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Groundwater qualitative prediction using artificial neural networks and support vector machine model case Study: Sirjan plain

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Abstract

Groundwater resources are one considered as one of the most common and important resources of drinking, agriculture and industry water. Due to the lowering of groundwater levels and its volatility, groundwater quality is of utmost importance. The aim of this study is to identify the predictive ability of artificial neural network of Multi-Layer Perceptron (MLP) and Support Vector Machine model and adaptive neuro-fuzzy inference system in which the quality of groundwater in Sirjan Plain has been predicted. A case study was conducted on the Sirjan Plain located in the city of Sirjan in Kerman province. For this purpose, the data of rainfall, the water level in wells and UTM coordinates of intended wells have been used as input combinations and qualitative parameters of the water of wells as output parameters. After initial processes such as normalization, for double-layer neural network, 85% of data were used for training and 15% for validation, and the same ration were applied to ANFIS and SVM. After reviewing the fitness statistical criteria such as correlation coefficient (R), and Root Mean Square Error (RMSE), it was observed that neural network presented an acceptable result compared to SVM and ANFIS models.

Keywords: **Quantitative prediction, groundwater, SVM, ANFIS, MLP**

Introduction

After the glaciers, groundwater resources are the second largest freshwater resource in the world. In areas where there is no surface water such as lakes and rivers or they are unusable, groundwater needs are met by groundwater resources. In the world today, water resources are one of the pillars of sustainable development. Where wells are raised as resources for human communities' needs, in addition to the quantity and amount of river flow, water quality is also considered among important parameters. Qualitative parameters of water are among the components that must be accurately simulated and estimated. About a third of the world's population depends on groundwater and more than 70% of groundwater is used in agriculture (Office of Groundwater Studies, 2005). Therefore, agricultural and industrial development increased the harvest of these resources; and overexploitation of groundwater reservoirs made the rate of aquifer recharge insufficient of water pumping and harvesting and land subsidence. In recent decades, significant concerns have been raised due to the increased water demand and reduc reduced renewable water resources per capita and how to use these resources in the optimal, effective and efficient way, to ensure sustainable development, is one of the most important topics in international circles. Since Iran is located in arid and semi-arid area, and the country's average annual rainfall is 250 mm, (Office of Basic Studies of Water Resources, 2003) in many parts of the country, the problem of providing water for agricultural, industrial and drinking uses has long existed. Because of the limited surface water resources in many parts of the country, groundwater is considered as the best available resource to supply water needs of human beings, so that growing harvest of this resource has imposed irreparable damage to the environment. Groundwater is the main source of water supply for agriculture, industry and drinking in the region of Sirjan. Rapid population growth in the last 20 years, agricultural development and the arrival of the new drilling machines in the area, significantly increased drilling deep and semi-deep wells, resulting in overexploitation of groundwater, and this process has led to decline in groundwater levels. Since Sirjan Plain is located in the vicinity

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of the salt pan, the decline in water level caused saltwater advance into freshwater aquifers and consequently reduced the quality of groundwater. According to recent droughts and the continuous decline in groundwater levels, lack of other resources for water consumption, in the near future, the region of Sirjan will face an environmental crisis. Now many wells are abandoned unused and the area under cultivation has decreased and only the species resistant to salt can be cultivated. Thus, the attention to water resources management in this area is necessary. (Almasry et al., 2005)

