

Application of Artificial Neural Network to Predict Total Dissolved Solids Variations in Groundwater of Tehran Plain, Iran

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Abstract

In an attempt to examine groundwater quality in Tehran with respect to the consumption pattern in the last ten years, five distinct neural network scenarios of different total dissolved solids (TDS) input and output parameters were set up. It is observed that, in order to forecast with a great deal of trial and error, the tangent algorithms with the momentum-training algorithm turns out to be less erroneous in contrast to the sigmoid algorithms with Levenberg-Marquet. The occurrence of maximum error implies maximum determination coefficient of 0.96. Moreover, in line with the neural network laid out in two layers, NRMSE is supposed to run out at 0.175, the average normal absolute value of error is expected to be 0.11 and the estimate is supposed to be excellently acceptable. The neural network involves the predominance of sulphate and chloride ions over the sodium parameter.

Keywords: *Forecast, Groundwater, Neural network, TDS, Tehran*

1. Introduction

When it comes to water resources provision and application management, predicting groundwater quality cannot be dispensed with. Groundwater is a major source of water supply in different cities around the world and therefore several studies have highlighted different aspects of groundwater such as, storage potential, hydrogeology, water quality, vulnerability and sustainability and so on (Pandey and Kazama, 2011; 2012; Pandey et al., 2011; 2012; Chapagain et al., 2010). A variety of factors contribute to variations in groundwater quality. Their inherent uncertainty carries weight, as more than one variable affect quality of water. The inhomogeneity of the medium has thrown the quality prediction and the approaches adopted by researches into complexity (Esmaeili et al., 2004). The TDS (total dissolved solids) parameter constitutes one of the fundamental parameters as

regards drinking and agricultural water. This is directly linked to water salinity, sodium absorption coefficient and drinking water quality (Asghari Moghaddam et al., 2006; Jamshidzadeh and Mirbagheri, 2011; Mehrdadi et al., 2012). TDS has been examined in this research, on this account. One suitable approach to look into groundwater behavior is applying computerized models. Consequently, it is necessary to get a proper insight into the mechanism of quality fluctuations with time and predicting it by means of governing pattern so as to enquire into the situation of groundwater table and the quantity of accessible water (Tahmasebi and Zomorrodian, 2004). On this ground, considering the lack of a physical understanding of the nature of the problem, Artificial Neural Network can model the dynamic behavior of a non-linear process only through

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training. The predicted characteristic makes the artificial neural network more flexible against unfavorable mistakes and renders them ineffective (Coulibaly et al., 2001; Asghari Moghaddam et al., 2006; Dehghani et al., 2009). Artificial neural networks are considered as convenient substitutes for regressions and empirical models to predict the behavior of water resources, owing to their time reliability and adaptability to unpredicted changes. These are applied not only in qualitative predictions, but also in predicting ground water situation and volume. A great deal of modeling has been done in this regard (Kumar et al., 2002; Coppola et al., 2003; Hosaini et al., 2007; Khalili et al., 2008). As for the prediction based on neural network, (Mehrdadi, et al., 2012) have made an attempt to predict the TDS parameter with the neural network in Fajr Purification Center in the south of Iran in 2012. Other examinations using similar modeling conducted by Zare Abyaneh, et al. (2011) to predict nitrate parameter have been successful. Furthermore, a similar research, with the modeling constructed by Zare Abyaneh, et al.(2009), to predict the level of ground water in Malayer desert, has come up with comparable results with similar modeling.

