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AN AUGMENTED WAVELET DE-NOISING TECHNIQUE WITH NEURO-FUZZY INFERENCE SYSTEM FOR WATER QUALITY PREDICTION

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Abstract. *Johor River Basin is located in Johor state, Malaysia, which is significantly degrading due to human activities and development along the river. Accordingly, it is very important to implement and adopt a water quality prediction model that can provide a powerful tool to implement better water resource management. Several modeling methods have been applied to this research including: Multi Layer Perceptron Neural Networks (MLP-ANN), Radial Basis Function Neural Networks (RBF-ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS). Nevertheless, the data arising from monitoring stations and experiment may be polluted by noise signals owing to systematic errors and random errors. This noisy data often make the predict task relatively difficult. Therefore, this study suggests an augmented Wavelet De-noising Technique with Neuro-Fuzzy Inference System (WDT-ANFIS). In this study, the water quality parameters in the domain of interests are dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD). Two scenarios were introduced: Scenario 1 was to construct prediction model for water quality parameters at each station, while Scenario 2 was to construct prediction model based on the value of same parameter at previous station (upstream), and both were based on the value of the twelve input parameters. The WDT-ANFIS was verified based on field data from 2009-2010. The WDT-ANFIS model outperformed all the proposed models and improved predicting accuracy for all water quality parameters. Scenario 2 performed more adequately than Scenario 1 with significant improvement ranging from 0.5% to 3.1% for all water quality parameters at all stations. The verification of the proposed model showed that the model satisfactorily predicted all the parameters (R^2 values bigger than 0.9).*
Keywords: MLP-ANN, RBF-ANN, WDT-ANFIS

1. **Introduction.** Increasing concerns about the environment, associated with limited budget, are generating increasing interest in rational and cost-effective approaches for water quality management. Because water quality management will have direct impacts on human health, improvement in the quality of water available for human consumption will contribute to the reduction of health hazards [1]. Water quality modelling is the basis of water pollution control project. It predicts the water quality tendency of varieties according to the current water environment quality condition, transfer and transformation rule of the pollutants in the river basin. In addition, several water quality models, such as determistic and stochastic models have been developed in order to manage the best

practices for conserving water quality [2,3]. Most of these models are very complex and require a significant amount of field data to support the analysis. Furthermore, many statistical-based water quality models, which assume the relationship between response variable and prediction variable, are linear and distributed normally. However, the accurate and efficient modelling of water quality in complex water bodies is still challenging due to the complexity and variability of the real world, the uncertainty in model structure and model parameters, and the error in measured data. Therefore, traditional data processing methods are no longer efficient enough for solving the problem [4]. More efforts need to be made to be improving the reliability of models results. Recently, Artificial Intelligence (AI) technique has been accepted as an efficient alternative tool for modeling of complex non-linear systems. The models usually do not consider the internal mechanism but build models via the relationship between inputs and outputs. At present, AI has been used intensively for prediction in a number of water-related areas [5-11]. The above study efforts were normally based on an assumption that the data to be used should be reliable and accurate. However, the data arising from investigation and experiment may be polluted by noise signals due to the subjective and/or objective errors [12]. For example, the experiment errors may be resulted from measurement, reading, recording, and external conditions. Since these noisy signals are probably to distort the results of models, it is a must to remove them (that is, signal denoising) before using any original data. Signals can be denoised through the application of a set of linear filters [13]. However, one problem of these filters is that they are more appropriate in linear systems than nonlinear systems. In addition, Fourier analysis technique (FAT) is a classical tool for reducing noises, but it is only suitable for denoising data/signals containing steady noises. Due to the noises that are unsteady in real-world cases, its application is still limited. To overcome the problems of traditional denoising techniques, more sophisticated techniques such as wavelet de-noising technique (WDT) have been proposed. WDT is useful for denoising multi-dimensional spatial/temporal signals containing steady/unsteady noises. It has been widely applied to engineering systems for patterns recognition and knowledge discovery [14,15]. Nevertheless, few of these studies were applied to water quality management systems, where the water quality monitoring data needs to be used for parameter prediction [16]. In this article, an augmented WDT-ANFIS based on historical data of water quality parameters will introduce. In addition, a comprehensive comparison analysis was also carried out between the proposed model (WDT-ANFIS) and different techniques of Artificial Intelligence (AI) namely, the Multi Layer Perceptron Neural Networks (MLP-ANN), Radial Basis Function Neural Networks (RBF-ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) to evaluate the performance achieved after removing the noises from the data.

2. Methods and Materials.

2.1. **Study area and data analysis.** Johor is the second largest state in the Malaysia Peninsular, with an area of 18,941 km^2. The Johor River and its tributaries are important sources of water supply, not only for the state of Johor but also for Singapore. The river comprises 122.7 km long drains, covering an area of 2,636 km^2. It originates from Mount Gemuruh and flows through the southeastern part of Johor and finally into the Straits of Johor. The catchment is irregular in shape. The maximum length and breadth are 80 km and 45 km, respectively. About 60% of the catchment comprises undulating highlands rising to a height of 366 m, while the remainder encompasses lowland and swampy areas. The station's location map is provided in Figure 1. This station includes four locations along the main stream of the river, which are near to the mouth of the major tributaries.

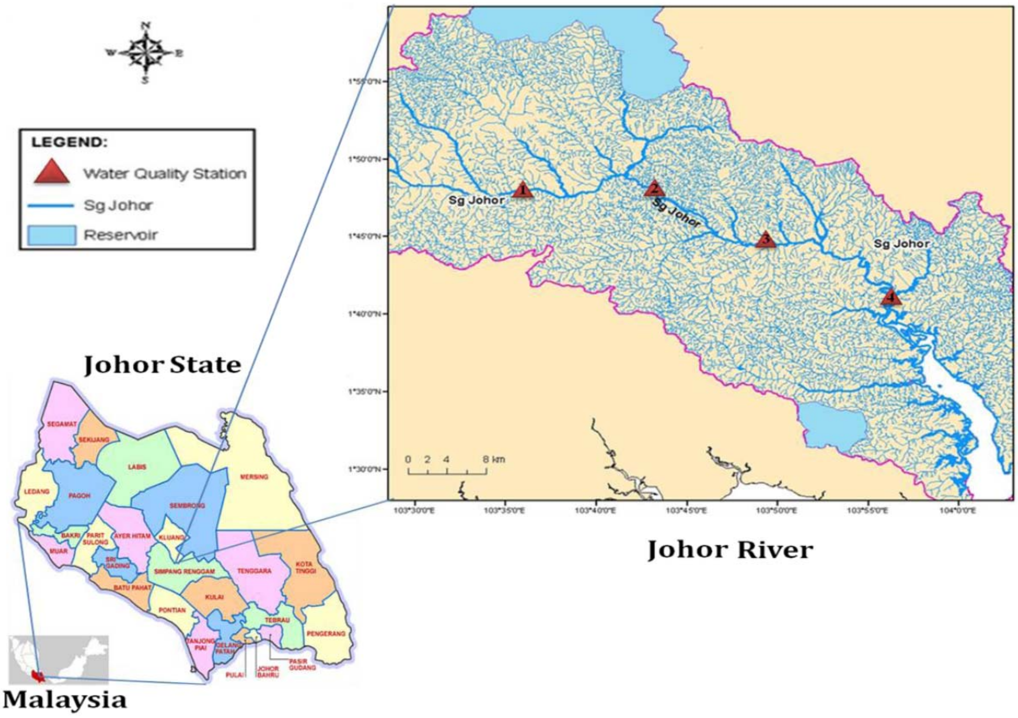


FIGURE 1. Map showing the geographical setting of the survey area with four field monitoring stations on the main stream

The proposed models in this research were constructed under the assumption that land use/cover has remained unchanged during the study period. However, land use/cover is an important factor for the prediction of water quality parameters. A more precise prediction of water quality parameters could be achieved by adding variables representing the land use/cover status into the model.

The area of research is based on the secondary data of water quality parameters of Johor River. In this study, the water quality parameters in the domain of interest are dissolved oxygen (DO), biochemical oxygen demand (BOD) and chemical oxygen demand (COD) due to their importance when studying the water quality status of any rivers. These water quality parameters were measured within the period of 1998-2007. The amount of dissolved oxygen present in a watercourse is one of the most important measures of the water quality. It is also commonly used as indicators of a river's health. The number of life forms that survive begins to decrease as the level of DO drops below 4 mg/l. In extreme cases, when anaerobic condition exists, most high forms of life are either killed or driven off. Eventually conditions like floating sludges, bubbling, odourous gasses and slimy fungal growths will subsist [17]. Most organic materials such as those from waste water treatment plants, industrial effluents and agricultural run-off are biodegradable. The amount of oxygen used in the metabolism of biodegradable organics is termed biochemical oxygen demand. When organic matter decomposes, microorganisms such as bacteria and fungi feed upon it and eventually it becomes oxidized. Biochemical oxygen demand (BOD) is a measure of the quantity of oxygen used by these microorganisms in the aerobic oxidation of organic matter chemical oxygen demand (COD) is a water quality parameter to indicate the level of pollution in the water based on chemical characteristics and is a measure of the amount of oxygen required to oxidize the organic matter chemically by a strong oxidant known as dichromate and sulfuric acid. COD is therefore an estimate of the amount of organic and reduced matter present in the water or better known as the amount of oxygen needed to chemically decompose the organic matter in the water. The basic statistical parameters, namely, minimum, mean, maximum, standard deviation (S.D.), and coefficient of variation (CV) of the input parameters used in this study, are presented in Table 1.