Research Literature Review

Large-scale climatic changes are human challenges due to industrial development and environmental problems, which lead to protracted droughts in some parts of the planet and unpredictable rainfall in some places.One of the most important characteristics of investigators' is the access to information of previous research studies. Due to the susceptibility of the information related to the underground water levels to rainfall, underground waters harvest, etc. the complexity of their analysis is not unexpected. In modern analysis systems, the researchers use new techniques capable of solving complex input data to achieve the best target output. One of the most important of these techniques is the use of Artificial intelligence techniques which make information analysis targeted using the neurons in the human brain capable of learning and modeling the related complexities. This technique has been used by researchers for many years in different scientific fields. In the nearest to this study, (Jalalkamali et al ,2011), Jalalkamali (2015) and (Jalalkamali et al, 2015) used these techniques for forecasting of drought and spatiotemporal groundwater quality parameters and groundwater level. An appropriate software based on intelligent methods of artificial neural network and support vector machine for timely prediction of 5-day biochemical oxygen demand. For this purpose, appropriate models were developed to achieve this using ANN and SVM models by considering BOD5 as a function of other variables of water quality. In ANN model development, the role of various training functions such as Levenberg-Marquette (LM) optimization algorithm, Reactionary Post-Propagation (RP) and Scaled Conjugate Gradient (SCG) were evaluated in optimizing ANN parameters. Moreover, two-stage network search optimization algorithm was used to optimize the SVM model parameters. The results indicate the superior performance of ANN model with LM algorithm (ANN (LM) model) compared to other two algorithms, the RP and the SCG. SVM model also had a good performance in BOD5 estimation, as the Pearson correlation coefficient for this model in the test was equal to 0.95. Finally, further investigation was carried out to evaluate one of the models of ANN (LM) and SVM based on developed difference ratio statistic; the results from this statistic indicate the superior performance of the SVM model compared to ANN (LM) for timely estimation of BOD5 in the river of Sefidrud. The use of MLP neural network to predict the water quality in the case study of predication of dissolved oxygen in Latian Dam tank; in the present study, it is tried to predict dissolved oxygen (DO) in Latian Dam tank using MLP-NN. Eight-year statistics of river water quality from 2002 to 2010 were used to achieve this goal. Six parameters of SO_4, SO_2, NH_3, NO_3, NO_2, PO_4 were considered as independent variables and DO as the dependent variable for modeling by MLP-NN model. The Root Mean Square Error (RMSE) statistic and coefficient of determination of R2 were used in order to evaluate the efficiency of the proposed model. The groundwater is considered as one of the major resources of drinking and agricultural water, particularly in arid and semi-arid areas. Correct understanding and methodical exploitation of them can play an effective role in sustainable development of social and economic activities in these regions. In terms of the ability of different networks used, leading artificial neural networks with Levenberg-Marquardt algorithm gave the best results. This structure could monthly predict the groundwater level in a 24-month period (from 2009 to 2011) with minimal root mean square errors of 16.2 and 31.2 training and testing stages. Support vector models (SVM) classifiers and support vector regression (SVR) in surface water quality data were created and used to optimize programs. Collection of samples was 1,500 representing 10 different samples in different sites for 15 years. The purpose of the study was to classify samples harvested from sites (location) and months (time) and groups that were similar to the water quality by observing changes in their numbers and to develop a proper

SVR model for predicting water BOD and variable factor. SVR model for predicting the amount of water BOD in training, evaluation and testing phase with high and acceptable correlation coefficient (0.952 and 0.909 and 0.907) by measuring the value and root mean square error were 1.32, 1.53 and 1.44 respectively.

Material and Methods

Sirjan Plain with an area of 7920 square kilometers is located in West of Kerman province, in the center of the city of Sirjan, and is semi-arid with an average rainfall of 5.141 mm. About 240 thousand people live in Sirjan Plain and its suburbs, and its economic system is based on the activity in the agricultural sectors. This region has the characteristics of the rural economy such that about 98% of the volume of water taken from groundwater is used in agricultural activities, especially pistachio orchards. Sirjan Plain is located at 331432 to 447415 length and 3195112 to 3315974 width in the UTM system. Its maximum and minimum heights are 2110 m and 1670 m, respectively. In this study, the data of rainfall, the water level in wells and UTM coordinates of the wells intended are used as input combinations and qualitative parameters of the well (Ca, Mg, Na, TDS, TH, Cl, So4, Hco3, Ec) as output parameters in order to predict the quality of groundwater in the following month. First, the model structure used in research is defined and executive program written. Then, the conditions and characteristics of the study area have been checked. Data of rainfall, the water level in wells and qualitative parameters of Sirjan Plain were studied (Table 1). According to Table 2, the data are divided into 8 input and 9 output subdirectories (qualitative parameters of wells).

