ARTIFICIAL NEURAL NETWORK MODELING OF THE WATER QUALITY INDEX FOR THE EUPHRATES RIVER IN IRAQ

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ABSTRACT

This study was aimed to investigate the development and evaluation of artificial intelligence techniques by using multilayer neural network. Levenberg–Marquardt back propagation (LMA) training algorithm was applied for calculating drinking water quality index (WQI) for Euphrates river (IRAQ). The transfer functions in the artificial network model were tangent sigmoid and linear for hidden and output layers, respectively. Eleven neurons presented for good prediction for results of (WQI) with a coefficient of correlation >0.97 and statistically calculated WQI values, inferring that the model predictions explain 94% of the variation in the calculated WQI scores. The WQI score of the Euphrates was 142 considered as poor. The analysis of sensitivity revealed that the total dissolved solids (TDS) is the highest effective variable with the relative importance of (26.3%), followed by electrical conductivity (EC) (23.1%), pH (17.3%), calcium (Ca) (0.149), chlorides (Cl) (11.2%), Hardness (5.7%), Temperature (1.3%), respectively. It can be concluded that the model presented in this study gives a useful alternate to WQI assessment, which use sub indices formulae.

Keywords: physiochemical, WQI, weighted- arithmetic, sensitivity analysis.

نمذجة الشبكات العصبية الاصطناعية لمؤشر نوعية مياه نهر الفرات في العراق

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المستخلص

تتحرى الدراسة تطوير تقنية الذكاء الاصطناعي من خلال استعمال الشبكات العصبية متعددة الطبقات لغرض حساب مؤشر نوعية المياه لنهر الفرات داخل العراق. تم اعتماد ثمانية خلايا عصبية في بناء النموذج وقد اعطت معامل ارتباط عالي اكبر من 0.97 مع القيم المحسوبة وفق الفحوصات المختبرية والحقلية. كما ان النتائج فسرت 94% من التباين لقيم نوعية المياه. من خلال تحليل النتائج بلغ تقييم نهر الفرات 142 كتقييم لمؤشر نوعية المياه مما صنفت نوعية المياه بأنها فقيرة.اظهرت نتائج تحليل الحساسية بأن الاملاح الذائبة لها اكبر تأثير على نوعية المياه وبنسبة اهمية (26.3)% تليها التوصيلية الكهربائية (23.1)% ، درجة الحموضة pH (17.3)%، الكالسيوم (14.9)%، الكلوريدات (11.2)%، العسرة (5.7)%، والحرارة (1.3)% على الترتيب. وبينت النتائج بأن النمذجة بأستخدام الشبكات العصبية ناجحة وفعالة في تقدير نوعية المياه.

الكلمات المفتاحية: الفيزيوكيميائية، مؤشر نوعية المياه، الحساب الموزون، تحليل الحساسية.

*Received:14/1/2020, Accepted:22/4/2020

INTRODUCTION

Studies on water quality of rivers are enormously important. Especially when rivers are the essential supplies of water. Turkey is the source of the Euphrates river, it passes through Syria lands enters Iraq western borders in Al-Qaem, it passes through 1060 km of Iraq lands. Iraq needs Euphrates water as a water supply for drinking, industrial, and irrigation uses. Deterioration of water quality may outcome from different activities, such as wastewater from discharge outlets, thermal pollution from power plants, industrial wastewater, and lands runoff discharge into river banks which is mostly difficult to be determined. Water quality can be evaluated by comparing specific standards with water properties (13). Water quality index (WQI) can be considered as a single value combining a group of multiple constituents according to their concentrations (2). They have been designed to translate the aptness of water in specific uses. The basic concept of these indices is a comparison of selected water constituents with water quality standards. The earlier water quality index (WQI) was formulated by Horton (17) choosing specific water quality parameters and determining weights applied into a single function. Many studies on WQI for different locations and methodologies were carried such as (5, 9, 10, 16, 18, 20, 23, 25, 26, 28-32). Also, some studies where adopted for the Euphrates river or its branches (1, 3, 15, 19, 24). The study of forecasting models, constructed on Artificial Intelligence tools with new approaches for solving problem, established an effective alternative to conventional methodologies to evaluate and predict water qualities. The Artificial Neural Networks (ANNs) represent an intelligence system that is capable of classifying the water body through an innovative and attractive solution by connecting output variables to input ones in a unified system. Several WQI estimation models had been developed using the ANN (6, 8, 11, 13, 14, 27). The objectives of the proposed study are: (i) evaluation of the water quality of Euphrates river. (ii) development of ANN model prediction of Euphrates WQI. (iii) assessment of the relative importance for each water quality parameter.

