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SOFT COMPUTING APPLICATION TO PREDICT IRRIGATION WATER QUALITY INDEX, CASE STUDY OF OUED HAMMAM NORTH-EAST ALGERIA

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Abstract: *Water quality for irrigation purposes has yet to be considered seriously in many places around the globe. The present case study at the Oued-Hammam watershed in northeast Algeria aims to investigate using a soft computing technique, namely an artificial neural network, to predict irrigation water quality indicators of Sodium absorption ratio (SAR) and Electrical Conductivity (EC). Fourteen water quality parameters were collected at Zit Emba reservoir from 2010 to 2022. Among them, four parameters, namely Sodium (Na), Calcium (Ca), Magnesium (Mg), and Bicarbonate (HCO_3^-), were used as inputs and SAR as an output. Also, five parameters of Total hardness (TH), Total dissolved solids (TDS), Calcium (Ca), Bicarbonate (HCO_3^-) and Sodium (Na) were used as inputs and EC as an output; the Pearson correlation matrix was used to select the input parameters with respect with the output parameter. The back-propagation neural networks learning algorithm was used to model the SAR and EC's irrigation water quality index (IWQI). The models' performances were evaluated using statistical criteria of correlation coefficient (R) and root mean square error (RMSE). Back propagation neural network learning algorithm maximum correlation coefficient for SAR and EC were 0.98077 and 0.97762, respectively, also with a minimum RMSE of 0.037 for SAR and 101.8 for EC. Thus, the current study suggests that artificial neural network (ANN) models are the most effective tools for predicting water quality parameters. Their outcome can be used effectively in managing and controlling water pollution around the watershed.*

Keywords: *Artificial neural network, Algorithm, Person correlation matrix, Sodium absorption ratio, Electrical Conductivity, Watershed.*

1. Introduction

Industrialisation and population growth are the key factors for water deficiency; without forgetting, other anthropogenic activities such as agriculture, mining, and fishing can lead to water pollution.
Humans abstract water from the hydrologic cycle for its essential economic usage and return it to the corresponding process after using it [1]. Materials that mix with water throughout the cycle can generate a notion of water pollution since they can change water's chemical, physical and biological properties after natural purification [2].
So, to understand the change in these properties, water quality assessment and forecasting should be done to comprehend the state of water and its suitability to serve a Specific intention, for example, drinking or irrigation. So far, large amounts of domestic and industrial waste continue to be directed to the water sources [3]; hence, water quality for irrigation might deteriorate, and plant productivity of any region can be affected.
The present study assesses irrigation water quality using a back-propagation learning neural network algorithm and the United States salinity laboratory method (USSL). USSL method typically considers two parameters, namely Sodium Absorption ratio (SAR) and Electrical conductivity (EC); the SAR can be estimated using Sodium, Calcium, and Magnesium concentrations present in water for irrigation[4].
A higher amount of Sodium reduces the soil infiltration rate, decreases soil stability, and

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increases the Sodium accumulation in the leaf tissue [5]. The surplus content of SAR can affect the leaves of plants like avocados, stone fruits, and almonds [6]. Soil permeability can also be affected by a higher amount of SAR. Electrical conductivity (EC) is defined as the capacity of water to transmit electrical current. It is directly proportional to the dissolved ions in the water and their charge; EC can affect crop growth directly by toxicity or deficiency or indirectly by changing plant nutrient availability [7]. The combined techniques of Irrigation water quality index (IWQI) and Artificial neural network (ANN) could be used in assessing the state of water for Irrigation purposes because these techniques can convert the complex data that have to be performed into an understandable way for the policymakers and public can be informed on the quality of water. In present years, various models, including traditional mechanistic applications, have been involved so that managing the water quality of these models requires different input data, which cannot be readily available and makes it a costly and time-consuming process. ANN is the appropriate approach for water quality modelling [8].

The main objective of the present work is to develop an artificial neural network (ANN) model of the Oued-Hammam watershed to understand the classification of Sodium absorption ratio (SAR) and Electrical conductivity (EC) in water for irrigation so that it can be used to predict water quality and hence crop production improvement.

