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Research Article

QUALITATIVE MODELING FORTHE MINÂB RIVER USING MULTI-LAYER NEURAL NETWORKS

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ABSTRACT
Rivers are the most important and common sources for supplying potable, agricultural and industrial water and they have a lot of qualitative fluctuations due to passing through various river-beds and regions and direct connection with their surrounding environment. Therefore, surveying and forecasting the changes in qualitative parameters of water along a river must be taken into consideration. To make this real, a variety of water quality models are used in field of management and maintaining water quality most of which require entry parameters that are either hard-to-access or their measurement is time-and-cost-consuming. Having the capability to forecast - among the existing models - the artificial neural models are more interested.

Keywords: *Artificial Intelligence, Qualitative Modeling, Multi-layer Neural Networks, the Minâb River*

INTRODUCTION
Due to natural complexity of the problems in modeling the qualitative forecast, it seems that the artificial neural networks can determine the non-linear formulas dominating the qualitative evaluation processes without solving the differential equations dominating the problems. In hydraulics and hydrology engineering designs, water quality evaluation in the aquifer district is one the important dilemmas resulted from its general behavior.
Artificial neural networks are non-linear structures with the ability to describe the complex non-linear processes connecting the inputs and outputs of every system. Different applications of the artificial intelligence systems have been recently presented in different scientific attitudes. For example, problems which have been studied by artificial neural networks and phase-neural deductive systems are: forecasting the level of ground water resources, qualitative forecast, predicting during the fluid, estimating and forecasting the precipitation location and time, estimating the sedimentary discharge of the rivers, runoff modeling and forecasting water demands.
In this paper, considering the above mentioned, artificial neural networks application in rivers engineering has been discussed as well as qualitative modeling estimation of which the first given data between 0.05 and 0.95 were normalized and then, after developing neural networks, were used in order to train them.
Some qualitative modeling tasks from the previous studies which were done by means of artificial intelligence are mentioned below:
Hamidreza (2008) forecast the Zayandehrood River qualitatively using a phase-deductive model. Its application was presented by a set of actual data gained from Zayandehrood River based on a set of a variety of data and illustrated by ANFIS. Using comparative phase-neural deductive systems can be brought forth to be discussed as a result of a new application in forecasting the quality status of the rivers with enough data to be used in education, calibration and authentication phases.
Research by Mirzaei *et al.,* (2010) on the Soufichay River in the Eastern Azerbaijan province, by means of DO and BOD qualitative information along the measured length of the river, and comparing them with the calculated values resulted from neural networks, clarified it that the neural networks can well forecast the changes in qualitative parameters of the river by a minimum number of the parameters and allowable accuracy.
Misaghi *et al.,* (2004) qualitatively forecast the Zayandehrood River using artificial neural networks. This study was performed on the Zayandehroud River in the central region of Iran using qualitative information calculated via DO and BOD in 14 stations set along the river up to Gav-e-Khouni swamp

(marsh). Then, the results gained from artificial neural networks models were compared with QUAL2 qualitative model which shows that the neural networks are capable enough to simulate the variations occur in qualitative parameters.

Using neural networks by Lalaham *et al.*, in 2005 in evaluating the ground water level of an aquifer in the northern France showed that the Multi-layer Perceptron networks with minimum median neuron make the best forecast in a short period of time.

Studies performed by Streekant *et al.*, (2009) confirms that the capability of neural networks in forecasting the ground water level with the average square root error of 4.5 meters and determination factor of 0.93.

Mayer and Dendi (1996) during the study for estimating the salinity of the Marie River by means of artificial neural networks come up with this fact that the neural network model with training algorithm of regression emission has been an accurate tool in estimating the rate of the quality loss in this river and the difference between the observed values and the simulated ones is between 46 and 53 micro-mouse over centimeter.

Sandho and Finch (1995) emphasized on the ability of the artificial neural networks to predict the daily and actual rate of salinity in different areas water and ability to estimate the density of Attune, Anune, EC and TDS in these regions were emphasized.

