ARTIFICIAL NEURAL NETWORKS MODELLING FOR AL-RUSTUMIYA WASTWATER TREATMENT PLANT IN BAGHDAD

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ABSTRACT

In the present research, Artificial Neural Networks (ANNs) were developed for modelling the performance of Al-Rustamiya wastewater treatment plant, Baghdad, Iraq. There were created two models and the outputs were the removal efficiency of BOD and COD parameters. Four main input parameters were selected for modelling, namely Total suspended solids (TSS), Total dissolved solids (TDS), chloride ion (Cl-), and pH. Influent and effluent concentrations of the parameters were collected from Mayoralty of Baghdad for the period from 2011 to 2021. The results of the modelling were in terms of mean square error (MSE) and correlation coefficient (R). The results indicated that the ANNs models were accurately able to predict the removal of the BOD, and COD, and the optimum topology of the ANNs is obtained at 13 neurons in the hidden layer for both with 3.09 MSE, 0.96 and 4.28 MSE, 0.96 R for BOD and COD respectively.

KEYWORDS

ANNs, BOD, COD, modelling, wastewater

PAPER INDEX

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INTRODUCTION

The change in the life styles due to urbanization and industrial practices has resulted in increasing production of wastewater that adversely impacts on human lives [1]. Water can be contaminated by human utilization in any mixture of mechanical, residential, businesses, storm water, surface overflow, and inflow of sewers [1, 2]. Wastewater treatment plants (WWTPs) are considered as significant infrastructure for a society. With the realization of the importance of such plants, the achievement of integrated and efficient units demands adequate operational and maintenance practices. Wastewater treatment plants mainly consist of three process, primary, secondary, and tertiary treatments. The combinations of these processes depends on the characteristics requirements of effluent [3]. Typically, the reduction degree in the biological oxygen demand (BOD) as well as chemical oxygen demand (COD) represent the basic indicator of the effectiveness of the plant [4, 5].

Moreover, modelling of WWTPs represents a difficult task as the treatment involves complex processes. The physical, biological, and chemical stages of the treatment plants provide non-linear performance which is complicated to presented in linear models. Thus, providing an efficient monitoring technique can be accomplished by the development of non-linear model to predict the performance of the treatment plant under previous observed water characteristics. Artificial neural networks (ANNs) represent computerized non-linear models for simulating the decision-making and functions of the brain of humans. It is being used for many wastewater quality issues. It has also been properly used in the modelling of the WWTPs for predicting wastewater characteristics, controlling stages of treatments, and providing estimation of effluent characteristics [6-9].

ANNs are usually used for predicting the parameters of water quality. It solves an issue through the development of a memory with the ability to relate large input data with a set of outputs [10]. A significant feature of the ANNs is its ability to handle considerable and complicated systems with various related parameters [11]. ANNs forms the basis of deep learning where the modelling algorithms are inspired by the brain structure of humans. After taking in the data, the ANNs train themselves for the recognition of data patterns and providing outputs. The model consists of grouped artificial neurons representing the core units of the modelling process [12]. The model represents an alternative method to conventional water quality models through the provision of advanced predictions and forecasts [13, 22].

In Baghdad, the capital city of Iraq, Al-Rustumiya WWTP is one of the main sewage water treatment facilities in the country. The plant recently has been expanded (3rd expansion) with the construction of nearby new plant for increasing capacity purposes. It releases the treated waters in Diyala River and then into the Tigris River [14, 15]. This study aims to at develop an ANNs model in MATLAB for investigating correlation between pairs of parameters to predict the performance of the 3rd expansion plant in terms of the removal efficiency of BOD, and COD. This work can assist in facilitating assessment or process control of effluent quality.