2. Geographical location of the study area

The Oued-Hammam (Figure 1) watershed is in the Skikda region northeast of Algeria, covering an area of 485km² and controlled by the Zit Emba reservoir at a coordinate of 36.6836° N, 7.3020° E. The Oued-Hamman is one of the most potential tributaries of the west Kebir Wadi and takes its source at the level of Djebel BouSba at an altitude of 623m. The watershed (Figure 2) which flows into the dam has a subtropical climate characterized by hot summers and comparatively mild and rainy winters, An average annual temperature of the order of 17.3°C with a minimum of 9.3°C in January and a maximum reach of 26.5°C in August. Potential evapotranspiration closely related to temperatures varies between 35 mm in December to 200 mm in July and the average annual threshold of 1306 mm. This reservoir is intended for drinking and irrigating the Ben-Azzouz, Azzaba plains, and neighbouring areas.

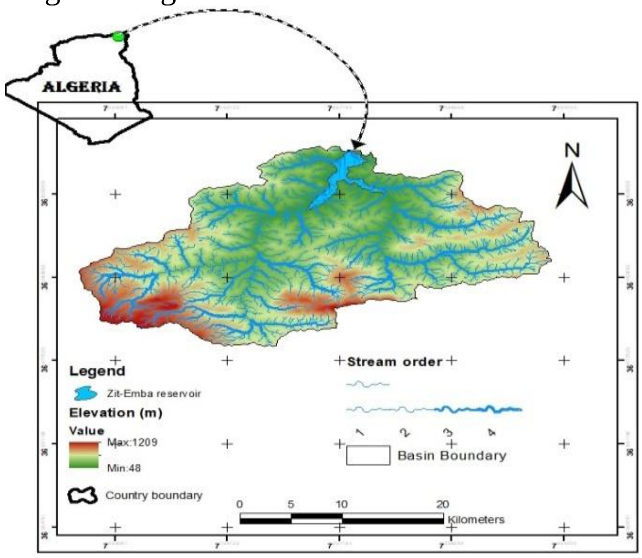

Fig. 1. Geographical location of Oued-Hammam watershed (Source: own elaboration).

Fig. 2. Oued-Hammam watershed

2.1 Data collection

Water samples were collected each month from 2010 to 2022, and the sampling station was Zit Emba reservoir. Fourteen water quality parameters were collected and analyzed for 13 years. The parameters which were investigated during this study are shown in Table 1.

Table 1.
Parameters collected at the Zit-Emba reservoir.

No:	Parameter	Units
1	Potential Hydrogen (pH)	-
2	Electrical Conductivity (EC)	[µS/cm]
3	Calcium (Ca^{2+})	[meq/l]
4	Magnesium Mg^{2+})	[meq/l]
5	Sodium (Na^{+})	[meq/l]
6	Bicarbonate (HCO_3^-)	[mg/l]
7	Potassium (K^+)	[mg/l]
8	Chloride (Cl)	[mg/l]
9	Total Hardness (TH)	[mg/l]
10	Total Dissolved Solids (TDS)	[mg/l]
11	Nitrate (NO_3^-)	[mg/l]
12	Nitrite (NO_2^-)	[mg/l]
13	Sulphate (SO_4^{2-})	[mg/l]
14	Phosphate (PO_4^{3-})	[mg/l]

3. Material and methods

3.1 Calculating of Sodium Absorption Ratio (SAR)

Estimations of SAR were done according to the [9] formula in which Sodium, Magnesium and Calcium parameters were used in the calculation.

$$\mathbf{SAR} = \frac{[Na^+]}{\sqrt{\frac{1}{2}\{[\mathbf{Mg^{2+}}] + [Ca^{2+}]\}}} \qquad (1)$$

where Na^+, Mg^{2+}, and Ca^{2+} in mill equivalents per litre (meq/l).

3.2 The general outlook of artificial neural network (ANN).

From 2008 to date, the application of ANN techniques in predicting water quality has become very popular. Many researchers employ this method to model and forecast water quality; in the present study, an artificial neural network algorithm was used to approximate irrigation water quality parameters (EC and SAR). ANN models are highly flexible function estimators that have demonstrated their usefulness in a wide range of water resources.