Ebrahim *et al.*, (2013-14) estimated the average daily flow rate of Shahpour River using Artificial Neural Networks. Artificial Neural Networks have resulted in a great evolution in dynamic systems behavior analysis in different engineering sciences. The MATLAB software has been used in study. Therefore, the hydrometric, pluviometric, vapometric and daily temperature data of Boushigan station on the River of Shahpour within a 9-year statistical period (2003 – 2012) were used for this model. Practical results of the model have expressed almost a high accuracy of the neural network in estimating and evaluating the flow rate of Shahpour River

Ali *et al.*, used Artificial Neural Networks to model the running water precipitation in Aliâbad station. In this research, they first checked the training algorithms effects after the dissemination as well as Genetics algorithm influence on the efficiency of the Artificial Neural Networks, then the results and accuracy rates of modeling were compared with both algorithms and the training one was determined to be adequate one (since it showed a better statistical performance). The results express the fact that a Neural Network trained through an algorithm after the dissemination holds more capability and accuracy than the one trained by Genetics algorithm. Aliabad station’s flow-rate of a week ago, two weeks ago, together with Bahman weir station’s flow-rate have been considered as the independent variables in Artificial Neural Networks design, which has made the model’s performance more consistent with the factual data. Artificial Neural Networks trained by algorithms after dissemination of the independent variables have expressed an absolute value of 3% for the relative variation and close-to-one correlation factor of fitting in predicting the whole data of the flow-rate running through Aliabad station. Since the model has showed the best performance and workability among the whole other analyzed models, has been introduced as the best model of all.

Artificial Neural Networks

Artificial neural networks are one of the most dynamic areas of artificial intelligence containing a lot of usages in different fields. Considering the capabilities and potentialities of this kind of artificial intelligence, its range of usability is increasing day by day.

Neural networks are able enough to be learned and can be used with experiences gained through the novel and similar issues. In fact, these networks are constructed by an input and an output layer as well as some hidden layers which are located between these two. The schematic structure of a set of multi-layer networks is shown in figure 2. In the first layer, no calculations take place and only the input data will be submitted via weighed connections to the neurons of the hidden layer. The output amount of the j^{th} neuron of the hidden layer will be calculated by formula 1. These networks are made up of one input and one output layer, and some hidden layers between these two. Schematic structure of a multi-layer network is shown in figure 2. In the first layer no calculations take place, only the input data will be submitted via the weighed connections to the neutrons of the hidden layer. The output amount of the jth neuron of the hidden layer will be calculated by formula 1.

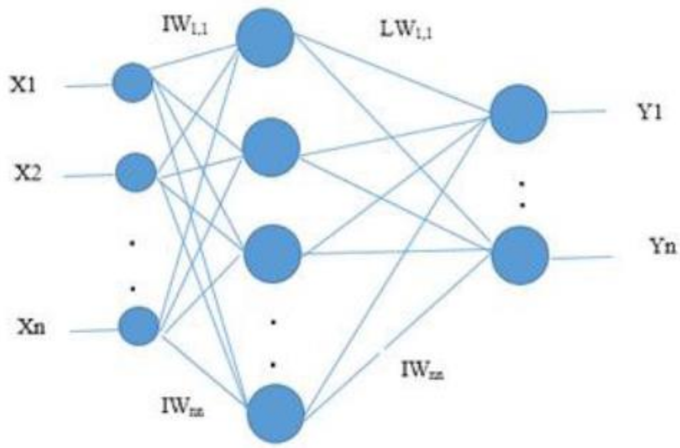

Figure 1: The architecture of Multi-layer neural networks

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

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.

$$H = J^T J \qquad (3)$$

$$g = J^T e$$

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.

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

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 Calcium, TDS and Electrical Conductivity inputs which have been already surveyed in order to find a good arrangement in the following six states,

1- Ca
2- Ca-1, TDS
3- EC, TDS, Ca
4- TDS-1, Ca
5- TDS
6- Ca-1, TDS-1

Input and Output Data for Normalizing the Data

Calcium, TDS and Electrical Conductivity parameters are set as the inputs of the neural network which are surveyed in six types of arrangement which have been already mentioned above.

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.

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

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	Number of Layers	Number of Neurons	RMSE
Comb 1	BR	3	10,5	0.015860643
Comb 2	BR	2	10	0.010798611
Comb 3	BR	3	10,5	0.081853528
Comb 4	GDX	2	20	0.088317609
Comb 5	BR	2	20	0.010557935
Comb 6	BR	3	10,5	0.064807407

