

## **PREDICTION OF DISSOLVED OXYGEN IN TIGRIS RIVER BY WATER TEMPERATURE AND BIOLOGICAL OXYGEN DEMAND USING ARTIFICIAL NEURAL NETWORKS (ANNs)**

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### **ABSTRACT**

The purpose of this study is to develop a feed-forward neural network (FFNN) model with back-propagation learning algorithm to predict the dissolved oxygen from water temperature and 5 days-biological oxygen demand in the Tigris River, Baghdad-Iraq. The Artificial Neural Networks model was implemented utilizing measured data that were gathered from laboratories of water treatment plant, Baghdad-Iraq, during the year 2008. The correlation analysis between dissolved oxygen and dependent parameters were utilized in selecting the major inputs from water quality parameters for commencing of ANN models. The performance of ANN models were tested utilizing the coefficient of correlation (R), the efficiency coefficient of Nash-Sutcliffe (NS), mean square error (MSE) and mean absolute errors (MAE). The outputs revealed that the feed-forward neural networks using back-propagation learning algorithm which was prepared by temperature and biological oxygen demand offered a relatively high correlation coefficient of 0.885, and efficiency coefficient of 0.782, meanwhile a reasonably low mean square errors of 1.133, and mean absolute errors of 0.369 values for whole array period. The results of the present study demonstrate that the artificial neural networks using FFNN model is capable to forecast the dissolved oxygen values with acceptable accuracy. This is suggesting that the artificial neural network is a useful tool for Tigris River management in Baghdad-Iraq.

**KEYWORDS:** FEED-FORWARD NEURAL NETWORK (FFNN), WATER QUALITY MODELING, DISSOLVED OXYGEN, TIGRIS RIVER.

### **1. INTRODUCTION**

Management of water quality problems play a significant role in controlling of water pollution and planning of river basin. The possibility of disposed pollutant to a river as municipal and industrial wastes is still a persistent concern to those consuming water for different purposes from rivers. Dissolved oxygen, DO, considered as a primary indicator of water quality parameter of the river and has gained tremendous attention in literature in recent decades. It relies on several factors such as oxygen depletion, salinity, temperature and others (Kalff, 2002; YSI, 2009). The level of dissolved oxygen is the criterion of health evaluation (Rankovic et al., 2010), that is repeatedly utilized for controlling of water quality at different aquatic systems

such as rivers, reservoirs and wetlands (Singh et al., 2009; Ay and Kisi, 2012; Kisi et al., 2013). The modeling of water quality using either deterministic (Garcia et al., 2002; Hull et al., 2008; Shukla et al., 2008) or statistical approaches (Boano et al., 2006) have recently received great attention as a result of its significant role in environment and human health. Hence; it is very necessary to generate a dissolved oxygen model of the Tigris River so that quality control measures can be optimized during the whole period of time.

Both Water Quality Simulation Program (WASP) (Wool et al., 2006) and Stream and River Water Quality Models (QUAL2K) (Chapra and Pellettier, 2003) are very complicated as more information of the river systems are required. It makes logic utilizing artificial intelligence

methods to generate the vital information about the water quality of river. Artificial neural network is frequently used in predicting of water quality parameters (Nash and Sutcliffe, 1970; French et al., 1992; Zhu and Fujita, 1994; Yi-Ming et al., 2003). An artificial neural network learns in such a way to solve a problem via developing a memory capable of relating large numbers of input data with a resulting set of outputs. ANN function similar to a “black box” model which is requiring no detailed information about the system (Ahmed et al., 2013). One of the paramount features of artificial neural network is their capability in handling large and complex systems with numerous interrelated parameters (Nourani et al., 2011). Artificial neural networks have successfully been utilized in a number of research concentrating on water quality prediction in lakes (Stefan et al., 1995), rivers (Singh et al., 2009; Niroobakhsh et al., 2012), reservoirs (Kuo et al., 2007; Rankovic et al., 2010;) and wastewater treatment (Abyaneh, 2014).