2. Materials & Methods

2.1. Study Area

A description of study area with the city of Tehran as its center and an area of approximately 12981 square kilometers, the province of Tehran sprawls between 34' and 36.5' latitudes and 50' up to 53' longitudes. Tehran is the largest city and the capital of Iran, whose position is displayed in Fig.1. Populated by 8,429,807 million people, Tehran ranks as the world's 28th highly populated cityparamete. Together with its constituencies, this city has a population of 13,422,366 million and an area of 18,814 square kilometers. The altitude of the city varies between 2000 meters in the northernmost areas and 1050 meters in the southernmost regions, respectively. Tehran borders on mountainous areas on the north and desert areas on the south. This accounts for contrasting climates in the north and the south of the city. While the northern parts are characterized by their cold and dry climate, the southern parts experience hot and dry weather conditions. In a 30-year period, the

average annual precipitation has varied between 200 to 400 mm and the actual precipitation has come up to 230 mm. Today, piped water from dams such as Amirkabir, Latian and Larr has supplanted them and qanat and spring water are only used for agriculture and irrigation. Only some springs, mainly in the north-eastern parts of the province, have maintained their importance. The most important of them include Damavand, Ghale dokhtar, Abali, Valeh in Gachsar, Shahdasht in Karaj, Ali in Ray, Tizab and Galeh Gileh (Nasr-abad et al., 2008).

2.2. Analytical method

Parameters such as temperature, pH, Electric Conductivity, and Dissolved oxygen have been evaluated by means of portable instruments in the sampling site and the other parameters have been analyzed in the laboratory. Nitrate, nitrite, sulphate and flourine have been measured by the HACH instrument and US-EPA methods 8039, 8507, 8051 and 8029 have been employed respectively. All cations have been measured via EPA-3005 method and by means of the inductive flame atomic absorption spectrometer (FAAS). Standardized method number 4500 has been used to measure carbonate and bicarbonate anions and chloride measurement has been carried out applying argentometric method (Coppola et al., 2003; Biswas, 2005; Mehrdadi et al., 2009).

2.3. Data analysis

Different maxima, minima, averages and deviations of standard have been calculated, courtesy of SPSS 19. The same software is used to analyze and examine the relation among the pollutants, forming a correlation between them and the software SPSS 19. Examining the correlation coefficients thus appearing brings out the relative susceptibility of each parameter. Finally, we will turn to an examination of the recommended models with the designed neural networks to predict the TDS parameter. In the first stage, considering the correlations corresponding to the statistical data collected from 2002 Through 2011 in dry and wet seasons pertaining to samplings from 71 wells in different parts of the city of Tehran, the most significant correlation with the TDS parameter is observed among the parameters, in which the correlation has been worked out via SPSS 19 software.