3.2.1 Practical Applications.

In [10], ANN modelling techniques have performed better than classical models. ANNs are models influenced by biological neural networks [11]. This concerns the human brain's central nervous system in animals [12]. In general, ANN can be a system of interconnected "neurons"[13]. Weight parameters and activation functions are components of the neurons [14]. ANNs are generally divided into three layers: input, hidden, and output. When neurons receive information from different inputs, they obtain nonlinearity by activation functions. ANN models rely strongly on the quantity of data [15]. Hence, using comparatively small data sizes for predictors (inputs) is not encouraged since some helpful information is lost in short-term data, which might result in poor prediction results [16]. In addition, data splitting is an essential step in the modelling process. In our present study, data splitting was done randomly with a propagation neural network learning algorithm in which 75% of the data was used for training and 25% for Validation. Various tests were conducted to ensure that all training and validation modules were evaluated by trial and error to attain the best outcomes.

3.2.2 Back Propagation Neural Networks Learning Algorithm.

In between various learning algorithms, back-propagation is the most known and most applied learning algorithm among all neural network prototypes [17]. Forward-back propagation networks have antecedently been named as the most common type of ANN models used in water resources practical applications. In [18], it is suggested that the back-propagation algorithm relies on the generalisation delta rule. The back-propagation algorithm dataset of inputs and outputs is chosen from the training dataset, and the network computes the result depending on the input datasets. This output is deducted from the actual output to find the output-layer error. The error is back-propagated through the network, and the weights are suitably adjusted. The process proceeds for the number of dictated sweeps or until the desired error tolerance is reached. The root means square error (RMSE) above the training dataset is the distinctive target function to be minimised. It employs the back-propagation (BP) of the error gradient. This training algorithm is a technique that assists the spread of error to attain the best fit or minimum error. After the dataset has gone through the network in a forward direction and the network has predicted an output, the back-propagation algorithm spreads the error related to the output back through the model, and weights are aligned accordingly. The minimization of the error is achieved through various iterations. When the training phase is complete, and ANN performance is validated, the validation phase can suggest whether to retrain the model, depending on the model results.

Before training the dataset, the input data were normalized using the Z-Score normalization technique. The method is based on the calculation of the median absolute deviation [19], and the normalization score nv can be calculated as follows:

$$\boldsymbol{nv} = \boldsymbol{f}(\boldsymbol{v}) = \frac{\boldsymbol{v}-\boldsymbol{\alpha}}{\boldsymbol{\varphi}} \qquad (2)$$

where $\boldsymbol{\alpha}$ represents the mean value, while $\boldsymbol{\varphi}$ represents the standard deviation of the dataset.

