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Research Article

ESTIMATING THE LEVEL OF UNDERGROUND WATER IN SHAMIL & ASHKARA PLAIN BY ARTIFICIAL MULTI-LAYER NEURALNETWORKS

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ABSTRACT
Predicting the level-fluctuation of the underground water is an essentiality for managing the water sources to be supplied, planned and utilized properly. The underground water fluctuation is influenced by lots of factors of which the uncertainty - due to various variables effective on the balance sheet of the aquifer and heterogeneous nature of the environment - has caused a lot of complexities in predicting and researchers' attempts in surveying the changes. One of the suitable approaches to study the underground waters behavior is to apply the artificial intelligence models. Considering the heterogeneous nature among the effective phenomena, it is important to find a suitable relationship among them and presenting a relatively acceptable prediction for the future.

Keywords: *Artificial Intelligence, Predicting the Level of Underground Water, Multi-Layer Neural Networks, Shamil & Ashkara Plain*

INTRODUCTION
Modeling and predicting the hydrostatic level is one of the substantial and vital tasks to reach an optimized water sources management. One of ways used to predict the level of the underground water is to use the techniques of the artificial intelligence. Our study is aimed at surveying the efficiency of the neural networks techniques for estimating the hydrostatic level of the underground water. To be more precise in estimating the level of the underground waters, researchers became interested to use artificial intelligence systems such as artificial neural networks.
The artificial neural network contains non-linear structures which can describe the complex non-linear processes inter-relating every system's input and output data. Various approaches of the artificial intelligence systems method have been presented in different branches of science during the recent years. For example, problems analyzed by means of artificial neural networks and phased-neural deductive systems are: predicting the water level for the underground waters, qualitative prediction, and prediction during the fluid, estimating and predicting the raining location and time, estimating sediment discharge for rivers, modeling the runoff, and predicting the water demand.
Considering the above mentioned, in this paper artificial neural networks application in water-resource engineering and hydrology has been discussed as well as the way they are applied in estimating the underground water level in the light of the field information, where –at first- the given data between 0.05 and 0.95 were normalized and then after developing the neural network were used to train that.
Among the studies performed in predicting the water level by means of the artificial intelligence we can mention the following:
Chandramouli *et al.*, (2007) suggested a criterion to determine the frequency rate for training the Post-Emission Neural Networks. The study shows that too much or less than the requirement training can lead to pass the proper amount or not to reach the desirable response in order to determine the relationship between the input and output data.
Jothiprakash and Sakhare (2008) used the neural network model in a research with a training algorithm after distribution and employed three statistical criteria of MSE, RMSE, and R^2. The models performance showed that the artificial neural network can be used to predict the water level for the underground water.
Nikmanesh and Rakhshanderou (1390 S.H. / 2011-12 A.D) evaluated the capability of different artificial neural networks in predicting the water level of the underground water in an aquifer near Sa'adatshahr,

Fars province, and showed that these networks are suitable. Considering the capability of different used networks, the progressive artificial neural networks with Lavender Marquardt algorithm showed the best results. This structure could present a monthly prediction for the hydrostatical level of the underground waters in a two-year time interval (from 1383 (2004-5) to 1385 (2006-7).

Using artificial neural network, ZareAbyaneh *et al.*, (1390 (2011-12) simulated the hydrostatical level of Malayer plain in accordance with the meteorological data. Implementing the optimum neural network, they estimated the loss of 1.18 m in hydrostatical level for a 1.9% error. Bearing in mind the sufficient accuracy of the model and decreasing procedure dominated the water table, it can be recommended to use an artificial neural network as a tool with suitable speed and accuracy in simulating the level of the underground water in Malayer plain for its management.

During a research, Sreekanth *et al.*, (2009) showed that using neural network with a standard post-emission network and teaching LM algorithm with R2 = 0.93 and RMSE = 5/4 is the most proper model for predicting the level of underground water. Coppola *et al.*, (2005) used a simulating neural network model to predict the water-level for the underground water. Comparing with the numerical models, results gained via this model showed a high rate of accuracy in predicting the water level for a long-term perspective. Chehrafrooz *et al.*, (2012-13) attempted to predict the water surface fluctuations of the groundwater in Abadeh plain area using Artificial Neural Network. This paper, using the Artificial Neural Network, follows two goals including (a) determining the parameters affect groundwater surface in Abadeh plain area through 18-year time data, and (b) predicting groundwater surface within 28 selected piezometers, each of which holds particular properties of the studied plain. The best way to predict groundwater surface fluctuation is by means of FNN-LM Neural Network Model which was gained after 45 months with an accuracy over than R(2) = 0.952 and RMSE = 0.047, via selecting suitable parameters with the most acceptable time delay. Amirhossein *et al.*, simulated river flow using Smart Neural – Phasic Models of ANFIS for Ghare-Aghaj River, Bahman weir station. The research was performed by means of a phasic system based on adaptive neural networks, considering the existing data from Ghare-Aghaj River the network has been trained, and to check the accuracy and soundness some parts of data were applied as well as the results from the ANFIS model with different membership functions, by means of statistical tests like SSE, MSE, RMSE, R2. Finally, the ANFIS model with membership functions of GAUSS was used as the best model with the least error.