Sarkar and Pandey (2015) modeled the water quality of River using Artificial Neural Network system. They used a number of combinations of input variables consisting of flow discharge, pH value, travel time, electrical conductivity, temperature and BOD to predict dissolved oxygen. They obtained coefficient of correlation (R) ranged from 0.852 to 0.907 for training and from 0.654 to 0.928 for testing between the observed and simulated data of dissolved oxygen. Areerachakul et al. (2011) used COD, TKN, SS, NO<sub>3</sub>-N, NO<sub>2</sub>-N, NH<sub>3</sub>-N, total phosphorous, total coliform, pH value and BOD<sub>5</sub> as input variables to predict dissolved oxygen concentration. In their study, they obtained the coefficient of correlation (R) of 0.84 between measured and predicted values. Csábrági et al. (2015) used two artificial neural networks, namely Back-propagation Neural Networks (BPNN) and General Regression Neural Networks (GRNN) to predict DO concentrations for the Danube River of Europe. They utilized runoff, pH value, electrical conductivity and water

temperature as input variables. In their investigation, they found that the correlation coefficient of 0.85, 0.57 and 0.77 for training, testing and whole respectively by BPNN; meanwhile in the case of GRNN they achieved the coefficient of correlation of 0.93, 0.72 and 0.85 for training, testing and whole respectively. Singh et al. (2009) calculated dissolved oxygen and biochemical oxygen demand levels in the River of Gomti in India using eleventh water quality parameters as input variables. In their research, they obtained the coefficient of determination of 0.70, 0.74 and 0.76 for the training, validating and testing respectively. The capability of artificial neural networks in modeling both complex and non-linear problems lead the researchers to utilize this approach to predict the dissolved oxygen in a river.

The aim of this paper is to build a multi-layer feed-forward neural network with back-propagation model to predict the dissolved oxygen in the Tigris River, Baghdad-Iraq. The Tigris River has been chosen due to its significance in water supply as well as its high aquatic system importance. The proposed model may subsidize to more efficient water management as well as to prevent municipal and industrial wastes in disposing to Tigris River. It is worth noted that the developed model depends on the database of water quality variables measurement published by Matti (2014).

## 2. MATERIALS AND METHODS

### 2.1 Study area

The River of Tigris bisects the Baghdad city on a vast plain. It has a great importance in the present and it continuous into the future. This is so due to the effect of pollutants that comes from municipal wastes, industrial wastes, human activities and runoff from agricultural lands that located on the upstream of the city that deteriorates the water quality of the Tigris River day by day (Abu-Hamdeh, 2000). Hence; it becomes essential to study and evaluate

the Tigris River and demonstrating the appropriateness of the river for several purposes in a selected region. Therefore, the Tigris River in Baghdad city was

selected as the study site for artificial neural network applications. Eight sites of sampling along the Tigris River in Baghdad city were identified in Figure 1.



**Fig.(1):** Locations of sample sites on Tigris River (Matti, 2014)

## 2.2 Water quality data

The data set, that was published by Matti (2014), utilized in this study was created via monitoring of water quality of the Tigris River. Monthly sampling was tested in the laboratories of water treatment plants at eight sampling sites along the Tigris River (Figure 1). For the purpose of analysis 288 samples were chosen for the study. The physic-chemical

of water quality parameters measured are: Temperature, Turbidity, pH value, Total hardness, Iron, Chlorides, total dissolved solids, electrical conductivity, total suspended solids, Calcium, Sulfate, Nitrate, Fluoride, Total Alkalinity, Magnesium, dissolved oxygen, 5 days-biochemical oxygen demand and  $PO_4$  as shown in Table(1).