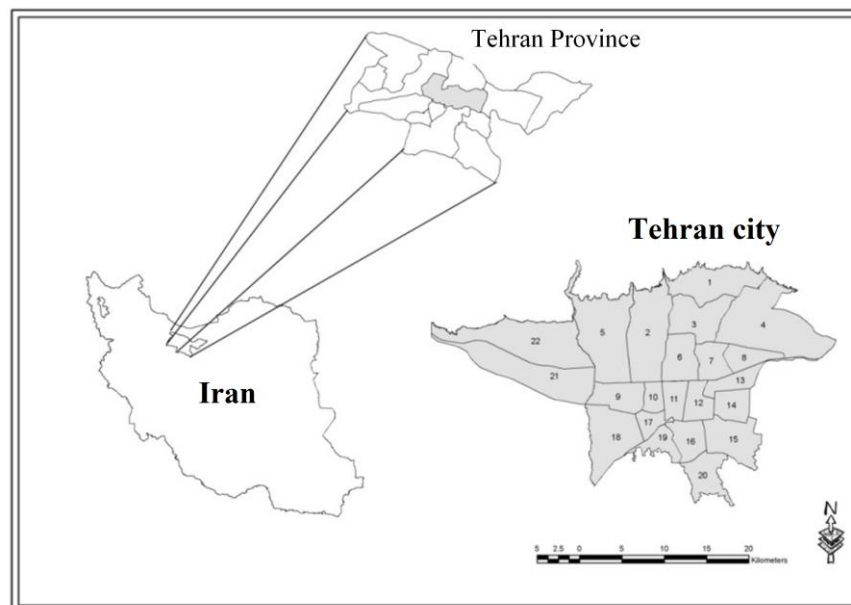


Figure1: The position of Tehran in Iran

2.4. Setting up ANN Models and required data are provided

The method of artificial neural network of multilayer Perspiring has been used to probe into the quality of groundwater of the plain of Tehran. This method makes for examining the qualitative changes of groundwater in different stages and bringing the selected information into the network. In line with the studies carried out, multilayer perspetron (MLP) with back propagation (BP) algorithm has been adopted in designing different structures of the neural network (Sreekanth et al., 2009). In the multilayer neural network, depending on the pattern of relation between the materials, input is put in first layer (X_i) and the output in the last layer (y) by means of neurons weights (W), bias (b) and the activity algorithm ($f(x)$) in the middle layer(s). The network design has been grounded on a combination of information on the parameters effective on the quality of the groundwater table in the past, in the shape of various structures of information fed into the input layer (Zare Abyaneh et al., 2009; 2010; 2011). In each structure, the input information, after processing, is put through to the next layer(s) through the output of the first layer neurons and finally,

provided that it is acceptable, to the network output (Fig.2). Otherwise, as the calculation error spills over into the previous layers, calculations are repeated. This process goes on as long as a suitable result comes out. Normalized information was used as the network input, in which the software normalizes information. Neural networks have flexible nonlinear function mapping capability that can approximate any continuous measurable function with arbitrarily desired accuracy, whereas most of the commonly used empirical models do not have this property. Second, being nonparametric and data-driven, neural networks impose few prior assumptions on the underlying process from which data are generated. Also, high computation rate, learning ability through pattern presentation, prediction of unknown patterns, and flexibility affronts for noisy patterns are other advantages of using ANNs. In this study, several training algorithms and functions embedded in the neural networks toolbox of Neurosolution software were adapted. Another advantage of this software is different algorithms, with various algorithms in the software bank (Zare Abyaneh et al., 2009; 2010; 2011). A distinct structure of the neural network, involving least error possibility, has been considered for any model, so as to make least

error-prone predictions. Heed should be taken of the fact that the structure of the neural network built into the first model necessarily implies the least error possibility. Error is even less likely in the second or third models and it is necessary to think of a new structure for the new model.

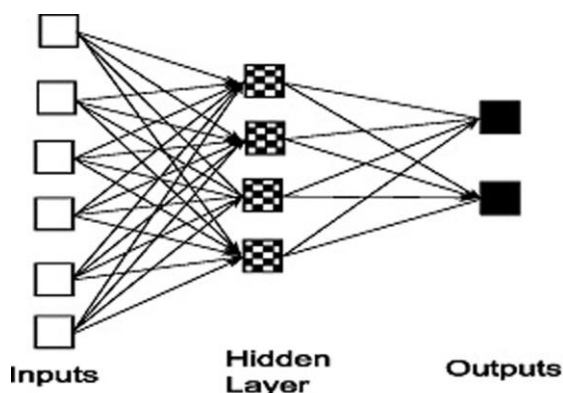


Figure 2: Neural network model applied in the research

In this research, the data has been divided into two groups randomly and based on the experiences, on the part of other researches and trial and error has been taken to all stages: training data, accounting for 70 percent and testing data, making up 30 percent of the total data. The sigmoid simulating tangent, linear sigmoid and linear tangent algorithms were applied in operating the neural network. Moreover, for each simulating algorithm different training rules, such as (Levenberg Marquate, momentum, coupling gradient) were put to use. Attempt was made for all training and simulating rules to be examined in a trial-and-error manner in order to achieve better results. To work out the optimized number of network calculation repetition, the trial-and-error approach was adopted and its pre-error was figured out via different numbers of calculation repetitions. It is worth mentioning that the input, middle and output neuron simulating algorithms were considered identical. In This regard, studies also implied That the simulating algorithms being the same, more satisfactory results come out, as opposed to the simulating algorithms corresponding to different layers (Tahmasebi and Zommodian, 2004; Zare Abyaneh et al., 2009; 2010; 2011). The total parameters examined that the timing series run to

1652, of which 1156 were set aside for network training and 496 parameters have been used for the final testing and analysis. With respect to percentage of the correlation grade, five recommended models were worked up. The input parameters, corresponding to each model are clearly shown. According to the arguments above and the total information related to any model, keyed into Neuro Solution software and applying a system under EXCEL software and the definitions corresponding to the neural network in the software.

