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Comparison performance of artificial neural network based method in estimation of electric conductivity in wet and dry periods: Case study of Gamasiab river, Iran

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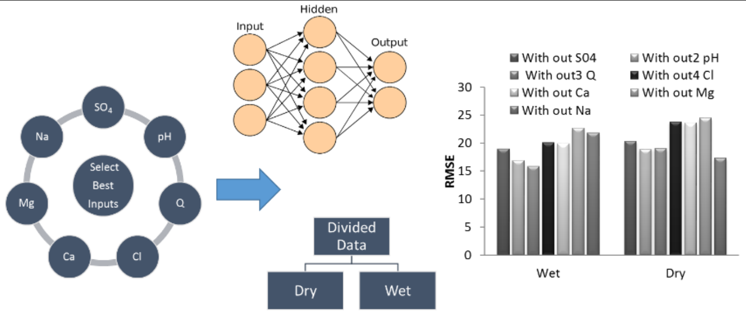
GRAPHICAL ABSTRACT



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ABSTRACT

The frequent occurrences of wet and dry in the catchment area of the Gamasiab river located in the west of Iran, in addition to affecting the quantitative status of surface water, has caused changes in the water quality of the basin. Therefore, modeling and prediction of Gamasiab river water quality in wet and dry periods are research priority. In this study, an optimized artificial neural network (ANN) trained with three different optimization algorithms namely; particle swarm optimization (PSO), genetic algorithm (GA) and imperialist competitive algorithm (ICA) was proposed for predicting the electric conductivity (EC). For this purpose, water quality data from 1967 to 2017 collected at the hydrometric station in the Gamasiab river were used for developing and testing the models. First, the study program was divided into two periods of wet and dry, this classification based on flow rate in the river. Then, in a preliminary statistical analysis, the effective parameters were determined for EC estimation. The performance of the applied methods showed that the ANN optimized using ICA algorithm was better than the ANN optimized with GA and PSO, and also the standard ANN without optimization. Overall, the ANN optimized with ICA has higher R and lower MARE and RMSE, with values of 11.56, 19.63 and 0.93, during the dry period, and 10.63, 17.19 and 0.97 during the wet period, respectively.

1. Introduction

Water is one of the permanent problems of agriculture and human life (Salimi et al. 2018, 2019a). While more than 71 % of the Earth's surface is covered with water, only 2.5 % of this water has quality for drink and less than 0.3 % is in rivers, lakes and atmosphere (Hassanvand et al. 2018, Salimi et al. 2019b). Rivers continue to provide the major part of fresh water for various uses (drinking,

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agriculture and the environment), and contributes to the sustainable development of human societies worldwide. However, industrial and welfare development with population growth have caused increasing tensions on the quantity and quality of rivers water in most parts of the world and threated presence of rivers, these important and valuable resources (Hassanvand et al. 2019). Therefore, modeling and assessment of river water quality have a great importance in the studies of the water resources (Najah et al. 2009). As it has several benefits, scholars have great tendency for application of artificial neural network (ANN) and adaptive neuro fuzzy inference system (ANFIS) methods for modeling water quality parameters (Olyaie et al. 2015; Orzepowski et al. 2017). Nowadays, many studies based on using artificial intelligence as a method to anticipate water quality parameters have been conducted all around the world (Barzegar et al. 2017; Nadaf Fahmideh et al. 2017; Nguyen et al. 2017). These methods have been used for weather forecasting and estimation of environmental and hydrological processes (Wang et al. 2014; Ay and Kisi 2017; He et al. 2018; Heidarzadeh 2017; Kisi et al. 2019; Nie et al. 2017). Electric conductivity (EC) is one of the most important indexes for classification of salinity and amount of sodium (Azad et al. 2018). It is important to measure the EC for drinking water, industrial and agriculture uses. One of the problems in surface waters assessment is the establishment of a water quality monitoring system with proper efficiency and determination of parameters that can accurately describe the water quality.