MATERIALS AND METHODS

Monitoring area and water quality data

A total of seven monitoring stations were chosen along the Euphrates river in Iraq. Coordinates and details of monitoring stations were listed in Table 1. The water quality of the Euphrates was assessed according to eight parameters, which were monitored monthly for the period (2005-2010) adopted from the Ministry of Water Resources (IRAQ) – Environmental Studies Center. The designated parameters are calcium (Ca), electrical conductivity (EC), sulfates (SO_4), total dissolved solids (TDS), chlorides (Cl), total hardness (TH), pH, and water temperature. The parameters were chosen according to importance and data availability in monitoring stations. The weighted arithmetic method was used to calculate the WQI, which was first suggested by Horton, R. K. 1965 (17) then modified by Cude, C. G. 2001 (7) was adopted in the study. WQI can be calculated by transforming different water quality parameters using different units (e.g. concentrations, ranges …etc.) into sub-index called a quality rating scale (q_i) having a range (0-100) score, the assignment of (q_i) for each parameter is calculated by dividing measured concentration value (c_i) by its standard value (S_i) and then multiplying by 100. The importance of each factor may be reflated by assigning relative weight (w_i) which was calculated by taking the inverse of the parameter standard value (S_i) suggested by the Organization, WHO. 2011 (21) and then water parameters rating scales were multiplied by their relative weights and finally aggregated by the arithmetic mean to get the overall water quality index (WQI) as in Equations 1, 2, 3:

Table 1. Coordinates of the monitoring stations

Location No.	Sampling Location	Coordinates	
		Latitude	Longitude
S1	Saqlawiyah	33° 23.774' N	43° 39.603' E
S2	Hindiyah	32° 43.697' N	44° 16.154' E
S3	Shenafiyah	31° 34.793' N	44° 38.748' E
S4	Semawa	31° 18.819' N	45° 18.853' E
S5	Nasiriyah	31° 02.492' N	46° 15.264' E
S6	Madina	30° 57.678' N	47° 16.288' E
S7	Qurna	30° 7.125' N	47° 10.5' E

$$q_i = \left(\frac{c_i}{s_i}\right) * 100 \quad (1)$$

$$w_i = \frac{1}{s_i} \quad (2)$$

$$WQI = \frac{\left(\sum_{i=1}^{n} w_i * q_i\right)}{\sum w_i} \quad (3)$$

Based to the overall WQI value calculated from Equation (3), the water quality is classified according to Table 2

Table 2. Water quality classification(12, 22)

WQI value	Quality
<50	Excellent
50-100	Good
100-200	Poor
>300	Unsuitable for drinking

Artificial neural networks (ANN)

Artificial neural networks ANN may be considered as an alternative and complementary technique to traditional water quality models by delivering superior forecasts and predictions compared to traditional models (4). The development of ANN models depends on the type and quantity of the data set, which means developing an accurate ANN model requires a preceding data measurement. The common type of ANN is multilayer neural network MPL which including three layers, the first one is the input layer which is considered for presenting data, the second hidden layer(s) used for processing the data, and the third is the output layer used for collecting the processed data and generating the output required results. Each layer comprises the number of neurons for the achievement of the required calculations.

RESULTS AND DISCUSSION

Water quality index

The water quality index for Euphrates was determined by applying Equations 1,2,3, with respect to their use for human consumption according to the standards suggested by the World Health Organization WHO, 2011. The results obtained are illustrate in Table 3. The overall calculated WQI value for the period (2005-2010) is 142 which can be classified as "poor quality" according to the classification in Table 2, this unacceptable water quality results from the decline in measured parameters generally from municipal and agricultural actions industrial wastes discharge into the banks of the river. The attained results show that most parameter concentrations are over the limit values of WHO, 2011, as shown in Table 3. It can be concluded that TDS, EC, and Hardness are caused by the concentrations of dissolved solids in the water. Ca is resulting from the dissolution of carbonate minerals. The highest values of Cl and SO_4 in water may outcome from contamination by municipal wastewater and surface runoff salty deposits on the soil surface and maybe ascribed to human activity.

