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Research Article

EVALUATION OF MULTILAYER PERCEPTRON MODELS AND ADAPTIVE NEURO-FUZZY INTERFERENCE SYSTEMS IN THE SIMULATION OF GROUNDWATER LEVEL (CASE STUDY: LAMERDPLAIN)

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ABSTRACT
Monitoring and planning are inevitable issuesin order to quantitative control and protection of groundwater resources across the country (Iran) especially warm and dry areas including the study case (Lamerd plain). In this regard, the simulation of water level and predicting the water table situation of the study case area were necessary which are addressed in this research. In recent years, the use of modeling based on the artificial neural network model of multilayer perceptron and also fuzzy set theory (adaptive neuro-fuzzy interference system) ANFIS in order to modeling hydrologic phenomena which have multi-functional dependence and high complexity and uncertainty, are investigated by researchers. Hence using and benefiting from the required information including the water level of observation well in Lamerd plain related to the years between 1998-2013 together with other necessary information including average monthly rainfall, temperature and water evaporation of Lamerd plain and its analysis according to the models based on artificial neural networks (MLP) and neuro-fuzzy interference system (ANFIS) were adopted in order to predict and simulate the groundwater level of Lamerd plain; the required results were obtained by emphasis on higher accuracy and lower scattering for modeling (ANFIS) with RMSE= 0.9987 and R2= 0.0163 in training stage, and RMSE=0.9753 and R2= 0.0694.

Keywords: *Multilayer Perceptron Model, Neuro-Fuzzy Interference System, Groundwater Level, Lamrd Plain*

INTRODUCTION
Nowadays, one of the most important issues that have engaged the researchers is the discussion related to "water as the most critical matter for human survival". More than two third of earth is covered by water. But the actual value and severe limitation of water resources for humankind are determined when we understand that only 2.5% of it is fresh water and appropriate for ordinary applications, and only 1% of it is accessible and recoverable.
Therefore, the study and planning in order to preserve the resources and optimization having technical and economic efficiency are required. Izadi *et al.,* (2007) have used the performance of different artificial neural networks ANN such as multilayer perceptron neural network, general and recurrent regression for predicting water level of Nishapur plain, and the results show that the general trained regression neural network with momentum algorithm had the best result for predicting groundwater level in the next 6 months for Nishapur plain.
Such that the considered performance criteria such as R2=0.937 and RSME=0.378 during test period states this issue. Amutha and Porchelvan (2011) used neuro-fuzzy interference system and the artificial neural system of radaial basis in order to the seasonal forecast of groundwater level in Malatar basin located in Vellore area on India. The obtained results showed that both models have the ability to forecast groundwater level whilst the ability of neuro-fuzzy interference system is more than artificial neural network.
Mayilvaganan used fuzzy logic and artificial neural network with Sigmoid function and back propagation algorithm in order to forecast groundwater level and the better results in terms of more accuracy and less

error were investigated. Alipoor *et al.*, using three methods of artificial neural network, ANFIS and time series and benefiting from the statistical data of temperature, humidity, rainfall and well water level of 14 observable wells forecasted water table and the obtained results represent effectiveness of neuro-fuzzy interference method in the forecast of well water level. Shafiei *et al.*, (2011) used artificial neural networks and neuro-fuzzy interference system in order to forecast Malaysia Klang river runoff and the ability for each of these methods was investigated.

The results show that neural and fuzzy interference methodshave higher accuracy and lower error than artificial neural network in forecasting the river runoff. Emamgholizadeh *et al.*, (2011) used artificial neural networks in order to forecast the groundwater level of Shahrud plain and the best results in terms of higher accuracy and lower error were investigated.

GyaneshShrivastava *et al.,* (2012) used artificial neural networks with network architecture of BPN and RBFN in order to forecast monsoon and other weather parameters.