Table 1: Input and output parameters used in the neural network

Input			Output
Rainfall data	The water level in wells	UTM coordinates of intended wells	Well qualitative parameters

Using monthly statistics is one of the notable features of this research. Since most calculations and hydrological studies are conducted in the form of monthly statistics and this time-series is highly regarded, it has been tried to examine monthly data instead of daily data, in order to predict safely using this time-series and provide a study with high approved reliability. Then, then information became standard to enter the three models. For this purpose, in the structure of the neural network, a back propagation feed-forward neural network is used in which the conversion function of hidden layers is a tangent sigmoid, and pureline linear function is used in its output layer due to training high speed, reduced time and optimal accuracy. Artificial neural networks are one of the basic branches of artificial intelligence. In recent years, there has been a continuous motion of purely theoretical research toward applied research particularly in the field of information processing, for problems for which no solution is available or are not easily solvable. With regard to this fact, there is a growing interest in the theoretical development of free model intelligent dynamic systems based on empirical data. Artificial Neural Networks (ANN) are part of this category of dynamic systems. Artificial neural networks are structural (network) composed of a number of units (artificial neurons) that are linked together in a network which are trained by processing on numerical data or examples and learn general laws. Special electrical and chemical processes in the brain and neural network form our thought processes. The basic unit of the neural system is a specific cell called neuron, and undoubtedly how the brain works and the secret of human’s intelligence lies there. Therefore, to investigate the neural system and understand how it works, we must first identify neurons. Despite large differences in size and appearance, neurons share some common characteristics. A number of short antennae exit from neuron cell trunk which are called dendrites. Dendrites and cell trunk receive the neural impulse from adjacent neurons and transfer them to other neurons or muscles and glands through a thin tube called axon. Axons, at the end of their length, are divided into a number of the narrow lateral strings and they also form small swellings called synaptic terminals. Synaptic terminal is not connected to neurons that are going to be stimulated, but there is a narrow gap between it and cell trunk or receptor neuron dendrites. The junction is called synaptic, and the gap is named synaptic cleft. When a neural impulse goes along the axon to the end and reach the synaptic terminals, secretes compounds called nerve-media.

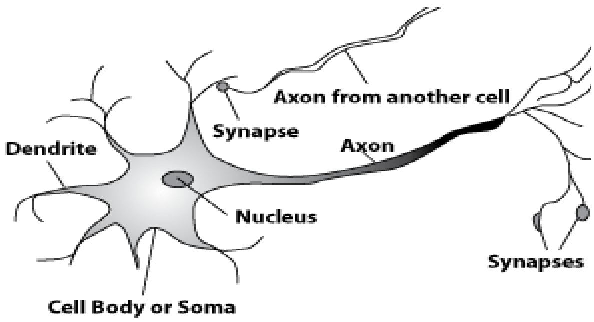

Figure 1. The main areas of biological neural cells

Nerve-media is distributed within the synaptic cleft and stimulates the next neuron; in this way, a neural impulse is transferred from one neuron to another. A large number of axons, from different neurons are connected to dendrites of a neuron in this way. Fragmentation of data is done to determine the number of data in training packets and testing, where 85% of data is considered for network training, and the remaining 15% is intended for network validation and testing. Network training algorithm is Levenberg-Marquardt. This algorithm is the fastest propagation algorithm that despite the fact that it requires more memory than the other algorithms, as the first and best known training algorithm administrator. This algorithm is the fastest post-propagation algorithm that requires more memory than the other algorithms, and is known as the first and best training algorithm with administrator.

Table 2. Maximum and minimum values of the input parameters to the neural network training stage

	max	min	mean	St. Dev.	Skewness
x	402100	350150	375668	14793.71	0.11
y	3291850	3207300	3256844	21119.32	-0.54
L(t-3)	125.89	24.41	57.04	20.18	1
L(t-2)	125.95	24.45	57.14	20.19	0.99
L(t-1)	126.04	24.49	57.23	20.19	0.99
R(t-3)	2.60	0	0.48	0.92	1.5
R(t-2)	12.80	0	3.29	4.21	1.14
R(t-1)	124.80	0	13.85	38.78	2.52
So_4	186.50	0.50	13.02	16.57	4.53
Cl	452	0.50	44.09	73.69	2.5
Hco_3	5.50	1.20	3.07	0.65	-0.11
TH	10000	90	900.65	1117.25	2.59
EC	24200	467	4725.64	5758.55	1.88
Na	441	1.7	42.26	68.72	2.99
Mg	100	0.5	8.27	10.57	2.79
Ca	100	0.8	9.75	12.33	2.47
TDS	21905	304	3175.3	4000.42	2.02