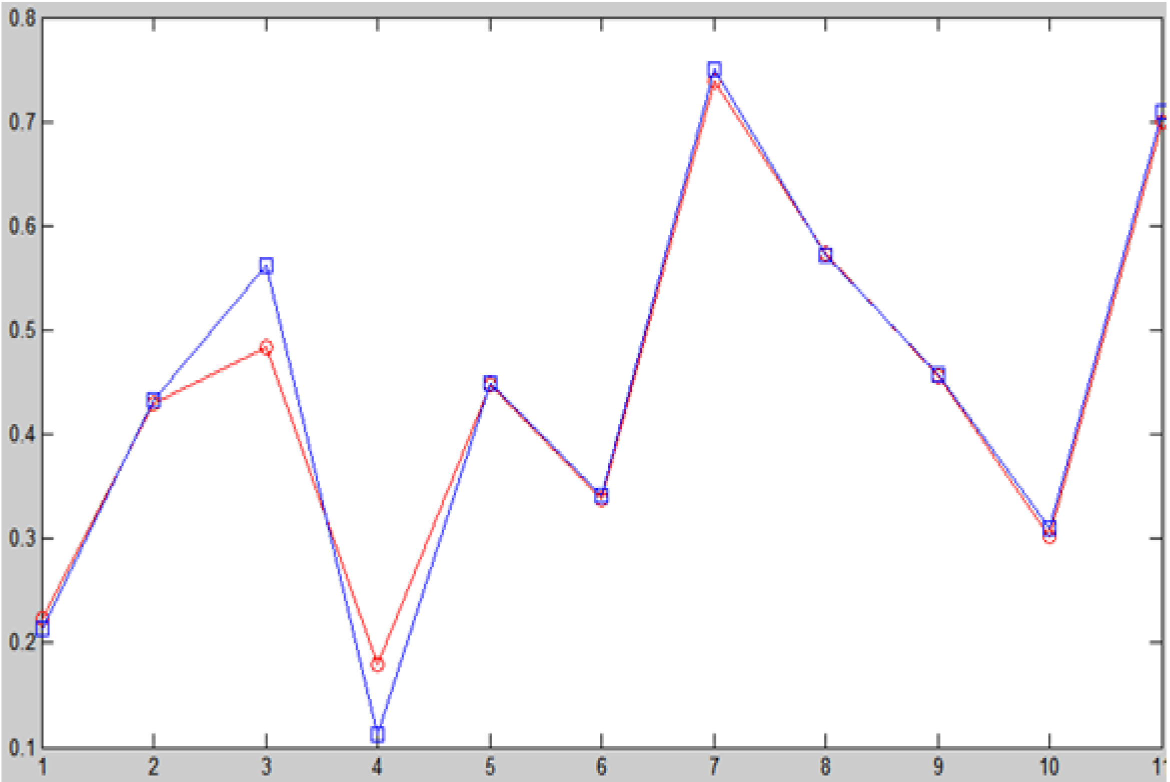

Figure 2: Results gained through the developed model of the Bayesian Regulation algorithm