The Study Case Area and Statistical Data of the Study Area

The study area of Lamerd is one of 42 study areas of the catchment in Mehran-Kal and Persian gulf islands and is located in the southwest of the catchment for all Mehran-Kal's rivers and Persian gulf islands with the code 2727 and its area is about 2833km2 which includes 1166.5 km2 of plain and the rest is mountains. This study area is located between 52˚-46́ and 54̊– 7́ of east longitude and 27̊– 2́ and 27̊– 39́ north altitude.

The highest place in these study areas in northeast of the area is 2157m above sea level and the lowest place with 348m above sea level in southeast.

Nerman, Khuzi, Ahel and Varavi settlements can be mentioned as the important population centers within this study area. A number of weather parameters such as rainfall, evaporation and temperature have more importance in balance relation and some other such as relative humidity and wind etc. have secondary importance.

The certain issue is that rainfall is the main source of incoming waters to the basins and the study areas, and evaporation is the most important factor for the outputs from the basins.

Groundwater

The study area of Lamerd with 2833 km^2 extent includes 1666.5 km^2 of mountainous areas and 1166.5 km^2 of plain. Also 628.2 km^2 of Lamerd area (upper Lamerd and Lamerd) which has Thyssen network, usable for drinking, industry or agriculture is considered as alluvial aquifer.

The survey of water resources in the study case of Lamerd has been performed during the years 1983 to 2003 in three intervals of 1983-85, 1995 and 2002-3. The numbers of wells, fountains and aqueducts in this area were 940, 46 and 8 respectively. The first network of observation wells is formed in the study area of Lamerd in 1998.

As it has been noted, one of the main components of balance is the rate of evacuation and removal of water from groundwater in the intended area.

The Network of Available Observation Wells in the Study Area

In the study area of Lamerd (a part of the study area) which is a part of the basin of MehranKal and Persian gulf islands, 6 piezometer and observation wells are already excavated and the information of water level height related to the years 1998 to 2003 is registered.

Therefore, the network of observation wells which their water level measurements are performed monthly has 6 wells and the total area of the polygon is 117.97 km^2 which its data is presented in the following.

As it can be seen in the graph, the total amount of produced water in the study area of Lamerd is 83.39 million cubic meters that considering the surface flow of 11.581 million m^3, its input reaches to 94.97 million m^3.

The net consumption of water in the study area is about 41.72 million m^3 and the exiting surface flow is 63.62 million m^3 and the exiting groundwater flow is 3.7 million m^3. Thus, it can be seen that the total amount of inputs and outputs is 109.04 million m^3 which is more than the total existing water in the area (14.07 million m3) that this volume is removed from the stationary reserve of alluvial aquifer of Lamerd.

Artificial Neural Networks

The neural and artificial networks are the flexible and mathematical models that can be used in the modeling of complex systems.

Also these networks are able to present a non-linear mapping between data and outputs with appropriate selection of the layers and neurons. The processing in artificial and neural networks is performed based on many processing units which are called neuron. Each neuron in each layer is connected to all the elements of the previous and next layers with a series of weights. The total ability of artificial neural network is learning the non-linear relation between data and generalizing the results for other data.

The most important networks in predicting and resolving non-linear problems are the networks called as multilayer perceptron (MLP). The training of these networks is performed using error back-propagation algorithm.

The inputs to the network are entered as a vector x(x1, x2, x3,….,xn) and each input is connected to node by a weight and finally a series of weights is related to the intended node in the form of weight vector w(w1,w2,w3,….,wn). W shows the weight which relates previous layer to the intended layer. The output for the node y is calculated by the following relation: y=f(x.w-b), where x is input data vector, w is weight vector and b is the value of threshold or bias. The transfer function inside each function is considered as the producer of that node outputs and one important and usually used application of transfer function is hyperbolic tangent.

