



## **DATA-DRIVEN MODELING FOR WATER QUALITY PARAMETERS PREDICTION OF THE DRAINAGE SYSTEM ASSOCIATED WITH LAKE MANZALA, EGYPT**

*Mosaad Khadr<sup>1</sup>, Mohamed Elshemy<sup>2</sup>*

*Irrigation and Hydraulic Engineering Department, Faculty of Engineering, Tanta University, Egypt*

<sup>1</sup>*E-mail: mosaad.khadr@f-eng.tanta.edu.eg*

<sup>2</sup>*E-mail: m.elshemy@f-eng.tanta.edu.eg*

### **ABSTRACT**

Lake Manzala is the largest of the Egyptian lakes along the Mediterranean coast and the most productive for fisheries. It is located on the Eastern margin of the Nile Delta between the Damietta Branch of the River Nile and Port Said on the Suez Canal. Two main drains namely, Bahr El-Baker Drain system and Bahr Hadous Drain system flow into Manzala Lake and drain a considerable volume of drainage water into the lake. Water body of Lake Manzala is affected qualitatively and quantitatively by drainage water that flow into the lake. In most cases of water quality modeling, mathematical models is a helpful tool that might be used to predict the parameters of water quality. Deterministic models are commonly used to simulate the system behavior. Most of these models can only be applied to simplified cases or to situations where the models are strictly calibrated and validated, with no adequate accuracy when applied to unrestricted conditions. However most ecological systems are so complex and unstable. Data-driven models are computing methods that are capable of extracting different system states without using complex relationships. The main objective of the present study is to exploit the capabilities of the adaptive neuro-fuzzy inference system (ANFIS) for drains system quality predictions with emphasis on total phosphorus (*TP*) and total nitrogen (*TN*). Discharge, *pH*, total suspended solids (*TSS*), electrical conductivity (*EC*), total dissolved solids (*TDS*), Temperature, dissolved oxygen (*DO*) and turbidity (*FTU*) were the input parameters of the ANFIS models. The models were calibrated and validated against the measured drainage water data for the period from year 2001 to 2010. Predicted and observed values of water quality parameters were evaluated using several common evaluation criteria. Results of model performance showed that the proposed ANFIS models were capable of simulating the water quality parameters and provided reliable prediction of *TP* and *TN*. Results showed also that the proposed models could be a good tool for Onsite Water Quality evaluation.

**Keywords:** Data-Driven Modeling, Water Quality Parameters, Lake Manzala, Egypt

### **1 INTRODUCTION**

The quality and quantity of water resource worldwide is a subject of ongoing concern (Diamantopoulou, 2005). Assessment and management of long-term water quality of water resources is also a challenging problem (Koschel, 2003; Parparov, 2006; Parparov, 2010). The determination of the water quality refers to the classification by considering the physical, chemical and biological characteristics according to the water usage range (Hambright, 2000). In water quality modeling, the mathematical modeling usually involves several parameters that cannot be measured or involve considerable expense (Rode, 2010; Celsemy, 2012). A deterministic model may also have inevitably errors originated from model structures or other causes. Water quality models are still therefore simplified approximations of reality, and they inevitably contain certain kinds of errors that result in uncertainty in the model results (Ghajarnia, 2011). Therefore the researchers tend to rely on conceptual or empirical models in practical applications to reduce this uncertainty. A new modelling paradigm such as data-driven modelling or data mining has recently been a considerable growth in the development and application of computational intelligence and computer tools with respect to water-related problems (Orouji, 2013; Edsel, 2011).

These techniques are an approach to estimate the water quality based on the field data sets and map the relationship between the water quality parameter according to the temporal and spatial variation (Liu, 2007; C.L. Wu, 2010). Data-driven models refer to a wide range of models that simulate a system by the data experienced in the real life of that system. Data-driven modelling (DDM) is based on analyzing of the data characterizing the system under study, in particular a model can be defined on the basis of finding connections between the system state variables (input, internal and output variables) without explicit knowledge of the physical behavior (Abrahart et al., 2008). Data-driven models include different categories generally divided into statistical and artificial-intelligent models (Kholghi, 2009) which includes neural networks, fuzzy systems and evolutionary computing as well as other areas within artificial intelligence and machine learning.