To achieve this goal, multivariate statistical methods such as principal component analysis (PCA) can be used (Singh et al. 2004). Analysis of the climate change effect on water quality has shown that changes in snowfall and summer rainfall relative to climate change in northeastern Asia have significant effects on surface water quality (Park et al. 2010). By examining the effects of flood and drought on the water quality of the rivers in Bohemia, it has been concluded that both periods of flood and drought have a significant effect on surface water quality (Hrdinka et al. 2012). Lindang (2017) reviewed the water quality index of Inaman River and proposed a fuzzy inference system model in a general manner for assessing the water quality. Leelavathy et al. (2016) studied the water quality analysis of Chanamar River and introduced the fuzzy inference method as a useful approach for measuring water quality. On other hand, many of effective parameters on water quality have a complex non-linear relationship with each other but traditional methods have not proper performance to solve these problems (Singh et al. 2009; Xiang et al. 2006). In recent years, the use of artificial intelligence models in many fields of water resources has been significantly increased, and understanding the specific roles of models and their specific capacities in devolving a nonlinear relation between a set of predictors and dependent variable is a challenge (Goyal and Ojha. 2011). Until now, numerous researches has been done using artificial intelligence methods to model and predict various hydrological phenomena such as water quality, sediment, surface water evaporation and etc. (Ebtehaj et al. 2019; Zeynnodin et al. 2019). In general, artificial intelligence techniques (AI) provided better accuracy than traditional and complex methods; also the AI techniques have potential to be used in modeling the water quality of rivers and can be a good alternative to the direct measurements of water quality, so it can have vital role in water quality management. Therefore, in this study, we used AI methods to estimate EC in river.

Table 1. General information of hydrometric station on Gamasiab river.

Station	River	Height	Longitude	Latitude	Flood	Drought
Aran	Gamasiab	1440	47-55-00	34-25-00	116	91
Hydar abad	Dinevarab	1290	47-27-00	34-26-00	134	113

Table 2. Statistical analysis of data.

Parameter	Min		Max		Average		Deviation from the criterion	
	Drought	Flood	Drought	Flood	Drought	Flood	Drought	Flood
Q	0	0	98.04	202.6	9.74	116.1	14.06	32.06
EC	220	124	765	660	496.4	427.4	102.07	86.6
pH	6.7	6.9	8.75	9	8.02	8	0.35	0.37
TDS	185	78	416	391	341.35	268.7	48.4	53.13
Ca	0.55	0.6	4.8	4.92	2.67	2.45	0.88	0.66
Mg	0.15	0.15	3.7	3.5	1.69	1.35	0.5	0.49
Na	0.05	0.06	2.4	2.9	0.89	0.6	0.45	0.44
Cl	0.1	0.1	1.5	2.8	0.7	1.35	0.32	0.28
SO_4	0.05	0.02	3.1	2.45	0.6	0.55	0.55	0.43
CO_3	0	0	3.9	1.1	0.13	0.14	0.47	0.18
HCO_3	0.96	0.85	7	5.66	3.9	3.44	0.97	0.79
Mg	0.83	0.43	284.5	283	72.2	43.02	104.5	79
P	0.63	0.63	303.5	297	76.16	48.4	109.9	88.24
T	0	0	28	30	16.66	8.6	6.8	4.8

2. Methodology

2.1. Case study

The study area is located between the geographical latitude range of 47°21′ to 47°54′ East, and 34°16′ to 34°53′ north, in the East of Kermanshah province, Iran. Gamasiab river (Fig. 1), in Gamasiab County west of Hamadan province, 74.7 km in length, is considered as case study. The direction of the river bed is from the east to west and north-west to south-west. This research done from entry point of the Gamasiab river, which contains 2 hydrometric stations (Table 1). The summary status of available station data is shown in Table 2, which Q is flow, pH is a scale used to specify how acidic or basic a water-based solution, T is temperature and TDS is total dissolved solids.

2.2. Artificial neural network

Artificial neural network (ANN) are a black box models inspired from the human brain and have ability to model complex systems with non-linear behavior. ANN first introduced by Rosenblatt (Rosenblatt. 1958), were completely comparable to the human's brain's, they have features that outperform them in some applications, such as feature selection or wherever it is needed to learn with a linear or nonlinear mapping (Pham et al. 2006). Structure of ANN is introduced by making pattern between nodes; determine connection weights method and activity function. An ANN mostly has one input layer, one or several hidden layers and only one output layer (Fig. 2). Input layer has a number of neurons equal to the number of input variables (Rumelhart et al. 1986). Output layer contain the estimated values of the dependent variable. The hidden layer contains several neurons determined by trial and error. The number of hidden layers and number of nodes in each hidden layer commonly determined by trial and error method (Bishop. 1995).