Introducing the Studied Region

Shamil and Ashkara plain has been chosen as the case study in this research. The plain, extended up to 1106 km2, is located in a geographical position between the 55o 53’ to 56o 19’ eastern longitude and 28o4’ to 28o18’ northern altitude in the north-eastern part of the Hormozgan province in Iran, near the borders of Kerman province. The annual average rate of precipitation in this plain is less than 200mm and the potential rate of evaporation is averagely 2640 mm, yearly. During the recent years, due to the agricultural activities enhancement and long-term droughts in this region, the volume of the stored underground water has been decreased intensively.

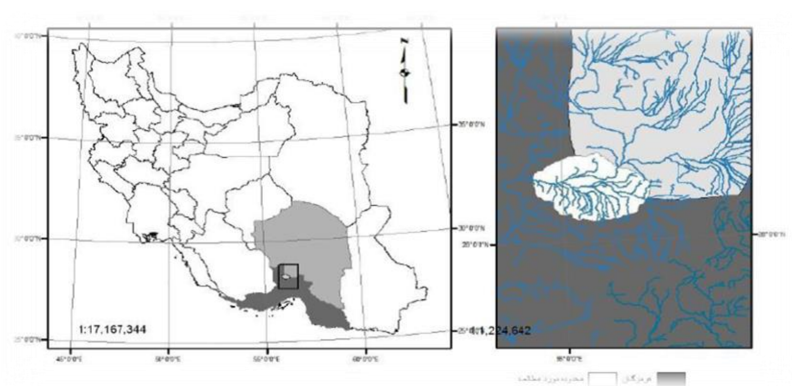

Figure1: Geographical position of Shamil and Ashkara plain

Artificial Neural Networks

Artificial neural networks are one of the most dynamic areas of the artificial intelligence with lots of applications in a great variety of different scientific courses. Based on the capabilities of this kind of artificial intelligence, there is an increasingly growth in its application.

Neural networks have the required ability in learning and they can use and apply the gained experiences in novel and similar issues. As a matter of fact, they are constructed by an input layer, an output layer and several hidden layers between these two layers. The schematic structure of a multi-layer network can be seen in figure 2. In the first layer no computation takes place and only the input data are presented via weighed connections to the neurons of the hidden layer. The rate of the output data from the j^{th} neuron of the hidden layer can be calculated by formula (1).

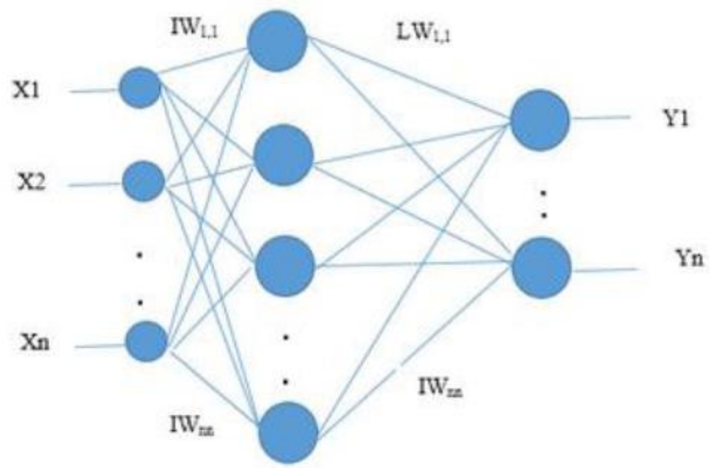

Figure 2: The architecture of the Multi-layer Neural Networks

$$v_j = \sum_{i=1}^{m} f\,(IW_{j,i} X_i + b_j) \qquad (1)$$

The function f in the recent formula addresses the motional function, which is generally considered as the ***S***-shape functions; where m is the number of input patterns, $IW_{j,i}$ is the connection weight between the j^{th} neuron of the hidden layer and i^{th} training pattern of the first layer. The bias value b corresponds to all neurons in the hidden layer. This Sculler quantity causes the motional function move to the left side. The calculated values in the hidden layer are passed after giving them the weight through the motional function in the output layer, which is usually selected from the linear functions. The i^{th} input neuron in the output layer will be calculated by formula (2)

$$Y_i = \sum_{j=1}^{n} f\,(LW_{i,j} v_j + b_i) \qquad (2)$$

The total output of the network will be considered as an algebraic summation of the values resulted from the linear layer. Training the network is a process through which the weights and biases are getting improved so that the difference between the value resulted from the network and the target value will be the minimum. The process will be accomplished in two total phases (Hopfield, 1982).