**Table( 1):** Physic-Chemical parameters of water quality of Tigris River (Matti, 2014)

NO.	PARAMETERS	UNITS	Experimental value	
			min	max
1	Dissolved oxygen	mg/l	3.47	7.9
2	Temperature	°C	12	31.67
3	Turbidity	NTU	0.497	90
4	pH value	-	7.8	8.16
5	Total Hardness (as $CaCO_3$ )	mg/l	290.7	523.3
6	Iron	mg/l	0.153	2.23
7	Chlorides	mg/l	32	113.87
8	Electrical conductivity	$\mu S/cm$	607.16	3269
9	Total dissolved solids	mg/l	75	1324.7
10	Total suspended solids	mg/l	26.83	131
11	Calcium	mg/l	65	179.33
12	Sulfate	mg/l	190	405

13	Nitrate	mg/l	0.24	0.568
14	Fluoride	mg/l	0.06	0.26
15	Total Alkalinity	mg/l	0.073	173
16	Magnesium	mg/l	29	39
17	BOD <sub>5</sub>	mg/l	3.4	61.25
18	PO <sub>4</sub>	mg/l	0.0082	0.148

### 2.3 Input selection technique

An input selection approach was used to choose the inputs that are having medium to strong correlation with dissolved oxygen. The measured parameters of water quality in the Tigris River and correlation analysis with dissolved oxygen are shown in Table (2). Since a general suggestion for the present study is that an input should be removed if it has the correlation coefficient  $< \pm 0.3$ . Because smaller than this number means

weak correlation exists. As there are only two independent parameters, Table 2, namely BOD<sub>5</sub> and water temperature that shows a significant influence on dissolved oxygen have been selected as input variables for feed-forward neural networks using back-propagation learning algorithm. In contrast the rest of water quality parameters are found to be least effective variables, based on the goal of present study, on dissolved oxygen concentrations were removed.

**Table (2):** Results of correlation analysis of water quality parameters

	<i>DO</i>	<i>T °C</i>	<i>Tur</i>	<i>pH</i>	<i>TH</i>	<i>Fe</i>	<i>Cl</i>	<i>EC</i>	<i>TDS</i>	<i>TSS</i>	<i>Ca</i>	<i>SO<sub>4</sub></i>	<i>NO<sub>3</sub></i>	<i>F</i>	<i>TA</i>	<i>Mg</i>	<i>BOD<sub>5</sub></i>	<i>PO<sub>4</sub></i>	
<i>DO</i>	1.00																		
<i>T °C</i>	<b>0.34</b>	1.00																	
<i>Tur</i>	-	0.02	1.00																
<i>pH</i>	-	-	-	1.00															
<i>TH</i>	0.08	0.17	0.19	-	1.00														
<i>Fe</i>	-	0.01	0.25	0.04	-	1.00													
<i>Cl</i>	0.02	-	0.13	-	0.75	-	1.00												
<i>EC</i>	-	-	-	-	0.45	-	0.49	1.00											
<i>TDS</i>	0.18	0.18	0.04	0.06	-	0.27	-	0.31	0.11	1.00									
<i>TSS</i>	0.18	0.18	0.06	-	0.21	-	0.31	0.11	1.00										
<i>Ca</i>	0.07	0.01	0.61	0.04	-	0.34	-	-	-	-	1.00								
<i>SO<sub>4</sub></i>	-	0.13	0.14	-	0.88	-	0.84	0.41	0.29	-	1.00								
<i>NO<sub>3</sub></i>	0.03	-	0.12	0.29	-	0.28	-	0.91	0.49	0.31	-	0.87	1.00						
<i>F</i>	-	0.07	0.25	0.22	-	0.45	-	0.52	0.20	0.17	-	-	-	1.00					
<i>TA</i>	-	-	0.25	0.32	-	0.32	-	-	-	0.27	-	-	-	-	1.00				
<i>Mg</i>	0.04	0.45	-	0.36	-	0.36	-	0.15	0.14	0.02	0.25	0.31	0.32	-0.01	1.00				
<i>BOD<sub>5</sub></i>	-	0.04	-	0.27	0.27	-	0.27	-	0.15	0.14	0.02	0.25	0.31	0.32	-0.01	1.00			
<i>PO<sub>4</sub></i>	0.10	-	0.13	0.31	-	0.23	-	-	-	-	-	-	-	0.45	-	1.00			
	0.06	0.19	0.25	0.39	0.39	0.14	0.30	0.26	0.00	0.17	0.33	0.40	0.07	0.18	-	1.00			
	-	-	0.00	0.06	0.36	0.14	0.30	0.26	0.00	-	0.22	0.12	0.07	0.08	-	-	1.00		
	0.16	0.50	-	0.41	-	0.47	0.16	0.08	-	0.13	0.43	0.58	-0.44	0.01	-	-	1.00		
	-	0.21	0.06	-	0.41	-	0.47	0.16	0.08	-	0.43	0.58	-0.44	0.01	-	-	1.00		
	<b>0.61</b>	-	0.19	0.19	0.09	0.09	0.26	0.08	0.09	0.22	0.24	0.28	0.02	0.24	0.09	0.01	0.08	1.00	
	0.02	-	0.15	-	0.12	-	0.26	0.08	0.09	0.20	0.24	0.28	0.02	0.24	0.09	0.01	0.08	1.00	
		0.14	0.02	0.02	0.06	0.06													