The use of ANNs and Fuzzy logic has many successful applications in hydrology, in modelling rainfall-runoff processes (Dawson CW, 1998); Dibike et al. (Dibike Y, 1999 ); Abrahart and See (Abrahart RJ, 2000); Govindaraju and Ramachandra Rao; replicating the behaviour of hydrodynamic/hydrological models of a river basin where ANNs are used to provide optimal control of a reservoir (Solomatine DP, 1996); for modelling stage-discharge relationships (Sudheer KP, 2003 ); simulation of multipurpose reservoir operation (Fontane, 1997; Shrestha et al., 1996, Khadr 2014); deriving a rule base for reservoir operation from observed data. The development and current progress in the integration of various artificial intelligence techniques (knowledge-based system, genetic algorithm, artificial neural network, and fuzzy inference system) in water quality modeling, sediment transportation, evaporation, *DO* concentration, and depth integrated estimation of *DO* etc. have been studied by many researchers (Broomhead, 1998; Dogan, 2009; Ranković, 2010). In this paper, adaptive neuro-fuzzy inference system (ANFIS) model was developed for prediction and simulation of water quality in drains system associated with lake Manzala, Egypt with emphasis on total phosphorus (*TP*) and total nitrogen (*TN*). The model developed using various combinations of daily input variables which are: discharge, *pH*, total suspended solids (*TSS*), electrical conductivity (*EC*), total dissolved solids (*TDS*), Temperature, dissolved oxygen (*DO*) and turbidity (*FTU*).

## 2 MATERIALS AND METHODS

### 2.1 Site Description and Water quality parameters

El-Manzala Lake, which is located at the northern edge of the Nile Delta, is the largest of the Egyptian lakes along the Mediterranean coast (Figure 1) (Bek, 2010; El-Adawy, 2013; Abdel Ghaffer, 2006). The lake is bordered at the north by a sandy margin which separates the lake from the Mediterranean Sea except at three outlets where exchange of water and biota occurs. These outlets are El-Gamil, El-Boughdady, and the new El-Gamil (Abdel Mola, 2012). The eastern side of the lake is connected with the Suez Canal through El-Raswa Canal, a few kilometers to the south of Port Said City. To the west, the Damietta branch of the Nile River borders the lake. The southern side of the lake is bordered by cultivated land (Ali, 2008). The Lake is exposed to high inputs of pollutants from industrial, domestic, and agricultural sources. The southern region of the lake characterized by lower values of salinities and high concentration of nutrients and heavy metals as result of receiving high volumes of low salinity drainage water through different drains. The region in the North Eastern area of the lake characterized by high salinity values and low nutrient concentration as a result of seawater intrusion through the outlet openings. The Lake is enriched by drainage water transplanted by drains system which are connected to the Lake at the South and South Eastern Borders. Six major drains contribute a flowrate of 4170 million cubic meters annually (Shakweer, 2005). The main two drains flow into El-Manzala Lake, which are considered in this study, are Bahr El-Baker Drain system and Bahr Hadous Drain system. They drain a considerable volume of drainage water into the lake. Both systems consist of several sub-catchments. Bahr El Baqar drain, which is heavily polluted and anoxic over its entire length, transports untreated and poorly treated wastewater to Lake Manzala over a distance of 170 km. Table 1 presents some statistical characteristics of the data used in this paper.