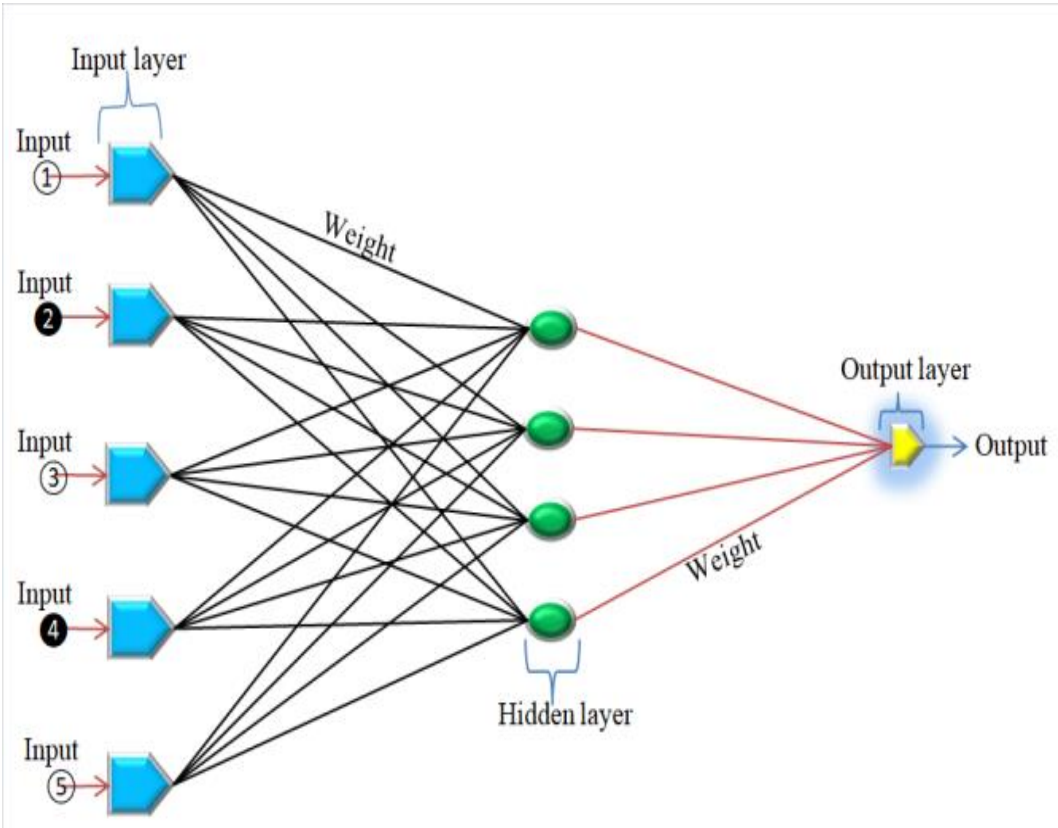

Fig. 3. An example of artificial neural network architecture with one input layer (five input parameters), one hidden layer (four nodes), and one output layer (One output parameter), source: own elaboration.

4. Results and discussions

4.1 Selection of the input parameters

Monthly water quality parameters from 2010 to 2022 were measured from the station. Parameters including pH, HCO_3^-, K^+, Na^+, Mg^{2+}, TH, TDS, PO_4^{3-}, SO_4^{2-}, NO_2^-, NO_3^-, Cl, and Ca^{2+} were analyzed using the Pearson correlation matrix to understand the relationship between them and the output parameters (EC and SA. Those with a high association with (SAR and EC) were chosen as input parameters.

Table 2

Pearson correlation matrix between parameters

Parameters	*pH*	*Ca^{2+}*	*Na^{2+}*	K^+	*Mg^{2+}*	*TH*	HCO_3^-	PO_4^{3-}	*TDS*	NO_3^-	NO_2^-	*EC*	*SAR*	SO_4^{2-}	*Cl*
pH	1														
Ca^{2+}	-0.24	1													
Na^{2+}	-0.24	0.193	1												
K^+	-0.19	-0.01	-0.17	1											
Mg^{2+}	0.265	-0.62	-0.52	0.127	1										
TH	-0.16	0.603	0.28	-0.04	0.023	1									
HCO_3^-	-0.27	0.377	-0.08	0.005	-0.12	0.402	1								
PO_4^{3-}	0.28	-0.43	-0.31	0.069	0.429	-0.25	0.025	1							
TDS	-0.16	0.563	0.28	-0.04	0.023	1	0.402	-0.25	1						
NO_3^-	-0.21	-0.03	-0.19	0.123	-0.04	-0.13	0.046	-0.05	-0.13	1					
NO_2^-	-0.1	-0.21	-0.02	-0.06	-0.07	-0.14	0.19	0.122	-0.14	0.121	1				
EC	-0.19	0.655	0.235	-0.03	-0.08	0.789	0.238	-0.43	0.789	-0.23	-0.29	1			
SAR	-0.17	0.707	0.937	-0.19	0.427	-0.01	0.34	-0.19	-0.01	-0.15	0.07	-0.06	1		
SO_4^{2-}	-0.02	0.311	0.122	0.055	0.057	0.553	-0.23	-0.18	0.553	-0.18	-0.35	0.482	-0.03	1	
Cl	0.082	-0.11	0.238	-0.2	0.088	0.055	-0.18	-0.14	0.055	-0.16	0.118	0.133	0.244	-0.18	1

4.2 Training of the Back Propagation Neural Networks Learning Algorithm.

A trained Model can be assessed by comparing its predicted parameters to the measured parameters in the overfitting test dataset. Various criteria were adopted for evaluating the models developed, in which model performance was assessed using respected statistical error measures, the Root mean square is d error (RMSE), and the coefficient of correlation (R). Scatter plots And time series plots are used to compare the measured and predicted parameters visually.

$$the \quad RMSE = \sqrt{\frac{\sum_{i=1}^{n}[y(i) - z(i)]^2}{n}} \tag{3}$$

$$R= \sqrt{1 - \frac{\sum_{i=1}^{n}[y(i)-z(i)]^2}{\sum_{i=1}^{n} z(i)^2 - \frac{\sum_{i=1}^{n} y(i)^2}{n}}} \tag{4}$$

where n is the number of data points, $y(i)$ is the i-th measurement, and its corresponding prediction is $z(i)$.

Table 3

Different input combinations are used in modelling.