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WORK METHOD

1. DESCRIPTION OF THE STUDY AREA

Baghdad is the capital city of Iraq with an area approximately equals 800 square miles and population of 7.145 million according to the water and sewage sector report [16]. Three significant central WWTPs were built in Baghdad., namely Al-Karkh wastewater treatment plant, Southern Al-Rustumiya WWTP numbered 0, 1, and 2, and Northern Al-Rustumiya WWTP (3rd expansion). The effluent from the old plant being discharged in Tigris River while for the 3rd expansion, it is being discharged in Diyala River (also known as Sirwan River). The 3rd expansion of the plant began in 1984. Approximately third of the population in the city depends on the Al-Rustumiya WWTP [17]. The plant lies on the south-east part of Baghdad, Iraq, on Diyala River with longitudinal coordinate of 44˚32´05˝E and latitudinal coordinate of 33˚17´15˝N. The plant was mainly designed for the treatment of domestic wastewater which serves a population of 1500000 [17]. The plant consists of conventional activated sludge for biologically treating carbon compounds with average wastewater influent capacity equals 300MLD [17]. Figure 1 showed the 3rd expansion of the plant.

Figure 1. Al-Rustumiya WWTP3rd expansion in Baghdad, Iraq [14].

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2. DATA COLLECTION

The required data were obtained from Al-Rustamiya WWTP administration Office Mayoralty of Baghdad, over the period of ten years from January 2011 and December 2021 on a monthly basis. Two locations were selected: at entrance of the plant, and after secondary treatment. The selected physiochemical parameters included the biochemical oxygen demand (BOD5), chemical oxygen demand (COD), chloride (Cl-) and Total dissolved solids(TDS), and total suspended solids (TSS). The Removal efficiency of BOD, and COD were determined using Equation (1):

$$\text{Removal efficiency (\%)} = \frac{\text{input value} - \text{output value}}{\text{input value}}\, x\; 100 \qquad (1)$$

3. ANNS MODELLING IN MATLAB

The ANNs were created in MATLAB. This software allows creation, usage, export, and input of neural networks. Two models were created, with 4 inputs and 1 output. The modelling procedure and equations were based on Tümer and Edebali [18], Ammari [19] and Alsulaili and Refaie [20].

The ANNs architecture was defined by its number of layers and their neurons. Feedforward multi-Layered perception ANNs consist of various artificial neurons known as nodes, or processing elements (PEs). These are normally arranged in three layers, input, hidden or intermediate, and output layers. As was indicated in Figure 2 that for each processing element, the input from a layer (xi) was multiplied by an adjustable connection weight (wij). The summation was performed for the weighted inputs with the addition of a threshold value (θj). The resulted combined input was then transferred to activation function (f(ij)) for generating the output (yj). This output was then used as input for the next layer. The activation function represents the nonlinear mapping tool in the network before delivering the output to the next layer.

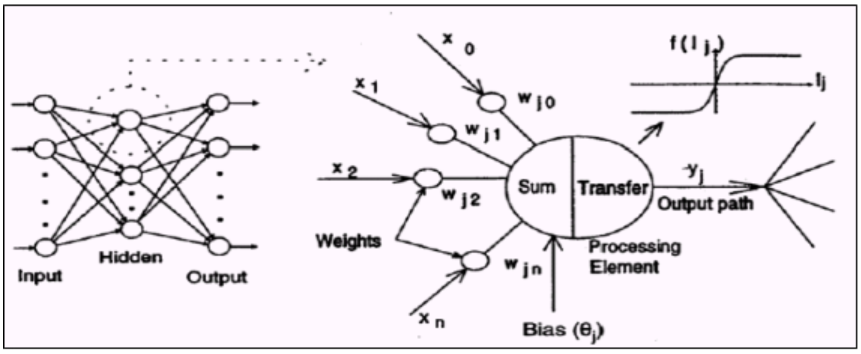

Figure 2. Typical structure and operation of ANNs [21].

The summary of the process was indicated in Equations (1 & 2) as follows:

$$\text{Summation f(IJ)} = \sum \text{Wij Xi} + \theta\text{j} \qquad (2)$$

$$\text{Transfer (yj)= f(Ij)} \qquad (3)$$

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Where,

f(IJ) is the level of activation at j node,

Wij is the weight of the connection between the nodes i and j,

xi is the i node input and equals 0, 1,2, …,n,

θj is the threshold for j node,

j is the j node output, and

f(ij) is the activation function.