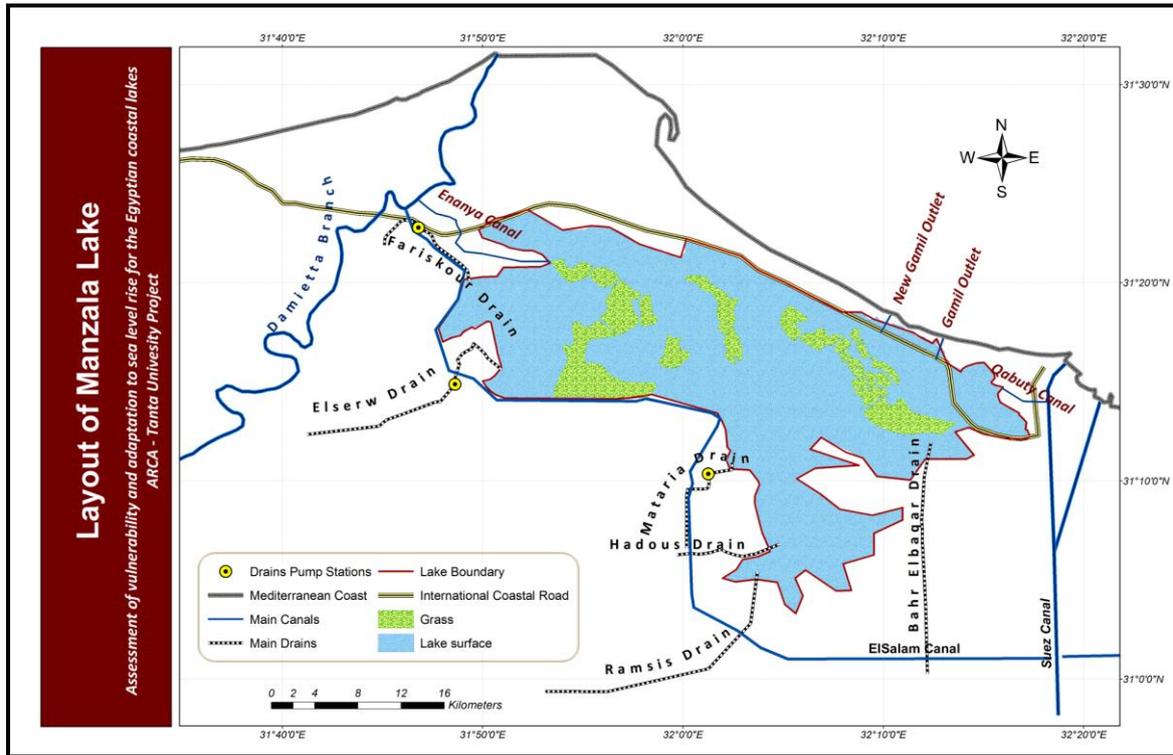


Figure 1. Layout of El-Manzala Lake and main canals and drainage system associated with it

Table 1. Statistical measures of quality parameters in Bahr El Baqar and Bahr Hadous drains

	Bahr El-Baqar drain				Bahr Hadous drain			
	Min.	Max.	Mean	Std.	Min.	Max.	Mean	Std.
Discharge (m <sup>3</sup> /s)	42	59.9	50.38	4.93	2.34	11.65	5.44	2.77
PH	0	197	77.26	42.09	0.00	499.00	38.54	51.81
TSS (µg/L)	6.6	8.45	7.48	0.28	6.82	8.41	7.52	0.27
EC (µg/L)	1.15	6.57	4.36	0.94	0.50	2.28	1.41	0.27
TDS (µg/L)	291	4468	2779.1	645.21	342.0	1420.00	967.11	183.36
Temperature (C <sup>o</sup> )	13	31	23.05	5.31	11.00	32.00	21.90	5.35
DO (µg/L)	0.36	5.6	2.27	1.08	0.08	7.80	1.58	1.52
FTU	39	200	108.73	44.7	14.00	73.00	39.59	15.41
TP (µg/L)	0.14	1.87	0.92	0.3	0.05	2.08	0.79	0.36
TN (µg/L)	0.7	55.6	15.41	13.44	0.31	80.77	10.29	13.17

## 2.2 Adaptive Neuro-Fuzzy Inference System – ANFIS

Fuzzy systems present particular problems to a developer then rules have to be determined somehow (Zadeh, 1973). ANFIS was introduced as an effective tool to represent simple and highly complex functions more powerfully than conventional statistical methods. An adaptive neuro-fuzzy inference system (ANFIS) is a fuzzy inference system formulated as a feed-forward neural network. Hence, the advantages of a fuzzy system can be combined with a learning algorithm (Venugopal et al., 2010). Neuro-fuzzy modeling is a technique for describing the behavior of a system using fuzzy inference rules within a Neural Network (NN) structure. Using a given input/output data set, adaptive neuro-fuzzy inference system (ANFIS) constructs a FIS whose member ship function parameters are

tuned using a back propagation algorithm (Labani M.M., 2010). So, the FIS could learn from the training data. In this study, the ANFIS model was developed in the MATLAB environment.

ANFIS was used to extract the relation of the total phosphorus (TP), total nitrogen (TN), Discharge, pH, total suspended solids (TSS), electrical conductivity (EC), total dissolved solids (TDS), Temperature, dissolved oxygen (DO) and turbidity (FTU). The consequent part is total phosphorus (TP) or total nitrogen (TN). The structure of the ANFIS model consists of a Sugeno type fuzzy system with generalized bell input membership functions and a linear output membership function. The Sugeno model makes use of if rules to produce an output for each rule. It is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that in the Sugeno type rule outputs consist of the linear combination of the input variables plus a constant term; the final output is the weighted average of each rule’s output. Adaptive neuro-fuzzy inference system mimics the operation of a Takagi–Sugeno–Kang (TSK) fuzzy system. Figure 2 presents the typical architecture of ANFIS with a multilayer feed-forward network, which is linked with a fuzzy system for two inputs ( $x$  and  $y$ ). Fuzzy inference systems are composed of five functional blocks and the ANFIS model contains the following (Venugopal et al., 2010):