The adequacy of the ANN is evaluated by considering the coefficient of determination (R^2) defined on the basis of TDS estimation errors, also the values of root mean square error (RMSE), normal root mean square error (NRMSE), mean absolute error (MAE) and Normal mean absolute error (NMAE) are used as the index to check the ability of model. The acceptance criterion rests on the quantitative error passing into the calculations and observations, including maximum R^2 , minimum RMSE and MAE value of error, being less than 1 and the relative error is computed through the following equations (Asghari Moghaddam et al., 2006; Coppola et al., 2003; Coulibaly et al., 2001; Kumar et al., 2002).

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (TDS \text{ actual} - TDS \text{ forecast})^2}{n}} \quad (1)$$

$$NRMSE = \frac{RMSE}{TDS \text{ average}} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (TDS \text{ actual} - TDS \text{ forecast})^2}{\sum_{i=1}^n (TDS \text{ actual} - TDS \text{ average})^2} \quad (3)$$

$$MAE = \frac{\sum_{i=1}^n |TDS \text{ actual} - TDS \text{ forecast}|}{n} \quad (4)$$

$$NMAE = \frac{MAE}{TDS \text{ average}} \quad (5)$$

In these equations:

R: the maximum determination coefficient, RMSE: the minimum root mean square error, MAE: the mean absolute value of error, NRMSE: the normal root mean square error, actual TDS: the TDS coming out after the tests, forecast TDS: the TDS figured out via the neural network, average TDS: the mean TDS resulting from the tests and n stands for the number of the parameters to be examined.

3. Results and Discussion

3.1. Groundwater quality characteristics

Different maxima, minima, averages and deviations of standard for major anions and cations as well as sodium absorption ratio (SAR), total hardness (TH), electrical conductivity (EC) and TDS are indicated in Table 1.

In conformity with Table 2, the TDS parameter turned out to be most closely related to the sulphate ion (0.959), with sodium (0.947) and other parameters following. On This ground, the parameters corresponding to any model will be set out in line with the correlations in Table 2, which are to be ruled out in order of insignificance in the models. The parameters are gradually narrowed down in Table 3 and finally the fifth model has been built up, characterized by the least possible parameters and the closest correlation with the TDS parameter.

As Fig. 3 illustrates, it is concluded, in view of the Surfer software based on Kriging Interpolation, that the highest magnitude of TDS applies to the

southern and eastern areas. Inquiring into the different parameters pertaining to these areas, the maximum increase and decrease with the TDS parameter turn out to grow from the chloride, sulphate and sodium parameters, which points out the significance of the fifth model (Coppola et al., 2003; Asadpour and Nasrabadi, 2011; Abbasi Maedeh and Mehrdadi, 2012).

Sulphate and EC have shown the closest correlation with the TDS parameter, as regards the parameters of Table 2, in which the correlation has been computed via Pearson method by means of SPSS software, and bicarbonate bears the least correlation. According to the results indicated in Table 2 (Correlations of TDS with other input parameters) five models for ANN input parameters are constructed. The most significant point in selection of parameters is attributed to their correlation to TDS. In Table 3 five recommended input parameter models in neural network are shown.

