International Research Journal of Natural Sciences

Vol.2,No.3,pp.25-38, September 2014

Published by European Centre for Research Training and Development UK (www.eajournals.org)

PREDICTION OF WATER QUALITY OF EUPHRATES RIVER BY USING ARTIFICIAL NEURAL NETWORK MODEL (SPATIAL AND TEMPORAL STUDY)

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ABSTRACT: *Euphrates river is one of the most important rivers in Iraq. The monitoring and assessment of the water quality of this river spatially and temporally are a challenging problem. In this study, Artificial Neural Network model (ANN) model was used for prediction and forecasting the monthly Total Dissolved Solid (TDS) parameter in water. In the ANN model calibration, a computers program of multiple regressions (MLR) is used to obtain a set of coefficients for a linear model .Six sampling stations located along the Euphrates River were chosen. The period of study extended during 1999 and 2013.The input parameters of the ANN model were the flow rates of Euphrates River, the year, the month and the distance of the sampling stations from the upstream of the river. The results indicate that the discharge and distance had the most significant effect on the predicted TDS with a relative importance of (75 %) and (61%) respectively, followed by year and month with a relative importance of (33%) and (4%) respectively. The output was TDS of the water. The forecasting ability of these models is accessed on the basis of correlation coefficient, MAPE and RMSE. Using the connection weights and the threshold levels which obtained from ANN model, the equation of TDS concentration in p.p.m. for Euphrates river can accurately predict the TDS with a correlation coefficient, RMSE and MAPE were 0.928, 319.5 and 21.26% respectively. It is important in water quality management and finding the missing data. The concentration gradient of TDS of Euphrates river reaches between A-Qaim-Fallujah, Fallujah-Hindiyah, Hindiyah-Kufa and Kufa-Nassriyah were 0.0, 0.45, 3.0 and 10.0 p.p.m/Km. Comparison between final result of ANN and Multiple Regression Analysis showed the result in ANN models (RMSE and MAPE) values were less than them in multiple regression model which show higher accuracy of ANN model. So, ANN could explain the variability of the TDS of water in Euphrates river with more efficiency and outperform Statistical technique in forecasting. The advantages of using ANN model are to provide a new alternative to MLR and some other conventional statistical techniques which are often limited by strict assumptions of normality, linearity, variable independence, one pass approximation and dimensionalit*y.

KEYWORDS: ANN , MLR, Euphrates River, Distance ,Time and Discharge.

INTRODUCTION

Artificial neural networks (ANNs) have become a popular approach for environmental modeling in the last two decades. In this study, Artificial Neural Networks (ANN) was used to predict the monthly values of water quality (TDS parameter) of Euphrates River –Iraq, temporally and spatially. ESCWA (2013) shown that the TDS variations along Euphrates river since 1996 were between 450 to 3300 p.p.m.The neural network model demonstrated potential for use as a river management and forecasting tool to predict the effects of flow augmentation and near-term weather conditions on Tualatin River dissolved oxygen concentrations, Stewart A. R.(2002).

The concern about water quality in inland water bodies such as lakes and reservoirs has been increasing. Owing to the complexity associated with field collection of water quality samples and subsequent laboratory analyses, scientists and researchers have employed remote sensing techniques for water quality information retrieval, Sudheer, K.P. (2005),. Due to the limitations of linear regression methods, many researchers have employed the Artificial neural network(ANN) technique to decor relate satellite data in order to assess water quality. The results indicate that this approach could significantly reduce the effort and computational time required to develop an ANN water quality model.

Artificial Neural Network comprises of several techniques. One of this technique that is widely being used is the Back-Error Propagation (BEP) ,Ali, M. Z. (2007) . BEP of ANN was used in this research in conjunction with the Interim National Water Quality Standard (INWQS) data for Malaysia. The findings of the study shows that the classification results based on the evaluation of the water quality variables were good when compared with the results obtained from other water quality classification models, which include: the Department of Environment Water Quality Index (DOE-WQI), the Harkins'-WQI, Mahalanobis Distance Classifier, Maximum Likelihood Distance Classifier and the Decision Tree Classifier. The accuracy for BEP of ANN was found to be 86.9% and correlated well with all of these five models. The highest correlation was, with the Mahalanobis Distance Classifier and the DOE-WQI. The analysis on sensitivity shows that the BEP of ANN was sensitive to Dissolved Oxygen, a condition similar to the DOE-WQI model. Artificial Neural Networks (ANNs) were used to derive and to develop models for prediction the monthly values of some water quality parameters of the river Axios at a station located Axioupolis site of Greece by using the monthly values of the other existing water quality parameters as input variables.The monthly data of twelve water quality parameters and the discharge, for the time period 1980-1994 were selected for this analysis.The results demonstrate the ability of the appropriate ANN for prediction of water quality parameters. Diamantopoulou ,M.J. (2005). Muhittin, A.(2008) shown that ANN has high prediction capacity of DO and ANFIS has low with respect to ANN. Failure of ANFIS was due to low functionality of Matlab ANFIS Graphical User Interface. For ANN Modeling effect of meteorological data on DO data on surface of the lake was successfully described and summer month super saturation DO concentrations were successfully predicted.