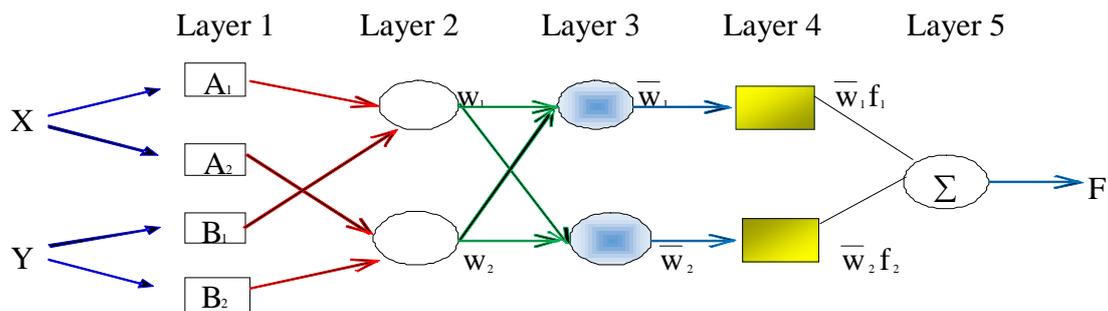
1. A rule base containing a number of if-then rules,
2. A database which defines the membership function,
3. A decision making interface that operates the given rules,
4. A fuzzification interface that converts the crisp inputs into “degree of match “with the linguistic values like high or low etc.,
5. A defuzzification interface that reconverts to a crisp output.

The rule base in the Sugeno model has of the form:

$$\text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1 * x + q_1 * y + r_1 \tag{1}$$

$$\text{If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2 * x + q_2 * y + r_2 \tag{2}$$

Where  $x$  and  $y$  are predefined membership functions,  $A_i$  and  $B_i$  are membership values,  $p_i$ ,  $q_i$ , and  $r_i$  are the consequent parameters that are updated in the forward pass in the learning algorithm, and  $f_i$  is the outputs within the fuzzy region specified by the fuzzy rule.



**Figure 2: An ANFIS architecture for a two rule Sugeno system**

Let the membership functions of fuzzy sets  $A_i$  and  $B_j$ , be  $\mu_{A_i}$  and  $\mu_{B_j}$  respectively. The five layers that integrate ANFIS are as follow: Let the output of the  $i^{th}$  node in layer 1 is denoted as  $O_{1,i}$ , then,

Layer 1: Every node  $i$  in this layer is an adaptive node with node function

$$Q_{1,i} = \mu_{A_i}(x) \text{ for } i = 1, 2, \text{ or } Q_{1,i} = \mu_{B_{i-2}}(y) \text{ for } i = 3, 4 \tag{3}$$

Where  $x$  (or  $y$ ) is the input to the  $i^{th}$  node and  $A_i$  (or  $B_{i-2}$ ) is a linguistic labels.

Layer 2: This layer consists of the nodes labeled which multiply incoming signals and send the product out. Each node output represents the firing strength of a rule.

$$O_{2,i} = w_i = \mu_{A_i}(x) \mu_{B_i}(y) \quad \text{for } i = 1, 2 \tag{4}$$

Layer 3: In this layer, the nodes labeled N acts to scale the firing strengths to provide normalized firing strengths.

$$O_{3i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i=1,2 \tag{5}$$

Layer 4: The output of layer 4 is comprised of linear combination of inputs multiplied by normalized firing strengths. This layer’s nodes are adaptive with node functions.

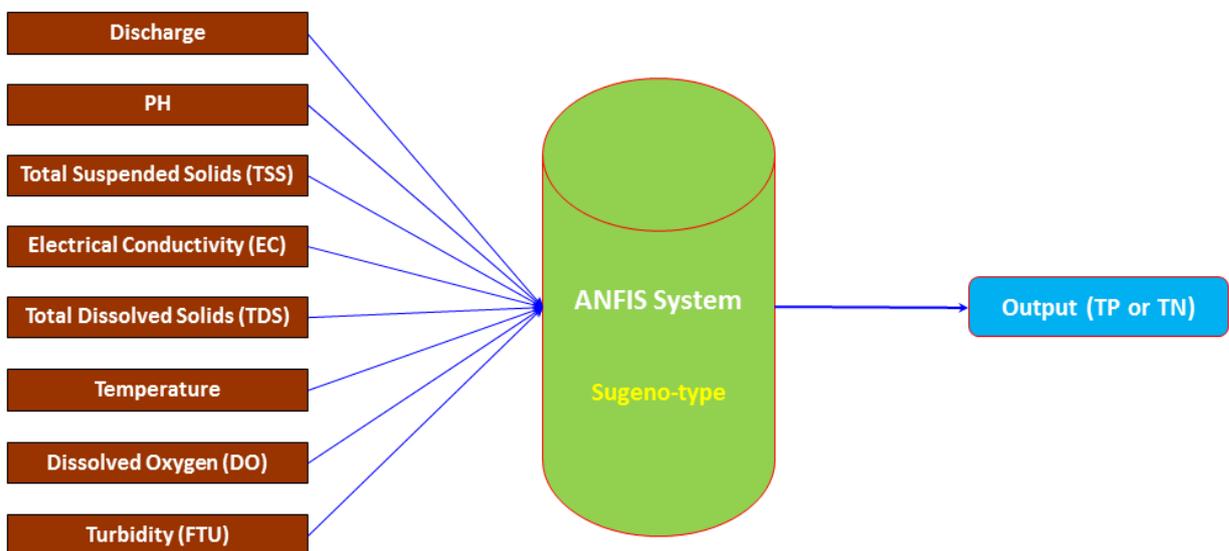
$$O_{4i} = w_i f_i = w_i (p_i x + q_i y + r_i) \tag{6}$$