Then, various input patterns were provided and imported to the models using autocorrelation test. Neurons with high input alone are not usually enough to solve engineering problems. For example, to model the maps that have two outputs, two neurons are required that operate in parallel. In this case, we will have a layer composed of several neurons. Network input and output are shown with P and a vectors, respectively. It should be noted that each neuron is connected to all inputs. In this state, the matrix has S rows and R columns.

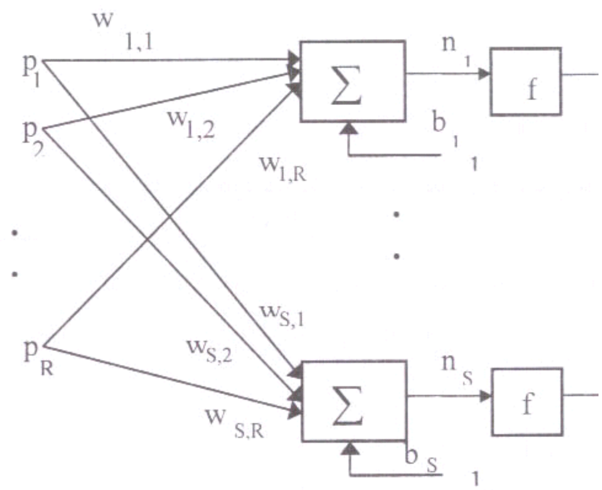

Figure 2. Single-layer network with S neurons

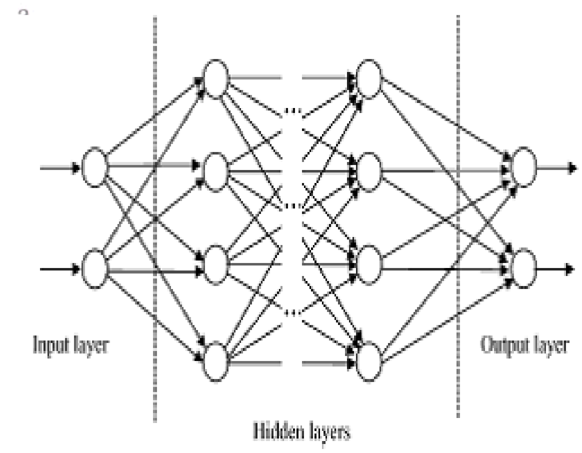

Figure 5: Multi-layer feed-forward network

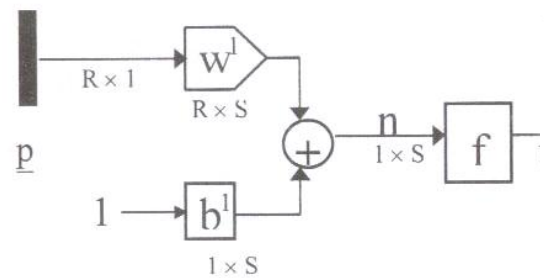

Figure 3. Compact and matrix form of single-layer network with S neurons

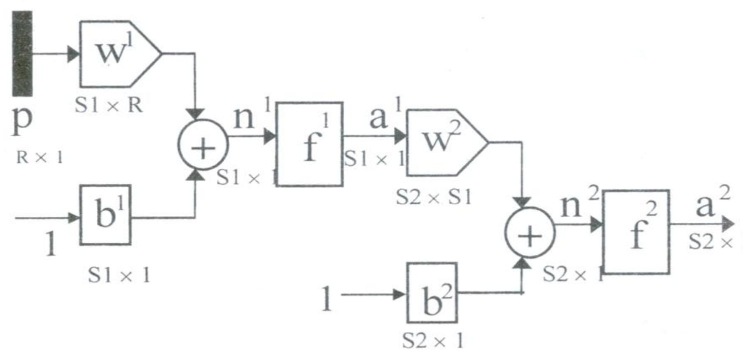

Figure 6: Two-layer feed-forward network

SVM model which are based on probability training theory, is a new class of models that are used for classification and prediction in various sciences. (figure 7)