Table 1

Descriptive statistics of the parameters

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
EC	1652	9345	285	9630	1465.96	33.426	1358.584	1845751.478
TDS	1652	6488	164	6652	917.95	21.947	892.037	795730.189
SO ₄	1652	56.03	.51	56.54	5.7627	.18747	7.61964	58.059
Cl	1652	45.43	.17	45.60	4.7044	.14597	5.93308	35.201
HCO ₃	1652	11.70	1.05	12.75	4.2436	.05253	2.13503	4.558
TH	1652	2437.0	35.0	2472.0	394.273	8.5322	346.7881	120262.018
SAR	1652	28.163	.234	28.397	3.35509	.077013	3.130188	9.798
K	1652	.30	.01	.31	.0362	.00094	.03822	.001
Na	1652	58.17	.33	58.50	6.8964	.19966	8.11530	65.858
Mg	1652	29.68	.16	29.84	2.9509	.08397	3.41309	11.649
Ca	1652	31.50	.40	31.90	4.9346	.09568	3.88892	15.124

Table 2

Correlations of TDS with other input parameters

		EC	TDS	TH	SAR	SO ₄	HCO ₃	Cl	Na	Mg	Ca	K
EC	Pearson Correlation	1	.993**	.921**	.633**	.958**	.560**	.939**	.957**	.900**	.853**	.656**
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652
TDS	Pearson Correlation	.993**	1	.923**	.617**	.959**	.548**	.930**	.947**	.902**	.855**	.655**
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652
TH	Pearson Correlation	.921**	.923**	1	.345**	.904**	.515**	.866**	.778**	.943**	.956**	.629**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000	.000	.000	.000	.000
	N	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652
SAR	Pearson Correlation	.633**	.617**	.345**	1	.573**	.539**	.545**	.785**	.401**	.264**	.368**
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.000	.000	.000	.000	.000
	N	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652
SO ₄	Pearson Correlation	.958**	.959**	.904**	.573**	1	.460**	.845**	.917**	.889**	.833**	.617**
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000
	N	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652
HCO ₃	Pearson Correlation	.560**	.548**	.515**	.539**	.460**	1	.395**	.542**	.583**	.407**	.463**
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000	.000	.000	.000	.000
	N	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652
Cl	Pearson Correlation	.939**	.930**	.866**	.545**	.845**	.395**	1	.893**	.814**	.830**	.608**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000		.000	.000	.000	.000
	N	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652
Na	Pearson Correlation	.957**	.947**	.778**	.785**	.917**	.542**	.893**	1	.790**	.693**	.609**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000
	N	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652
Mg	Pearson Correlation	.900**	.902**	.943**	.401**	.889**	.583**	.814**	.790**	1	.804**	.661**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000
	N	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652
Ca	Pearson Correlation	.853**	.855**	.956**	.264**	.833**	.407**	.830**	.693**	.804**	1	.541**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000
	N	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652
K	Pearson Correlation	.656**	.655**	.629**	.368**	.617**	.463**	.608**	.609**	.661**	.541**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	
	N	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652	1652