Where,  $w_i$  is the output of layer 3, and  $\{p_i, q_i, r_i\}$  are the parameter set. Parameters of this layer are referred to as consequent parameters.

Layer 5: This layer consists of a single node, computes the final output as the summation of all incoming signals

$$O_{5i} = \sum_{i=1} \bar{w}_i f_i = \frac{\sum_{i=1} w_i f_i}{\sum_{i=1} w_i} \tag{7}$$

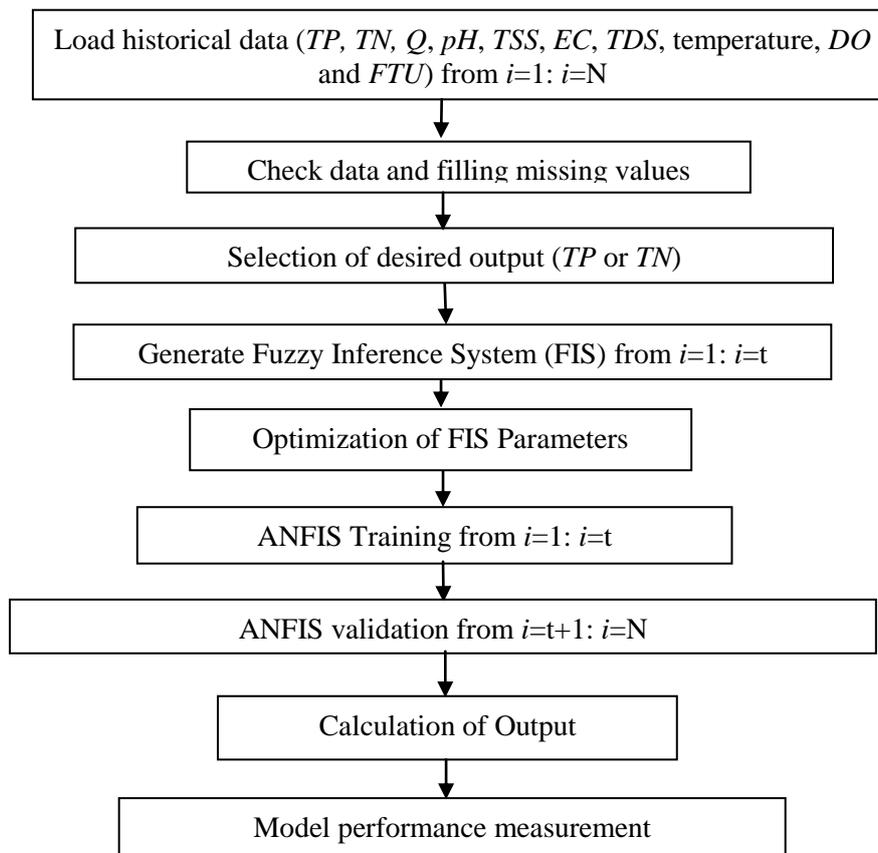
Layers represented by squares are adaptive and their values are adjusted when carrying out the system training. Layers represented by circles remain invariable before, during and after the training (Kablan, 2009). Figure 3 illustrates the network used in this paper and consists of 8 inputs, and 1 outputs membership function (TP or TN).



**Figure 3: An ANFIS architecture for a two rule Sugeno system**

### 3 RESULTS AND DISCUSSION

The Adaptive Neuro-Fuzzy Inference System (ANFIS) was used to derive and to develop models for prediction of water quality parameters in Bahr El-Baker Drain system and Bahr Hadous Drain system. To simulate and predict the behavior of quality parameters in the two Drain systems, a time series of the ten previously noted parameters in a 10-year (120-month) period was used. For ANFIS models construction, monthly data set has been randomly partitioned into two parts for the training and testing processes by considering 70 and 30% respectively, which are common divisional percentages in data-driven models. Accordingly, data set divided into used 7 and 3-year periods, respectively, for the training and testing data sets. Fuzzy inference system structure of a Sugeno-type is then generated using subtractive clustering and the separate sets of input and output data as input arguments and this was applied to TP and TN as well. The aim of this step is to determine the number of rules and antecedent membership functions and then uses linear least squares estimation to determine each rule's consequent equations to cover the feature space. A hybrid learning algorithm was used to identify parameters of Sugeno-type fuzzy inference systems by applying a combination of the least-squares method and the backpropagation gradient descent method for training FIS membership function parameters to emulate a given training data set. The network is trained to obtain the nearest output to the target. In order to find the best model, an optimization model was developed to find the ANFIS parameters that give best performance. The performance function that was used for feed-forward is the root of mean square error between the network outputs and the target output. More than 119 models were tested to select the best model which fits data space with best performance. Once the best working model is selected through ANFIS training, the TP and TN predicted values of will be worked out and compared with actual measured values to evaluate the prediction results as shown in figure 4.