TABLE 1. The basic statistical analysis for six water quality parameters

	Unit	Mean	Minimum	Maximum	SD	CV
SN01						
DO	mg/l	6.25	2.91	7.34	0.59	9.52
COD	mg/l	22.14	3.00	56.00	6.67	30.13
BOD	mg/l	1.80	1.00	5.00	0.87	48.36
SN02						
DO	mg/l	6.14	4.84	6.96	0.42	6.83
COD	mg/l	23.28	9.00	42.00	7.09	30.45
BOD	mg/l	2.26	1.00	16.00	2.21	97.57
SN03						
DO	mg/l	5.80	3.97	6.78	0.69	11.95
COD	mg/l	20.28	1.00	45.00	8.45	41.67
BOD	mg/l	2.05	1.00	9.00	1.74	84.59
SN04						
DO	mg/l	5.54	4.41	7.53	0.67	12.07
COD	mg/l	19.28	1.00	38.00	6.16	31.92
BOD	mg/l	1.86	1.00	9.00	1.57	84.68

2.2. **Proposed techniques.** Wavelet analysis represents the next logical step after short-time Fourier transforms (STFT). It is based on a windowing technique with variable-sized regions. Wavelet transform (WT) allows the use of long time intervals where we want more precise low frequency information, and shorter regions where we want high frequency information [18]. In general, the major advantage offered by wavelets is the ability to perform local analysis; that is to analyze a localized area of a larger signal. The discrete-time WT of a time domain signal $x[k]$ is given as [16]:

$$DWT(m,n) = 1 \Big/ \sqrt{2^m} \sum\nolimits_k x[k]\psi[2^{-m}n - k] \tag{1}$$

where $\psi(n)$ is the mother wavelet while m and k are, respectively, the scaling and shifting indices. The scaling gives the DWT logarithmic frequency coverage in contrast to the uniform frequency coverage of the STFT. This analysis method then consists of decomposing a signal into components at several frequency levels, which are related by powers of two (a dyadic scale) [18]. The filtering approach to multi-resolution WT is to form a series of half-band filters that divide a spectrum into a high frequency band and a low frequency band. It is formulated on a scaling function or low-pass filter (LP) and a wavelet function or high-pass filter (UP) [19]. Wavelet Multi-resolution analysis (WMRA) builds a pyramidal structure that requires an iterative application of scaling and wavelet functions to low-pass and high pass filters, respectively. These filters initially act on the entire signal band at the high frequency (small-scale values) first and gradually reduce the signal band at each stage. As in Figure 2, the high-frequency band outputs are represented by the detail coefficients (Dl, D2, D3), and the low-frequency band outputs are represented by the approximation coefficients (Al, A2, A3).

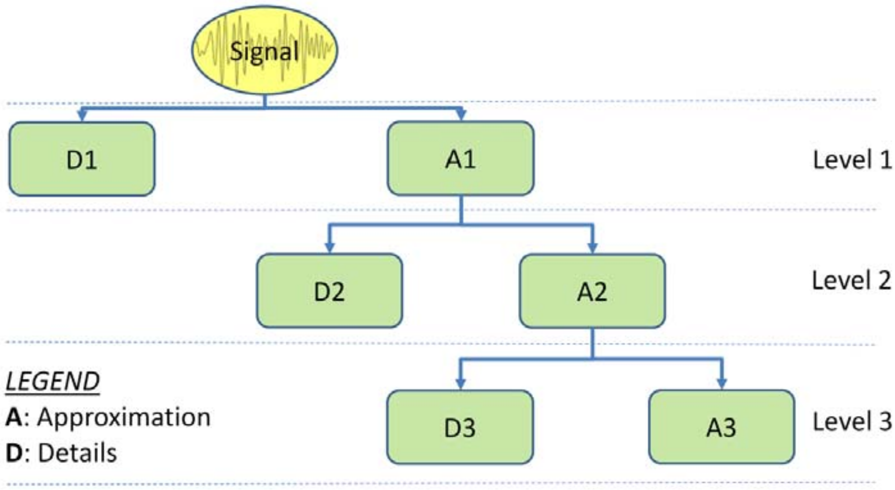


FIGURE 2. Scheme representing of the pyramid structure representing WMRA

Adaptive neuro-fuzzy inference system (ANFIS), first was proposed by Jang in 1993 [20], can achieve a highly nonlinear mapping and it is superior to common linear methods in producing nonlinear time series [21]. Throughout this research, it was considered the ANFIS architecture for the first order Sugeno fuzzy model [22]. The ANFIS is a multilayer feed forward network which uses neural network learning algorithms and fuzzy reasoning to map an input space to an output space [23]. Assuming the fuzzy inference system under consideration has two inputs, x and y, and one output, f for a first-order Sugeno fuzzy model, a common rule set with two fuzzy if.then rules can be expressed as:

$$\text{Rule 1: If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1x + q_1y + r_1 \tag{2}$$

$$\text{Rule 2: If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2x + q_2y + r_2 \tag{3}$$

where A_1, A_2 and B_1, B_2 are the membership functions (mfs) for inputs x and y, respectively; p_i, q_i and r_i ($i = 1$ or 2) are linear parameters in the consequent part of the first-order Sugeno fuzzy model. Figure 3(a) illustrates the fuzzy reasoning mechanism for this Sugeno model to derive an output function (f) from inputs x and y. The corresponding equivalent ANFIS architecture is showed in Figure 3(b), where nodes of the same layer have similar functions. ANFIS consists of five layers as shown in Figure 3(b).

In fact, the prediction procedure is, by definition, an operation through which the future water quality parameter patterns can be provided. In this study, the WDT-ANFIS with its non-linear and stochastic modeling capabilities was utilized to develop a prediction model that mimicked the water quality parameter patterns at Johor River based on the 12 input parameters (Scenario 1), which can be expressed as follows:

$$\begin{aligned} WQIP_N = {} & f_{WDT\text{-}ANFIS}(Temp_N + COND_N + SAL_N + TUR_N + NO_{3N} \\ & + CI_N + PO_{4N} + Fe_N + K_N + Mg_N + Na_N + E\text{-}coli_N) \\ N = {} & 1, 2, 3, 4 \end{aligned} \tag{4}$$

where $WQIPN$ is the water quality index parameters at station N, and $f_{WDT\text{-}ANFIS}(.)$ is the non-linear function predictor constructed by the WDT-ANFIS network. Hence, a total of four models for the water quality parameters predictions were constructed at each station. Most of the recent studies attempted to predict the concentrations of water quality parameters at each station. Generally, the water pollution of a downstream station is affected by the discharge of the local area from the upstream station [24]. Hence, it was required to consider the effect of water parameters at the upstream station in the proposed model. Therefore, the second scenario (Scenario 2) was formed to establish

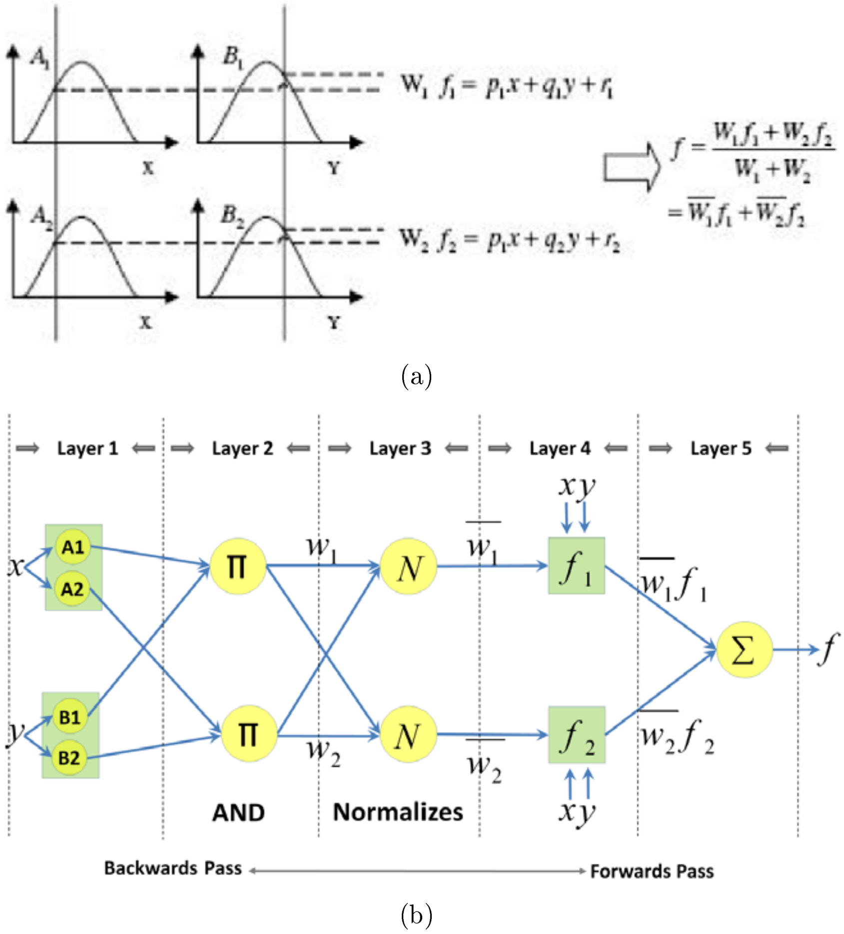


FIGURE 3. (a) A two input first order Sugeno fuzzy model with two rules; (b) equivalent ANFIS structure

the model prediction for the water parameters at each station based on the 13 input parameters. The predicted WQIP at the previous station (upstream) can be expressed following Equation (5). This procedure of using the predicted WQIP can be repeated for the third and fourth stations at downstream. The schematic representation of the proposed networks for Scenario 2 is shown in Figure 4. In addition, in order to investigate the efficiency of the proposed model (Scenario 2), the verification based on collection of field data within duration 2009-2010 is presented.

$$\begin{aligned} WQIP_{N+1} = \; & f_{WDT\text{-}ANFIS}(Temp_N + COND_N + SAL_N + TUR_N + NO_{3N} + CI_N \\ & + PO_{4N} + Fe_N + K_N + Mg_N + Na_N + E\text{-}coli_N + WQIP_{pN}) \end{aligned} \tag{5}$$

3. **Performance Criteria.** Due to the fact that water parameters had been truthfully monitored over the 5-year period, the performances of the proposed models could be examined and evaluated. The performances of the models were evaluated according to three statistical indexes. Coefficient of Efficiency (CE) is often used to evaluate the model