The objectives of this study are to study the temporal and spatial changes in water quality TDS of the surface water of the Euphrates River in Iraq using ANN model and to know the reasons for these changes.

MATERIAL AND METHODS

Study Area

Euphrates is the longest river in western Asia. The total length is 2780Km. In Iraq, its length is 1200 Km.The majority of the water resources of the Euphrates are located in the Turkish territories of Anatolia,. Euphrates enters Iraq at Hasaibah. Its annual flow at the Iraqi border is of the order of 28 to 30 km3·year−1, Ministry of Water Resources(2013). The catchment area of Euphrates river in Iraq is 177000 Km^2 which represents 40% of the total catchment area (Mete Erdem (2002)). In Iraq, 360 km from the border, the river reaches a giant alluvial delta at Ramadi where the elevation is only 53 m a. s. l. From that point onward, the river traverses the deserted regions of Iraq, losing part of its waters into a series of desert depressions and distributaries, both natural and man-made. Euphrates has number of small tributaries in the central and southern parts of Iraq for irrigation purposes. No tributaries contributes water into the river within Iraqi territories, Fig.(1).The mean daily discharge of the Euphrates River inside Iraq (at Hit) is 909 m3/s .Inside Iraq, no tributary contributes water to the river. The river supplies a number of small canals in the central and southern parts of Iraq for irrigation purposes. Some of its water is diverted to the Habaniya reservoir during floods, which is situated about 40 km south of Ramadi. About 135 km south of Faluja, the Hindiya barrage diverts a maximum discharge of 471.5 m3/s to small parallel tributaries . The Euphrates channel south of Kifil is divided into two main channels (Kufa and Shamiya), and they joins again at Mushkhab. Further downstream, the channel splits again about 25 km south of Shanafiya and rejoins near Samawa. Then the river enters Hamar marsh at AL-Nassriah, where it forms two main channels within Hamar marsh. One of the channels (nor- thern) joins the Tigris River at Qurna (known as the Shat Alarab River) while the other channel joins the Shat Alarab River at Karmat Ali.

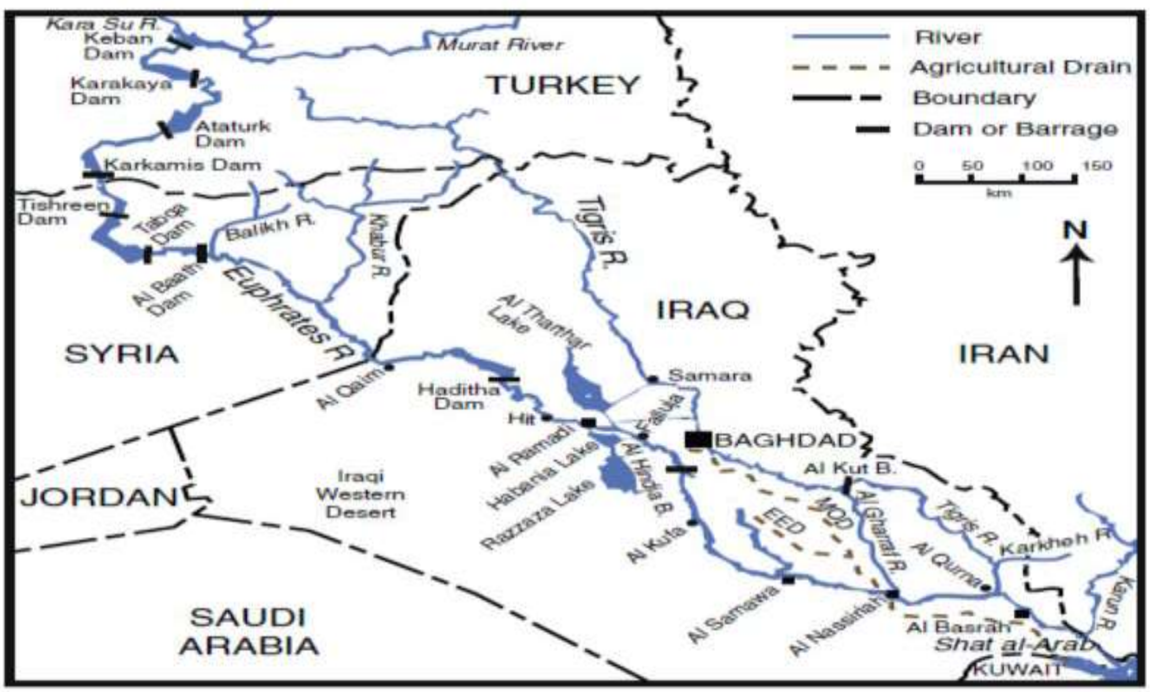

Fig.(1): Euphrates River and Water Quality Sampling Stations.