## 2.4 Artificial Neural Networks and Training Algorithm

In general, the model of artificial neural networks is involved of three layers namely input, hidden and output layers. Every layer involves of numerous nodes. Each node within a layer works in a similar logical way. Data is conveyed from an input layer to another layer in successive operations. The nodes of input layer comprise the values of input. Every element within the hidden layer processes the result of inputs into the outputs neuron. The Hidden layer patterns that need to be added in the neural network model can be either single layer or multiple layers. Arguably, the neural network using back-propagation algorithm is widely used training algorithm for neural network applications (Civelekoglu et al., 2007).

An architectural multilayer perceptron network used in the present study shown in Figure 2 is one sample of artificial neural network which is widely utilized to solve the number of various problems, river water quality modeling is one of them (Haykin, 2005; Musavi and Golabi, 2008). Each layer is involved of elements that are interrelated with each other by synaptic weight. An activation function which is a specific mathematical function receives input values from prior layers

and produces output for the subsequent layer. In this research study, Levenberg-Marquardt algorithm was utilized for training the neural networks and hyperbolic tangent sigmoid was selected as transfer activation function between input layers and hidden layers, and hidden layers and output layers. The parameters, weight and biases, of artificial neural networks are adjusted in order to minimize the sum of mean square error between the observed and simulated data of neural network. The Neural Network Toolbox of MATLAB 2010a was used for artificial neural network applications. It is worth remembered that 75% of the sample data were assigned for training and 25% of them were allocated for testing purposes. The predicted value of neuron can be written as:

$$\text{predict} = f(n) \quad (1)$$

$$\text{Where } n = \sum_{j=1}^k w_j x_j + b \quad (2)$$

Where:  $x_1, x_2, \dots, x_k$  are the input signals;  $w_1, w_2, \dots, w_k$  are neuron weights,  $b$  is value of bias, and  $f(*)$  is an activation function.

Sigmoid activation function is most commonly used in the construction of artificial neural network.

An example of sigmoid is the hyperbolic tangent function (Haykin, 1999):

