted the measured data than mamdani fuzzy model. Considering the complexity of the relationship between the input and the output, results obtained are very accurate and encouraging. The good architecture of neural networks can be formed by trial and error.Adding hidden layers and neurons, changing activation functions, or even new neural networks methods are not guaranteed to give successful results. The best function and architecture of neural networks based on the experiments conducted was the ANN results have the lowest value of RMSE and the highest value of R^2. The lower RMSE obtained by the ANN method suggests its good generalization capability. The result of ANN experiments in this study proves that neural networks give better forecasting results than the fuzzy method. The good result of neural networks experiments demonstrated the ability of neural networks to perform well with limited data.

ACKNOWLEDGMENT

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

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