During the going-round phase the output value of the network will be calculated once the network operation from the entrance to the exit position is performed. It will then be improved by means of some methods such as gradient descent, weights value, and biases gained via the output layer in a direction opposite the direction of the network. This task will be continued through a frequent process until the error function of the network sets below a certain value and/or the number of repetitions of the network reaches a certain quantity. Three Levenberg Marquardt, Bayesian rule, and Descending Gradient methods have been used to achieve the weights and bias values.

In this Levenberg Marquardt algorithm which is one of the most applicable algorithms for learning the multi-layer networks with π-shape error emission rule, the attempt is to reduce the calculations by ignoring the calculation of Hessian Matrix. When the efficiency function is like the summation of the squares-of-the-squares, the Hessian Matrix and the Gradient will be calculated as formulas (2) and (3), respectively.

$H = J^T J$ (3)

$g = J^T e$

J is Jacobean Matrix contains the first derivatives of the network errors towards the weights and biases and e is the network error vector.

Levenberg Marquardt algorithm uses the following approximate to calculate Hessian Matrix.

$X_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e$ (4)

When µ is zero, this function will change into a Newton method with Hessian Matrix approximate and when µ is a huge number, it will change into the Conjugate Gradient method with a small step. Therefore, after each reduction in the efficiency function, it will be decreased and will only increase when the trial step increases the function efficiency.

The existing data are formed to predict the hydrostatic level from the temperature, evaporation and respiration inputs which have been already surveyed in order to find a good arrangement in the following six states,

1- W-1, **2-**W-1, **3-** W-2, **4-** P-1, P-2,W-1,W-2, **5-** E-1, W-1 and **6-** P-1, E and W

Input and Output Data for Normalizing the Data

The parameters of temperature, evaporation and respiration are set as the inputs of the neural network which have been checked through six types of the above mentioned arrangements.

To analyze the artificial neural network the data will be normalized. The reason is that entering the raw data will cause to speed reduction and network accuracy, thus the data entered into network will be normalized as well.

In this study formula (5) has been used to normalize the data which standardizes the input data between 0.05 and 0.95.

$x_i = 0.95(x - x_{min}/x_{max} - x_{min}) + 0.05$ (5)

In this formula, x_i is the normalized input data, x is the actual value of the input data, x_{min} and x_{max} are the minimum and maximum input data, respectively. Finally, the output of the network can be returned to its basic state by reversing the standardizing algorithm; also, MSE (Mean Square Error) rate has been used to find the evaluation index.

Methods and Conclusion

As it was previously mentioned in this paper, the networks training was implemented by means of three well-known algorithm used in neural networks and the results were studied out in different situations including number of various layers and neurons, learning methods and totally 109 situations which are divided into six overall categories and the best result was obtained in each of these six situations.

Table 1: The best result obtained through each arrangement

Arrangement	**Training Algorithm**	**Numbers of Layers**	**Number of Neurons**	**RMSE**
Comb 1	GDX	3	15, 10	0.01463
Comb 2	BR	3	10, 5	0.01191
Comb 3	BR	2	15	0.01089
Comb 4	LM	2	10	0.0132
Comb 5	BR	3	15, 10	0.008967
Comb 6	LM	3	20, 10	0.1673

Following, you may see a sample of the developed model results which have been trained by three algorithms.