No	Input combination for SAR	Input combination for EC
1	***Na^{2+}***	**TH**
2	***Na^{2+}*& *Ca^{2+}***	**TH&TDS**
3	***Na^{2+}*, *Ca^{2+}*& *Mg^{2+}***	**TH, TDS, & *Ca^{2+}***
4	***Na^{2+}*, *Ca^{2+}*, *Mg^{2+}*& HCO_3^-**	**TH, TDS, *Ca^{2+}*& HCO_3^-**
5	-	**TH,TDS, *Ca^{2+}*, HCO_3^-& *Na^{2+}***

Table 4

The statistical description of parameters

Parameters	Mean	Standard Deviation	Variance	Kurtosis	Skewness	Minimum	Maximum
pH	7.786	0.218	0.047	0.621	0.159	7.3	8.3
Ca^{2+}	69.225	12.214	149.201	10.006	-2.121	10.3	89.9
Na^{2+}	45.882	6.754	45.625	4.022	-1.332	20	58
K^{+}	2.961	3.032	9.198	39.847	5.988	1	23
Mg^{2+}	17.039	5.953	35.438	24.46	3.881	3	52
TH	472.619	33.816	1143.55	1.126	-0.122	372.2	562.4
HCO_3^-	146.664	20.098	403.938	0.603	-0.66	91.5	184.2
PO_4^{3-}	0.074	0.072	0.005	2.798	1.484	0	0.32
TDS	472.619	33.816	1143.55	1.126	-0.122	372.2	562.4
NO_3^-	1.759	1.752	3.071	2.301	1.406	0	8
NO_2^-	0.062	0.074	0.005	5.253	2.099	0	0.37
EC	677.058	41.438	1717.18	0.635	-0.989	560	730
SAR	0.981	0.158	0.025	1.697	-0.567	0.524	1.358
SO_4^{2-}	99.96	19.544	381.998	1.786	1.112	70	166
Cl	85.843	10.171	103.454	0.409	0.161	65	115

Our present case study of the Oued-Hammam watershed will discuss the observed results of Electrical conductivity (EC and Sodium absorption ratio (SAR).

Electrical Conductivity (EC), usually a high level of EC, originates from weathered sedimentary rocks or anthropogenic activities such as industrial, agriculture, and sewage flow [20]; it is an indirect way to measure total dissolved salts and is measured in (µs/cm). The present study EC varies from 560 µs/cm to 730 µs/cm with an average of 677.058 µs/cm, according to [9] (Table 5). The electrical conductivity of the Oued-Hammam watershed is regarded as C2–Good, which is suitable for agricultural use.

Sodium Absorption Ratio (SAR) is an essential parameter for the determination of the suitability of irrigation water as it helps to understand water Solidity; in the present study, SAR varies from 0.524 to 1.358 with an average of 0.981, according to [9] (Table 5), Sodium Absorption ratio of Oued-Hammam watershed is regarded as S1–Excellent which is suitable for agriculture use.

Table 5

Salinity classes of irrigation waters Laboratory staff

Electrical Conductivity (µs/cm)	**USSL Class**	**Suitability**	**Sodium absorption ratio (meq/l)**	**USSL Class**
<250	C_1	Excellent	<10	S_1
250 – 750	C_2	Good	10-18	S_2
750 – 2250	C_3	Satisfactory	18-26	S_3
> 2250	C_4	Bad	>26	S_4

