MODELING OF RIVER WATER QUALITY PARAMETERS USING ARTIFICIAL NEURAL NETWORK – A CASE STUDY

[1]AMMAR SALMAN DAWOOD, [2]HALEEM K. HUSSAIN, [3]AYMANALAK HASSAN

Department of Civil Engineering, College of Engineering, University of Basrah, Iraq

Abstract- In river water quality management, it is very important to use an effective approach to characterize complex water quality processes. This work is referred to the employment of Neural Network models to predict the water quality parameters in the Shatt Al Arab River. In the analysis of the models, the most ordinarily used feed forward error back propagation neural network technique has been utilized. Monthly data sets on turbidity, total hardness, total dissolved solids, and electrical conductivity have been employed for the analysis. The monthly data of four parameters, for the time period 2007-2012 were assigned for this analysis. The results present the ability of the suitable ANN models to predict the water quality parameters. This supplies a very useful tool for estimating the water quality of the Shatt Al Arab River.

Key words- Water quality, ANN, Prediction, Shatt Al Arab River.

I. INTRODUCTION

The problem of water quality management plays an significant role in river basin planning and water pollution control. On the last decades, there has been an altering necessitate for water quality monitoring of many rivers by uniform measurements of different water quality variables. The probability of a pollutant being discharged to rivers as industrial and municipal waste disposal is a constant attention to those amusing and using water from rivers. For prediction of total dissolved solids in a river under assumptions of interest, different deterministic models have been tried in the past. In biological organisms, a computational method animated by the studies of the brain and nervous system, is called an Artificial Neural Network (ANN). It performs highly idealized mathematical models for our present understanding for such complex systems. One of best characteristics of the neural networks is their ability to learn. The process of learning for ANN called trainingthe neural network. The training of ANN regulates itself to develop an internal set of features that it utilizes to classify information or data. In contrast with the ordinary methods, ANNs afford incomplete data, sacrificial results, and have less vulnerability to outliers.

On the last about two decades, ANN have sustain an volatile growth in application in most all the areas of research [1-5]. The ANN method has various advantages over semi-empirical or traditional phenomenological models, because they involve known the set of input data without any assumptions [6]. The ANN acquires a mapping for the input and output variables, which can afterward be used to predict required output as a function of desirable inputs [7]. Any smooth, measurable function between input and output vectors can be approximate with a multi-layer neural network by choosing a suitable set of connecting weights and transfer functions [6]. ANN models have been exceedingly employed for water quality problems [8-10]. The major aim of the present work is to build an artificial neural network (ANN) model for Shatt Al Arab river water quality and explain its application in the complexity data of water quality as how the model have the ability of the improvement for the interpretation of the results.

II. STUDY AREA AND DATA COLLECTION

Shatt Al Arab River composes the primary source of freshwater to the Arabian Gulf. It plays a significant role for the marine habitats in the Gulf's north-eastern coastal areas. This river is located in southwest Asia of about 200 km in length. It is formed by the meeting of the Euphrates and the Tigris in Basrah Governorate of the southern Iraq. Shatt al Arab River remains a source of conflict in the area of limited access to water resources and the insistence of open sea borders. Shatt Al Arab has several tributaries along its course, the most important joining tributaries are Karun and the Karkheh Rivers, which are supplied the fresh water to Shatt Al-Arab river. During the last years, Karun and Karkheh tributaries was diversion inside the Iranian borders, and this action increases the salinity in the Shatt Al-Arab River. This not only impend s the marine ecosystems in the Gulf, as well as imperils agrarian action along the Shatt Al Arab.

The data of water quality for the years 2007 to 2012 used in this study were collected from station on Shatt Al Arab River as shown in Fig.1. Monthly data sets on turbidity, total hardness, total dissolved solids, and electrical conductivity were available and used for the analysis water quality of Shatt Al Arab River.