Table 3. Parameters concentrations and WQI values

Parameter	Minimum	Maximum	Average C_i	S_i	W_i	q_i
TDS	100	6750	2238.9	500	0.002	447.8
Hardness	104	2125	826.1	500	0.002	165.2
Ca	8	360	117.8	200	0.005	58.9
Cl	24	2298	569.1	250	0.004	227.6
SO_4	107	2088	783.6	250	0.004	313.4
EC	690	8920	3348.4	250	0.004	1339.3
Temperature	10	35	23.3	20	0.050	116.6
pH	3.92	8.93	7.9	7.5	0.133	105.7
				$\sum$	0.204	28.97
					global WQI = 142	

ANN model development

The training algorithm of Levenberg–Marquardt back propagation (LMA) was used for the application of ANN for prediction of water quality. Matlab program version (R2010a) was used to operate this algorithm. All the parameters tests values were entered into the network in order to learn the potential effect and relation between water quality parameters with their resulting categories. The measured experimental data were divided to specify the architecture of ANN, and the percentages of 60, 20, and 20% were chosen for training, validation, and test subsets, respectively. The training subset is the main one, and the pattern of the data can be specified according to this subset through updating the weights and biases of the network. The network quality can be improved based on the second subset, while the performance of the trained network is checked using the test subset through the correction to avoid the overtraining of the network. Through this study tangent sigmoid (tansig) and linear (purelin) transfer functions were selected at hidden layer and output layer respectively. Input parameters of the model were the water quality parameters designated earlier and the WQI score was the target parameter. The ANN topology was optimized through the minimum mean square error (MSE) for the prediction and training sets. The results showed that 11 hidden neurons revealed the minimum MSE for the network of WQI as shown in Figure 1. While training was stopped after ward when reached 18 epochs for the LMA since the difference increases between the validation and training errors (Figure 2). Figure 3 shows a plot of LMA regression for training, validation, and testing with correlation coefficients of more than 0.97 for all data. The optimum topology of the ANN network was found to be 8:11:1, as shown in Figure 4. The ANN model for WQI prediction provides several advantages over the traditional methods through utilizing preliminary information to create a model that is capable of calculating WQI directly from a raw dataset without using sub indices. The developed ANN model generally, may be considered as a simple, fast, and more accurate tool of calculation of the WQI in comparison with other conventional methods.

Importance of water quality parameters

A study of sensitivity analysis was applied to assess the importance for the 11 water quality parameters with respect to the overall WQI. Generally, it refers to the evaluation of the importance of predicted parameters in the constructed models. The analysis grades the interpreter variables conformably with the decline in model accuracy rate which arises when a particular variable is omitted from the model. Garson equation (1991) illustrated below applies to the neural net weight matrix for determining the input parameters importance by the sensitivity analysis:

$$= I_j = \frac{\sum_{m=1}^{m=Nh}\left(\left(\frac{|W_{jm}^{ih}|}{\sum_{k=1}^{k=Ni}|W_{km}^{ih}|}\right)\times|W_{mn}^{ho}|\right)}{\sum_{k=1}^{k=Ni}\left\{\sum_{m=1}^{m=Nh}\left(\frac{|W_{km}^{ih}|}{\sum_{k=1}^{Ni}|W_{km}^{ih}|}\right)\times|W_{mn}^{ho}|\right\}} \qquad (4)$$

where *Ij* is the relative importance of the *jth* input variable, *Ni* are the numbers of input neurons and *Nh* are the numbers of hidden neurons, *W*'s are connection weights; the subscripts n, m, and k denote to output, hidden and input neurons, respectively. Superscripts *o*, *h* and *I* denote to output, hidden and input layers, respectively. Examining the effects of the input parameters on the output parameter WQI was carried out applying sensitivity analysis equation (4) revealed that TDS is the higher effective variable with relative importance of (26.3%), followed by EC (23.1%), pH (17.3%), Ca (0.149), Cl (11.2%), Hardness (5.7%), Temperature (1.3%), and the SO_4 has no observable effect as shown in Figure 5.