Backpropagation algorithm is normally used for excellent results and easy application. The ANNs data propagation began at the input layer at which the information was provided. In order for the weights to be assigned, the network utilized the presented information and learning rule for the production of input and output maps with negligible errors. This is called training or learning which was divided into supervised and unsupervised learnings. Feedforward ANNs usually works with supervised learning. In this, model inputs and desired outputs were provided to the network. Errors were determined through the network by comparing the desired and actual ANNs produced outputs. These errors were then utilized for adjusting the weights given to the connections between the input and the outputs for reducing the errors between the actual output and the desired ones. Thus, the network learns for the presented data for adjusting the weights and capturing the relationship between the input and the output without the need of any previous knowledge about such relationship. Thus it regulates the bias and weights of the Multi-Layered perception ANNs. In order to evaluate the efficiency of the treatment plant, the backpropagation algorithm was improved by the incorporation of Levenberg-Marquadrt algorithm. This algorithm is a local optimization algorithm with a gradient basis. The advantage of its utilization over normal backpropagation is the better stability, advanced performance, and faster and advanced training and convergence properties.

Several forms are available for the activation function. The most commonly known were used in this research which was hyperbolic tangent transfer and logistic sigmoid functions. The functions are presented in Equations (4 & 5):

Hyperbolic tangent transfer function $$f(I_j) = \frac{e^{(I_j)} - e^{-(I_j)}}{e^{(I_j)} + e^{-(I_j)}} \quad (3)$$

logistic sigmoid function $$f(I_j) = \frac{1}{1 + e^{-(I_j)}} \quad (4)$$

RESULTS AND DISCUSSION

1. REMOVAL EFFICIENCY OF BOD AND COD

Figures 3 presented the average yearly removal efficiency of BOD and COD from Al-Rustumiya WWTP. The figure indicated that the removal efficiencies were variable for both water parameters, mostly more than 80% and having approximately the same trend. The greatest removal efficiency occurred in 2020 with about 93% for BOD and 95% for COD. Generally, the removal efficiency of the plant increased from 2015 onwards. The lowest BOD and COD removals occurred in 2012. This could be attributed to the improper aeration in the aeration basin, or the measurement of high concentration of settling microbial mass in the secondary clarifier.

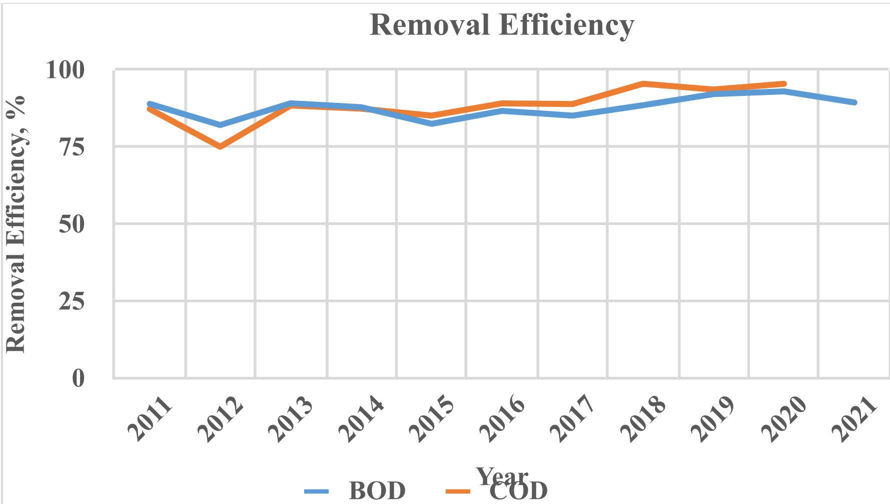

Figure 3. Removal efficiency of BOD and COD from Al-Rustumiya WWTP.

2. ANNS

The results of the ANNs modelling were evaluated in terms of Mean Square Error (MSE) and correlation coefficient (R) The functions are presented in Equations (6&7):

$$\text{Correlation coefficient (R)} = \frac{\sum_{i=1}^{n}\left(X-\bar{X}\right)\left(Y-\bar{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(X-\bar{X}\right)^2\left(Y-\bar{Y}\right)^2}} \quad (6)$$

$$\text{Mean Square Error (MSE)} = \frac{\sum_{i=1}^{n}(X-Y)}{2} \quad (7)$$

where X= observed yt , $\bar{X}$ = mean of X, Y= predicted yt, $\bar{Y}$= mean of Y, and n= number of observations.