Input and Output Parameters:

In this study, ANN model was applied for data of six water quality sampling stations (Al-Qaim, Fallujah, Hindiyah, Al-Kufa, Al-Samawa and A—Nassriyah) which locate on Euphrates River as shown in, Figure (1). These data were collected from Ministry of Water Resources and Ministry of Environment (2013). Location coordinates of these stations are presented in Table(1).

The ANN model inputs were the monthly discharge (Q) in m^3/sec, distance (D) in m ,of the gage station from the upstream of the Euphrates River at Hasaibah, the year (Y) and the month of the data (M). The output of the model was the water quality parameter, Total Dissolved Solid (TDS) in(p.p.m.). The data set has a record length of 15 years covering between (1999-2013).

Table (1): water quality stations along Euphrates Riever.

Station	Geographic Coordinate	
	Latitude	Longitude
Al-Qaim	34° 23.87’	41° 03.2’
Al-Fallujah	33° 21.00’	43° 45.6’
Al-Hindiyah	32° 43.66’	44° 16.16’
Al-Kufa	32° 37.00 ′	44° 02.00’
Al-Samawa	31° 18.82’	45° 17.85’
Al-Nassriyah	31° 02.73’	46° 14.38’

ANNs Technique

In the study, the ANN model was developed based on the FFBP (Feed Forward Back Propagation) , (Dolling, O.R., and Varas, E.A. 2002) as shown in Fig.(2). It processes information in interconnecting processing elements. The model consists of one input layer, one or more hidden layers and one output layer. The model parameters comprise of many transfer functions (Sigmoid(logistic) Function ($f(x)=\frac{1}{1+e^{-x}}$), the hyperbolic tangent (tanh) function, the sine or cosine function and the linear function) , learning rate of (0.0-1.0) and momentum rate of (0.0-1.0) . The default values of learning and momentum rates are 0.2 and 0.8 respectively. A neural network is a method that is inspired by the studies of the brain and nerve systems in biological organisms. Neural networks have the capability of self-learning and automatic abstracting. Applying this technique may reduce the time of modeling the complex systems. Artificial neural networks are important alternatives to the traditional methods of data analysis and modeling.

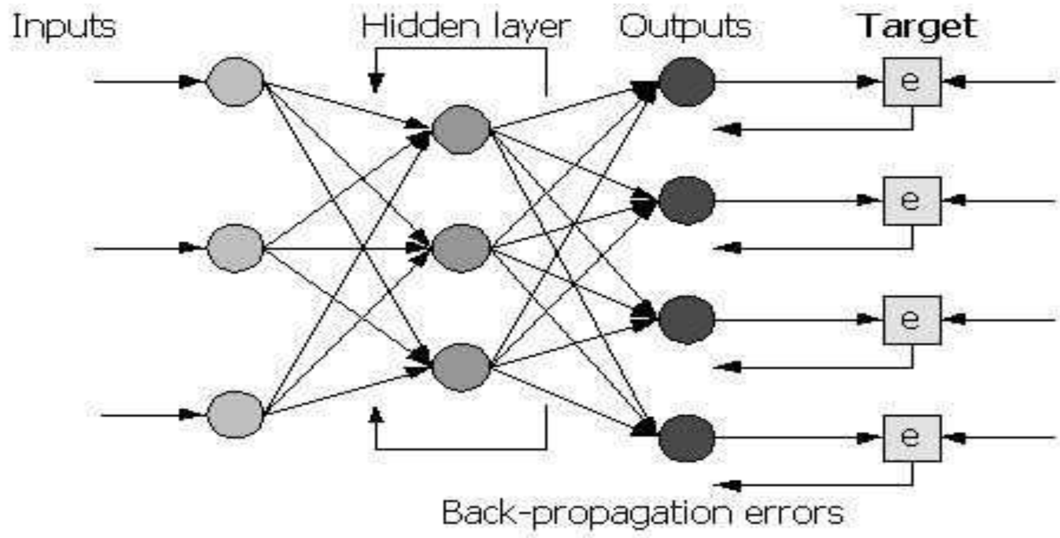

Fig.(2): Typical Structure of ANN

The Artificial neural networks are divided into two periods. In the first period neural network is trained to represent the relationships and processes within the data. After the network is adequately trained, it is able to generalize relevant output for the set of input data. This output is compared with observed data from the real life. This second period is called as testing period. The network is trained and tested on sufficiently large training and testing sets that are extracted from the historical time series. The performance of FFBP (Feed Forward Back Propagation) was found superior to conventional statistical and stochastic methods in continuous flow series forecasting (Brikundavyi et al. 2002; Cigizoglu 2003; Jain and Indurthy 2003; Kisi 2005). However the FFBP algorithm has some drawbacks. It is very sensitive to the selected initial weight values and may provide performance under different applications that differ significantly.