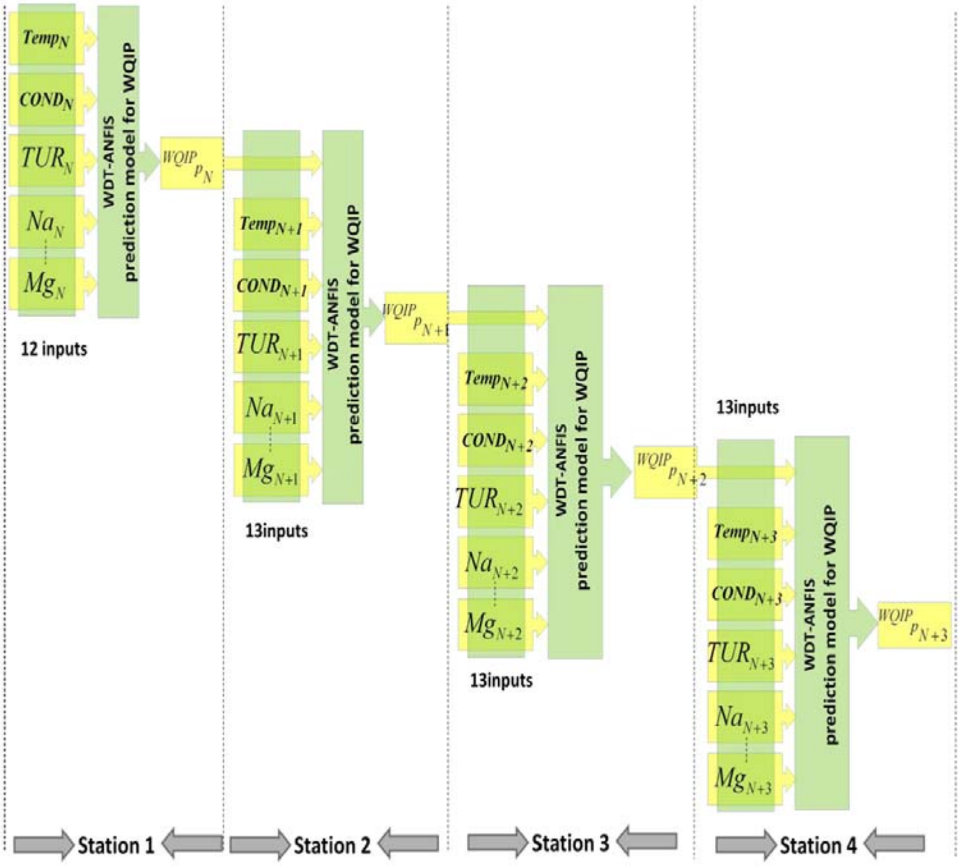


FIGURE 4. The schematic representation of the proposed networks for Scenario 2

performance, introduced by Nash [25]

$$CE = 1 - \frac{\sum_{i=1}^{n}(X_m - X_p)^2}{\sum_{i=1}^{n}(X_m - \bar{X}_m)^2} \tag{6}$$

where n is the number of observations, X_p and X_m are the predicted and measured parameter, respectively, and $\bar{X}_m$ is the average of measured parameter. The Mean Square Error (MSE) can be used to determine how well the network output fits the desired output. The smaller values of MSE ensure better performance. It is defined as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_m - X_p)^2 \tag{7}$$

The coefficient of correlation (CC) is often used to evaluate the linear relationship between the predicted and measured parameter. It is defined as follows:

$$CC = \frac{\sum_{i=1}^{n}(X_m - \bar{X}_m)(X_p - \overline{X_p})}{\sqrt{\sum_{i=1}^{n}(X_m - \bar{X}_m)^2 \sum_{i=1}^{n}(X_p - \overline{X_p})^2}} \tag{8}$$

4. **Result and Discussions.**

4.1. **Optimal parameter selection for proposed models.** The development of an ANN model usually consists of three steps. The first step is the training stage, where the network is subjected to a training set of input-output patterns. The second step is the validation stage, where the performance of the network is tested on patterns that have not been 'seen' by the network during the training stage. The third step is the testing stage, where the performance of the network is tested based on the unknown patterns that have not been 'seen' during both stage training and validating stages [26]. Six MLP-ANN architectures were developed (one for each parameter). All six networks utilize the Levenberg-Marquardt Back Propagation algorithm (LMA) during the training procedure. Three activation functions were used: the log-sigmoidal (logsig) function, tan-sigmoidal (Tansig) and the linear transfer function (purelin). Once the network weights and biases are initialized during the training process, the weights and biases of the network are iteratively adjusted to minimize the network performance function mean square error (MSE) – the average squared error between the network outputs and the target outputs.

In order to find the optimum result for this study, varying values of learning rate (lr) introduced to the networks. In fact, the learning rate is crucial for backpropagation learning algorithm since it determines the magnitude of weight changes. However, training with smaller learning rate values tends to slow the learning process and it is not preferred. On the other hand, training with larger learning rates values may cause network oscillation in the weight space. One way to improve the gradient descent method is to include an additional momentum parameter (mc) to allow for larger learning rates resulting in faster convergence while minimizing the tendency to oscillation [27] The idea of introducing the momentum term is to make the next weight change in more or less the same direction as the previous one and hence reduce the oscillation effect of larger learning rates. Since there are few systematic ways of selecting the learning rate and momentum simultaneously, the best values of these learning parameters are usually chosen through experimentation. As the learning rate and the momentum can take on any value between 0 and 1, it is actually impossible to do an exhaustive search to find the best combinations of these training parameters. In this study, different learning rate and momentum were investigated on the both networks, in practice; 0.9 and 0.85 were chosen as the optimum learning rate and momentum for the DO, BOD and COD model, respectively.

A learning matrix including 60% training samples drawn from data was used in training each network. In order to achieve fast training convergence to the target MSE of 0.0001, the input and output data were normalized with respect to the corresponding maximum values in the input vectors using linear normalization functions. Data normalization is often performed before training process begins. Training, validation and testing processes of the MLP-NN model were performed to minimize the Mean Square Error (MSE) between the output and the desired response, as shown in Figure 5. It was apparent that the performance goal was achieved in less than 24 and 15 iterations (epochs) for DO and COD, respectively.

One of the most important characteristics of MLP-ANN technique is the number of neurons in the hidden layer. If an insufficient number of neurons are used, the network will be unable to model the complex data and the resulting fit will be poor. On the contrary, if too many neurons are used, the training time may become excessively long and the network may over fit the data. In this study, different MLP-ANN architectures were used to examine the best performance. In fact, there is no formal and/or mathematical method for determining the appropriate "optimal set" of the key parameters of Neural Network. Therefore, it was decided to perform this task utilizing the trial and error method. The neurons of the hidden layer were randomized from $N = 1$ to 20 neurons and the best number of nodes in the hidden layer is the one that gives the lowest error [28].

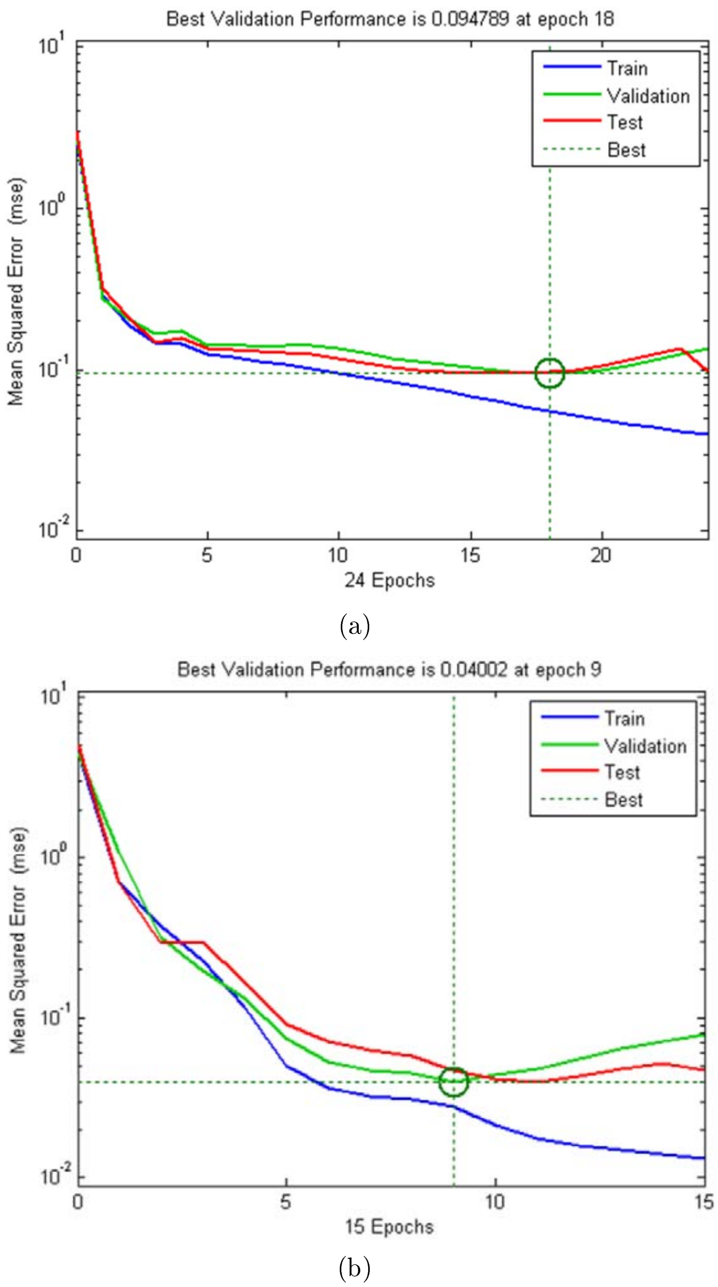
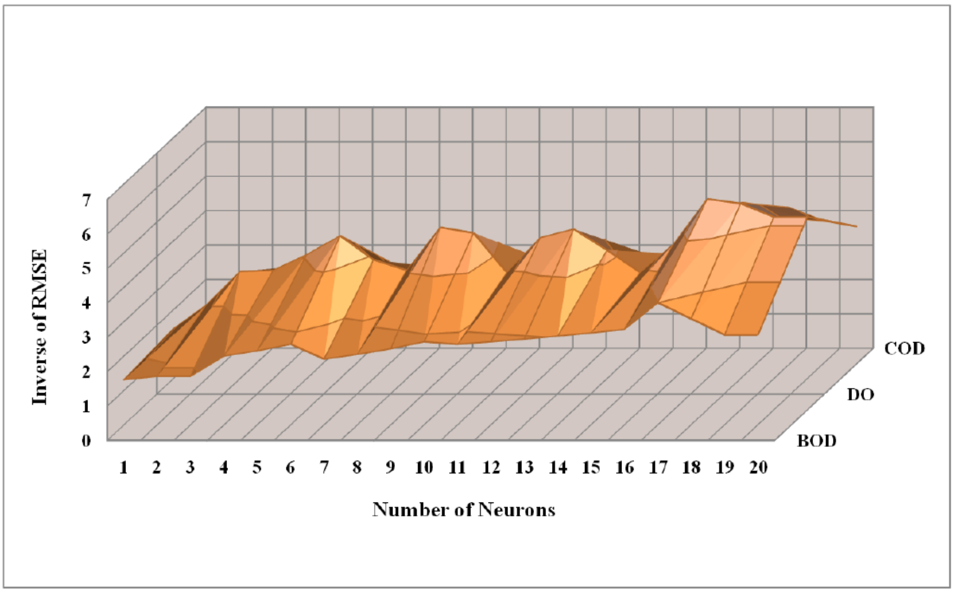