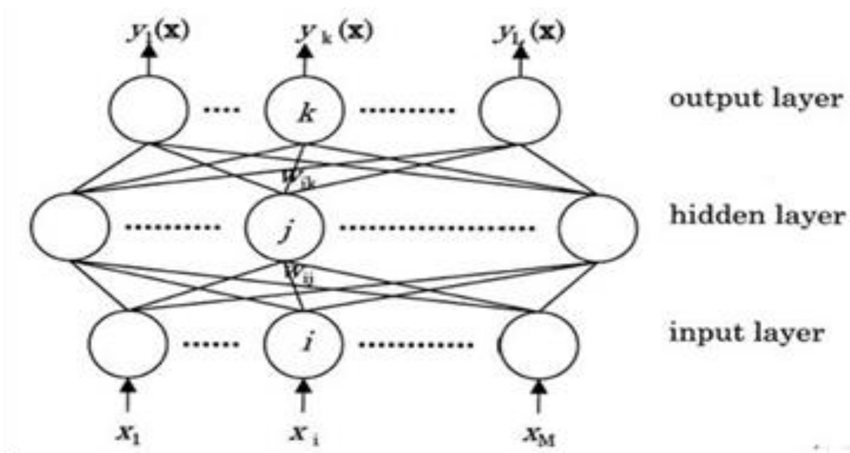


Figure 2: three-layer perceptron network structure

Neural-Fuzzy Interference System

Neuro-fuzzy network structure is made by combining the structure of neural network and fuzzy system that this structure benefits the advantages of both neural network and fuzzy logic; i.e. the teachable character of artificial networks, and also the modeling ability of fuzzy systems (ANFIS) that causes the increase of decision-making power in uncertain conditions and certainty are used in the structure of neuro-fuzzy network structure.

Recently, fuzzy logic is suggested for modeling reservoirs management and solving their ambiguous features.

However, the main problem of fuzzy logic is that there is no cinematic process to design a fuzzy controller. In the other words, a neural network has the possibility to learn from the environment (input-output pairs) to arrange its structure and to adapt its interaction by a method. ANFIS has a good capability in training, building and categorizing and also have this advantage that allows the extraction of fuzzy rules from numerical data or expert knowledge and makes comparatively a rule-based.

ANFIS structure includes 5 layers with a number of input variables which each input has two or more membership functions. In the first layer, the dependency level of each input to different fuzzy intervals is determined by user.

The weight of rules in the second layer is obtained with multiplying input values and the node to each other. In the third layer, the calculation of relative weight for the rules is performed. The forth layer is the rules layer which is resulted from operation on input signals to this layer. The final layer is network output which aims at minimizing the difference between the obtained output from the network and real output.