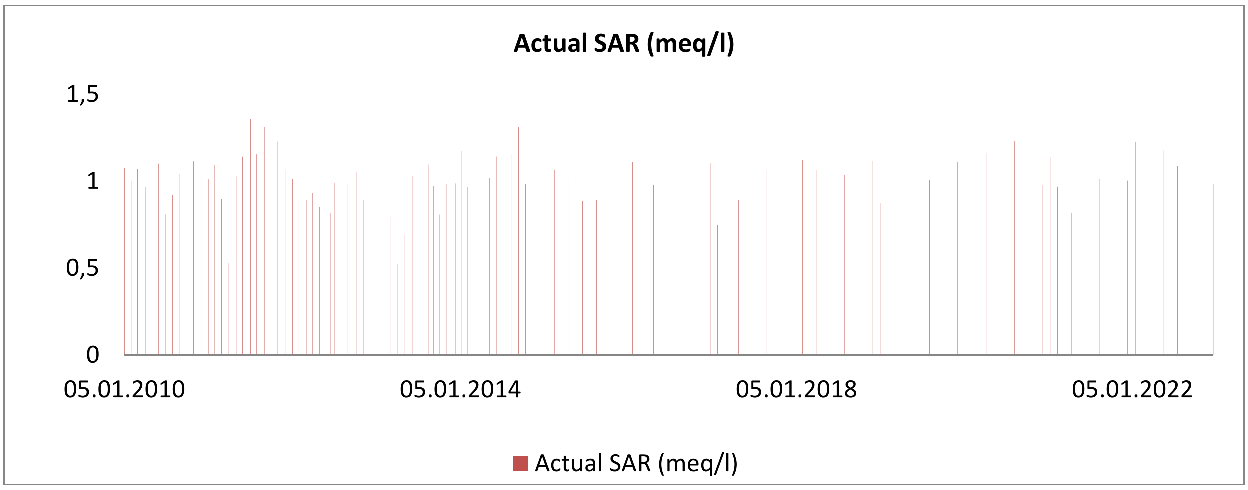

Fig.4 Variation of calculated Sodium absorption ratio (SAR) from 2010 to 2022

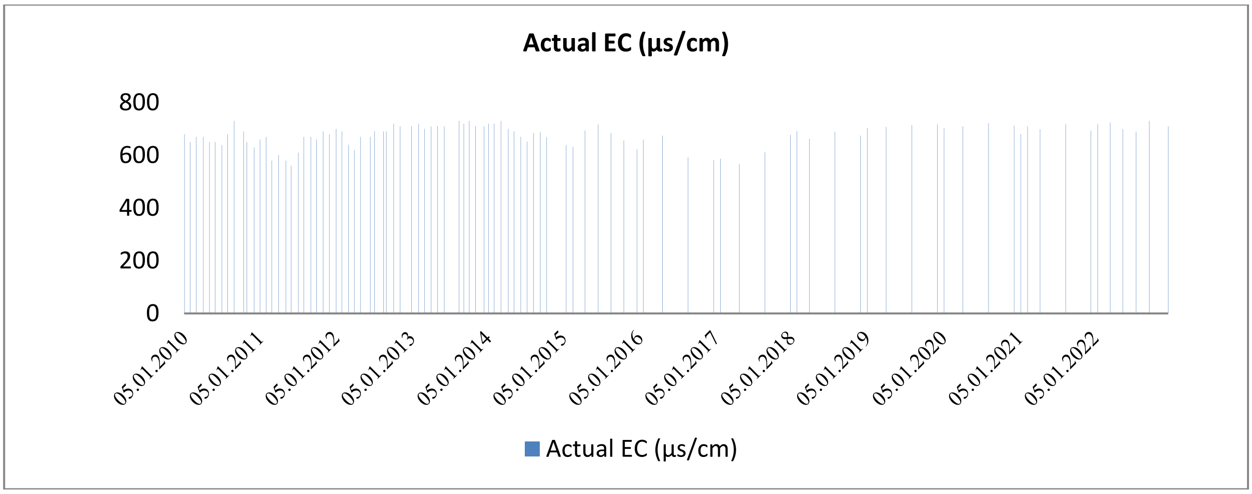

Fig. 5 Variation of measured Electrical Conductivity EC from 2010 to 2022

4.3 Analysis using artificial neural network technique.

Modelling using ANN is a common technique in which models are designed and tested so that the best number of nodes in the hidden layer and transfer functions can be determined. Setting several nodes is the crucial phase in ANN modelling; many nodes may lead to overfitting, while a small number might need to capture more information. Two ANN models were designed for the prediction to predict the Oued-Hammam watershed. The model was trained and then validated, and the best model was selected using the criteria of maximum correlation coefficient (R) and The minimum root mean square error (RMSE).

The selected ANN for the SAR model comprises one input layer with four input water quality parameters, two hidden layers with ten nodes, and one output layer with one output parameter. In comparison, the EC model comprises one input layer with five input water quality parameters, one hidden layer with twelve nodes and one output layer with one output parameter. Both ANN models (SAR and EC) were trained using the Back propagation artificial neural learning algorithm (BP).