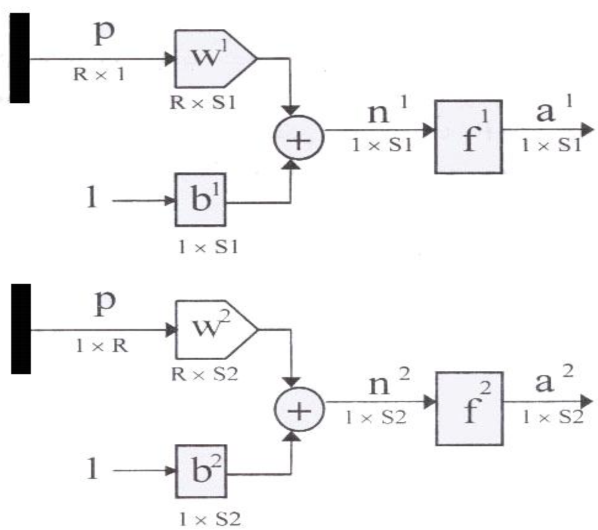

Figure 4. Combined layer with two kinds of motion function

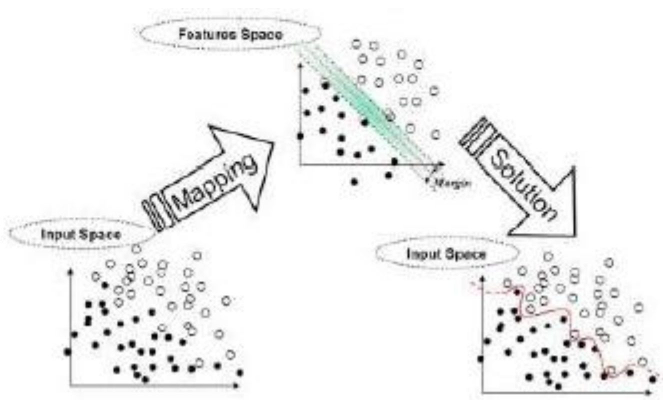

Figure 7: The SVM algorithm

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In single-layer networks, the input vector p is connected to the output vector by layer neurons (computational elements) according to equation. The network is a simple form of feed-forward networks. In this section, we extend the idea of feed-forward networks to multi-layer networks. Each layer has its own weight matrix (w), bias vector (b), net input vector (n) and output vector. The network usually includes an input layer, some hidden layers (middle) and an output layer.
Recently, these models are used in a wide range of hydrological problems. However, similar to any mathematical and statistical models, SVM models also have disadvantages. Presence of a large number of input variables is the most important problem in the development of these models. The large number of input variables may hinder finding the optimal model by SVM. Several methods have been proposed to reduce the number of input variables including principal component analysis method. Fuzzy Inference System (FIS) is established based on IF-THEN rules, so that using the rules, the relationship between a number of input and output variables can be achieved. So the FIS can be used as a predictive model for situations where input or output data have high uncertainty, because in such circumstances, classical predicting methods such as regression cannot well consider the uncertainties in the data. The main problem of fuzzy logic is that there is no kinematic process for designing a fuzzy controller. In other words, a neural network has the ability to be trained from the environment (input-output pairs), self-organize its structure and adapt its interaction in a way. To this end, ANFIS model which had the ability to combine both of these methods is available. At this stage, using trial and error, the best input combinations and hidden layer neurons for single-layer and double-layer neural network were calculated based on minimum error. Then it is compared to the error value obtained from the SVM and ANFIS. In this study, regression SVM model (SVR) is used with radial basis function (RBF) kernel function where the parameters include C and ε. Therefore, 85% of data are used for training and 15% for network testing. Also in this section, Sugeno Fuzzy Inference System with subtractive clustering is used by which the number of membership rules and functions are defined. The membership function for inputs and outputs are bell-type and linear, respectively. Then using least squares estimation, the equation of each of the rules is set. In this system, 85% of data are used for education and 15% for network testing. (Cortes et al., 1995)