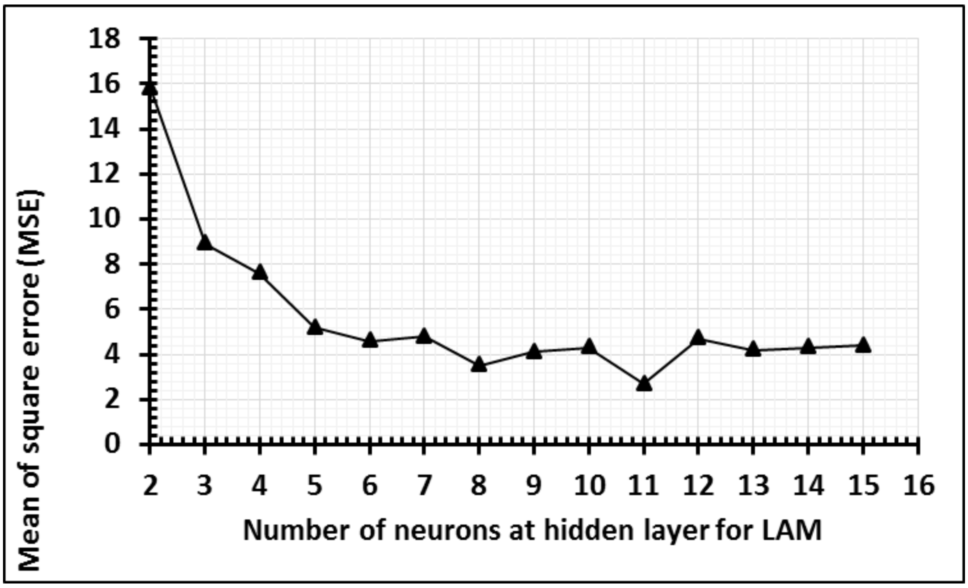

Figure 1. **Dependence between MSE and number of neurons at hidden layer for the LMA**

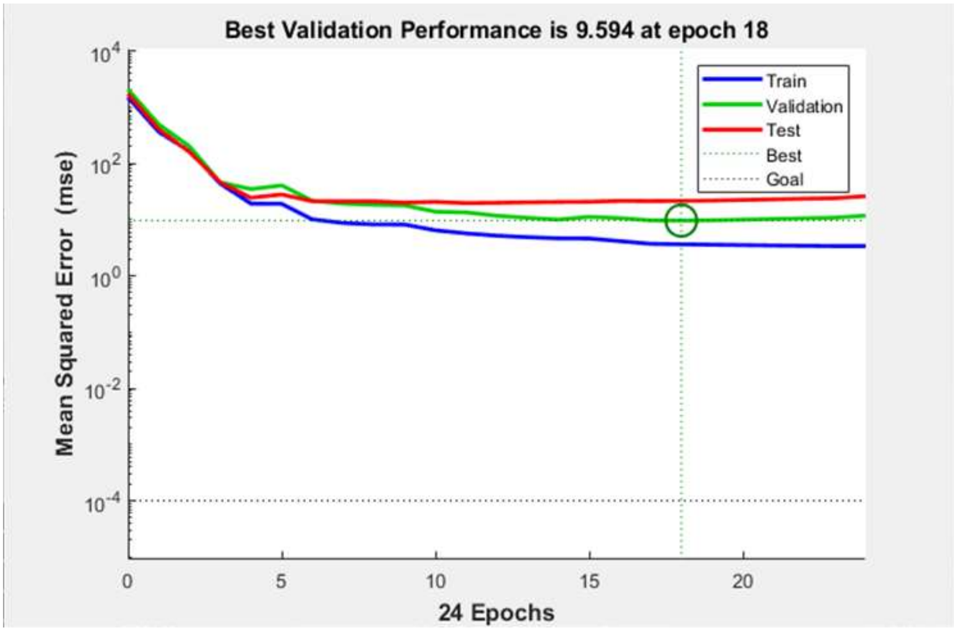

Figure 2. Training, validation, and test mean square errors for the Levenberg–Marquardt algorithm