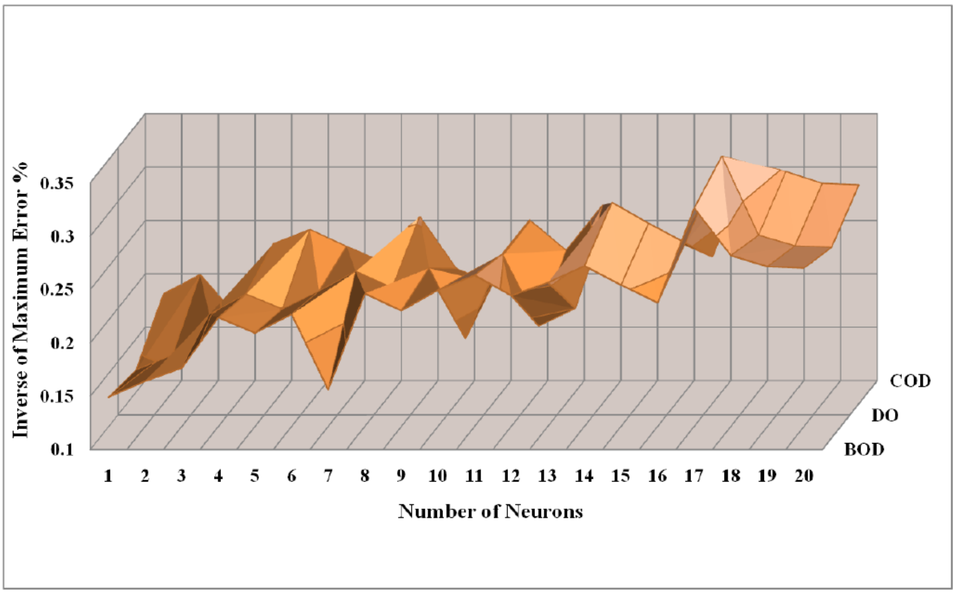
FIGURE 5. The networks convergence during training, (a) DO and (b) COD

The optimum number of neurons was determined based on two performance indices. The first index is the root-mean-square error (RMSE) value of the prediction error and the second index is the value of the maximum error. Both indices were obtained while examining the ANN model with the water quality parameter data between 1998 and 2007. In fact, in developing such a predicting model using Neural Network, the model could perform well during the training period and might provide a higher level of error when evaluating during either the validation or testing period. In the context of this study, these performance indices used to make sure that the proposed model could provide consistent levels of accuracy during all periods.

The advantages of utilizing these two statistical indices as a performance indicator of the proposed model are first, to make sure that the highest error while evaluating the performance is within the acceptable error for such a forecasting model. This is done while utilizing the RMSE to ensure that the summation of the error distribution within the validation period is not high. Consequently, by using both indices it guarantees the consistent level of errors by providing a great potential for having the same level error while examining the model for unseen data in the testing period. In order to show how the trial and error procedure for selecting the best number of neurons of certain ANN architecture was performed; the relationship between the numbers of neurons versus RMSE and maximum error are presented in Figure 6 for better visualization.



(a)



(b)

FIGURE 6. Neural network performance utilizing different number of neurons, (a) inverse of RMSE and (b) inverse of maximum error %

The inverse value of both RMSE and maximum error were used as seen in Figures 6(a) and (b) instead of the real values. It is interesting to observe the large number of local minima that exist in both domains. Changing the number of hidden neurons to

TABLE 2. The ANN architecture for each parameter

Parameter	No. of neuron	RMSE	Maximum error (%)	TFHL	TFOL	TA
DO	17	0.17	2.92	TS	PL	LMA
BOD	17	0.28	3.07	TS	PL	LMA
COD	18	0.24	3.29	LS	PL	LMA

TFHL: Transfer Function between input layer and Hidden Layer
TFOL: Transfer Function between hidden layer and Output Layer
TA: Training Algorithm
LS: Log sigmoid
TS: Tan sigmoid
PL: Pure-line
LMA: Levenberg–Marquardt Algorithm

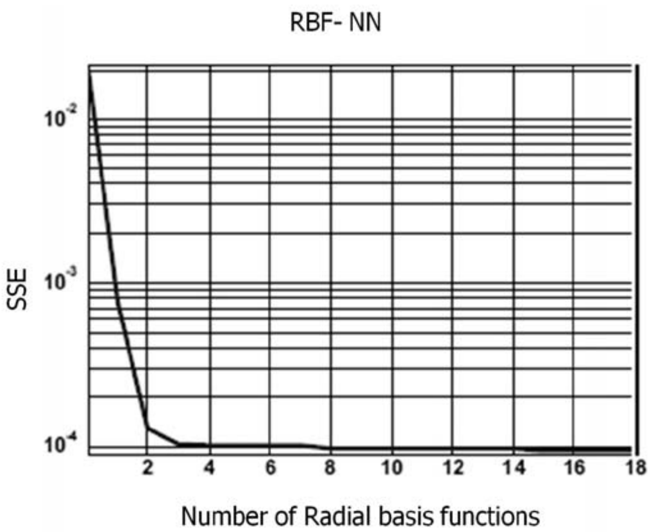


FIGURE 7. The training behaviour of the RBF-ANN

the network clearly affects the prediction performance to a significant degree. It clearly shows that the prediction performance increases as the number of hidden neurons were increased (from 1 to 18), with a corresponding decrease in RMSE and maximum error for all parameters. However, adding-up the hidden neurons further (19 to 20) to the network resulted in a drop of prediction performance. For example, It can be observed that the best combination of the proposed statistical indices for evaluating the predicting model for the DO when the ANN architecture has 17 neurons, achieving RMSE 0.17 and maximum error 2.92%. While the best combination of the proposed statistical indices for evaluating the predicting model for the BOD when the ANN architecture has 18 neurons, achieving RMSE 0.24 and maximum error 3.29%. The optimal numbers of neurons for the rest parameters are presented in Table 2.

In case of radial basis function several trials were performed utilizing different numbers of radial basis functions and spread values to achieve the target SSE of (1×10^{-4}) and the best possible performance. All of the networks successfully achieved the target, and the convergence of the SSE of one module during the training procedure is presented in Figure 7. During the training process, the RBF-ANN adjusted the initial value of spread to minimize the SSE to reach the performance goal for the DO. This spread is incremented

TABLE 3. RBF-ANN structures that were used to predict water quality parameters at both locations

Number of Radial Basis Function	Spread value	Output Layer
18	0.5	DO
8	0.7	COD
8	0.9	BOD

(by a certain predefined ratio) if the SSE continuously decreases during training to hasten system convergence.

The ability of the RBF-NN model to achieve the performance goal depends on the predefined internal RBF-NN parameters, such as the number of radial basis functions and the spread. The contribution of each input parameter to the desired output, whereas the spread controls the adaptive changes that the RBF-ANN makes to the radial basis functions during the training procedure. Optimization of the internal RBF-ANN parameters is an important process for adequate mapping. This optimization was performed by an extensive trial and error process in which the RBF-NN parameters were tuned to obtain the optimal values of internal RBF-ANN parameters that were capable of mimicking the sequences of the water quality parameters patterns. Table 3 depicts all RBF-ANN structures that were used to predict water quality parameters at both locations.

In fact, one of the challenges in modelling with ANFIS is determining its optimal learning parameters (number of membership function and initial value of step size) prior to training such that optimal training is accomplished. Two approaches have been recommended by many researchers for determining the optimal learning parameters of learning environments such as ANFIS: optimization algorithms [29] or by trial-and-error [30]. While finding the optimal learning parameters might be guaranteed by optimization techniques (derivative free or derivative based optimization), the optimization alternative has the drawback of being computationally expensive. On the other hand, trial-and-error approach has been proven efficient if the target root mean square error can be met. The trial-and-error approach has also the advantage of yielding a knowledge rule-base that has a lower probability of over-fitting the training dataset compared to that of the optimization approach. We, therefore, excluded the optimization alternative and determined the optimal learning parameters of ANFIS using the trial-and error approach.

For each of water quality parameter we used same architectures that presented in previous section. Where, twelve inputs were used to predict the water quality parameters. It is to be noted that there is no analytical method to determine the optimal number of MFs. The optimal number of MFs is usually determined heuristically and verified experimentally. Hence, the number of MFs is selected in trial and error basis. In the meantime, it is noted that we have tried four types of membership function: (a) triangular, (b) trapezoidal, (c) gaussian, and (d) bell-shaped to construct the fuzzy numbers. After a large number of trials, as a result bell-shaped distributed membership function compared with the others have obtained the minimum relative error. Table 4 illustrates the number and the types of MFs that adopted in this study to create modules. The ANFIS module is trained until reaching certain minimum error or after completing certain number of training epochs. In this study, the less no. of iteration was introduced in order to consume the time in Figure 8. Training and cross-validation process of the WDT-ANFIS module were performed to minimize the Root Mean Square Error between the output and the desired response shown in Figure 9. It is obvious in that the performance goal of 10^{-4}

was achieved in less than 100 epochs, while the same goal could not be achieved in Figure 8. This result depicts that the WDT-ANFIS capable to consume the time.

Table 4. Number and types of MFs for each module

Parameter	AFNIS Module	
	MFs (Type)	MFs (Number)
DO	gbellmf	3
COD	gbellmf	4
BOD	gbellmf	3

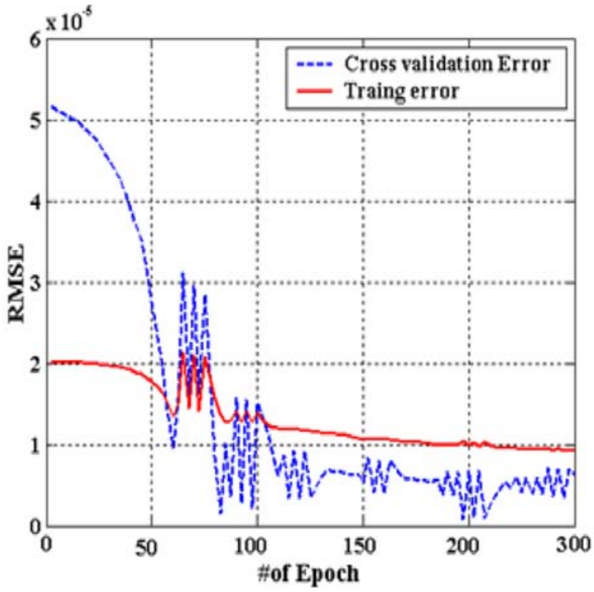


Figure 8. Change of the RMSE of ANFIS module during training and cross-validation

4.2. **Sensitivity analysis.** To evaluate the effect of input parameters on the model, three evaluation processes were used. The first assessment process was based on partitioning the neural network connection weights in order to determine the relative importance of each input parameter in the network [31,32]. In this study, the proposed network consisted of five environmental parameters. Assuming the connection weights from the input nodes to the hidden nodes demonstrate the relative predictive importance of the independent parameter, the importance of each input parameter can be expressed as follows:

$$I_j = \frac{\sum_{m=1}^{m=N_h} \left(\left(\left| W_{jm}^{ih} \right| \Big/ \sum_{k=1}^{N_i} \left| W_{km}^{ih} \right| \right) \times \left| W_{mn}^{ho} \right| \right)}{\sum_{k=1}^{k=N_i} \left\{ \sum_{m=1}^{m=N_h} \left(\left(\left| W_{jm}^{ih} \right| \Big/ \sum_{k=1}^{N_i} \left| W_{km}^{ih} \right| \right) \times \left| W_{mn}^{ho} \right| \right) \right\}} \tag{9}$$

where I_j is the relative importance of jth input parameter on the output parameter, N_i and N_h are the numbers of input and hidden neurons, respectively, and W is the connection weight. Meanwhile, superscripts 'i', 'h' and 'o' refer to the input, hidden and output layers, respectively, whereas subscripts 'k', 'm' and 'n' refer to the input, hidden and output neurons, respectively. Table 5 shows the connection weights values for the proposed model that used to predict the DO. It is important to note that Garson's