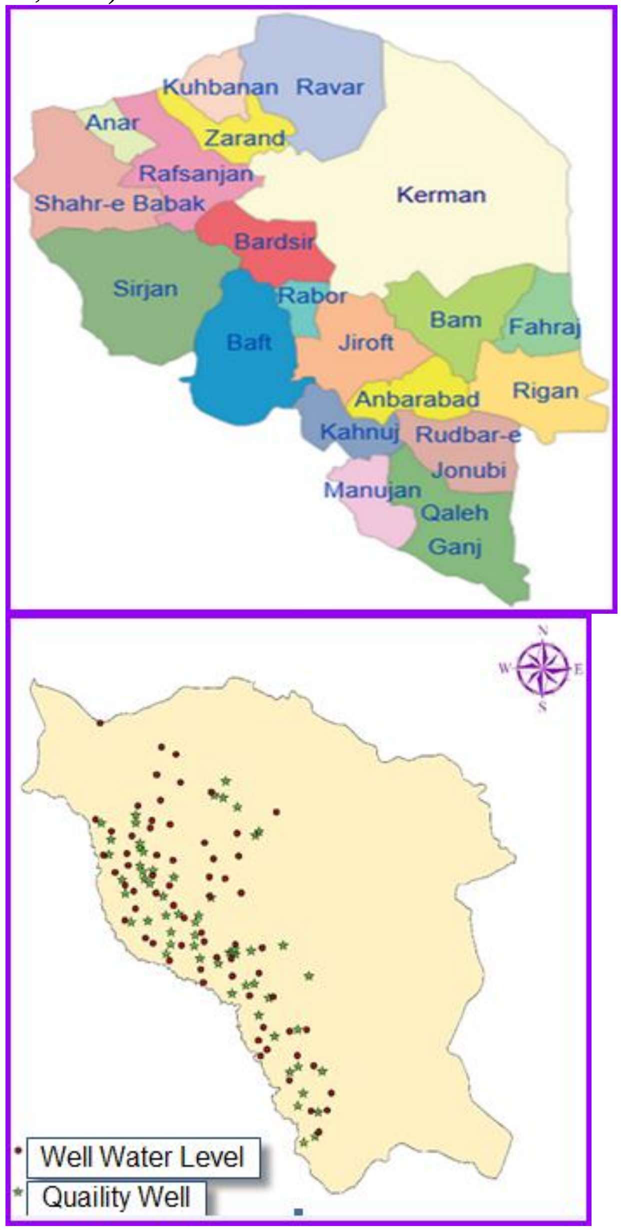

Figure 8: Geographical location of the study area

Results and Discussion

In this section, the achievements and results of the research are presented. In the following tables and graphs, applications output, their error rates, distribution and time series of training stages and models testing are presented. Inputs different patterns are provided using autocorrelation test and enter the models. These models include: UTM coordinates of the well, rainfall of 1, 2 and 3 months ago, the water level of 1, 2 and 3 months ago. At this stage, using trial and error, and constant number of hidden layer neurons in a single-layer and double-layer neural networks, the best input combinations are selected and neural network error is calculated for each combination of input. In the next stage, considering the best input combinations constant, the number of hidden layer neurons for both neural networks is calculated based on minimum error. The results of regression SVM model (SVR) with RBF kernel function, in which the best combinations of input C and ε parameters have been obtained based on trial and error and the least amount of error.