III. ARTIFICIAL NEURAL NETWORKS (ANNS)

Artificial Neural Networks (ANNs) are a form of artificial intelligence whose paradigm architecture is inspired by the way biological nervous systems such as the brain. The key element of this paradigm is composed of a large number of simple processing units (neurons/nodes) specific problems. The neuron model shown represents the basis of the artificial neuron model. A biological neuron is constituted of four primary parts: dendrites, synapses, axon and the cell body. First, the dendrites receive signals from other neurons.The axon of a single neuron assists to form synaptic connections with the other neurons. The incoming signals from dendrites are totaled by cell body of a neuron. If the input signals are sufficient to stimulate the neuron to its threshold level, the neuron sends an impulse to its axon. On the other hand, if the inputs do not achieve the required level, no impulse will occur. Therefore, an ANN has ability to extract patterns and derive meaning from complicated or imprecise data that are too complex to be noticed by other computer techniques [11].

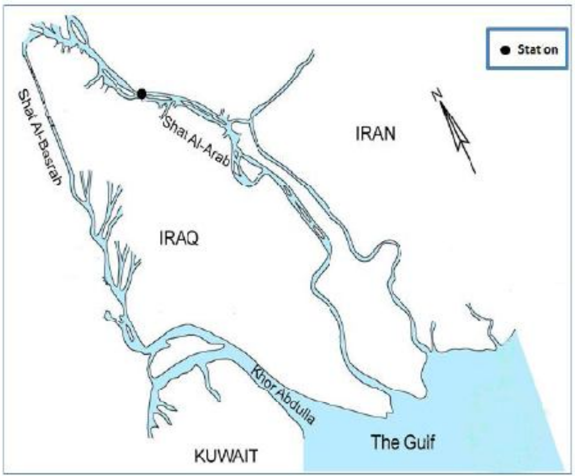

Fig.1 Map of the study area

A. Architecture and performance of ANNs model

ANNs has a different structures and topology. Several authors have reported the structure and the operation of ANNs [11]. The commonest type of Ann's structure consists of a number of artificial neurons, variously known as "nodes" or "units" that are usually arranged in layers. A layer of "input" units is connected to a layer of "output" units and one or more intermediate layers called hidden layers. The basic element of a neural network is the artificial neuron, which consists of three main components namely, weights, bias, and an activation function.

ANNs are used as so called "black box tools" whose rules of operation are completely unknown. This is often review as being their major disadvantage as no realizing of the underlying relationship between inputs and outputs can be gained and no straightforward relationship between inputs and outputs can be found. Furthermore, NNs are not able to explain in an understandable way the process through which a given decision was made. Neural networks are commonly classified by their network topology (i.e. feedback, feedforward) and learning or training algorithms (i.e. supervised, unsupervised) [12]:

(i) Feed-forward artificial neural network: the connections between the processing elements are in the forward direction only in which signals travel one way only frominput to output. Feed-forward ANNs are extensively used in pattern recognition;

(ii) Feedback networks can have signals traveling in both directions by introducing loops in the network.

To construct ANNs model, the available data are grouped into three subsets:

(i) Training set to build the neural network model.

(ii) An independent validation set to estimate the performance ofthe trained network in the deployed environment.

(iii) Testing set is utilized to check the model performance at several stages of training and to decide when to stop training to avert the over-fitting [13].

Multi-layer feed forward neural network with back propagation points the architecture and learning algorithm of the neural network. Back propagation algorithm is one of the generality widely employed supervised training methods for training the multilayer neural networks due to its naivety and applicability [14]. It is based on the generalized delta rule and was generalized by Rumelhart et al. (1986) [15]. The algorithm is simply based a weight correction procedure. It consists of two passes: a forward pass and a backward pass. In the forward pass, first, the weights of the network are randomly formatted and an output set is found for a given input set where weights are kept as fixed. The error between the output of the network and the target value is propagated backward during the backward pass and utilized to update the weights of the previous layers [16]. Feed-forward networks are often have one or more hidden layers of sigmoid neurons followed an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions permit the network to learn nonlinear and linear relationships between input and output vectors. Tangent sigmoid nonlinear transfer function is remark useful for neural networks where speed is important and the exact shape of the transfer function is not.