Table 5. Connection weights between the input and hidden layers (W_1) and weights between hidden and output layers (W_2)

Neuron	W_1												W_2
	Input parameters												Target
	COND	TEMP	NO3	SAL	TURB	Cl	PO4	K	MG	NA	FE	E-coli	DO
1	−0.13	−1.18	−0.61	−0.71	−0.23	−0.22	−0.70	−0.40	0.18	0.01	−0.17	−0.50	0.98
2	1.14	1.37	1.33	−0.34	0.17	0.51	−1.67	0.51	−0.23	−1.11	−0.97	1.62	0.51
3	−0.01	1.19	0.37	0.22	−2.08	1.72	−1.27	0.39	1.31	2.16	−0.67	−1.24	−0.73
4	1.07	−0.20	0.59	−0.44	0.06	−0.36	−1.11	1.08	0.53	−1.04	1.64	−1.50	0.07
5	−1.56	1.74	0.61	0.65	−1.09	0.21	−0.26	−0.72	0.34	0.96	−0.40	−0.88	−1.70
6	−1.01	−0.07	0.25	−0.98	−0.07	0.74	−0.88	−0.88	−1.35	−0.53	−0.65	−0.84	0.39
7	−0.08	0.65	0.51	−0.75	−0.10	0.66	−1.51	0.47	−0.69	0.23	0.28	−0.12	−1.33
8	0.48	−0.88	−0.36	0.56	0.62	−0.65	0.18	−0.42	−0.67	−1.09	0.50	1.53	−1.81
9	1.41	−0.39	−0.29	−0.19	3.03	−0.41	0.34	0.20	0.44	0.52	−1.83	0.17	0.36
10	0.46	0.32	0.66	1.05	−0.82	−0.60	0.36	2.20	0.79	−0.44	0.90	1.72	−0.32
11	−0.97	−1.49	0.12	1.83	−0.73	−2.58	0.31	0.70	−1.44	1.62	1.31	−0.11	0.26
12	0.95	0.32	−0.71	−0.84	1.89	1.36	−0.13	0.13	−1.17	0.65	0.00	0.57	−0.57
13	0.26	0.87	0.92	−0.66	−0.17	2.50	0.91	−0.24	0.74	−1.79	1.22	−1.04	0.30
14	0.25	−0.75	1.57	−1.04	−0.87	0.06	−1.85	1.78	0.82	−2.40	−0.64	0.15	−0.80
15	1.30	−0.83	−0.10	0.14	−0.74	0.45	−2.12	−0.57	0.59	1.98	−0.39	0.74	1.08
16	0.39	0.00	−0.65	0.22	0.06	−0.91	−0.91	0.54	0.00	−0.96	−0.78	−0.19	−0.06
17	0.50	0.48	1.57	−1.08	−0.98	−0.09	−0.24	0.46	1.85	0.69	0.18	−0.34	−0.40

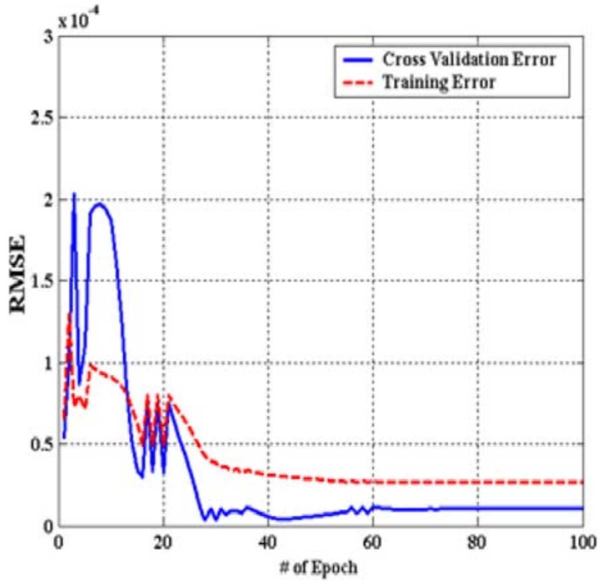


FIGURE 9. Change of the RMSE of WDT-ANFIS module during training and cross-validation

algorithm uses the absolute values of the connection weights when calculating parameter contributions.

The second assessment process was to evaluate relative importance of each of the input parameters on the model. The relative importance of each of the input parameters is shown in Figure 10. The relative importance showed the significance of a parameter compared with the others in the model. Although the network did not necessarily represent physical meaning through the weights, it suggested that all the parameters had strong effects on the prediction of all output parameters, where the predictor contributions ranged from 5 to 15%. It was obvious that the most effective inputs were those which included oxygen containing (NO_3) and phosphate (PO4). On the other hand, Temp and pH were found to be the least effective parameters. Moreover, COND revealed the highest contribution on the proposed model for DO. In the case of BOD, it was obvious that the most effective input was CI.

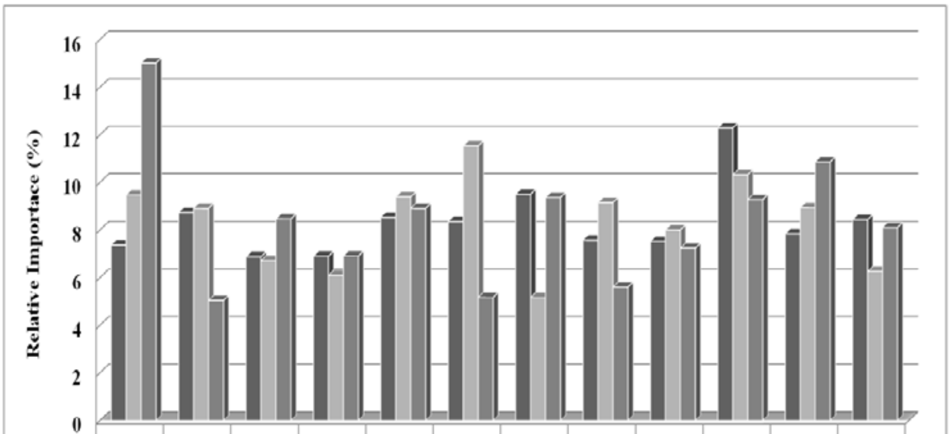
The third assessment process was to construct 5 models using a single parameter to determine the most effective input [33]. The correlation coefficients (R^2) of the input parameters are provided in Figure 11. Several parameters are available for the sensitivity study of each parameter of the water quality model. The intention is not to present all the performed tests, but rather to show the effect of some of the main parameters. In this study the authors focused on DO. The most effective inputs were those include the oxygen containing (PO4). Salinity provided the lowest contribution to the proposed model, which agrees with previous evaluations of parameter combinations.

4.3. **Comparative analysis.** All models presented in the previous section were compared in order to provide the precise prediction to the water quality parameters at Johor River. Figure 12 illustrates the comparison between the predicted DO versus the observed DO using 45° line of graph and two deviation lines from the 45° line for both validation and testing data sets for the developed models. It was obvious that MLP-ANN could predict the DO with relatively low level of accuracy, whereby the error for majority of the records did not reach 15%, while the error of a few records fell within 15%. Apparently, the scatter plot of the RBF-ANN model showed that the error was approximately close on the ideal line, which remarkably did not exceed 13%. Meanwhile, the scatter plot of the ANFIS models showed that the error approximately fell on the ideal line except for a few records, which remarkably exceeded 9%. These records were more deviated from the observed value attributes due to the fact that the extreme values found in the samples were polluted by noise signals owing to systematic and random errors.

For further assessment, the proposed models were compared with the results reported in the literature. Soyupak [34] employed the ANN modelling approach to calculate the pseudo steady state time and space dependent DO concentrations in three different reservoirs, with entirely different properties. The correlation coefficients between neural network estimates and field measurements were higher than 0.95. In addition, Sengorur [35] employed the feed-forward (FF) type ANN for computing the monthly values of DO. The findings demonstrated that the ANN results were very close to the observed values of DO where the correlation coefficient equalled to 0.9186. Ying [36] adopted the BP neural network to forecast water quality at Yuqiao Reservoir. The correlation between the forecast and actual measured of DO values was 0.9418. Likewise, Kuo [37] used the back-propagation neural network for predicting the dissolved oxygen in the Te-Chi Reservoir in Taiwan. The correlation coefficients between the predicted values and measured data of DO were above 0.7 for training and testing data sets.

Meanwhile, Zaqoot [24] used the ANNs-Multilayer Perceptron (MLP) network to predict the next fortnight's dissolved oxygen concentrations in the water of Mediterranean Sea along Gaza. The coefficient of determination between the measured and model computed values of DO was 0.996. On the other hand, Singh [38] constructed an artificial neural network (ANN) model to predict the water quality at Gomti River, India. The coefficients of determination between the measured and model computed values of DO for the training, validation and test sets were 0.70, 0.74 and 0.76, respectively. Furthermore, Rankovic [39] developed a feed-forward neural network (FNN) model to predict the dissolved oxygen in Gruza Reservoir, Serbia. The correlation coefficients between the predicted values and measured values of DO were 0.974 and 0.8738 for training and testing data sets, respectively.

The proposed model showed efficiency in predicting the concentration of dissolved oxygen in the Johor River, and it was compatible with the results of other researchers/authors.