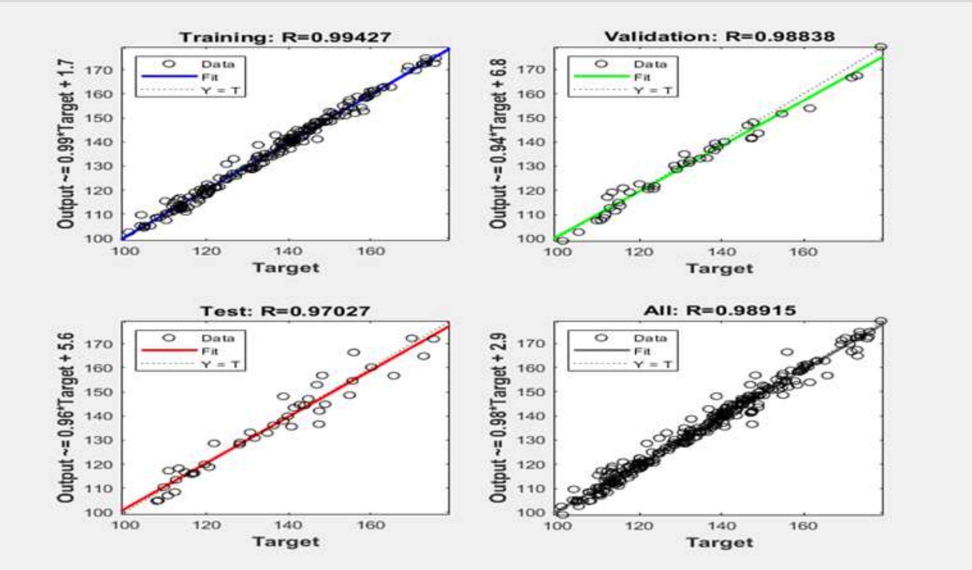

Figure 3. Training, validation and testing regression for the Levenberg-Marquardt algorithm