$$f(n) = \frac{1 - e^{-n}}{1 + e^{-n}} \quad (3)$$

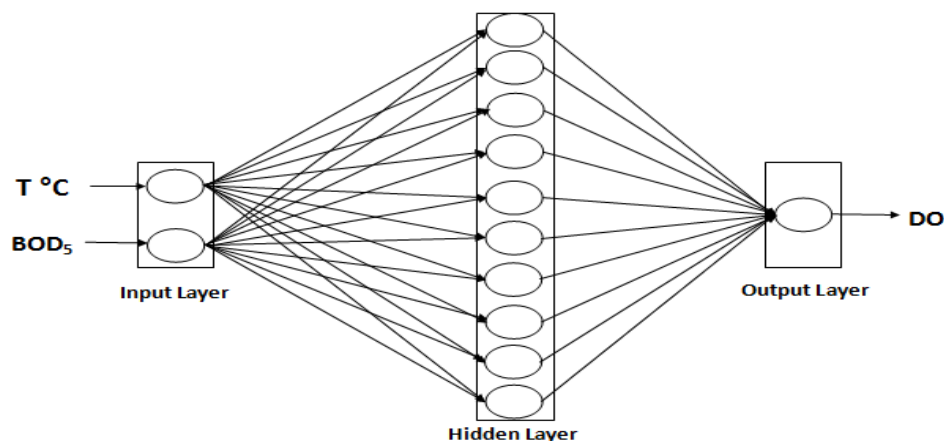


Fig. (2): Architecture of multi-layer perceptron of artificial neural networks

## 2.5 Performance evaluation parameters

In the present study, several statistical measures were considered to evaluate the performance of trained artificial neural network such as: R, MSE, MAE and NS. Various types of information regarding the predictive capabilities of the model were provided by each MSE and MAE. The former estimates goodness-of-fit to high dissolved oxygen whereas the latter distributes the prediction errors apart from giving the performance index in terms of prediction of dissolved oxygen. The smaller values of mean square and mean absolute errors confirm good overall performance of artificial neural networks. Nash-Sutcliffe efficiency coefficient ranged from minus infinity to 1.0, with higher values demonstrating better agreement between experiments and modeled data (Nash and Sutcliffe, 1970). The parameters are determined using the following equations:

$$R = \frac{\sum_{k=1}^N (P_k - \bar{P})(O_k - \bar{O})}{\sqrt{\sum_{k=1}^N (P_k - \bar{P})^2 \sum_{k=1}^N (O_k - \bar{O})^2}} \quad (4)$$

$$MSE = \frac{1}{N} \sum_{k=1}^N (O_k - P_k)^2 \quad (5)$$

$$MAE = \frac{1}{N} \sum_{k=1}^N |O_k - P_k| \quad (6)$$

$$NS = 1 - \frac{\sum_{k=1}^N (O_k - P_k)^2}{\sum_{k=1}^N (O_k - \bar{O})^2} \quad (7)$$

Where  $O_k$  and  $P_k$  the network measured and simulated values from the  $k^{\text{th}}$  element;  $\bar{O}$  and  $\bar{P}$  represent their average values respectively and  $N$  represent the number of sample data.

## 3. RESULTS AND DISCUSSION

The ANN model was trained using ten neurons in the hidden layer, for training, testing and all array, training + testing, for an input combination of water temperature and 5 days-biological oxygen demand. The ANN model that had a relatively higher value of correlation coefficient (R) was tabulated and four statistical performance parameters were

computed to assure the dissolved oxygen prediction capability of the selected model of ANN architecture. The coefficient of correlation, mean square error, mean absolute error and Nash-Sutcliffe efficiency coefficient as computed performance parameters for the training, testing and whole array data sets utilized for the model prediction of dissolved oxygen are presented in Table 3. The measured and predicted dissolved oxygen concentrations in whole array utilizing feed-forward neural network with back-propagation learning algorithm has been demonstrated in Figure 3. The scatter plot of observed and ANN-predicted concentrations of dissolved oxygen for FFBP is shown in Figure 4. The developed model with considered input parameters ( $T$  °C and  $BOD_5$ ) is found to be appropriate for the prediction of dissolved oxygen with relatively high correlation coefficient and efficiency coefficient, and reasonably low mean square error and mean absolute error. It can be seen from Table 3 that the respective coefficient of correlation is 0.885, 0.869 and 0.885 for training, testing and whole array period. However, the value of mean square error is 1.031, 0.143 and 1.133 for training, testing and whole array period respectively. Evaluation of average prediction error is not the only important statistical parameter when evaluating the performance of every single model for its applicability in forecasting dissolved oxygen but the distribution of prediction errors are also essential to be evaluated accordingly. So far, the global statistics as the statistical performance assessment criteria was employed that did not offer any knowledge on the distribution of errors. Hence, it is highly required to test the model which is utilizing some other criteria of performance evaluation such as MAE to verify the robustness of the model developed. The index of MAE offers an indication about whether a model prone to underestimate or overestimate. The value of mean absolute error is 0.384, 0.325 and 0.369 for training, testing and whole array period

respectively. Since the results of MAE are more symmetric around zero the proposed model performed well in predicting the dissolved oxygen.