	COND	TEMP	NO3	SAL	TURB	Cl	PO4	K	MG	NA	FE	E-coli
DO	7.3777	8.7432	6.8780	6.8984	8.5459	8.3665	9.5074	7.5802	7.5203	12.297	7.8408	8.4439
BOD	9.4785	8.9200	6.7197	6.0972	9.3917	11.536	5.1676	9.1593	8.0036	10.325	8.9423	6.2574
COD	15.022	5.0410	8.4694	6.9087	8.9194	5.1680	9.3680	5.6047	7.2407	9.2829	10.865	8.1087

FIGURE 10. The relative importance of each input parameter

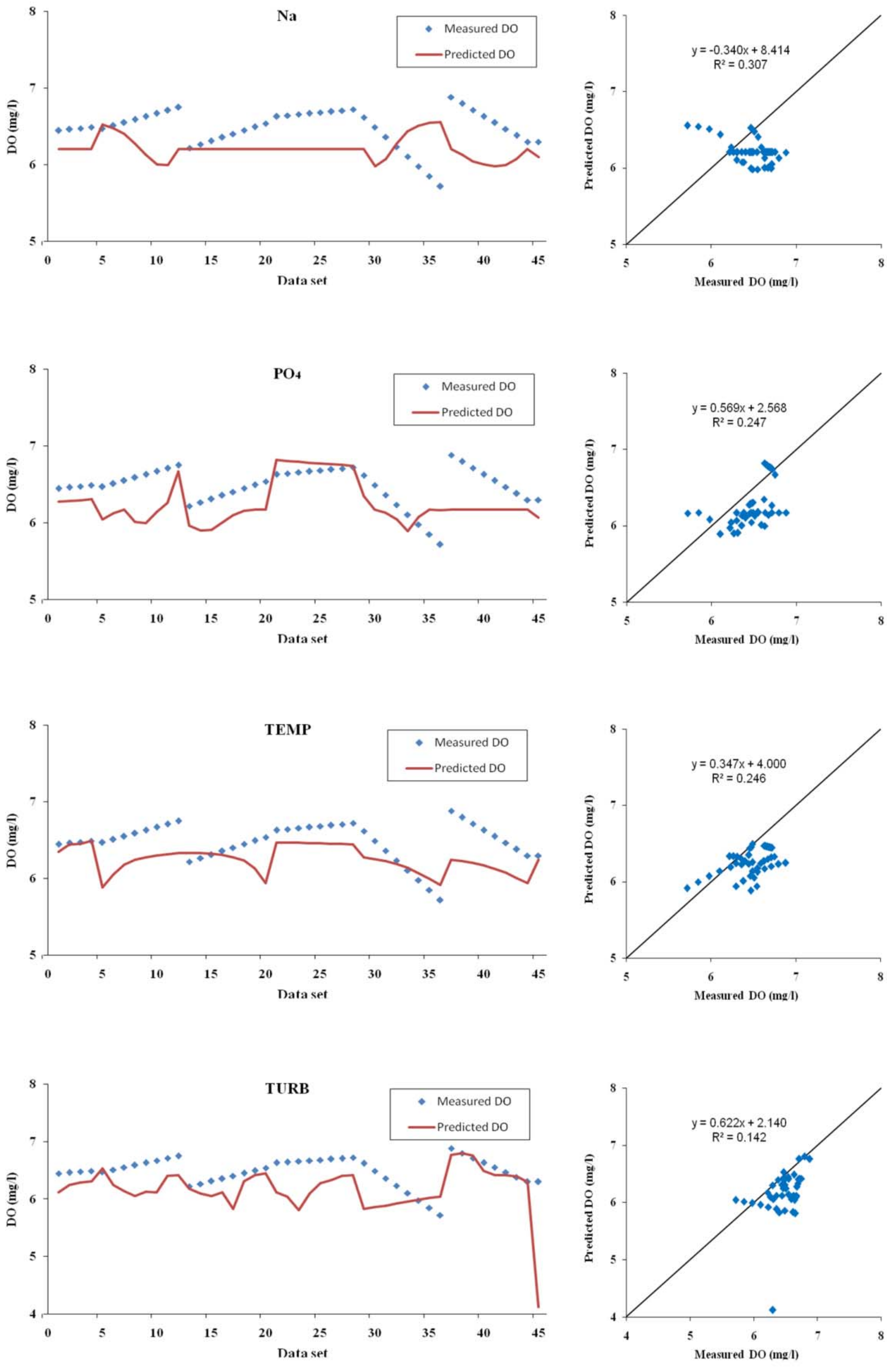


FIGURE 11. Comparison of predicted and measured DO values using single input

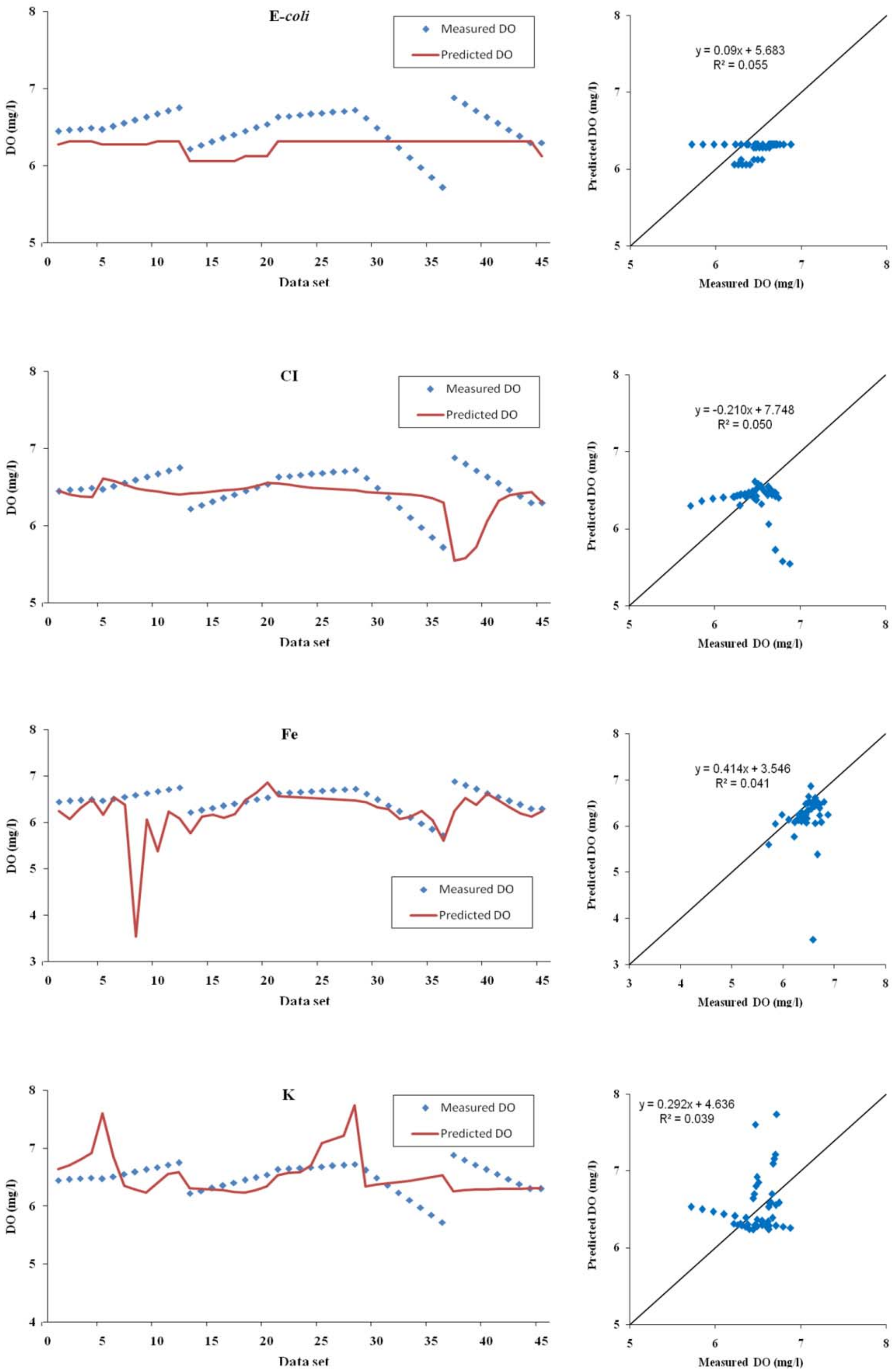


Figure 11 Continued

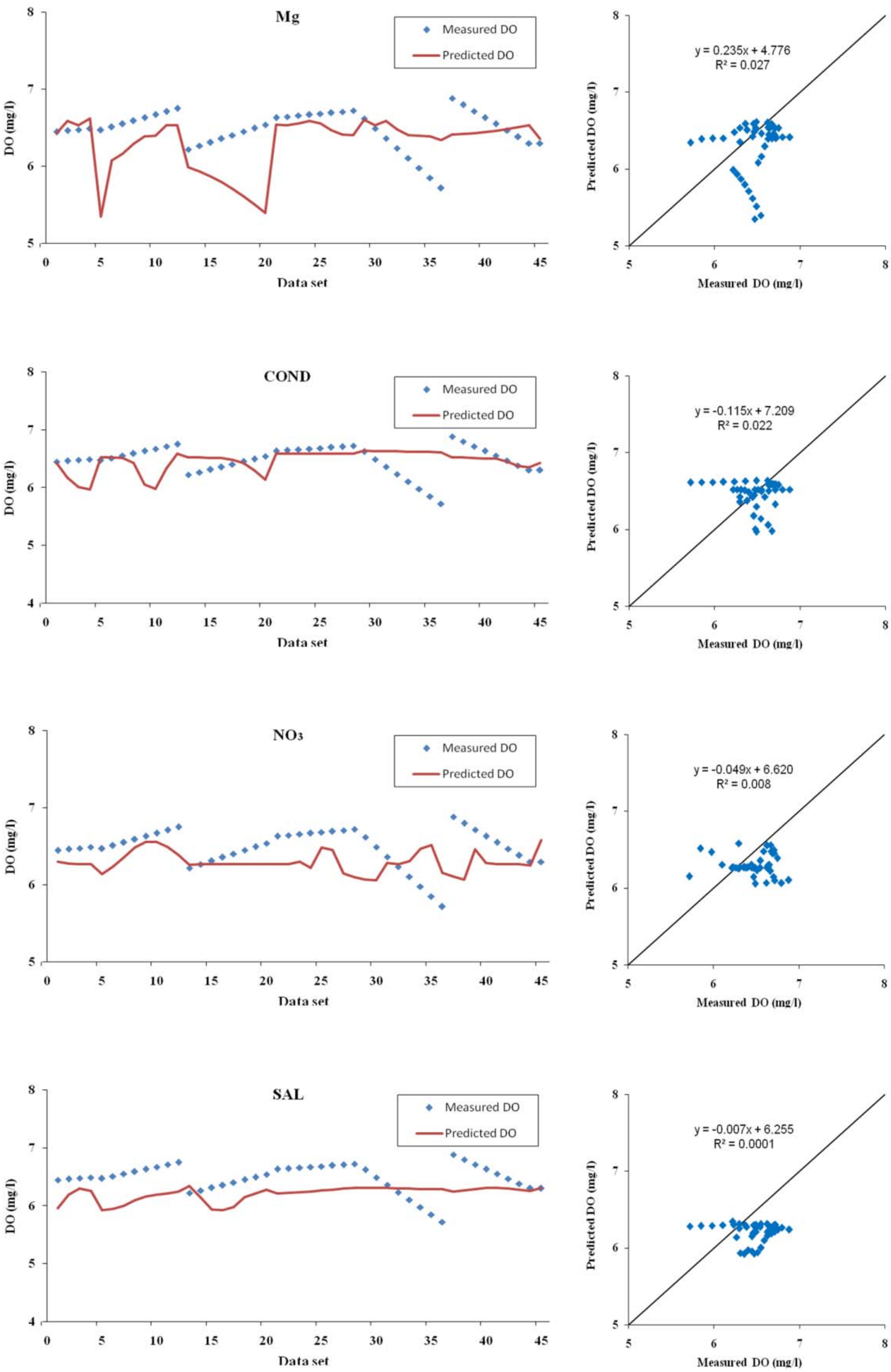


Figure 11 Continued

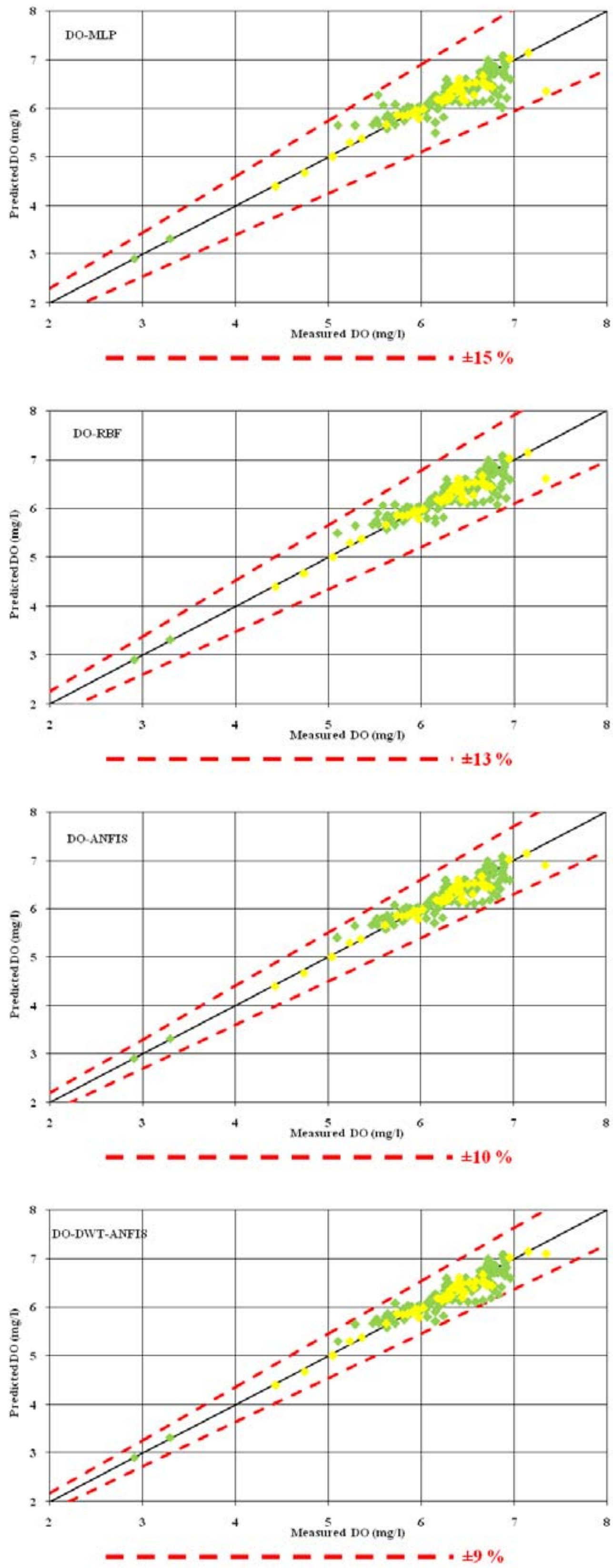


FIGURE 12. The comparison between the predicted versus observed DO utilizing different techniques

High coefficients of correlation were obtained between the observed and predicted values for the test sets of 0.97, 0.95, 0.94 and 0.95 for all stations. These results revealed that the input parameters selected in this study had direct relevance with the target (DO). The selection of input parameters might affect the model output remarkably [35]. The results also indicated that the proposed model was basically an attractive alternative, offering a relatively fast algorithm with good theoretical properties to predict the dissolved oxygen and can be extended to predict different water quality parameters.

In case of BOD Figure 13 illustrates the comparison between the predicted versus observed BOD using 45° line of graph and two deviation lines from the 45° line for both validation and testing data sets for developed models. It was obvious that MLP-ANN can predict the BOD with relatively low level of accuracy, whereby the error for majority of the records did not reach 18%, while the error of a few records fell within 17%. Apparently, the scatter plot of the RBF-ANN model showed that the error remarkably fell on 15%. While, the scatter plot of the WDT-ANFIS models showed that the error approximately fell on the ideal line except few records, which remarkably exceeded 11%. These records were more deviated from the observed value attributes due to the fact that the extreme values were found in the samples which were polluted by noise signals owing to systematic and random errors. The same result was achieved by the model that used to predict COD as shown in Figure 14, when the scatter plot of the ANFIS models showed that the error approximately fell on the ideal line except few records, which remarkably exceeded 15%. These records were more deviated from the observed value attributes due to the fact that the extreme values were found in the samples which were polluted by noise signals owing to systematic and random errors.