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These are the most common criteria for the evaluation of a model's performance. The MSE provides the difference between the outputs and the targets. The R coefficient reflects how well the created model fits with used outputs. An R equaling 1 means a very close relationship while an R equaling 0 means a random relationship. Models were carried out for the removal efficiency of both BOD and COD. They represent the main parameters for evaluating organic pollution. They provide measurements of organic matter and oxygen demands.

2.1. ANNS FOR BOD MODELLING

The modelling results in terms of the MSE with the number of hidden layers are shown in Figure 4. and Table 1. The results indicated that the MSE was significantly decreased with the increase in the number of hidden neurons from 2 to 9 and the minimum MSE result is obtained at 13 hidden neurons. Afterward, training was stopped when reached 90 epochs for the Levenberg–Marquardt algorithm as shown in Figure 5. This is because of the difference between the training and validation errors increases. A plot of Levenberg–Marquardt algorithm regression for training, validation, and testing with R is shown in Figure 6. This revealed that the R values were 0.98, 0.94, 0.88, and 0.96 for training, validation, testing, and for all data respectively. Thus, the optimum topology of the ANNs is obtained at 13 neurons in the hidden layer with 3.09 MSE and 0.96 R. The architectural model of the optimum topology is shown in Figure 7. This is 4:13:1, indicating the input layer with the used four parameters, thirteen neurons at the hidden layers, and the output layer in terms of the removal efficiency of the BOD.

Figure 4. Mean Square Error (MSE) with different numbers of neurons at the hidden layers for ANNs modelling of BOD output.

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Table 1. ANNs details for BOD modelling.

BOD			
Model No.	**No. of neurons at hidden layers**	**MSE**	**Correlation Coefficient (R)**
1	2	15.72	0.80
2	3	14.13	0.83
3	4	13.59	0.83
4	5	12.83	0.84
5	6	9.75	0.88
6	7	6.00	0.93
7	8	4.87	9.43
8	9	3.42	0.96
9	10	3.96	0.95
10	11	3.41	0.96
11	12	4.00	0.95
12	13	3.09	0.96
13	14	4.43	0.95
14	15	3.21	0.96

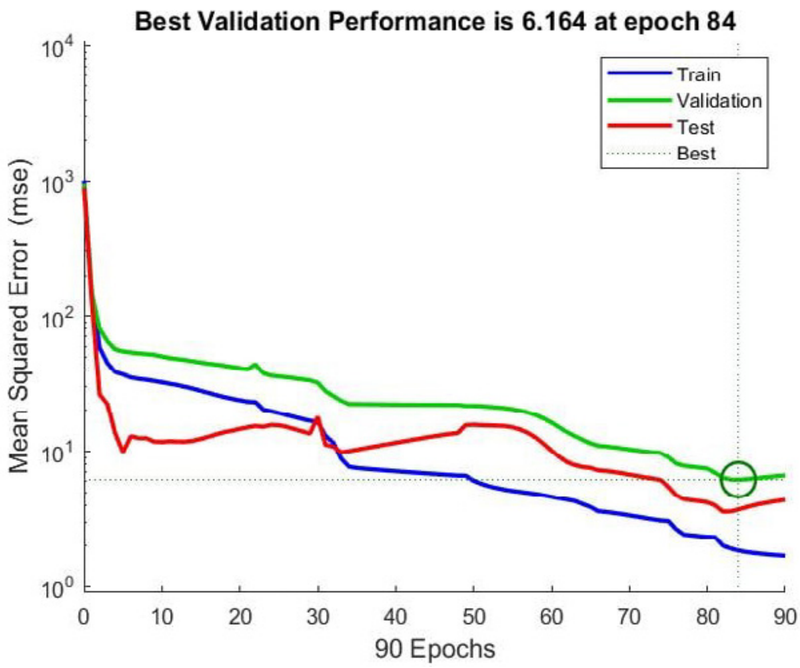

Figure 5. Training, validation, and test mean square errors for the Levenberg–Marquardt algorithm for BOD removal.