B. Optimal ANNs model selection

The accuracy of a NN model is chiefly dependent on the network architecture and parameter settings. However, one of the most important tasks in ANN studies is to detect this optimal network architecture, which is based on finding the numbers of optimal layers and neurons in the initial weights for each run in each time, which substantially changes the performance of the trained NN and NN architecture are kept constant. The empirical equation that used is described as [17]:

$$m=\sqrt{i+o}+c \quad \text{.....................................(1)}$$

Where, m, i, and o are the number of nodes in hidden layer ，the number of input parameters and the number of output parameters ，respectively ；c is a constant between 1 and 10.

C. Evaluation of ANNs models performance

Many statistical criteria are usable to compare the goodness/adequacy of any model. The performance evaluation statistics used in this work for ANN training are mean square error (MSE), root mean square error (RMSE), and coefficient of correlation (R). These parameters have been determined applying the following equations:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i - o_i)^2 \quad \text{..............................(2)}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - o_i)^2} \quad \text{..............................(3)}$$

$$R = \frac{\sum_{i=1}^{n}(t_i - \bar{t})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^{n}(t_i - \bar{t})^2 \sum_{i=1}^{n}(o_i - \bar{o})^2}} \quad \text{..............................(4)}$$

Where, t_i is the target value, o_i is the output value, n is the total number, $\bar{t} = \frac{1}{n}\sum_{i=1}^{n} t_i$, $\bar{o} = \frac{1}{n}\sum_{i=1}^{n} o_i$

IV. APPLICATIONS OF ANN AND THE RESULTS

The statistical measures of monthly water quality variables at the Shatt Al Arab station, for the period 2007-2012 (72 data), used in this analysis, are given in Table 1.

Table 1.Statistical parametersof water quality at the Shatt Al Arab River for the study period 2007-2012.

Parameter	Turbidity (NTU)	Total hardness (mg/L)	Total dissolved solids (mg/L)	Electrical conductivity (μmhos/cm)
Sample Size	72	72	72	72
Mean	44.034	1034.155	2702.903	6012.208
Min	4.933	380.986	1060	2016.122
Max	290	3096.13	6913	14711.21
Range	285.07	2715.14	5853	12695.09
Std. Dev.	64.935	493.992	1224.025	2658.04

In order to get a better result from ANNs performance, a network model need to be formulated in a systematic manner. The important step in the developing of ANN models is to choose the model input variables that have the generality significant impact on the model performance. The input variables were selected based on results obtained with statistical analysis, since three independent variables have chosen to construct the ANN model. The input layer has three neurons corresponding to the predictors (turbidity, total hardness, and total dissolved solids) in the prediction model1 and the input layer has also three neurons corresponding to the predictors (total hardness, total dissolved solids, and electrical conductivity) in the prediction model2.

As mentioned earlier, a multilayer feed forward neural network with back propagation is one of the almost used supervised training methods to train the multilayer neural networks because of its simplicity and applicability. Therefore, in this work feed-forward back propagation network was chosen to build the prediction models for the target output (electrical conductivity for prediction model1 and turbidity for prediction model2).

By applying the above equation (Eq.1),number of hidden neurons was ranged from 3 to 13 for this study. Thus, in this study the numbers of neurons in the hidden have been determined based on the maximum value of the coefficient of correlation.

Three data sets were used; a training set was used to generate the ANN model, while a validation and test sets was used to assure the generalization capabilities of the model. One has to match with the model performance that can significantly alter depending on the partitioning of the data into the training and validation sets. To overcome this problem, the measured data set is randomly divided into three subsets: training set (70%), validation and testing sets (each is 15 %). An ANNs was built, trained, and implemented using MATLAB neural toolbox using back propagation with Levenberg-Marquardt algorithm (MATLAB 2014a).

Monthly electrical conductivity (EC) estimates by the Neural Network for Model1 versus monthly electrical conductivity (EC), at the station on Shatt Al Arab river, are shown in Figure 2 (a) and Figure 2 (b), for the training and the test set, respectively. Turbidity (Tur) estimates by the Neural Network for Model2 of Fig. 3 versus monthly measured turbidity (Tur), at the same station, are shown in Figure 3 (a) and Figure 5 (b), for the training and the test set, respectively.