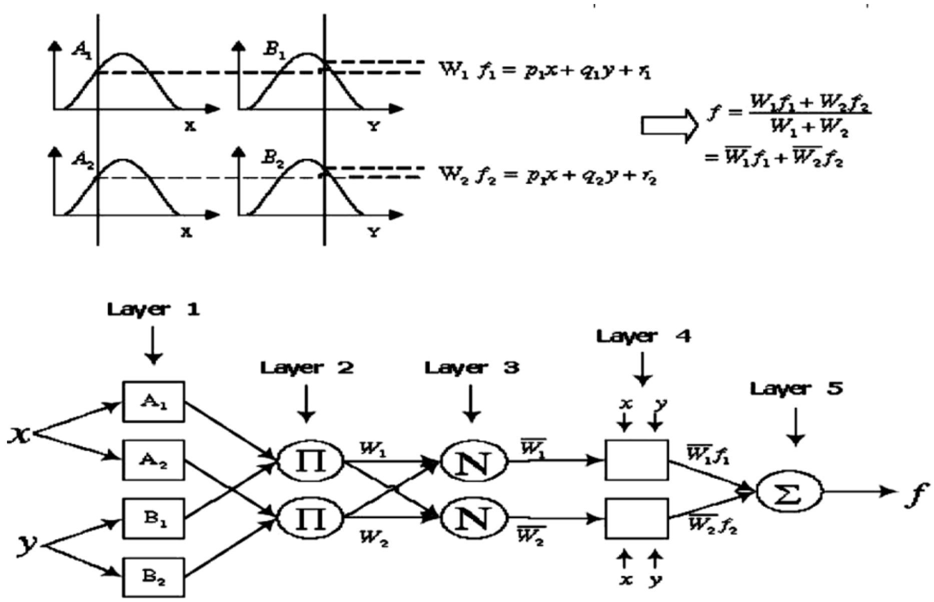


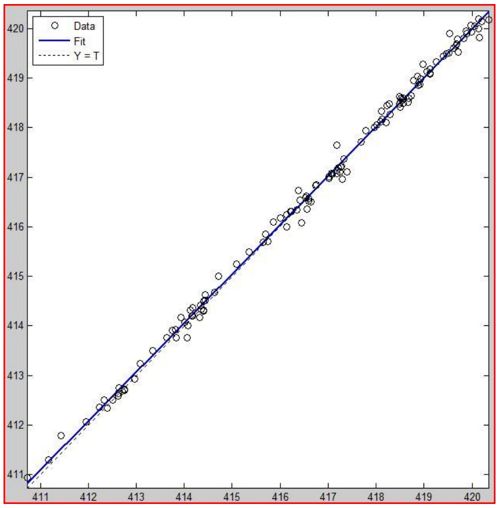
Figure 3: First order Sugeno fuzzy model and ANFIS system

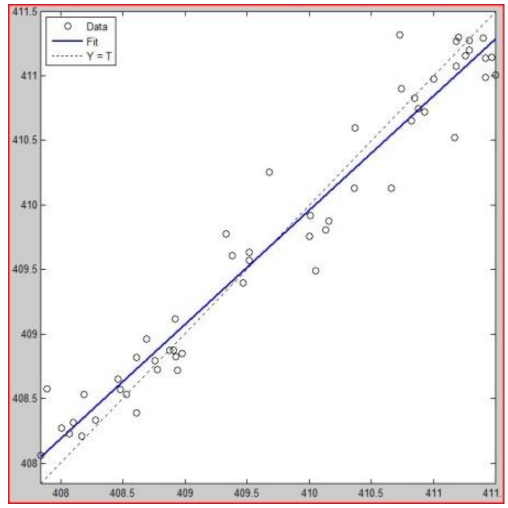
Modeling Based on Artificial Neural Network

The set of test data which tests the ability of model generalization must represent all data set. In this study, different percentages of data are selected for education and finally for each of the performance steps, 70% of all available data are used for education and the remaining 30% for the test. Based on this, monthly statistical data (March, 1998 to December, 2008) is exploited as education input and the rest of statistical data for the test. In this evaluation, two-layer and three-layer networks with learning algorithm Levenberg-marquardt (LM) and the algorithm gradient descent with momentum (GDX) with transfer functions of tansig and logsig in the middle layer and linear function of purelin in output layer are used.

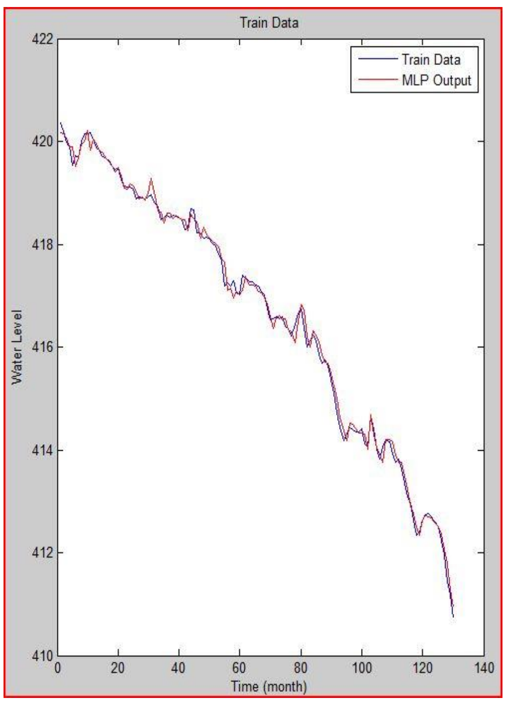
Also to evaluate the results and to compare the models statistically, two statistical criteria are used in this research; correlation coefficient (R2) and root-mean-square error (RMSE) which was used to represent the error between observation and model predictions in this study.