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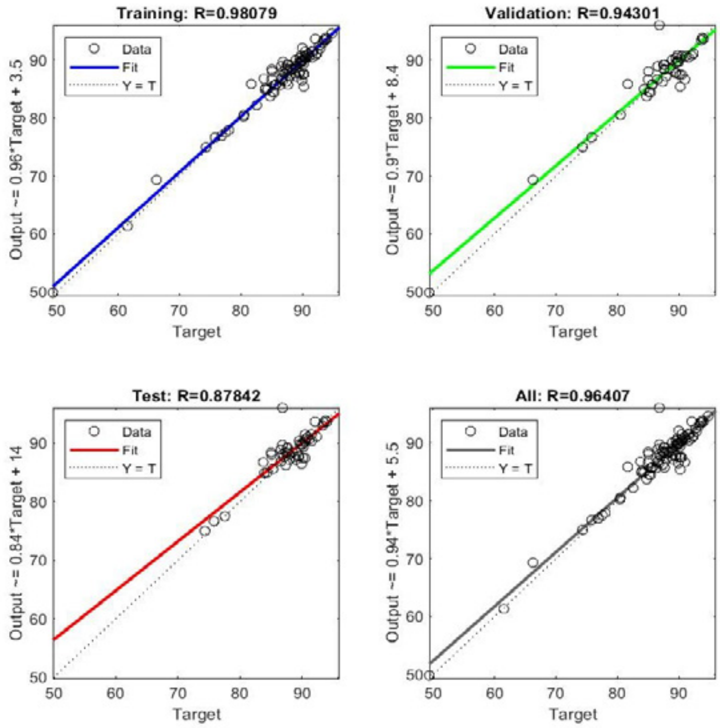

Figure 6. Training, validation and testing regression for the Levenberg–Marquardt algorithm for BOD removal.

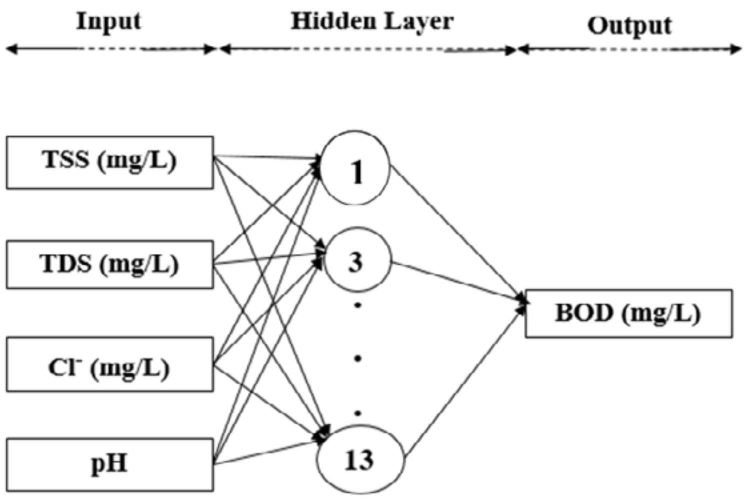

Figure 7. The architecture of the ANN model for the prediction of BOD removal.

2.2. ANNS FOR COD MODELLING

The modelling results in terms of the MSE with the number of hidden layers are shown in Figure 8. and Table 2. The results indicated that the MSE was significantly decreased with the increase in the number of hidden neurons from 2 to 11 and the minimum MSE result is obtained at 13 hidden neurons. Afterward, training was stopped when reached 78 epochs for the Levenberg–Marquardt algorithm as shown in Figure 9. This is because of the difference between the training and validation errors increases. A plot of Levenberg–Marquardt algorithm regression for training, validation, and testing with R is shown in Figure 10. This revealed that the R values were 0.96, 0.94, 0.96, and 0.96 for training, validation, testing, and for all data respectively. Thus, the optimum topology of the ANNs is obtained at 13 neurons in the hidden layer with 4.28 MSE and 0.96 R. The architectural model of the optimum topology is shown in Figure 11. This is 4:13:1, indicating the input layer with the used four parameters, thirteen neurons at the hidden layers, and the output layer in terms of the removal efficiency of the COD.