Root mean square error (RMSE) and correlation coefficient (R) as computed for the training and validation dataset for the two models (SAR and EC) are shown in

Table 6, SAR with the RMSE of 0.036 and 0.044 in the training and validation phase respectively, and the respective correlation coefficient of 0.99 for the training phase and 0.98 for validation phase, likewise EC with the RMSE of 110.8 and 53.1 in the training and validation phase respectively, and respective correlation coefficient of 0.96 for the training phase and 0.98 for validation phase. The correlation coefficient values between the back Propagation artificial neural learning models predicted parameters and actual parameters for the Sodium absorption ratio (SAR) showed higher accuracy than that of the Electrical conductivity (EC) model.
Figure 6 presents the plots between actual SAR and predicted SAR parameters; also, Figure 7 shows the relationship between the actual EC and the predicted EC. The figures (8 and 9) reveal a positive relationship between predicted and actual parameters. The results indicate the performance of the artificial neural network in predicting water quality indicators (SAR and EC). The Present study suggests that a back propagation artificial neural learning algorithm can be used to monitor the SAR and EC of the Oued-Hammam watershed for irrigation purposes, and it can be used to monitor and control watershed pollution trends. So, ANN has been seen as efficient in predicting water quality.

Table 6

Performance of back propagation artificial neural learning algorithm for modelling the SAR and EC in the Oued-Hammam watershed.

Model	ANN-Architecture	Dataset	Root mean square error (RMSE)	R
SAR	4-10-1	Training	0.036	0.9939
		Validation	0.044	0.9871
EC	5-12-1	Training	110.8	0.9693
		Validation	53.1	0.9827

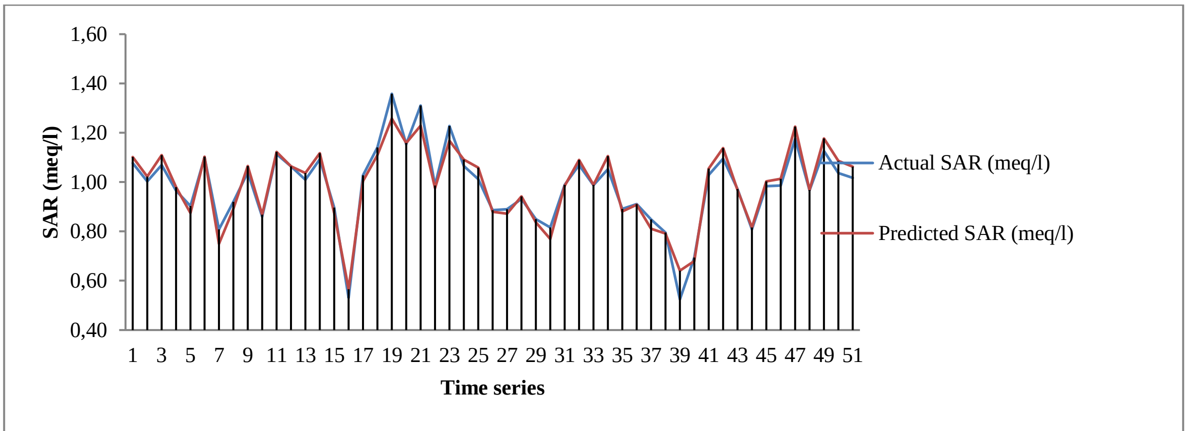

Fig. 6 Actual and predicted Sodium absorption ratio according to the backpropagation algorithm in the validation phase.

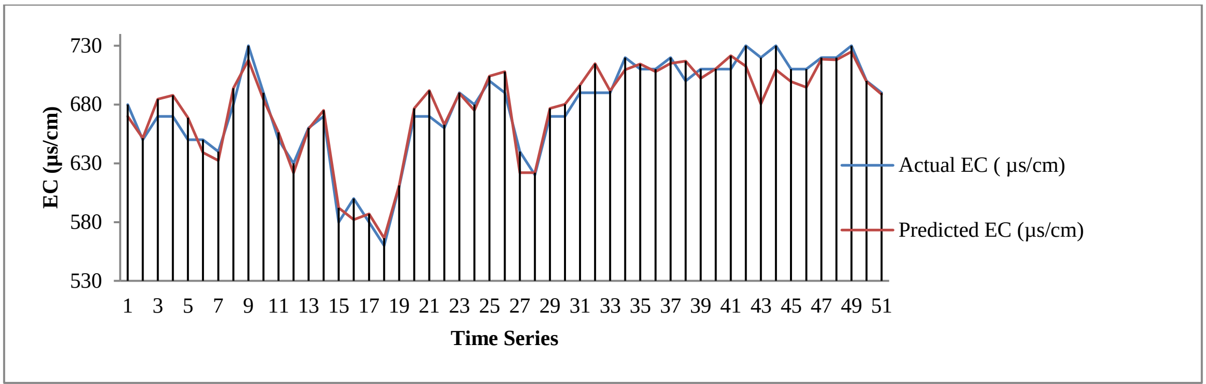

Fig. 7 Actual and predicted Electrical conductivity "EC" according to the backpropagation algorithm in the validation phase.