2.3. Particle swarm optimization (PSO) algorithm

The particle swarm optimization (PSO) algorithm was proposed by Kennedy and Eberhart (Sudheer et al. 2009) for optimization of continuous nonlinear functions and has been used successfully in various science fields. This PSO algorithm is an evolutionary computation technique inspired by flying birds or fish movements and exchange of information between them. In this algorithm, each solution is only a particle in search spatial. All of the particles have a specific fitness that is evaluated by the fitness function. Moreover, each particle has a position in an n-dimensional spatial of the problem which is shown by Eq. 1, in t^{th} repetition. This particle has a velocity

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conducting its movement and is shown by a vector in t^{th} repetition (Eq. 2). Then the particle uses a memory known as P vector in order to store its former best position in each repetition (Eq. 3).

$$X_i^t=(X_{i1}^t,\dots,X_{in}^t) \quad (1)$$
$$V_i^t=(V_{i1}^t,\cdots,V_{in}^t) \quad (2)$$
$$p_i^t=(p_{i1}^t\cdots p_{in}^t) \quad (3)$$

In each search repetition, each particle is updated by considering the two best values. The first value is related to the best solution which particle has experienced. This value is called the best P. The second best that is followed by the PSO algorithm is the best position that is obtained in population so far. This optimized value is called the most appropriate g. After finding these two values, the position and velocity of each particle are updated by Eqs. 4 and 5.

$$V_i(t+1)=WV_i(t)+C_1 r_{(1,i)}(t)(p_i(t)-X_i(t))+C_2 r_{(2,i)}(t)(p_g(t)-X_i(t)) \quad (4)$$

$$X_i(t+1)=X_i(t)+V_i(t+1) \quad (5)$$

In the above relations, t indicates the repetition number and C_1 and C_2 are learning factors. Generally, $C_1= C_2=2$ that controls the amount of a particle displacement in a repetition. r_1 and r_2 are two steady random numbers in (0, 1) interval. W indicates the inertial weight that gets the initial value in (0, 1) interval. In the PSO algorithm, the population gets the initial value by random solutions and the population fitness is calculated respectively until obtaining the end condition and P_{best} and g_{best} values, velocity and position are updated respectively. At least, the g_{best} and its fitness are indicated as the output (Salman et al. 2009). Fig. 3 indicates the flowchart of the PSO.

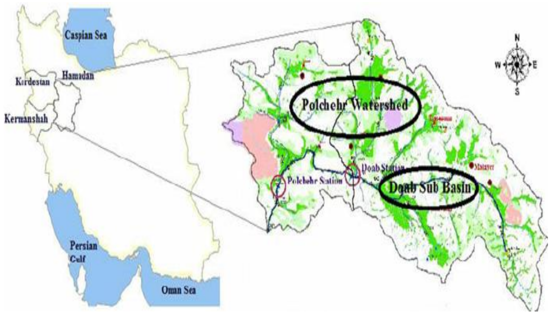

Fig. 1. Gamasiab route (Salimi et al. 2019b).

2.4. Genetic algorithm

Nature always has been the greatest and best human being's teacher. Human beings have made tools and techniques by seeing nature that mostly is best between similar methods. Genetic algorithm is one of these methods. Genetic algorithm is one of numerical optimization which based on Darvin theory and inspired from natural inheritance. Because of high ability of this method, it has been used in many branches and applications. Currently this method can solve many problems; such as designing optimize frames and optimize hydraulic structures. Genetic algorithm, starts searching operation from many points in response space, each of these point was a primary pattern or in a different explanation this was a chromosome. Regarding this, the genetic algorithm first creates many chromosomes, which is called the primary population. Initial population making can be done randomly or with user's opinion. After creating initial population of genetic algorithm, these chromosomes which are in fact the primary pattern were studied and in proportion to their preference values were attributed to each of them, until they were near to purpose condition of user. After checking all preference of population society, genetic algorithm chooses preference population to make next generation and delete other. Then, selected populations are subjected to random actions such as selection, transplantation and mutation for the next generation. After applying these functions, a new generation is created which is usually more preference than their predecessor. New generation is better than previous generation and this cycle will continue to meet the criteria for stopping the algorithm, at last the best populations were convergent and that would be final result (Sette and Boullart. 2001).