4.4. **Scenarios and verification.** Ying [36] showed that the selection of affecting factors (i.e., the input parameters) plays a key role since these factors have great impact on the forecast results. Thus, it was evident that the low correlation in this study was attributed to the fact that, the input parameters did not include all the relevant parameters. In addition, water pollution at the downstream station was related to the discharge from the upstream station.

Hence, to overcome the problem, this study introduced another approach (i.e., Scenario 2) so that a high level of accuracy could be reached. This approach was related to the prediction of the water quality parameters, with consideration of the actual one at the upstream station as the input to the model, as expressed by Equation (5). For the best analysis, this study adopted the accuracy improvement (AI) index for the correlation coefficient statistical index to measure the significance of the proposed Scenario 2 over Scenario 1, expressed as follows:

$$AI(\%) = \left(\frac{CC_{Scen2} - CC_{Scen1}}{CC_{Scen2}} \right) \times 100 \tag{10}$$

where CC_{Scen2} is the value of the correlation coefficient for Scenario 2, while CC_{Scen1} is the same statistical index for Scenario 1. Examining Table 6 carefully, it can be observed that Scenario 2 was more adequate than Scenario 1, with a significant improvement for all stations ranging from 0.5% to 3.1%. Prediction accuracy was significantly improved after introducing Scenario 2 for all stations. For example, in case of the DO, Scenario 2 performed more adequately than Scenario 2 with significant improvement in the AI ranging from 2.1% for Station 2 and 4 to 3.1% for Station 3. The same level of improvement for both BOD and COD was also achieved, where AI ranged from 0.5% for Station 2, to 1.1% for Station 1 and Station 3. These results showed that Scenario 2 was not only capable of improving the accuracy for certain parameter but the model was also capable

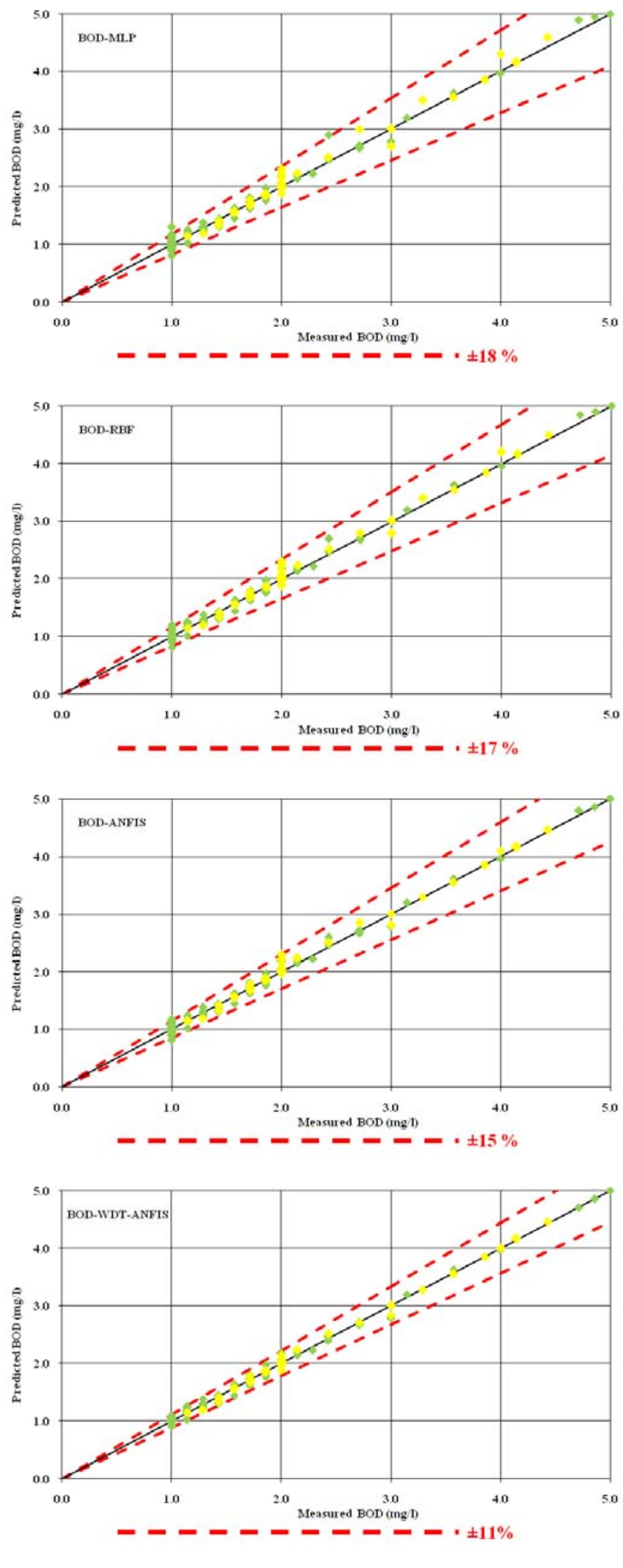


Figure 13. The comparison between the predicted versus observed BOD utilizing different techniques