** Correlation is significant at the 0.01 level (2-tailed).

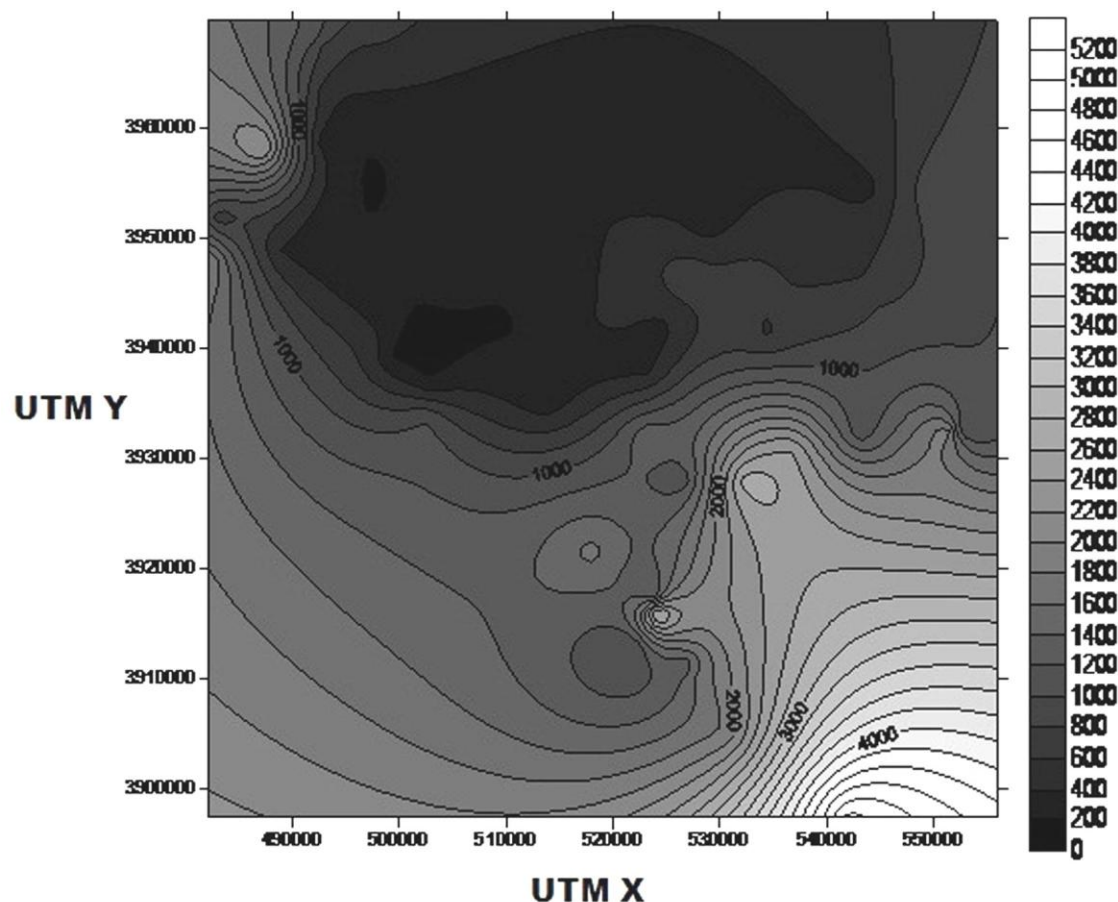


Figure 3: The distribution of the TDS parameter in Tehran based on Kriging Interpolation

Table 3

The structure of the recommended model in the neural network

Model Number	Input Parameter
1	SO ₄ , Na, Cl, Th, Mg, Ca, K, SAR, HCO ₃
2	SO ₄ , Na, Cl, Th, Mg, Ca, K, SAR
3	SO ₄ , Na, Cl, Th, Ca, K
4	SO ₄ , Na, Cl, Ca
5	SO ₄ , Na, Cl

3.2. Performance of the ANN

Considering the five models of neural network developed grounded on structures in the Table 4,

the following results were brought out by trial and error.

The best ANN architecture was chosen and evaluated among various ANN architectures with different number of neurons in hidden layers. How to choose the best structure is based on the lowest error and highest correlation. Table 4 represents results obtained from ANN of feed forward back-propagate (FFBP) type with different learning algorithms. Table 4 shows that the FFBP architecture (3-4-4-1) is the best architecture ($R^2 = 0.969$, MAE= 114.24 and RMSE=175.15).

Looking into the models, it is found out that, forecasting the TDS parameter in the first and second models involve a greater magnitude of error, as they have more input parameters. Therefore, this indicates the inefficiency of the simulating and training algorithms. In the third to the fifth models the error declines as the simulating and training algorithms are kept constant. It is also

revealed that error dwindles to its minimum as the number of input neurons decreases and an extra layer is built into the fifth model. By contrast, the third and fifth model, consisting of 6 and 3 parameters, respectively result in acceptable error. Diagrams 4 and 5 graph out the distribution of the predicted data(the vertical axis) and the observed data(the horizontal axis) in the testing stage of the fifth model. In figure 4 the association between the input and output data of the neural network in the form of a linear equation and deviation of standard in the first quadrant bisector is also displayed. It should be noted that the closer the data get to a one-to-one diagram, the more reliably the model evaluates the TDS proportion.