**Figure 4: Flowchart of the water quality parameters simulation using ANFIS**

To compare the performance of the data-driven models, some comparison criteria were employed. The measures that were used in this paper include; Mean Absolute Deviations (*MAD*), the coefficient

of determination ( $R^2$ ), Root Mean Square Error ( $RMSE$ ) and correlation coefficient ( $C_r$ ). To investigate whether there is a significant difference between the mean from the observed and predicted data for various lead-time, a two-sample  $t$ -test for the means was employed in the analysis. . The performance criteria calculated using the following equations:

$$MAD = \frac{\sum_{i=1}^n |WQ_{oi} - WQ_{fi}|}{n}$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (WQ_{oi} - WQ_{fi})^2}{\sum_{i=1}^n (WQ_{oi})^2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (WQ_{oi} - WQ_{fi})^2}{n}}$$

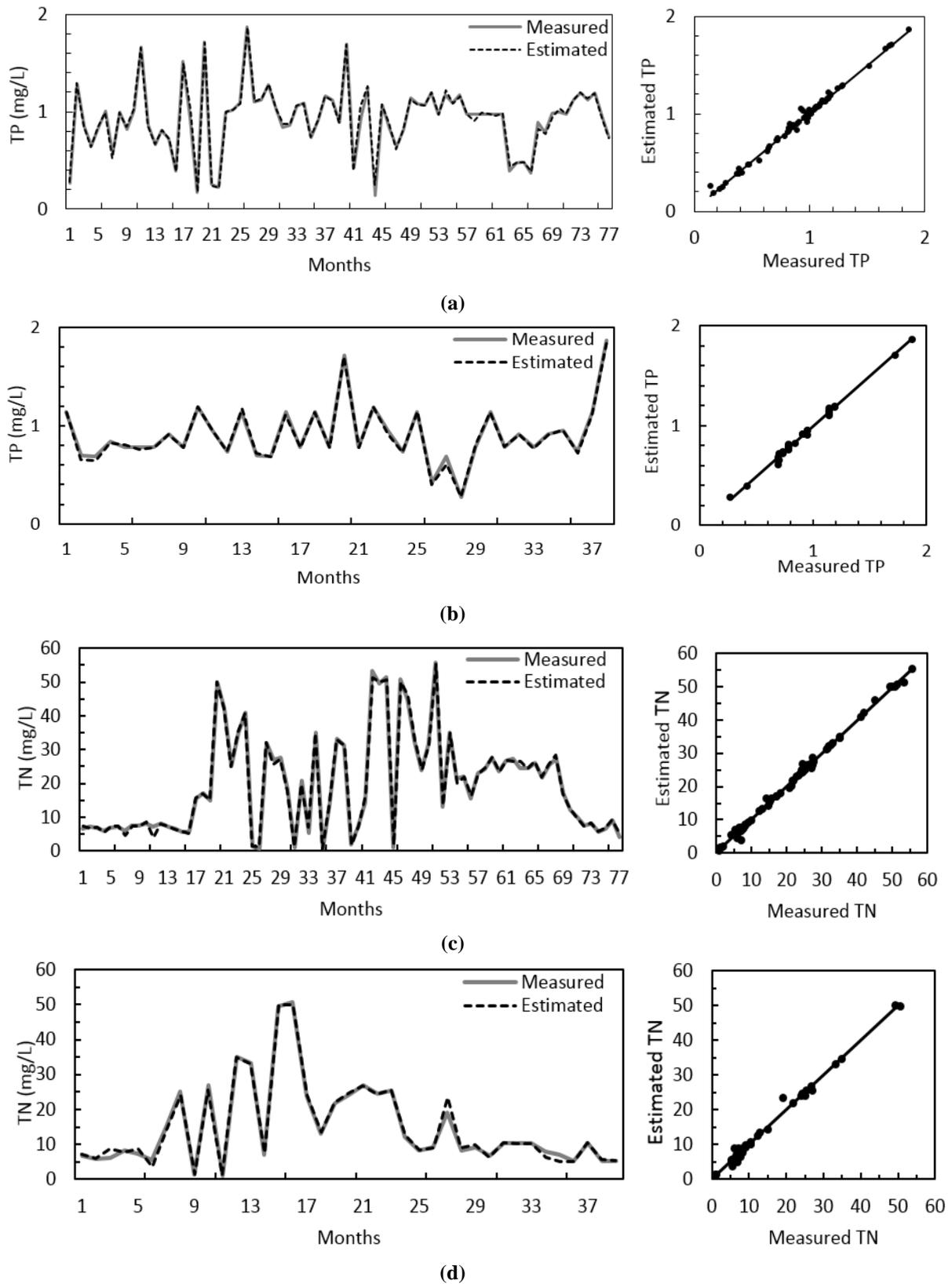
$$C_r = \frac{\sum_{i=1}^n WQ_{oi} WQ_{fi} - \frac{(\sum WQ_{oi})(\sum WQ_{fi})}{n}}{\sqrt{\left[ \left( \sum_{i=1}^n WQ_{oi}^2 - \frac{(\sum_{i=1}^n WQ_{oi})^2}{n} \right) \left( \sum_{i=1}^n WQ_{fi}^2 - \frac{(\sum_{i=1}^n WQ_{fi})^2}{n} \right) \right]}}$$