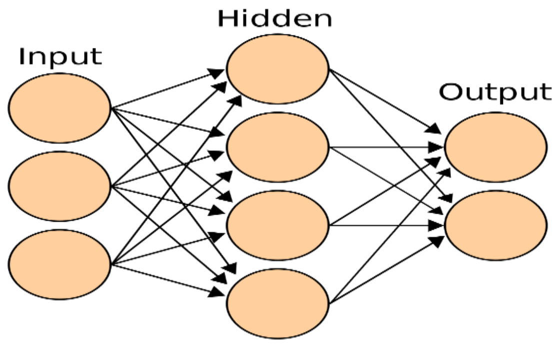

Fig. 2. ANN structure.

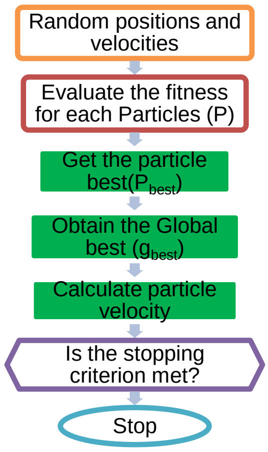

Fig. 3. Flowchart of particle swarm optimization algorithm (PSO).

2.5. Imperialist competitive algorithm

Recently, imperialist competitive algorithm (ICA) was introduced by Esmaeil Atashpaz and Caro Lucas (Atashpaz-Gargari and Lucas. 2007). ICA was inspired from the society phenomenon instead of nature. Creator of this algorithm analyzed imperialist historical phenomena as one social and political evolution of human societies and with modeling this process, one powerful algorithm for optimization were expressed. In ICA, there were number of countries. This collection of countries is random point in searching space. Then, some powerful country chooses as imperialist and other countries as colonial country. In first run of algorithm, random countries were build and numbers of them were as powerful and imperialist. Then, other countries randomly attributed to one of imperialist. Numbers of colonies of an imperialist depend on their power. In this algorithm, imperialist countries by applying the policy of absorbing (assimilating) on different aspects (for example language and culture) colonize other countries. This subject modeled by the random movement of each colonial country toward its imperialist country in search space.

According to Fig. 4, movement of colonial country will happen to its imperialist country with (α) length and (θ) angle which this values where determined randomly. It may possible during run of algorithm, one colonial country was powerful than its imperialist country. In this situation, imperialist country and colony country will be replaced. In other word, all colonial countries in previous step will belong as next step imperialist and the movement direction of colonial countries will be toward the new imperialist country. In each step of algorithm repetition, it wills competition between imperialist. In this competition, the imperialist which have less power than the other imperialist, loss one of its colony. In this process, weakest colony of weakest imperialist randomly joined to other imperialists. The probability of assigning this new colony to each imperialist is also proportional to their power. If one imperialist lost all colonies, it will be one of colony for other imperialist. The algorithm continues till one of imperialist remains. In this situation, all colony countries are one imperialist and algorithm end. Fig. 5 shows ICA's flowchart.

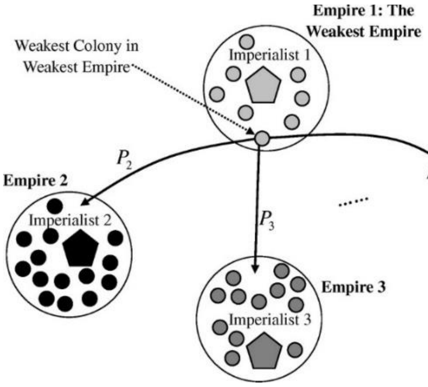

Fig. 4. Sample of ICA (Atashpaz-gargari and Lucas (2007)).