Division of Data

The way that available data are divided into training, testing, and validation subsets can have a significant influence on the performance of an artificial neural network ANN (reduction in RMS error), (Gavin J. B. and Holger R. M.(2002). The data are randomly divided into three sets (training, testing and validation). In total, 80% of the data are used for training and 20% are used for validation. The training data are further divided into 70% for the training set and 30% for the testing set. These subsets are also divided in such away that they are statistically consistent and thus represent the same statistical population.The data base used for the ANN model comprises total of (404) individual cases. Missing data were found in each of the water quality sampling stations. Ranges of the data used for the input and output variable are summarized in Table (2).

Table 2 : Ranges of the data used for the ANN model

Model variables	Minimum value	Maximum value
Discharge of the river, m^3/sec	10	1410
Distance from upstream, Km	50	905
Month	1	12
Year	1999	2013
TDS, p.p.m.	312	4690

Statistical Analysis

To examine how representative the training, testing and validation sets are with respect to each other, T-test and F-test are carried out. These results indicate that training, testing and validation sets are generally representative of a single population.

Scaling of Data

Nonlinear activation functions such as the logistic function typically have the squashing role in restricting or squashing the possible output from a node to, typically, (0,1). Data normalization (scaling) is often performed before the training process begins. When nonlinear transfer functions are used at the output nodes, the desired output values must transformed to the range of the actual outputs of the network. It may still be advantageous to standardize the outputs as well as the inputs to avoid computational problems (meet algorithm requirement and to facilitate network learning,Srinivasan(1994)).For each type of normalization , the following formula is used Guoqiang ,Z. and Eddy P. E. (1997) :

$$\mathbf{X_n = (X_0 - X_{min})/(X_{max} - X_{min})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where X_n and X_0 represent the normalized (scaled) and the original data,X_{max} and X_{min} are the maximum and minimum of data.

Model Architecture

The difficult task in the development of ANN models is determining the model architecture (the number of the hidden layer nodes and the values of learning and momentum rates).The number of nodes in the input and output layers are restricted by the number of model inputs and outputs, respectively. There is no direct and precise way of determining the best number of nodes in each hidden layer. A trail and error procedure for determining the number and connectivity of the hidden layer nodes can be used.

The process of optimizing the connection weights is known as (training) or (learning). This is equivalent to the parameter estimation phase in conventional statistical models. Stopping criteria are used to decide when to stop the training process. They determine whether the model has been optimally or sub-optimally trained. Training can be stopped, when the training error reaches a sufficiently small value or when no or slight changes in the training error occur. When, the training and stopping criteria of the model have been successfully accomplished, the performance of the trained model should be validated. The purpose of the model validation is to ensure that the model has the ability to generalize within the limits set by the training data. The coefficient of correlation(r),the root means squared error, RMSE, , and the mean absolute percentage error (MAPE)(Sabah,S.F. and Ahmed, S. (2011)), were the main criteria that were used to evaluate the prediction performance of ANN models .Sabah, S.F.(2011) stated that the MAPE around 30% is considered a reasonable prediction. The coefficient of correlation is a measure that is used to determine the relative correlation and the goodness-of-fit between the predicted and observed data. The RMSE is the most popular measure of error and has the advantage that large errors receive much greater attention than small errors.

ANN Application

Using the default parameters of the ANN model (0.2 for learning rate and 0.8 for momentum rate), a number of networks with different numbers of hidden layer nodes (1-10) and with different transfer functions were developed. The best performance of these networks was with (3) hidden layer nodes and minimum values of correlation coefficient, RMSE and MAPE ,Table(3) .The best transfer functions for the input ,hidden and output layers were linear, tanh and sigmoid respectively. More than 250 trials were used in this study. The effect of the internal parameters controlling the back-propagation (momentum and learning rates) on model performance is investigated for the model with three hidden layer nodes, Table(3). The effect of the learning and momentum rates on the model performance are shown in figs.(3) and (4).Different values of learning and momentum rates were used, Table (3). It can be seen that the performance of the ANN model is relatively sensitive to learning rates in the range (0.05 to 0.60) then the prediction errors increase sharply to(494.7) , Fig. (3). Fig.(4) shows the effect of the momentum rate on model performance. It can be seen that the performance of the ANN model is relatively sensitive to momentum rate value of (0.8). The optimum values for learning and momentum rate used is 0.40 and 0.80 respectively. The coefficient of correlation, RMSE and MAPE were 0.928, 319.5 and 21.26% respectively. Also, the network with (3) hidden layer nodes has the lowest prediction error for the training and validation tests. However, it is believed that network with 3 hidden layer nodes is considered optimal, Fig.(5).