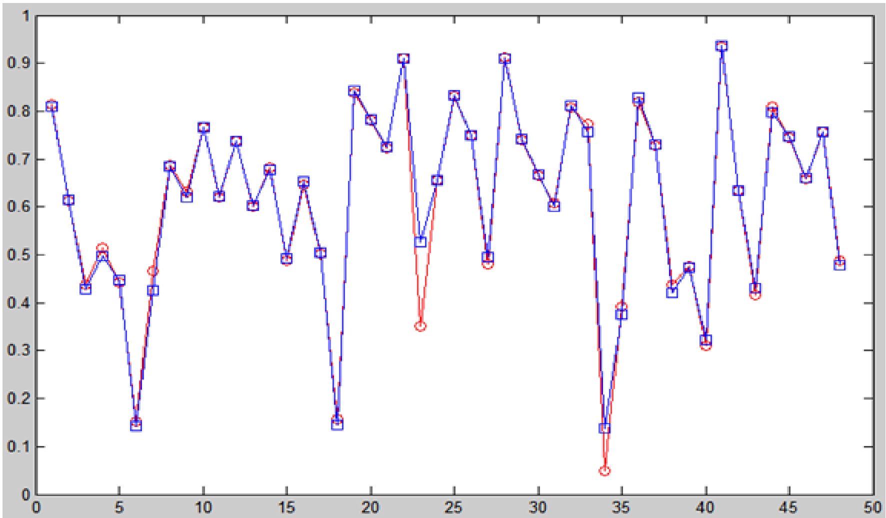

Figure 3: Results gained through the Levenberg Marquardt algorithm

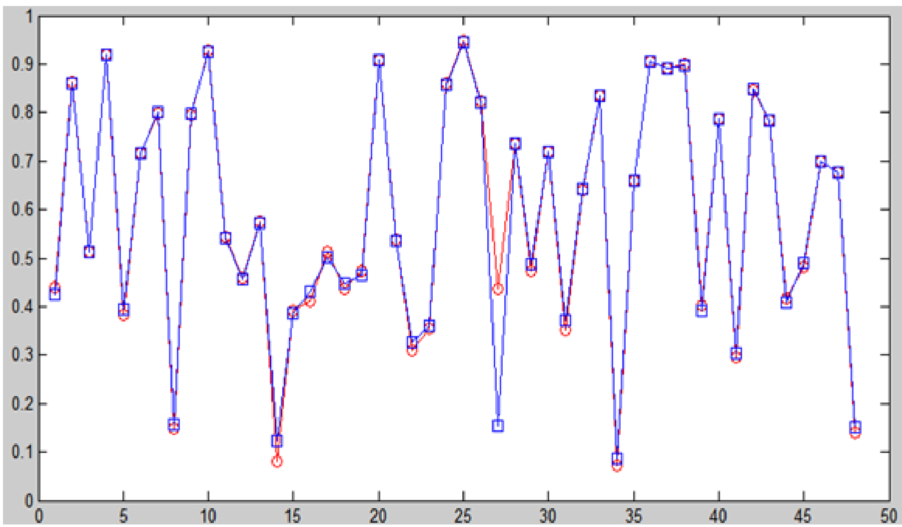

Figure 4: Results gained through the Bayesian Regulation algorithm

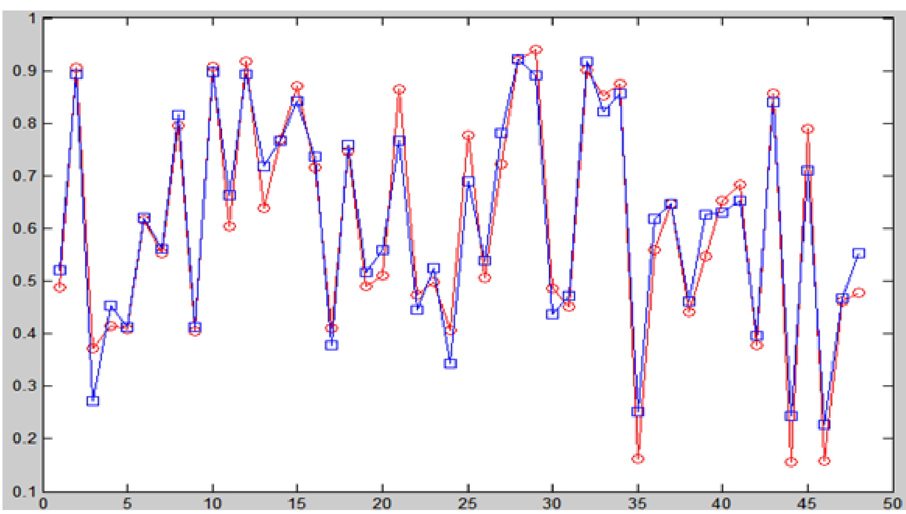

Figure 5: Results gained through the Gradient Descent algorithm

As it can be seen in most of the arrangements, the Bayesian algorithm has the capability to describe with a relatively acceptable accuracy, but totally, among the six notified arrangements, the fifth one has less error and it can be an acceptable arrangement in predicting tasks.

Conclusion and Suggestions

As it was mentioned, the neural networks were trained throughout this study by developing a neural network and holding the field information within six different arrangements for the input data of the issue and at the end, considering the resulted errors, the best arrangement was chosen with the error of 0.008967.

To improve the performance of the neural network it is proposed to use more powerful algorithms like Genetic algorithm and the other evolutionary algorithms such as Genetic, Ants and Honey bee's algorithms in order to train the network to regulate the weights and biases.

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