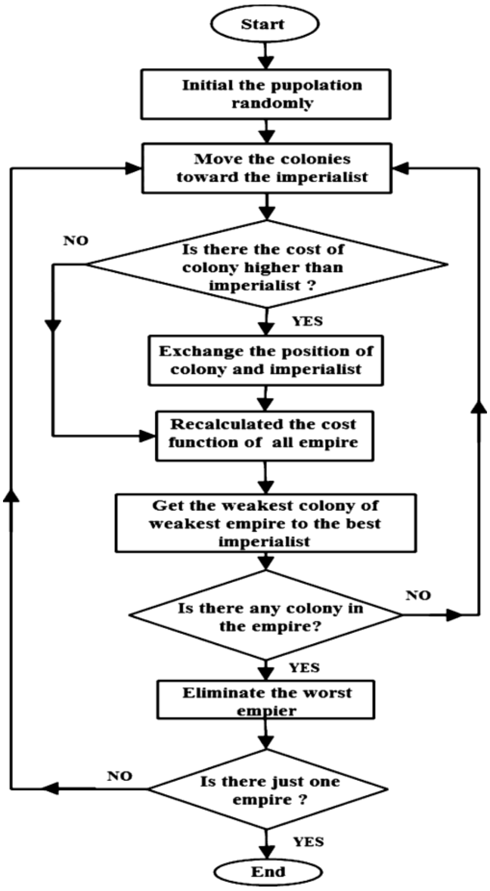

Fig. 5. Flowchart of ICA (Salimi et al. 2019).

2.6. Performance criteria

The statistical measures of root mean square error (RMSE), the correlation coefficient (R) and MAE are used in this study for the evaluation of the models performance which shown in Eqs. 6-8.

$$R = \left[\frac{\frac{1}{N}\sum (O_i - O_m)(P_i - P_m)}{\sqrt{\frac{1}{N}\sum_{i=1}^{n}(O_i - O_m)^2}\sqrt{\frac{1}{N}\sum_{i=1}^{n}(P_i - P_m)^2}} \right] \quad (6)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(O_i - P)^2} \quad (7)$$

$$MAE = \left(\left| \frac{O_i - P_i}{N} \right| \right) \quad (8)$$

P_i denotes the calculated values, O_i denotes the in situ measured, and N is the number of data points used. O_m and P_m are the average values of O_i and P_i.

3. Results and discussion

Water quality data for the Gamasiab basin were collected during the Periods from 1967 to 2017. In the environmental studies of water resource systems, drought and flood periods are considered. In the Basin of Gamasiab River maximum value of flow is in spring which contains more than 50 % of each year flow volume. Minimum season flow of that catchment area is about 5 % of each year flow volume which occur in autumn. In this research, water quality data in all hydrometric stations of Gamasiab river were investigated for the length of the statistical period, sampling number, sampling time during different months of the year and location of the stations. For determining the input parameters of the predicted models to estimate EC values, first Pierson coefficient between water quality parameters in drought and flood Periods were calculated by Minitab software (Tables 3 and 4).

For estimation of discharge, first effective parameters on it were classified according to the simulation results and then used for the modeling. Based on these, 6 months of years was considered as drought period (June, July, August, September, October, November) and 6 months as flood Period (December, January, February, March, April, May). All available water quality data (824 data) were from the period between 1976 and 2017. Most of samples belonged to the Pol Chahr station in flood Period with 195 samples and less of them is belonged to this station with 55 samples in drought period. Available data including EC, pH, CO_3, HCO_3, Cl, SO_4, Ca, mg, Na, K, Na, Na %, magnesium hardness, potassium hardness, temperature, TDS and flow discharge which resulted in 7 effective parameter including $S0_4$, pH, Q, Cl, Ca, Mg, Na in 2 main stations, were used as input variables to predict EC models. Normalization of data has been done using Eq. 9.

$$x_{normal\,(i)} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (9)$$

Table 3. Correlation coefficients between input parameters of water quality during low period.

Parameter	Q	T	TDS	EC	pH	CO_3	HCO_3	Cl	SO_4	Ca	Mg	Na	Na%	Mg	P
EC	-0.1	-0.01	0.99	1	-0.16	-0.05	0.8	0.5	0.25	0.6	0.6	0.35	-0.02	0.1	0.1

Table 4. Correlation coefficients between input parameters of water quality during wet period.