Ehsan et.al (2016) claimed that a model can yield perfect estimation when the NS criterion value reached one. Shu and Quarda (2008) pointed out a model could be considered as accurate when the NS criterion is greater than 0.8. It is seen from Table 3 that the values of NS for all cases are over 0.7. This shows that the achieved performance is good during training, testing and whole array and this model reached acceptable results. It was apparent that the present model usually provided with low values of MSE and MAE and relatively high R and NS, the performance of the FFBP model in the

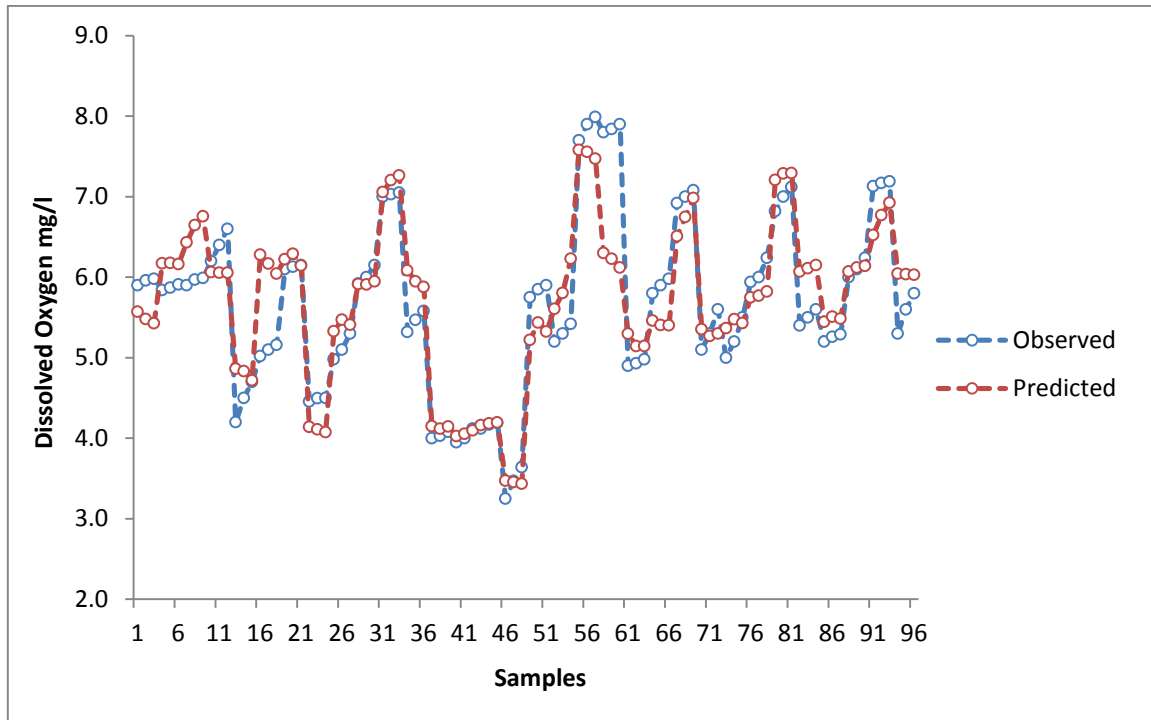
dissolved oxygen prediction was satisfactory.

Ahmed (2014) used feed-forward neural network model and a radial basis function neural network model to estimate the dissolved oxygen in the Surma River, Bangladesh. Despite a limited number of input variables that were consisted of BOD<sub>5</sub> and COD, the correlation coefficient between the observed and modeled concentration of dissolved oxygen was over 0.90. The paper demonstrated that the suggested model of ANN with minimum input variables such as water temperature and 5 days-biological oxygen demand may also be well used for predicting dissolved oxygen values.