Table 2. R values for EC and Tur optimized models, at the study area, for the training and the testing sets.

Size	EC ANN 3-12-1	Tur ANN 3-9-1
	R	R
Train(50)	0.90457	0.92218
Test(11)	0.96293	0.97851

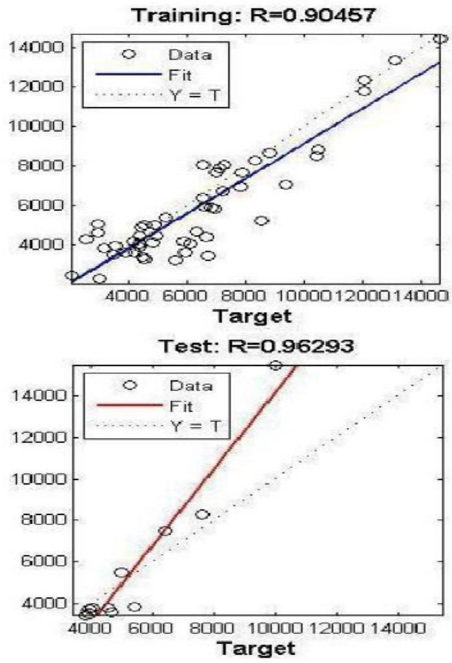

Fig.2 Monthly electrical conductivity (EC) estimates by Neural Networks versus the corresponding monthly measured values at study area, for the training and the testing sets

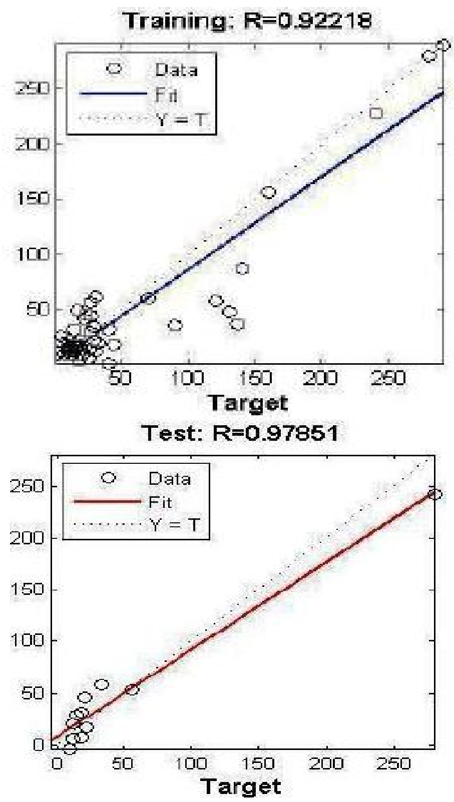

Fig.3 Monthly turbidity (Tur) estimates by Neural Networks versus the corresponding monthly measured values at study area, for the training and the testing sets

From Table 2 and Figures 2 and 3 clearly present the ability of the Neural Network models for the prediction of very well monthly values of concentrations of electrical conductivity (EC) and turbidity (Tur), at the monitoring station. Accordingly, the Neural Network models can be used for the prediction of water quality parameters.

CONCLUSION

In this paper, Neural Networks Models were developed for the prediction of monthly values of the two water quality parameters electrical conductivity (EC) and turbidity (Tur), at the station, of Shatt Al Arab River, Iraq. The monthly data of four water quality parameters (EC, Tur, TH, and TDS), for the time period 2007-2012 were selected for this analysis. For neural network models construction, monthly data is randomly divided into three subsets: training set (70%), validation and testing sets (each is 15 %), were used. The results, for the training and the test data sets distinctly prove the ability of the Neural Network models to predict very well the monthly values of (EC) and (Tur), at the monitoring station by using the monthly values of the other existing water quality parameters which are inserted as inputs into the optimized Neural Network models. Hence, the Neural Network models can be used for the prediction of water quality parameters.

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