Where  $WQ_o$  is the observed value,  $WQ_f$  is the predicted value and  $n$  is the number of data points. In statistics, the coefficient of determination,  $R^2$  is used in the context of statistical models whose main purpose is the prediction of future outcomes on the basis of other related information. The absolute fraction of variance,  $R^2$ . The  $RMSE$  is the square root of the variance of the residuals. It indicates the absolute fit of the model to the data—how close the observed data points are to the model’s predicted values. Whereas  $R$ -squared is a relative measure of fit,  $RMSE$  is an absolute measure of fit. Lower values of  $RMSE$  indicate better fit. The correlation coefficient a concept from statistics is a measure of how well trends in the forecasted values follow trends in past actual values (historical values). The  $MAD$  and the  $RMSE$  can be used together to diagnose the variation in the errors in a set of prediction. The  $RMSE$  will always be larger or equal to the  $MAD$ ; the greater difference between them, the greater the variance in the individual errors in the sample. If the  $RMSE = MAE$ , then all the errors are of the same magnitude.

Figures 5, 6 present the monthly values of total phosphorus ( $TP$ ) and total nitrogen ( $TN$ ) estimated by ANFIS versus the corresponding measured values for the training and the test data set and respectively for Bahr El-Baker Drain system and Bahr Hadous Drain system. It can be seen in Figures 5, 6 that the two curves of observed and estimated data almost overlap each other and the trend between the measured and estimated values is similar except few which are more deviated from actual measured values. The error rate of the model for the training period was rather small as shown in table 2. Simulation testing was then done to validate the prediction results of the model. The estimates of ANFIS models in validation phase are compared in Table 2. It is clearly seen from the table that the ANFIS performs satisfactory and the overall prediction results are fairly good from the  $RMSE$ ,  $MAE$  and  $R^2$  viewpoints. Correlation between the two groups of data indicates that the correlation coefficient for both  $TP$  and  $TN$  in case of Bahr El-Baker Drain is 0.901 and 0.857 respectively, however in Bahr Hadous Drain and analysis  $C_r$  equals 0.802 and 0.929 respectively. The two-sample  $t$ -test failed to reject the null hypothesis at the 5% significance level ( $h=0$ ) that both predicted and measured data comes from independent random samples from normal distributions with equal means.