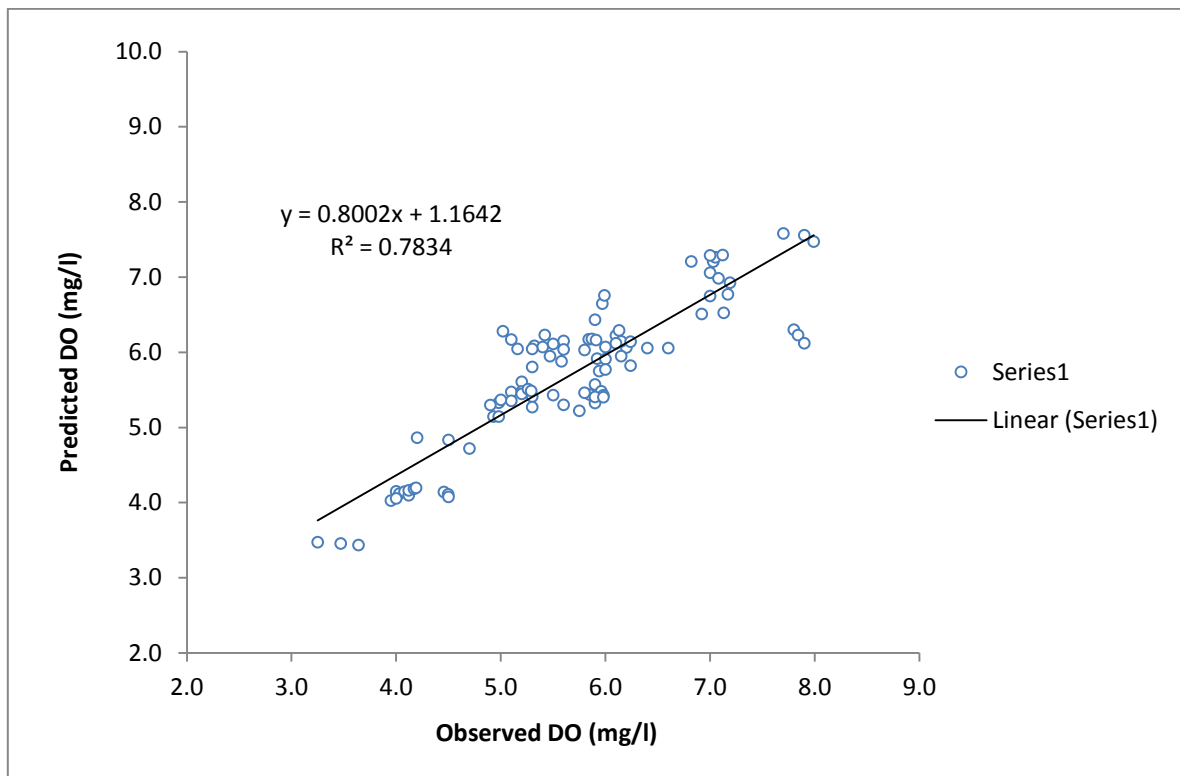
**Table (3):** The structure and the performance statistics of the FFNN back-propagation model during the training, testing and whole array periods

Input	T°C + BOD <sub>5</sub>			
Structure	2:10:1			
Performance parameters	R	MSE	MAE	NS
Training	0.885	1.031	0.384	0.784
Testing	0.869	0.143	0.325	0.717
All (Training + Testing)	0.885	1.133	0.369	0.782





**Fig. (3):** The observed and predicted dissolved oxygen in whole array period



**Fig.( 4):** Scatter plot of observed versus predicted dissolved oxygen concentrations in whole array period

#### 4. CONCLUSIONS

In this study, Artificial Neural Network models were implemented to predict dissolved oxygen in the Tigris River, Baghdad-Iraq. The suggested model demonstrated the capability of ANN in predicting the values dissolved oxygen in river water courses. The performance of ANN models were tested utilizing R, NS, MSE and MAE. The outputs revealed that the feed-forward neural network using back-propagation learning algorithm which was prepared by water temperature and 5 days-biological oxygen demand offered a relatively high correlation coefficient of 0.885 and efficiency coefficient of 0.782, meanwhile reasonably low mean square errors of 1.133 and mean absolute errors of 0.369 values for entire period. It has been assured that dissolved oxygen in the Tigris River can be forecasted with adequate accuracy from only a small data set utilizing feed-forward back-propagation. The achieved results could be utilized by water quality controller to be applied in water treatment and water management plan.

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