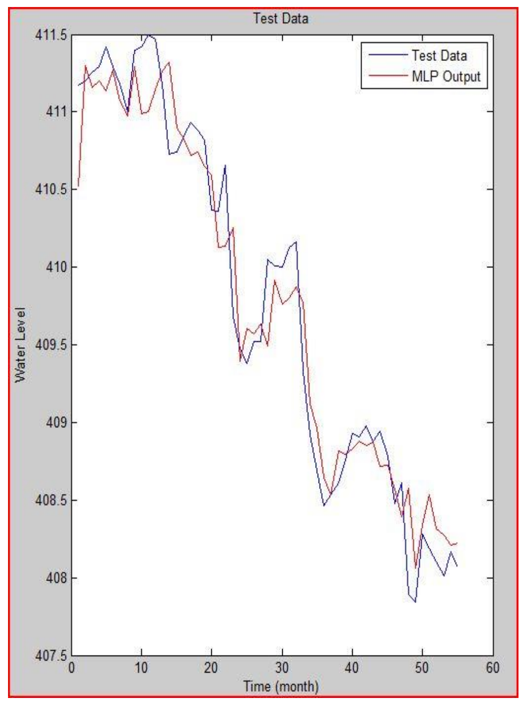
In this research, different input patterns for each parameter is created through their different time delays with regard to the results from data preprocessing and the determination of correlation coefficient for four mentioned parameters in Lamerd plain (water level in observation well, rainfall, temperature and evaporation). Also this research addresses the creation of various models with different nodes and validation step and test was performed on them after training models. For all patterns, the target matrix is water table in the time (ht+1). With regard to the obtained results and the comparison of RMSE and R2 values, different structures were specified in Lamerd plain which the best input pattern for the prediction of water level in training stage was three-layer network with 4 neurons in each layer and the learning algorithm LM with entry pattern including the statistical data of rainfall, temperature, evaporation and groundwater level for Lamerd plain; the best results obtained for artificial neural network have the values RMSE=0.0141 and R2=0.9981. Also the best results obtained for prediction in test stageare for two-layer network with four neurons in each layer and the training algorithm of LM with the values RMSE=0.0701 and R=0.9746.





The output results of training stage RMSE=0.0141 and R2=0.9981The output results of test stage RMSE=0.0701 and R2=0.9746





Training stage **Test stage**

Figure 4: The graph for the comparison of the calculated data of selected model with the observed data of Lamerd plain in training and test stages

Modeling Based on Neuro-Fuzzy Interference System

Anfisedit environment in MATLAB software is used to implement models. Different fuzzy membership functions and methodsare investigated to model each pattern to reach the best possible results. The membership functions utilized in this research are: triangular-shaped membership function (trimf), Trapezoidal-shaped membership function (trapmf), Gaussian curve membership function (gaussmf), Gaussian combinational membership function (gauss2mf), Generalized bell-shaped membership function (gbellmf), differential sigmoid membership function (dsigmf), product sigmoid membership function(psigmf) and Pi-shaped membership function (pimf). In this step, we address the modeling of

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plain groundwater level using adaptive neuro-fuzzy interference model. The groundwater level of Lamerd plain is in the time t+1 for all input patterns of target vector or network output.