Table 3. Results of the best combination of input and error in training and testing set for quality parameters in each of artificial neural system, SVM and ANFIS models

Out	Model	Properties	Input variable	Combination								Train		Test	
				x	y	L(t-3)	L(t-2)	L(t-1)	R(t-3)	R(t-2)	R(t-1)	RMSE	R	RMSE	R
Ca	MLP 1 Layer	Ne = 20	3	1	1	0	0	0	0	1	0	0.0792	0.72	29	0.77
	MLP 2 Layer	Ne L1= 15 , Ne L2= 15	3	1	1	0	0	0	0	1	0	0.0328	0.98	0.1253	0.78
	ANFIS	R=0.3 , epoch=15	5	1	1	0	0	0	1	1	1	0.1077	0.79	0.1308	0.77
	SVM	C=500 , epsilon=0.1	4	1	1	0	0	0	1	1	0	0.1202	0.73	0.1416	0.71
Mg	MLP 1 Layer	Ne = 21	3	1	1	0	0	0	0	1	0	0.0792	0.72	0.1299	0.77
	MLP 2 Layer	Ne L1= 15 , Ne L2= 16	4	1	1	0	0	0	1	1	0	0.0651	0.74	0.1209	0.77
	ANFIS	R=0.3 , epoch=16	5	1	1	0	0	0	1	1	1	0.1148	0.79	0.1478	0.77
	SVM	C=500 , epsilon=0.2	3	1	1	0	0	0	1	0	0	0.1305	0.73	0.1464	0.72
Na	MLP 1 Layer	Ne = 21	3	1	1	1	0	0	0	0	0	0.0482	0.95	0.0596	0.98
	MLP 2 Layer	Ne L1= 15 , Ne L2= 16	3	1	1	0	1	0	0	0	0	0.0864	0.85	0.0768	0.95
	ANFIS	R=0.3 , epoch=16	5	1	1	1	1	1	0	0	0	0.0792	0.87	0.0973	0.94
	SVM	C=500 , epsilon=0.2	3	1	1	0	0	1	0	0	0	0.1176	0.73	0.1681	0.94
TDS	MLP 1 Layer	Ne = 22	4	1	1	1	1	0	0	0	0	0.0337	0.98	0.0439	0.98
	MLP 2 Layer	Ne L1= 15 , Ne L2= 17	3	1	1	0	0	0	0	1	0	0.0295	0.99	0.0455	0.97
	ANFIS	R=0.3 , epoch=17	3	1	1	0	0	0	0	1	0	0.0683	0.93	0.0556	0.95
	SVM	C=500 , epsilon=0.3	4	1	1	0	1	0	0	1	0	0.1209	0.78	0.0737	0.93

TH	MLP 1 Layer	Ne = 22	4	1	1	0	0	0	1	1	0	0.0681	0.74	0.1242	0.77
	MLP 2 Layer	Ne L1= 15 , Ne L2= 17	4	1	1	0	0	0	1	1	0	0.0653	0.77	0.1218	0.78
	ANFIS	R=0.3 , epoch=17	5	1	1	0	0	0	1	1	1	0.1289	0.78	0.1685	0.76
	SVM	C=500 , epsilon=0.3	4	1	1	0	1	1	1	0	0	0.1355	0.76	0.1613	0.73
Cl	MLP 1 Layer	Ne = 23	3	1	1	0	1	0	0	0	0	0.0404	0.97	0.0493	0.95
	MLP 2 Layer	Ne L1= 15 , Ne L2= 18	3	1	1	0	1	0	0	0	0	0.0372	0.97	0.0505	0.95
	ANFIS	R=0.3 , epoch=18	3	1	1	0	0	0	0	0	1	0.0867	0.85	0.1179	0.91
	SVM	C=500 , epsilon=0.4	5	1	1	1	0	0	0	1	1	0.1122	0.77	0.1530	0.92
So_4	MLP 1 Layer	Ne = 23	3	1	1	0	0	0	1	0	0	0.0696	0.68	0.0451	0.86
	MLP 2 Layer	Ne L1= 15 , Ne L2= 18	6	1	1	1	1	1	1	0	0	0.0712	0.67	0.2082	0.86
	ANFIS	R=0.3 , epoch=18	3	1	1	0	0	0	1	0	0	0.0662	0.68	0.1865	0.85
	SVM	C=500 , epsilon=0.4	6	1	1	1	1	1	1	0	0	0.0712	0.67	0.2082	0.86
Hco_3	MLP 1 Layer	Ne = 24	3	1	1	0	0	0	0	0	1	0.0850	0.83	0.1075	0.69
	MLP 2 Layer	Ne L1= 15 , Ne L2= 19	3	1	1	0	0	0	1	0	0	0.0871	0.82	0.1222	0.59
	ANFIS	R=0.3 , epoch=19	3	1	1	0	0	0	0	0	1	0.0966	0.77	0.1916	0.65
	SVM	C=500 , epsilon=0.5	6	1	1	1	0	0	1	1	1	0.1200	0.61	0.2126	0.5
EC	MLP 1 Layer	Ne = 24	3	1	1	0	1	0	0	0	0	0.0273	0.99	0.0440	0.99
	MLP 2 Layer	Ne L1= 15 , Ne L2= 19	3	1	1	0	1	0	0	0	0	0.0191	0.99	0.0530	0.98
	ANFIS	R=0.3 , epoch=19	3	1	1	0	0	0	0	0	1	0.1155	0.88	0.0979	0.93
	SVM	C=500 , epsilon=0.5	4	1	1	1	0	1	0	0	0	0.1547	0.79	0.1104	0.93