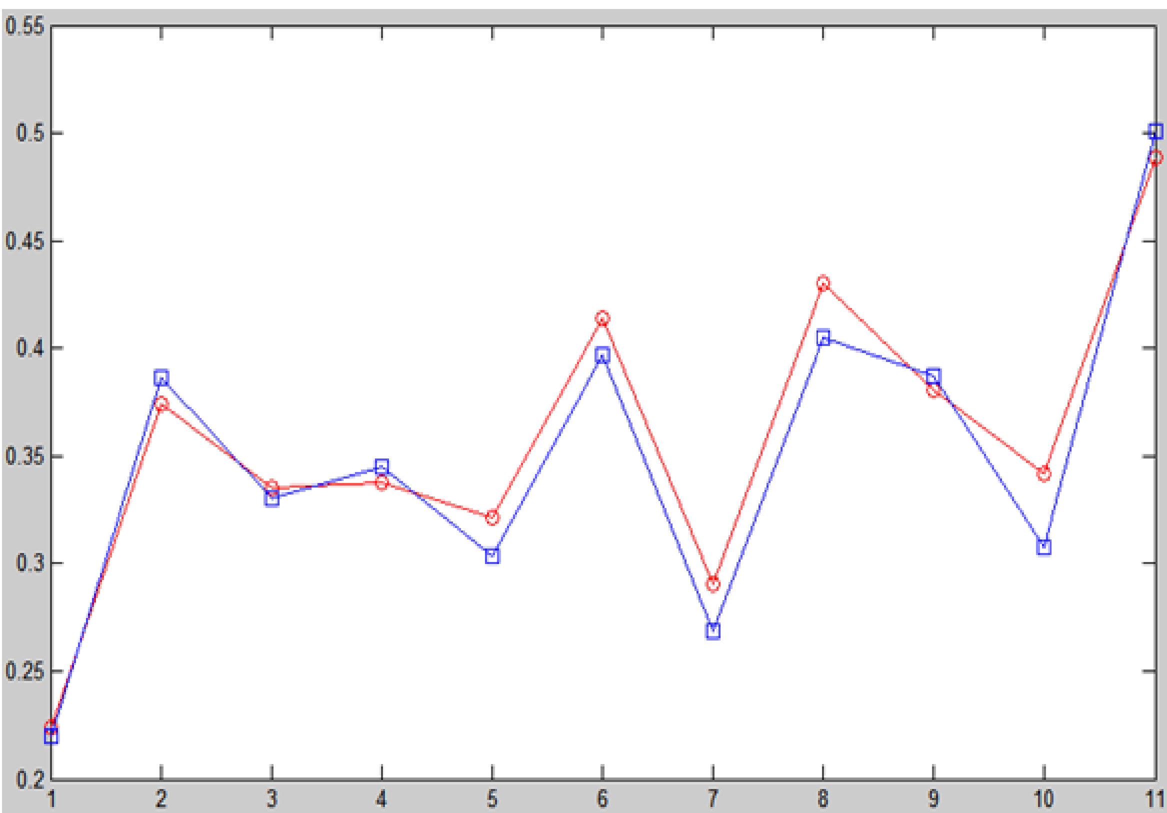

Figure 3: Results gained through the Bayesian Regulation algorithm

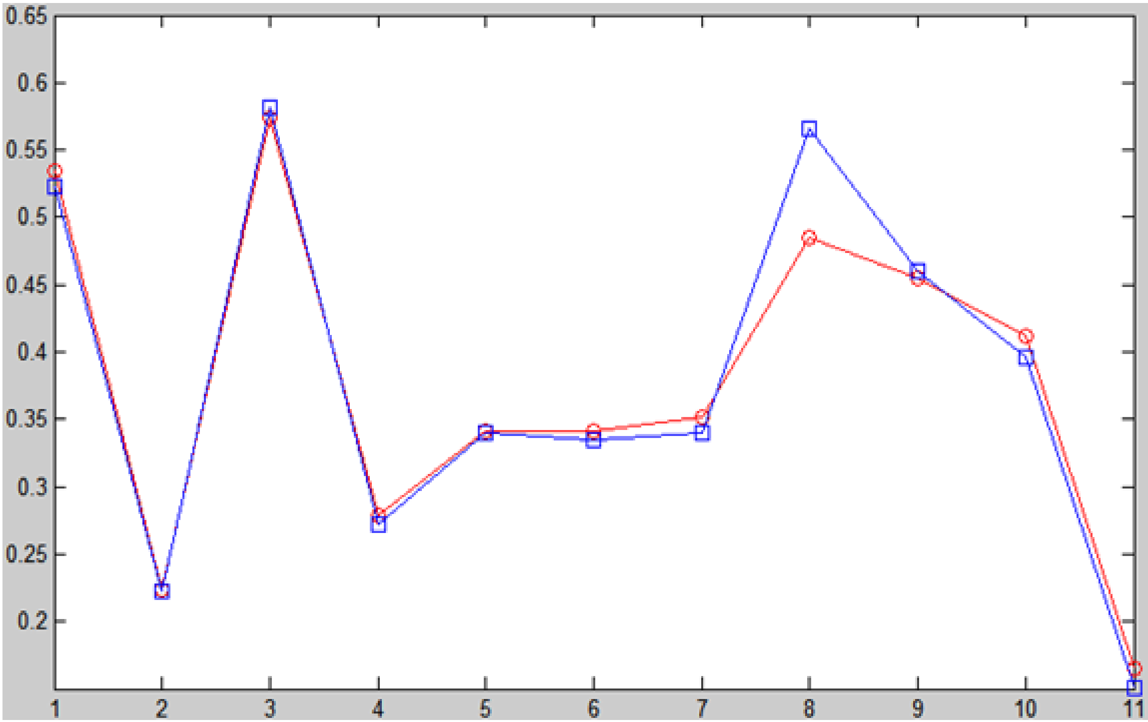

Figure 4: Results gained through the developed Levenberg Marquardt algorithm

As it can be seen in the above table, the Bayesian algorithm has the capability to forecast 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

There are a lot of models suggested and developed to manage better in order to maintain the quality of the water. Most of these models require input parameters, of which either their accessibility is difficult or their measurement includes spending a lot of cost and time. Among these the artificial neural networks- inspired by the human's brain structure – will be studied as suitable options in this paper.

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 0.010557935.

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 bees algorithms in order to train the network to regulate the weights and biases.

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