Parameter	Q	T	TDS	EC	pH	CO_3	HCO_3	Cl	SO_4	Ca	Mg	Na	Na%	Mg	P
EC	-0.03	-0.004	0.96	1	-0.1	0.028	0.7	0.36	0.22	0.4	0.6	0.4	0.212	-0.025	-0.04

Also, results and specifications of optimal models of ANN are shown in Table 6. According to Table 6, the imperialist competitive algorithm (200 countries, 30 empires and revolution rate of 0.3) for wet and dry Periods had the best performance among other ANN training algorithms. According to Table 6, the values of RMSE, MAE and R in dry and wet Periods for best network were (RMSE = 17.68, MAE=14.21, R = 0.97) and (RMSE = 16.94, MAE=11.96, R = 0.94) for the training phase and (RMSE = 19.63, MAE=11.56, R = 0.93) and (RMSE = 17.19, MAE=10.63, R = 0.97) for the test phase. According to Fig. 6, it can be seen during the study of drought period (6A) and dry Period (6B), the ANN model optimized by imperialist competitive algorithm, estimate the maximum values better than other networks. Although the correlation coefficient between observed and estimated data is about 95 % for wet and dry study, this value has been higher in the flood period. Also, in the following Figs. 6 a and b, the predicted values and observations are compared which indicates the accuracy of the imperialist competitive algorithm and the PSO Seems to have highest error.

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Table 5. Structure of optimized artificial neural network to estimate the EC in Gamasiab river.

Optimizer function	Feature
ICA	Num Country = 200 Intial Imp. = 30 Rev. Rate = 0.3
GA	Pop Size = 150 Max Gen. = 50
PSO	Swarm Size = 200 Max Iter. = 35

Table 6. Characteristics of optimized artificial neural network and the calculated statistical parameters to estimate the EC in Gamasiab river.

Study period	Model	Training			Test		
		MAE	RMSE	R	MAE	RMSE	R
Dry	ANN	16.65	26.35	0.94	18.34	29.36	0.89
	GA	13.26	19.58	0.95	16.23	22.41	0.94
	PSO	14.63	21.56	0.94	16.25	22.46	0.92
	ICA	14.21	17.68	0.97	11.56	19.63	0.93
Wet	ANN	21.43	23.65	0.91	16.56	26.23	0.91
	GA	15.64	20.46	0.93	13.53	21.64	0.93
	PSO	12.11	19.87	0.94	13.26	21.32	0.92
	ICA	11.96	16.94	0.94	10.63	17.19	0.97

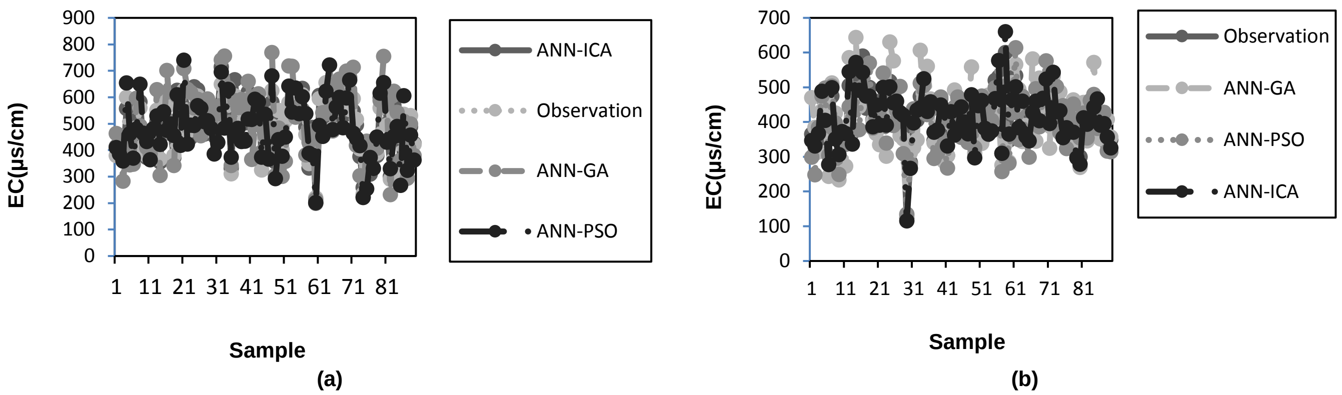

Fig. 6. Comparison between estimated and observed EC in (a) drought period and (b) flood period.