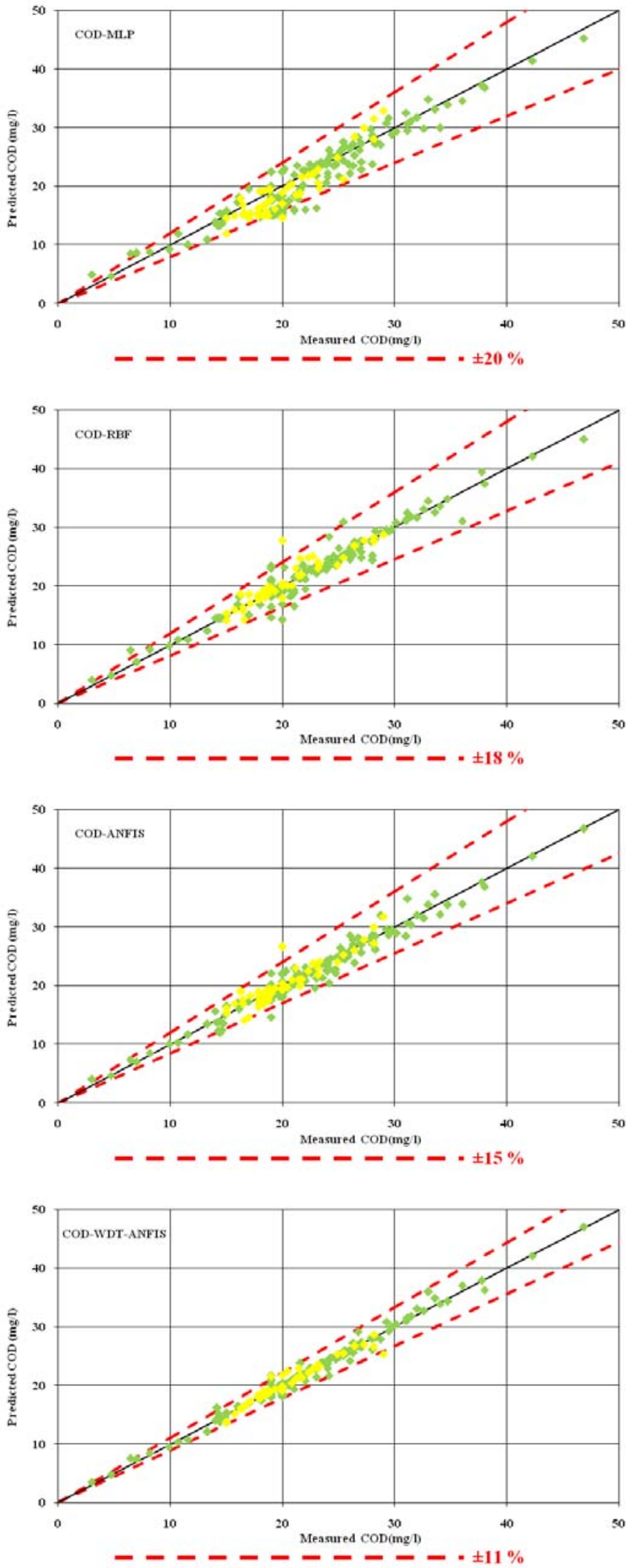


FIGURE 14. The comparison between the predicted versus observed COD utilizing different techniques

of capturing the temporal patterns of the water quality parameter which allowed it to provide significant enhancement for the stations.

Table 6. A summary of correlation coefficients for Scenario 1, Scenario 2 and the AI %

Model	SNO2		SNO3		SNO4		AI (%)		
	Scen1	Scen2	Scen1	Scen2	Scen1	Scen2	SNO2	SNO3	SNO4
DO	0.95	0.97	0.94	0.97	0.95	0.97	2.1	3.1	2.1
BOD	0.96	0.97	0.97	0.975	0.96	0.97	1.1	0.5	1.1
COD	0.96	0.97	0.97	0.975	0.96	0.97	1.1	0.5	1.1

The model needs to verify when the output results and the observed values are close enough to satisfy the verification criteria [40]. Therefore, in order to investigate the efficiency of the proposed model, the verification of the augmented wavelet de-noising technique with the Neuro-Fuzzy Inference System (WDT-ANFIS) based on the collection of field data within the duration of 2009-2010 is presented. The scatter plots between the observed and predicted values for each of the five selected water quality parameters are presented in Figure 15. The WDT-ANFIS model verified to predict the DO and COD concentrations performed very satisfactorily (i.e., R^2 values were equal or bigger than 0.9) for all stations. On the basis of these results, WDT-ANFIS exhibited good prediction performance.

5. **Conclusion.** Modelling water quality parameters is a very important aspect in the analysis of any aquatic systems. Prediction of surface water quality is required for proper management of the river basin so that adequate measure can be taken to keep pollution within permissible limits. Accordingly, it is very important to implement and adopt a water quality prediction model that can provide a powerful tool to implement better water resource management. Several modelling methods have been applied in this research including: Multi Layer Perceptron Neural Networks (MLP-ANN), Radial Basis Function Neural Networks (RBF-ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS). The results revealed that it was difficult to produce a reliable model with the MLP-ANN models due to the high variance and inherent non-linear relationship of the water quality parameters because of the stochastic nature and chemical process. In addition, the MLP-ANN models experienced slow convergence while training due to the requirement of relatively large number of hidden neurons. In the case of RBF-ANN, the predictive ability of the RBF-ANN was quite good for all the water quality parameters during the training phase, but less accurate during the validation and testing phases. The results showed that the ANFIS found a solution faster than the MLP-ANN and RBF-ANN and was the most accurate and reliable tool in terms of processing large amounts of non-linear and non-parametric data. It was also observed that the WDT-ANFIS model outperformed the ANFIS model and was able to provide improvement in predicting accuracy for all water quality parameters. It appeared that the WDT-ANFIS model was capable of achieving high level of accuracy in the prediction stage. Overall, in this research, WDT-ANFIS could therefore be declared as the best network architecture because it outperformed the ANFIS. These results showed that the WDTANFIS model was not only capable of improving the accuracy, but the model was also capable of capturing the temporal patterns of the water quality which allowed it to provide significant enhancement in prediction. As a result, the ANFIS model was more capable to capture the dynamic and complex processes that were hidden in the data itself for water quality parameter after being

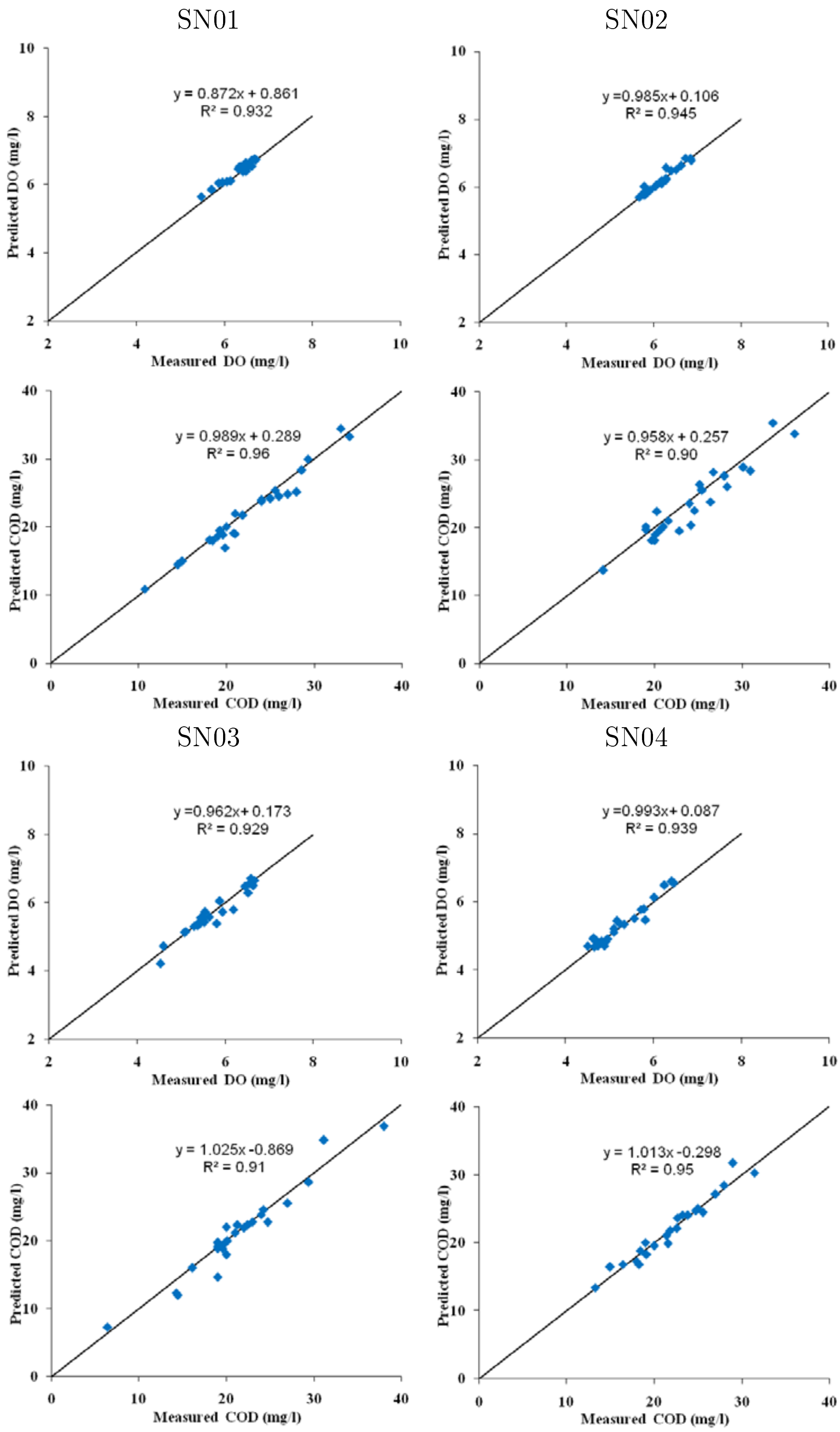


Figure 15. WDT-ANFIS model verification for each water quality parameter at each station

augmented with WDT. In comparison between Scenario 1 and Scenario 2, Scenario 2 was able to achieve a high level of accuracy in simulating the magnitude and patterns of all water quality parameters at all stations. It was obvious that the proposed WDT-ANFIS model with Scenario 2 provided predicted water quality parameters that were able to mimic the pattern (dynamics) in the observed values apart for those extreme values experienced during this period. In addition, the verification of the WDT-ANFIS based on the collection of field data within the duration of 2009-2010 showed that the WDT-ANFIS model performed very satisfactorily. Nevertheless, due to the fact that water quality forecast can be easily affected by external environment, the obtained model sometimes produced results which were much deviated from the actual values, therefore, further research needs to be done in future work to identify the suitable forecast model, understand its laws of changes and solve the problem of forecast deviation. In general, this research work has managed to integrate several analytical and modeling methods that would prove to be useful for various institutions that are directly involved in the management of river basins in Malaysia. Moreover, the tools used in this work could form a basis for a more effective decision making process on the part of the policy makers in order to help maintain and improve the management of river basins.

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