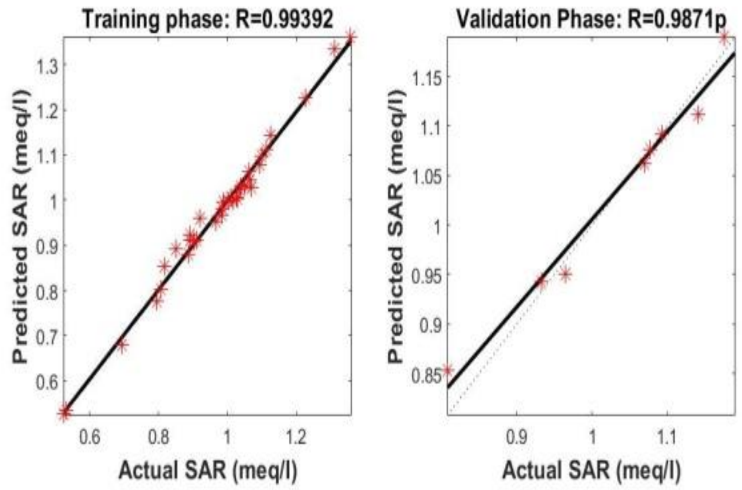

Fig. 8 Actual versus predicted Sodium Absorption ratio (SAR) by Backpropagation algorithm for training and Validation phase.

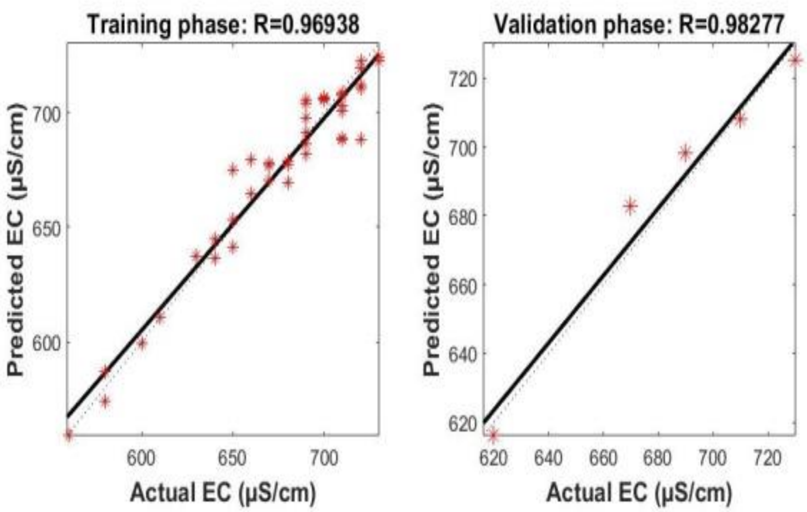

Fig. 9 Actual versus predicted Electrical Conductivity (EC) using Back propagation algorithm for training and Validation phase.

5. Conclusions

Electrical Conductivity and Sodium Absorption Ratio are the indicators used to determine water suitability for irrigation. In the present study, two artificial neural network models were constructed. The Back propagation artificial neural learning algorithm was used to predict EC and SAR using different input water quality parameters. Qualitative and quantitative criteria were used to validate and compare the models. The Backpropagation learning algorithm showed a high accuracy of 99% in the training phase and 98% in the validation phase in the prediction of SAR. In comparison, an accuracy of 96% in the training phase and 98% in the validation phase in the prediction of EC; thus Backpropagation learning algorithm was more efficient in the prediction of SAR than that of EC, rather than relying on conventional methods, which use a large amount of dataset and costly in the prediction of water quality we recommend the use of artificial neural network models in the management of water quality since they are not just high accuracy but also economically friendly and less time-consuming in control of irrigation water quality.

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