Table(3):Performance of ANN models for prediction (TDS) of Euphrates River.

Parameter effect	Model No.	Learn. Rate	Moment. rate	Hidden layer node No.	Corr. Coeff.	RMSE	MAPE %
Default values	1	0.2	0.8	1	0.894	549.7	40.62
	2	0.2	0.8	2	0.901	387.6	25.08
	3	0.2	0.8	3	0.905	373.9	23.13
	4	0.2	0.8	4	0.903	393.1	21.45
	5	0.2	0.8	5	0.899	395.9	26.42
	6	0.2	0.8	6	0.899	394.7	25.85
	7	0.2	0.8	7	0.903	382.9	24.23
	8	0.2	0.8	8	0.894	451.0	31.20
	9	0.2	0.8	9	0.899	391.1	25.73
	10	0.2	0.8	10	0.898	386.0	23.45
Momentum rates	11	0.2	0.01	3	0.901	396.8	22.34
	12	0.2	0.05	3	0.901	396.8	22.34

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	13	0.2	0.10	3	0899	383.9	24.55
	14	0.2	0.15	3	0.901	381.7	23.17
	15	0.2	0.20	3	0.902	385.8	22.49
	16	0.2	0.40	3	0.902	381.0	23.03
	17	0.2	0.60	3	0.902	381.0	23.03
	18	0.2	0.90	3	0.905	398.9	26.28
	19	0.2	0.95	3	0.889	670.6	45.32
Learning rates	20	0.05	0.8	3	0.911	363.5	21.64
	21	0.10	0.8	3	0.912	365.8	20.51
	22	0.15	0.8	3	0.912	369.9	20.31
	23	0.40	0.8	3	0.928	319.5	21.26
	24	0.60	0.8	3	0.912	363.7	20.68
	25	0.80	0.8	3	0.914	494.7	20.27
	26	0.90	0.8	3	0.908	403.1	30.01
	27	0.95	0.8	3	0.910	394.6	26.32
	28	0.99	0.8	3	0.910	382.1	24.82

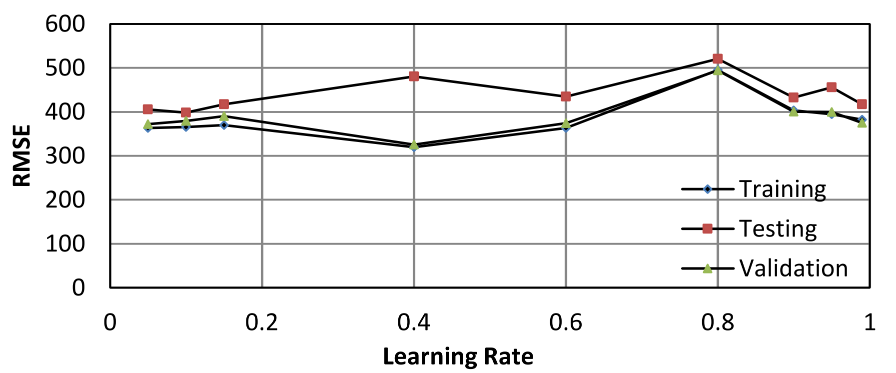

Fig.(3):Performance of ANN model with different values of learning rates,(β=0.8).

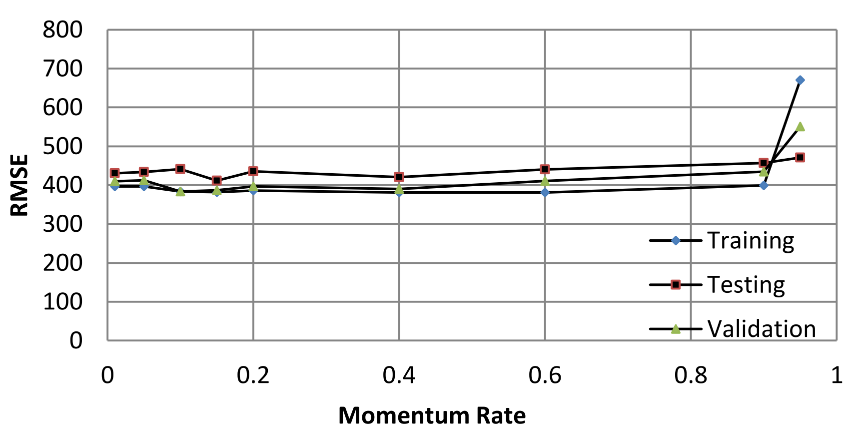

Fig.(4):Performance of ANN model with different values of momentum rates,(α=0.2).