As can be obtained from Table 3, the best model presented for each of the qualitative parameters was determined based on minimum error or maximum correlation coefficient.

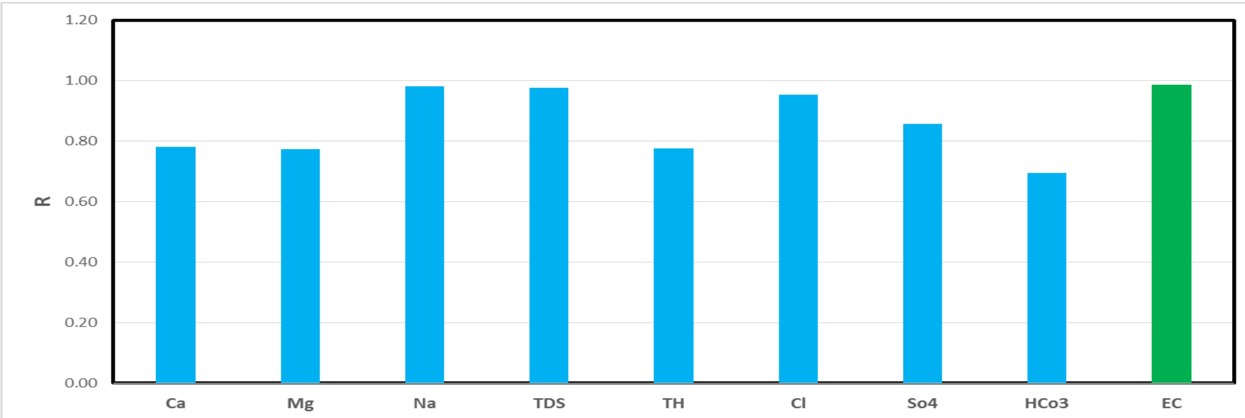

Figure 9: R value changes for different qualitative parameters

Conclusion

In this study, four methods of single- and dual-layer neural networks, support vector machine model and adaptive neuro-fuzzy inference system have been used to predict the groundwater qualitative parameters in Sirjan Plain. These models have great potentials and can be used as basic models to predict groundwater quality. To predict the qualitative parameters, data are standardized first and then input parameters are obtained based on a time delay using autocorrelation test; the use of these parameters results in increased accuracy in modeling. In the next stage, the parameters are imported to all three models, and prediction was done using different combinations of them. In order to predict qualitative parameters using single-layer and double-layer artificial neural networks, tangent sigmoid driving function and linear driving function are used for hidden layers and output layer, respectively; and post-propagation training algorithm is also used. In prediction of qualitative parameters using ANFIS, the bell membership function and linear function are used for hidden layers and output layer, respectively; and subtractive clustering technique is also used. Using subtractive clustering technique leads to a smaller ANFIS model structure and reduces the time of implementation of the model. Although the responses generated by all three methods have acceptable accuracy, single-layer artificial neural network for qualitative parameter of electrical conductivity (Ec) has the least amount of errors in the test phase (RMSE = 0.0440) and the highest correlation coefficient (R = 0.99). Although responses generated in all three methods have good accuracy, the superiority of single-layer and double-layer artificial neural networks is more significant that SVM and ANFIS models.

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