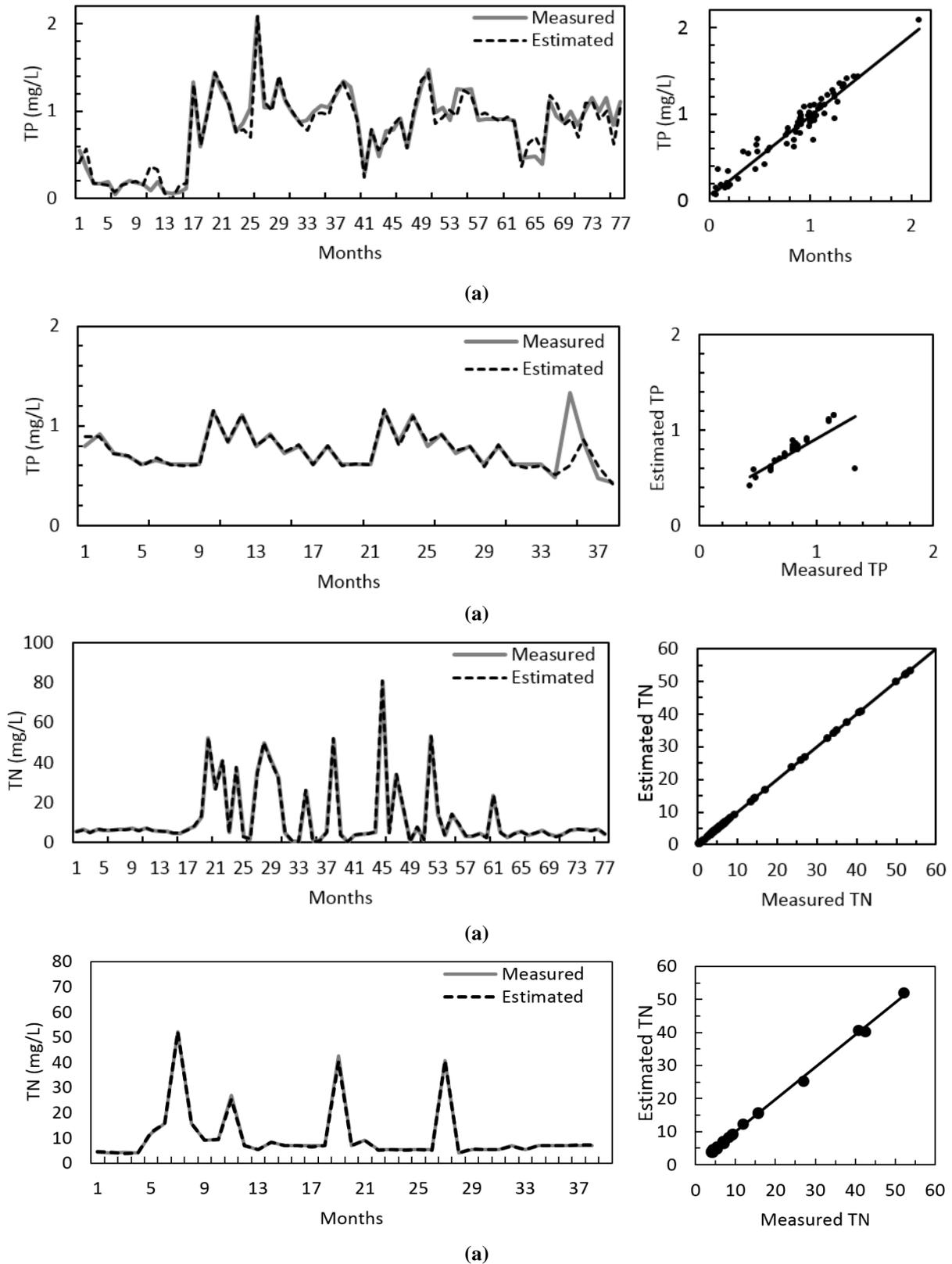
**Table 2. Statistical measures of quality parameters in Bahr El Baqar and Bahr Hadous drains**

		Bahr El-Baqar drain				Bahr Hadous drain			
		$MAD$	$R^2$	$RMSE$	$C_r$	$MAD$	$R^2$	$RMSE$	$C_r$
Training	TP	0.016	0.983	0.029	0.976	0.071	0.988	0.102	0.971
	TN	0.457	0.999	0.756	0.945	0.009	1.000	0.018	1.000
Testing	TP	0.015	0.941	0.023	0.901	0.036	0.976	0.122	0.802
	TN	0.682	0.917	1.109	0.857	0.209	0.909	0.478	0.829



**Figure 5. Observation and estimation of water quality parameters using ANFIS model in Bahr El-Baker Drain**

(a) TP training period; (b) TP testing period; (c) TN training period; (d) TN testing period



**Figure 5. Observation and estimation of water quality parameters using ANFIS model in Bahr Hadous Drain**

(a) TP training period; (b) TP testing period; (c) TN training period; (d) TN testing period

## 4 CONCLUSIONS

In this paper Data-driven models, that use previous experiences or measurements of a natural system and yield a synthetic relationship between inputs and output, were used for prediction of water quality parameters. This paper adopted ANFIS models to achieve easier and faster drains system quality predictions with emphasis on total phosphorus (*TP*) and total nitrogen (*TN*) at Bahr El-Baker Drain system and Bahr Hadous Drain system. Two main ANFIS models were constructed for Both *TP* and *TN*. The performance of the developed models was analyzed on a 10-years database of ten water quality parameters. Comparison between predicted and measured data, using several evaluation criteria, confirmed the accuracy of the developed ANFIS models. The correlation between the predicted and actual measured values was fairly good and suggested that the model is a useful tool for prediction of both *TP* and *TN* and it could be applied to real practice and as a tool for Onsite water quality evaluation.

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