3.3. Sensitivity of parameters

An examination of figure 6 shows that the sensitivity of different parameters in predicting the

neural network of the fifth model is observed for sulphate, chloride, and sodium parameters respectively. Less variations in sodium in contrast to the other parameters, can account for its lower significance. In fact, seeing that sodium forms a constituency of the soil of the region (Abbasi Maedeh and Mehrdadi, 2012), it goes through less variations, compared to sulphate and chloride, and plays a less pronounced role in predictions (Abbasi Maedeh and Mehrdadi, 2012).

3.4. Prediction of ANN

As the results of the artificial neural network indicate, TDS rate can be predicted by considering other water quality parameters. In other words, artificial neural networks, through exploring the relationship between the input parameters, is able to predict the parameter TDS.

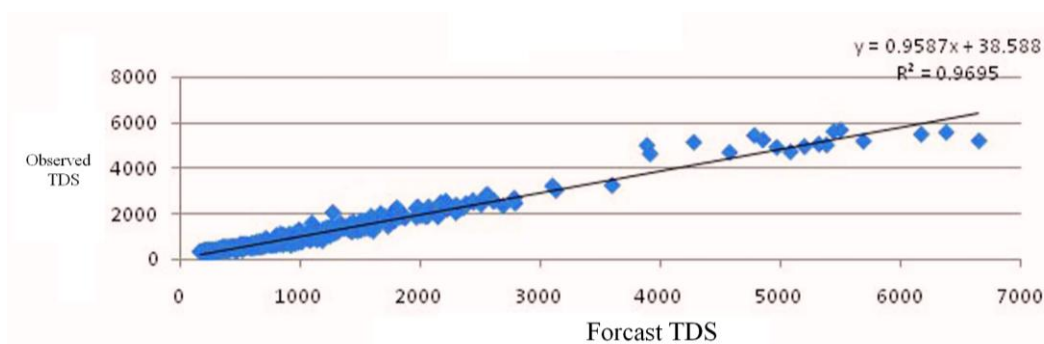


Figure 4: The distribution diagram of the TDS predicted and observed in model 5

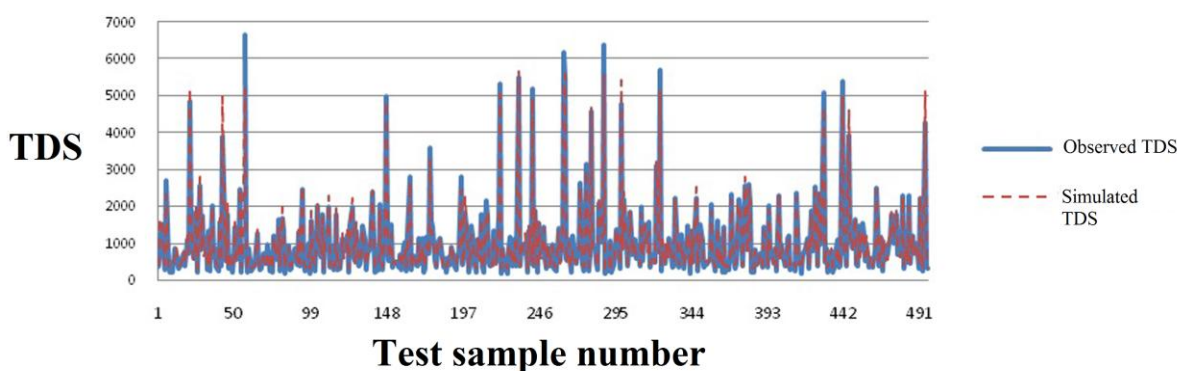


Figure 5: ANN results for Observed and Simulated TDS in test part

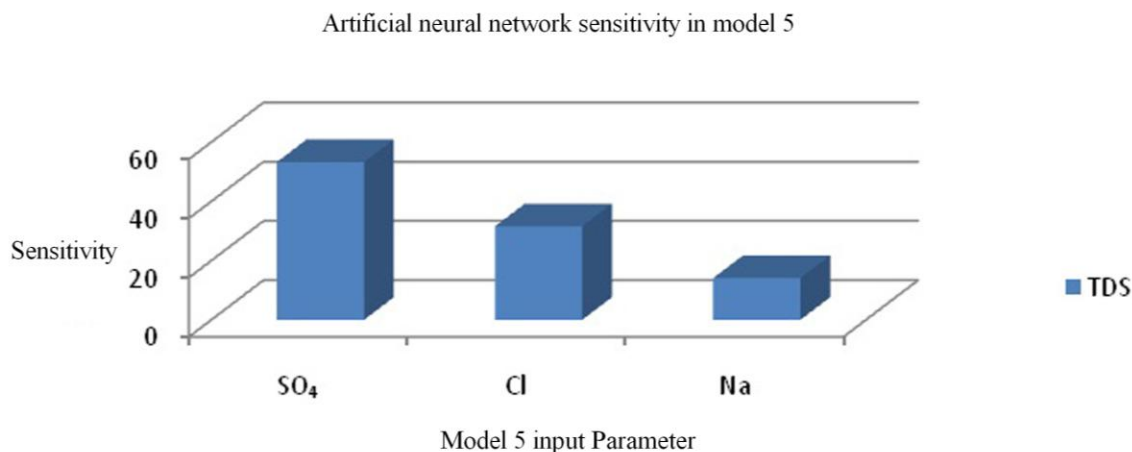


Figure 6: Sensitivity of different parameters in forecasting the neural network of the model 5

Since the comparison of ANN results with measured values of TDS, artificial neural network is showing high accuracy. Therefore, it can be stated that the performance of an artificial neural network is suitable for predicting output parameter. Eventually, by considering the model 5 ANN structure and the obtained equations shown in fig.4, we can predict the TDS parameter and find the most effective parameter that have ability for changing the TDS output results.

4. Conclusion