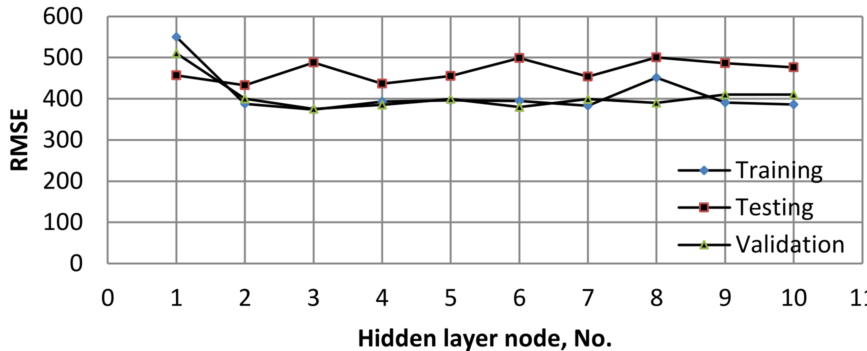

Fig.(5): Performance of ANN model with different values of hidden layer nodes,(α=0.2 and β=0.8).

RESULTS AND DISCUSSION

The ANN model was developed to simulate Total Dissolved Solid (TDS) in p.p.m. with respect to discharge of the Euphrates river , time and space. . It used an ANN architecture with one hidden layers (three nodes) and with different activation functions. The optimum learning rate of 0.4 and momentum of 0.8 were selected by many trials, as explained above. The sensitivities of the above parameters for the TDS prediction are estimated by using Garson (1991) and Goh (1995) methods. ANN connection weights were used in these methods, Table (4).The results indicate that the discharge and distance had the most significant effect on the predicted TDS with a relative importance of (75 %) and (61%) respectively, followed by year and month with a relative importance of (33%) and (4%) respectively. The results are also presented in Fig.(6).The minimum value of relative importance for the month variable is due to the water resources management. There are no monthly variations in flow rates from the regulators along Euphrates river as in the flow hydrograph. The developed ANN models accurately simulated the water quality(TDS) of Euphrates river. Typical ANN prediction model results are shown as a diagram of simulated and measured TDS concentration, for the total data (R = 0.923) , Fig.(7). A gap of TDS values between 1000 to 2000 p.p.m. ,is shown in Fig.(7),due to little data at Al-Kufa and Al- Samawa sampling stations.

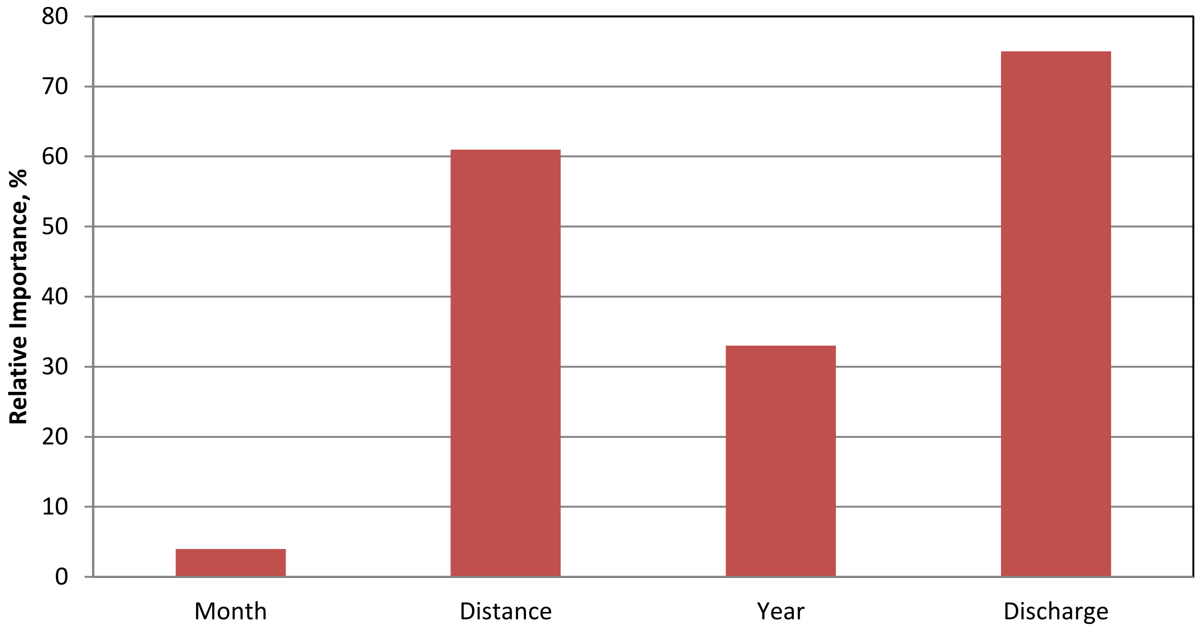

Fig.(6): Relative importance of the input variables for the ANN model.

Table (4): Weights and threshold levels for the ANN model.