Membership functions	Training		Test	
	R^2	RMSE	R^2	RMSE
Trimf-constant-haybrid	0.9987	0.0163	0.9753	0.0694
Trapmf-constant-haybrid	0.9978	0.0264	0.9717	0.0799
Gbelmf-constant-haybrid	0.9983	0.0212	0.9726	0.0774
Gaussmf-constant-haybrid	0.995	0.0178	0.9737	0.0735
gauss2mf-constant-haybrid	0.9981	0.0235	0.8595	0.4186
Pimf-constant-haybrid	0.9967	0.0405	0.9641	0.1020
Dsigmf-constant-haybrid	0.9969	0.0370	0.9612	0.1099
Psigmf-constant-haybrid	0.9969	0.0370	0.9612	0.1099

Figure 5: The results from modeling plain water level with adaptive neuro-fuzzy interference

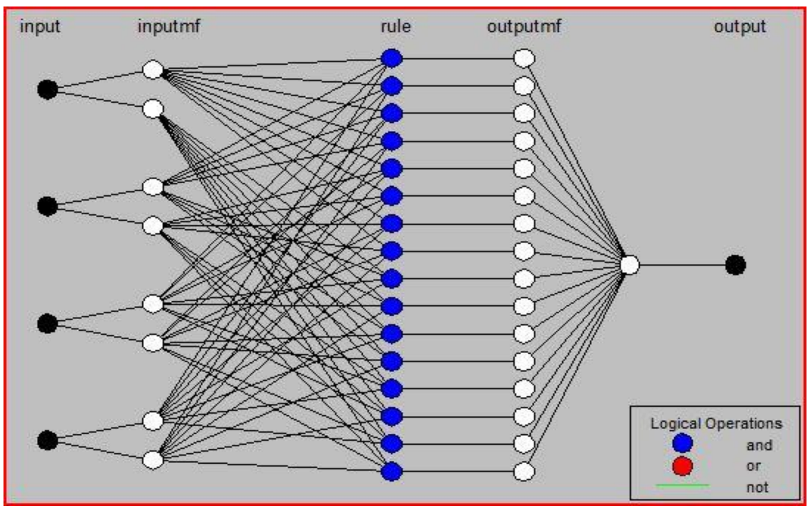


Figure 6: Schematic view of the selected model Anfis in the forcast of groundwater level of Lamerd plain