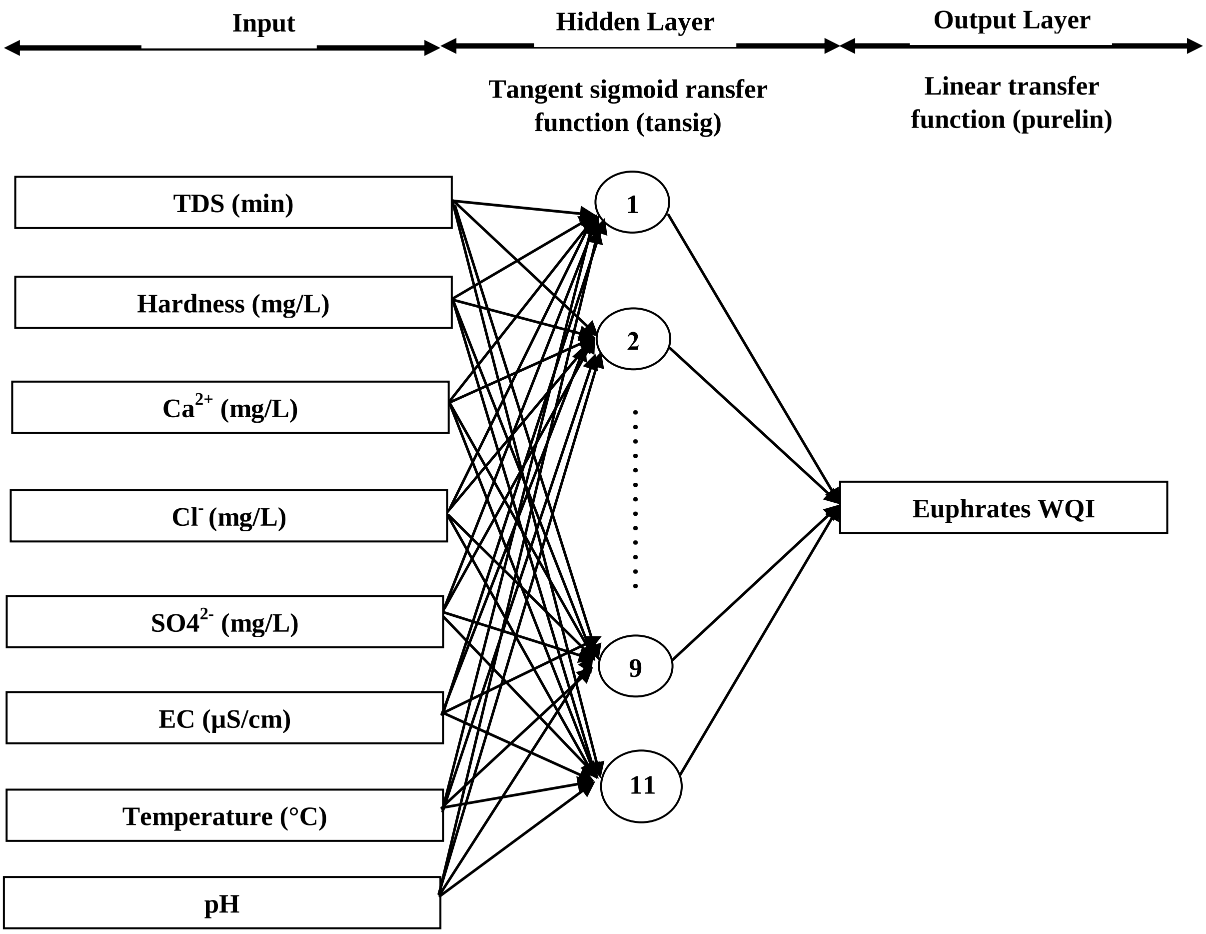

Figure 4. The architecture of the ANN model for the prediction of Euphrates water quality

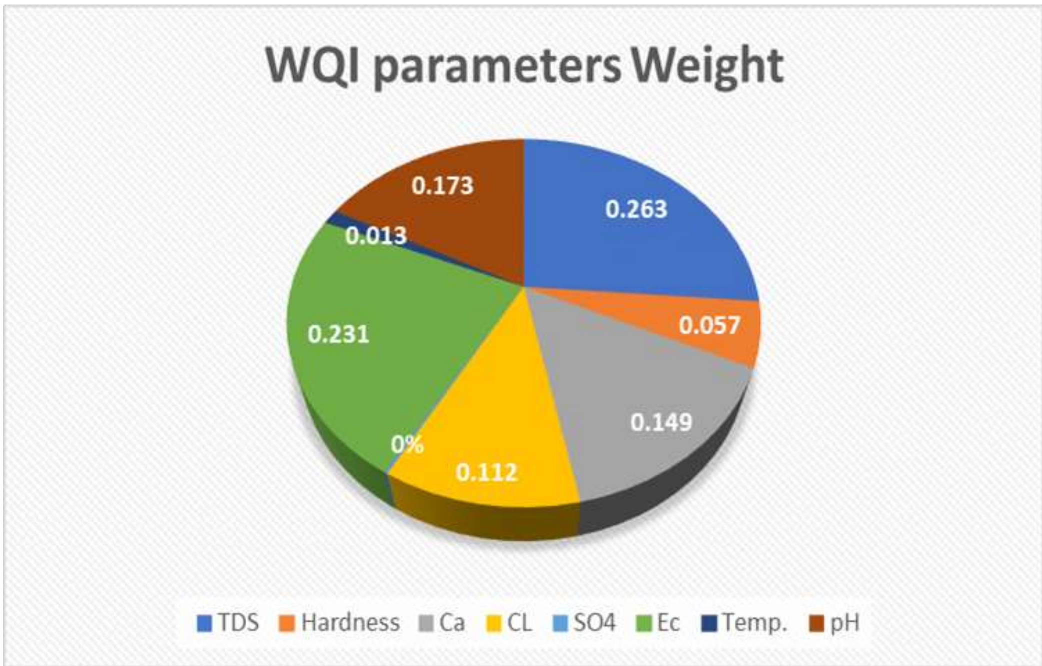

Figure 5. Pie diagram for different water quality parameters and their effect on Euphrates WQI

CONCLUSIONS

It was recognized that water quality of the Euphrates river for the period (2005-2010) could be classified as "poor quality" according to WQI score of 142. The application of neural network for prediction of water quality of a surface water body (Euphrates river) was studied through developing a model able to calculate and forecast the WQI. The ANNs consisted of 3 layers with sigmoid (for the hidden layer) and linear (for output layer) transfer functions effectively enabled easy classification of the WQI with correlation coefficient > 0.97. The sensitivity analysis revealed that the most influential parameter on WQI was TDS with a relative importance of 26.3% %), followed by EC (23.1%), pH (17.3%), Ca (0.149), Cl (11.2%), Hardness (5.7%), Temperature (1.3%) respectively. Eventually, the results reveal that the ANN establishes an effective tool for assessment of the river water quality through simplification the calculation of the WQI and that preserve considerable exertions and period by improving the calculations.

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