Hidde layer nodes	W_{ji} (weight from node i in the input layer to node j in the hidden lay				Hidden layer threshold Θ_j
	i=1	i=2	i=3	i=4	
j=5	0.180	0.144	-0.664	0.139	0.371
j=6	0.059	-0.398	-2.944	2.319	2.270
j=7	0.086	-0.150	-0.094	-0.327	-0.024

Outpu layer nodes	W_{ji} (weight from node i in the hidden layer to node j in the output layer)			Output layer threshold Θ_j
	i=5	i=6	i=7	
j=8	-0.026	-1.493	-0.006	-0.178

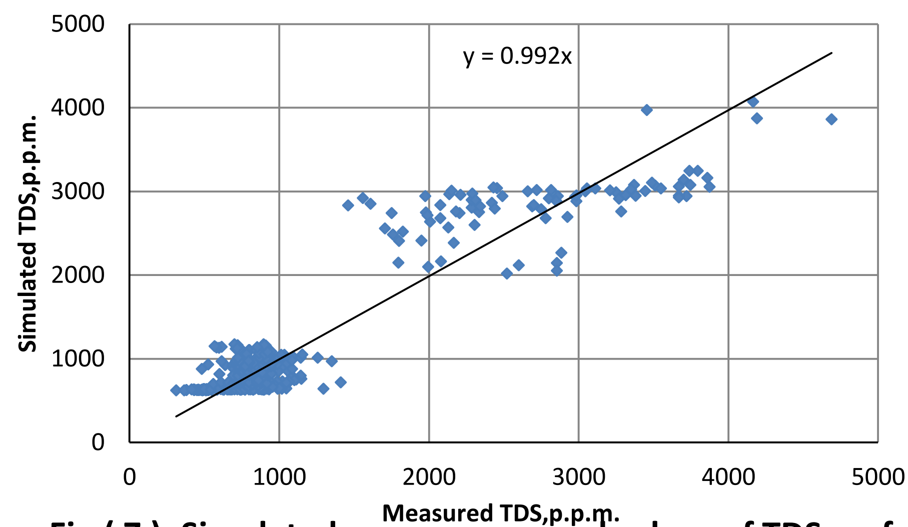

Fig.(7): Simulated versus measured values of TDS for total data by using ANN model.

Comparison of simulated water quality in Euphrates river is shown in Fid.(8).There is no trend in increasing of TDS in Al-Qaim sampling site. The progressive increase in TDS was directly proportional with distance after Al-qaim site but with low positive slope for (Al-Falluja to Al-Hindiyah) sites and high or sharp positive slope for (Samawa to Al-Nassriya) sites. This is due to the effects of upstream developments, drainage projects , direct sewage disposal into the river and agricultural activities.The concentration gradient of TDS of Euphrates river reaches between Al-Qaim-Fallujah, Fallujah-Hindiyah, Hindiyah-Kufa and Kufa-Nassriyah were 0.0, 0.45, 3.0 and 10.0 p.p.m/Km.

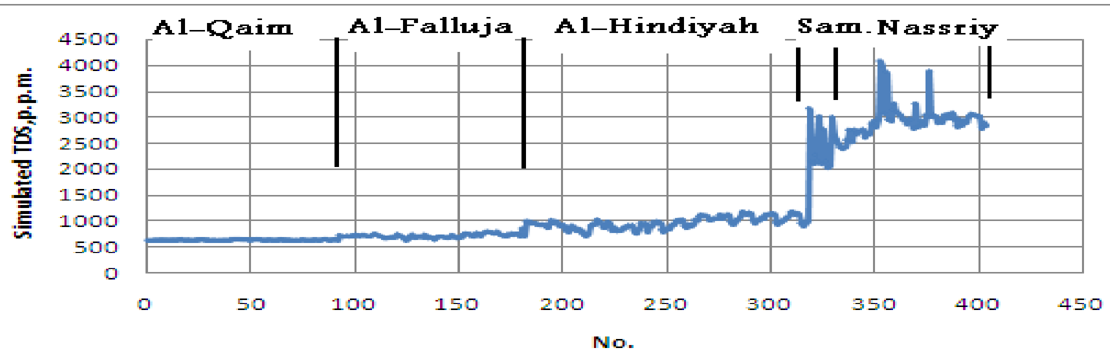

Fig.(8): Change of Simulated TDS with Distance and Yesr,Euphrates River.