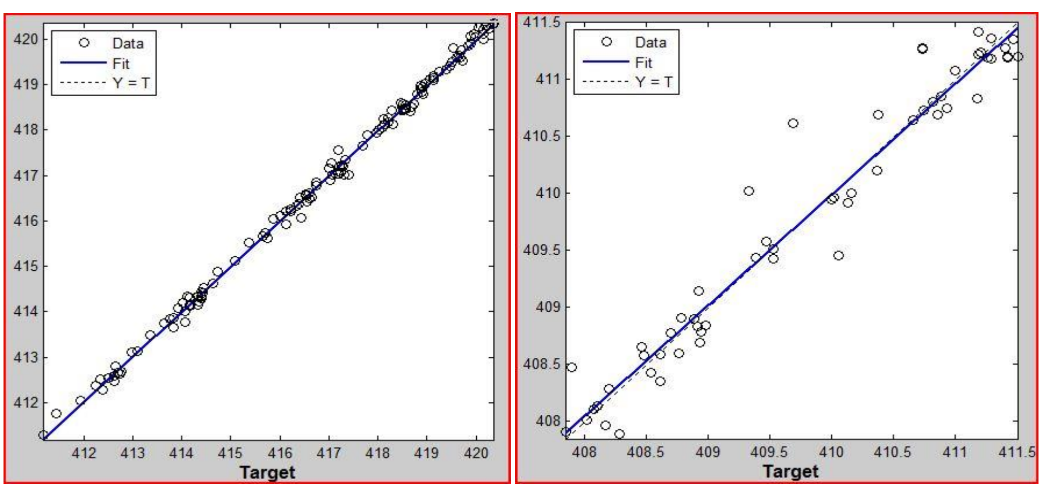
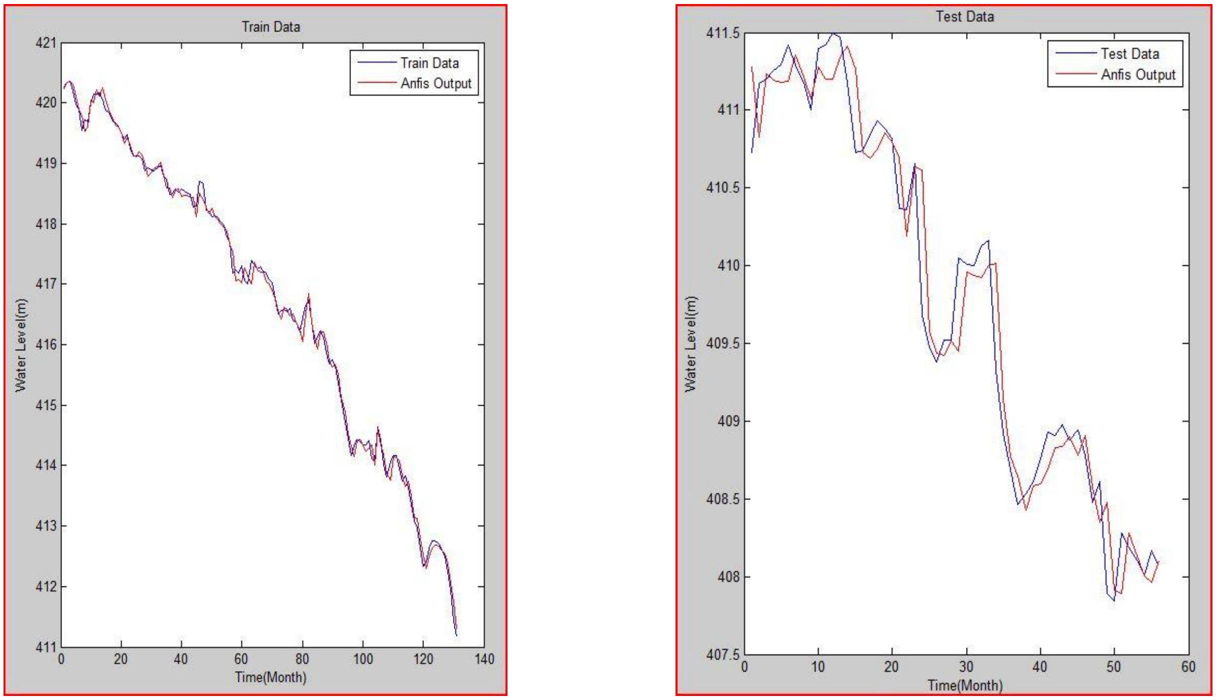


Figure 7: The output results of Anfis model for simulating groundwater level in Lamerd plain



Training stage **Test stage**

Figure 8: The graph for the comparison of calculated data in anfis model with the observed data of the groundwater level in Lamerd plain

CONCLUSION

Subject Analysis and Conclusion

With regard to the obtained results and the comparison of RMSE and R2 values related to different network structures in Lamerd plain, it was determined that the best input pattern for the forecast of plain groundwater level in training stage is the network with three middle layers and with four neurons in each layer and the learning algorithm Levenberg-marquardt (LM) with input pattern including previous information and data of rainfall, temperature, evaporation and groundwater level of Lamerd plain with the values RMSE=0.0141 and R2=0.9981 and also the obtained results to forecast test stage for two-layer network with 4 neurons in each layer and the learning algorithm LM with the values RMSE=0.0701 and R=0.9746,

Also based on the obtained results from modeling with neuro-fuzzy interference system, it was determined that the best result in modeling was using adaptive neuro-fuzzy interference network for groundwater level of Lamerd plain with the input pattern including the previous statistical data of rainfall, temperature, evaporation and groundwater level benefiting from Trimf-constant-haybrid membership function so that the results have the lowest value of RMSE=0.0163 and the highest value of R2=0.9987 in training stage and RMSE=0.0694 and R2=0.9753 in the test stage.

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