3.1. Sensitivity analysis

A sensitivity analysis determines how inputs will have effect on model's output. This technique is used within specific boundaries that depend on one or more input variables (Hassanvand et al. 2019). In this study, according to statistical analysis, the optimized ANN-based ICA was selected as the best optimizer and then sensitivity analysis on this network was performed. At the sensitivity analysis, any parameters used in our models as input to predict the EC are extracted individually and then the errors resulting from eliminating of each parameter were obtained. Afterward the most influential input parameter was obtained. Table 7 and Fig. 7 show effectiveness of all input variables for each individual Station. So, anybody can know what the most effective and ineffective parameters in predicting EC in this study are Mg and Na in dry period and Mg and Q in wet period, respectively.

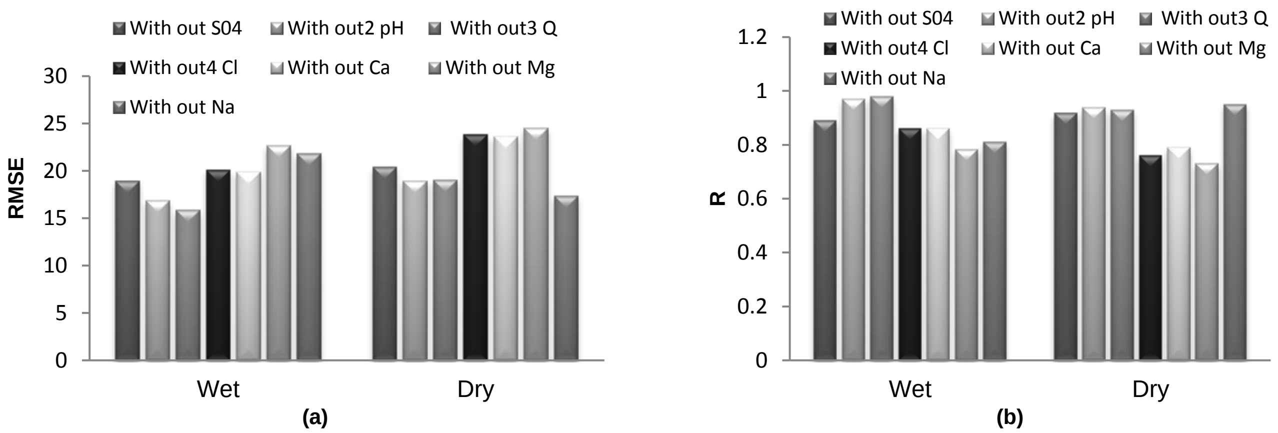

Fig. 7. Sensitivity analysis of ERROR calculation (a) RMSE and (b) R

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Table 7. Statistical indices after sensitivity analysis of EC estimates.

Study period	Error	With out $S0_4$	With out pH	With out Q	With out Cl	With out Ca	With out Mg	With out Na
Dry period	RMSE	20.4	18.9	19.0	23.8	23.6	24.5	17.4
	R	0.92	0.94	0.93	0.76	0.8	0.73	0.95
Wet period	RMSE	18.9	16. 9	15.8	20.1	19.9	22.7	21.8
	R	0.89	0.97	0.979	0.86	0.86	0.783	0.81

4. Conclusions

In this study, artificial neural network model with Meta algorithms optimizer has been used for modeling water quality specifications of the Gamasiab river in 2 hydrometric stations in separate drought and flood periods. For this purpose, observation data of 40 years (1976-2017) has been used and the aim is to predict electrical conductivity (EC) in river. The results have shown a highly desirable performance of imperialist competitive algorithm with considering of results during the test phase (RMSE=16.94, R=0.94). In addition, the predicted results of the flood period have higher accuracy than the drought period, because, the sensitivity of drought period's Data to natural factors and human errors. Based on sensitive analyze results, the most effective and ineffective parameters in predicting EC in this study were Mg and Na in dry period and Mg and Q in wet period, respectively.

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