Using the connection weights and the threshold levels which obtained from ANN model Table (4), the predicted TDS concentration in p.p.m.for Euphrates river can be expressed as follows:

$$TDS = (4690/(1+e^{(0.178+0.026\tanh(x1)+1.493\tanh(x2)+0.006\tanh(x3)}))+312 \quad \textbf{.........(2)}$$

Where:

$$X_1 = -20.18 + 10^{-5}(1600M + 1000Y - 80D + 3Q)$$
$$X_2 = 59.10 + 10^{-5}(500M - 2800Y - 350D + 53Q)$$
$$X_3 = 21.42 + 10^{-5}(780M - 1100Y - 11D - 7.5Q)$$

It should be noted that equation (2) is valid only for the range of values of (M, Y, D and Q)) given in Table(2). This is due to the fact that ANN should be used only in interpolation and not extrapolation (Tokar and Johnson 1999). Equation (2) is long and complex because it contains four independent variables. On the other hand, it can predict accurately the TDS of Euphrates river water (Fig.(7)) with a correlation coefficient equal to 0.923 and value of MAPE less than 30%.The equation length depends on the number of nodes in the input and hidden layers.

Multiple Regression

In the ANN model calibration,a computers program of multiple regressions is used to obtain a set of coefficients for a linear model and how well dose the linear model represent the observed data. The following regression models are derived for the TDS concentration of the Euphrates river water (p.p.m.):

$$TDS = M^{0.031} Y^{1.088} D^{0.125} Q^{-0.402} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where, M is the month, Y is the year, D is the distance in Km and Q is the discharge in m^3/sec. The correlation coefficient R , RMSE and MAPE are 0.771 , 584.2 and 29.84 % respectively,Fig.(8). Comparison between final result of ANN and Multiple Regression Analysis showed the result in ANN models(RMSE and MAPE) values were less than them in multiple regression model which show higher accuracy of ANN models. So, ANN could explain the variability of the TDS of water in Euphrates river with more efficiency.

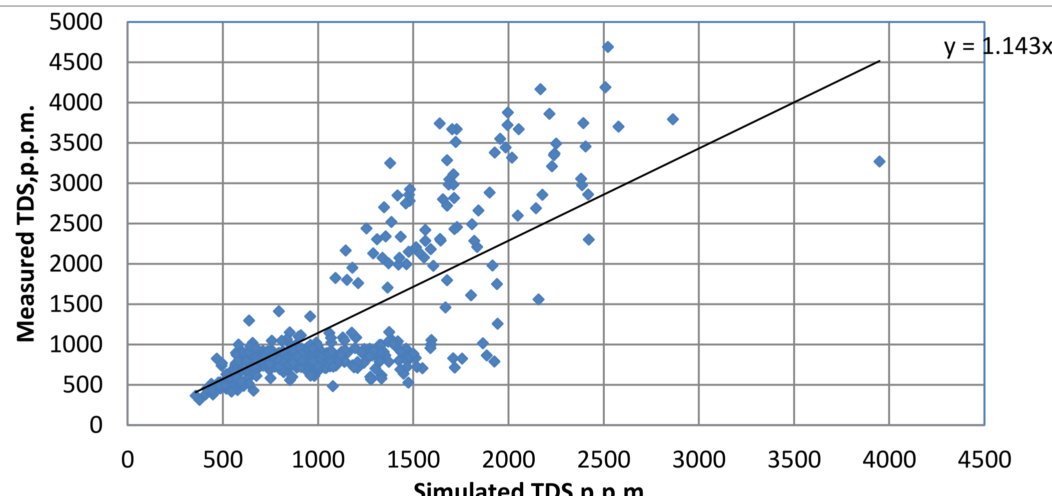

Fig.(8): Simulated versus measured values of TDS of Euphrates river water.

CONCLUSIONS

According to the result of ANN model in this study, it is found that the TDS increases with increasing time and distance from upstream, and that it is negatively correlated with the flow . These conclusions coincide with the results of previous investigations and MLR. Comparison between final result of ANN and Multiple Regression Analysis showed the result in ANN models (RMSE and MAPE) values were less than them in multiple regression model which show higher accuracy of ANN model. So, ANN could explain the variability of the TDS of water in Euphrates river with more efficiency and outperform Statistical technique in forecasting. The advantages of using ANN model are to provide a new alternative to MLR and some other conventional statistical techniques which are often limited by strict assumptions of normality, linearity, variable independence, one pass approximation and dimensionality. The predicted equation of TDS is important in water quality management and finding the missing data, temporally and spasially. Water quality of the Euphrates entering Iraq is affected by return flow from irrigation projects upstream of Hasaibah, and expected to get worse as more land comes under irrigation. The quality of the water in Euphrates river is further degraded downstream by return flows from land irrigated as well as urban pollution. Water quality degrades downstream due to poor infrastructure of wastewater treatment. The deterioration of water quality due to the decrease in the discharge rate of the river and the heavy pollution from many sources are becoming serious threats to the Euphrates river Basin. A problem is that there is no effective water monitoring network especially at al-kufa and Al-Samawa positions, making it difficult to address water quality and pollution, as the sources of pollution cannot be precisely identified. Hence, the rehabilitation and reconstruction of the water monitoring network is urgently needed for water security and management of water resources in Iraq.

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