Based on the results from the structures of different models of neural networks, it is observed that the fifth model with least amount of data and, hence least number of tests to find out the different parameters, turns out to be the most cost-effective and involves lowest error, as regards TDS parameter prediction of Tehran groundwater. With the momentum training algorithm and the tangent simulating algorithm, this model bears the advantages that follow, one of the reasons, to which the improvement of the results can be attributed is the open tangent interval (-1,1) (Zare Abyaneh et al., 2009; 2010; 2011). The emerging outcomes point to the maximum determination coefficient of 0.96, which considering the input parameter, shows the lowest error, as opposed to the other models. Moreover, owing to the two-layer neural network, the least normal root mean square error comes out at 0.175 and mean normal absolute value of error runs out at 0.11, which in

view of the inputs and the neural networks in other models, the estimate thus obtained is remarkably and favorably high. In light of the model developed, a better future estimate and a more reliable forecast to enhance the quality and application of groundwater can be made via controlling the sulphide, chloride and sodium parameters in forecasting the TDS parameter. Furthermore, probing into the input parameter sensitivities and their influences on the outcomes of neural network of the fifth model, it turns out that, in order of importance, sulphide, chloride and sodium make proportional contributions. The Pierson correlation table backs up the efficiency and acceptability of the pattern adopted for the neural network as well. Adequate attention should be paid to the difference between the sensitivities of sodium and chlorine parameters too. One of the main reasons is that this parameter is its geopogenic feature, which due to the salt lakes in the south of the city, carries weight (Baghvand et al., 2010, Jamshidzede and Mirbagheri, 2011), and the man-made nature of the chlorine parameter which originates from the urban and industrial activities and the inflow of washing and antiseptic substances, varying with the season (Baghvand et al., 2010).

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