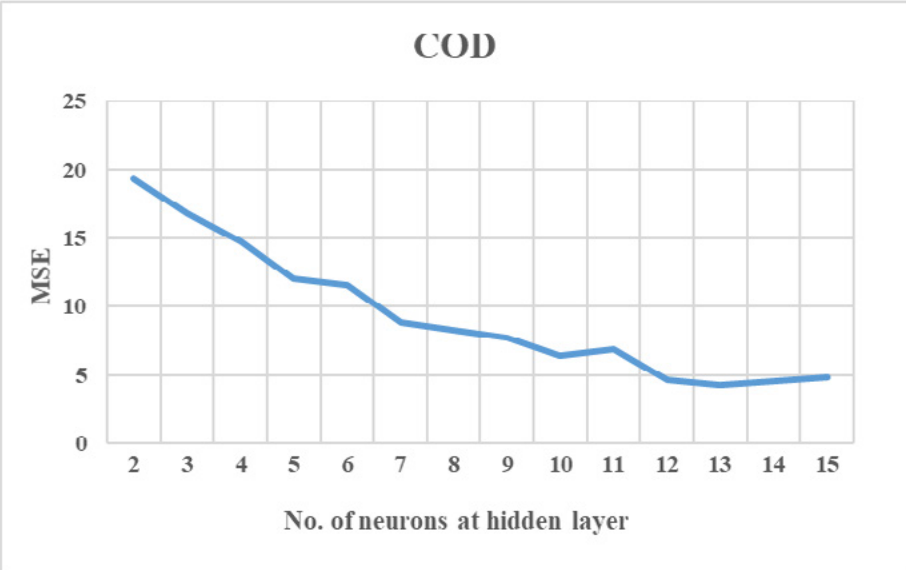

Figure 8. Mean Square Error (MSE) with different numbers of neurons at the hidden layers for ANNs modelling of COD output.

Table 2. ANNs details for COD modelling.

COD			
Model No.	**No. of neurons at hidden layers**	**MSE**	**Correlation Coefficient (R)**
1	2	19.34	0.79
2	3	16.79	0.82
3	4	14.74	0.84
4	5	12.03	0.87
5	6	11.58	0.88
6	7	8.81	0.91
7	8	8.31	0.90
8	9	7.68	0.91
9	10	6.36	0.93
10	11	6.85	0.93
11	12	4.61	0.95

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12	13	4.28	0.95
13	14	4.50	0.95
14	15	4.86	0.95

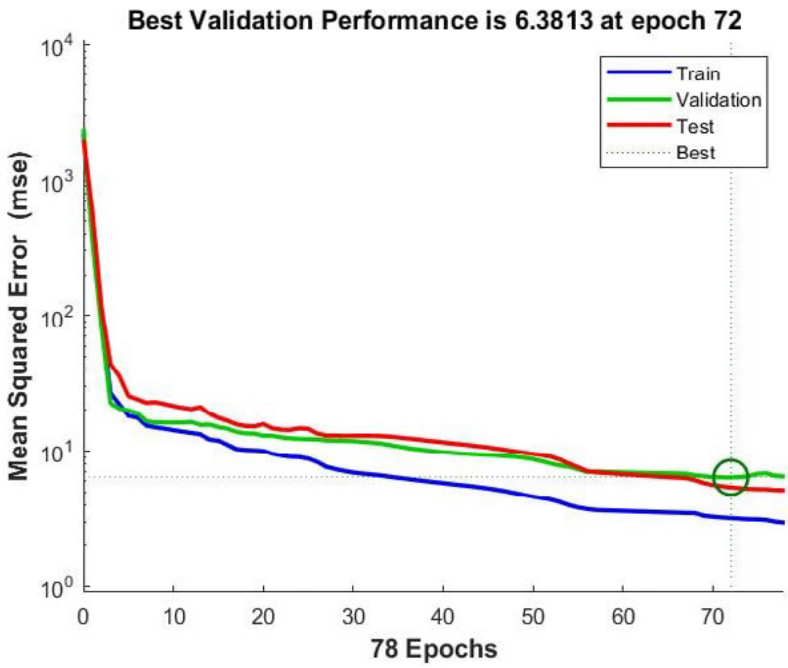

Figure 9. Training, validation, and test mean square errors for the Levenberg–Marquardt algorithm for COD removal.

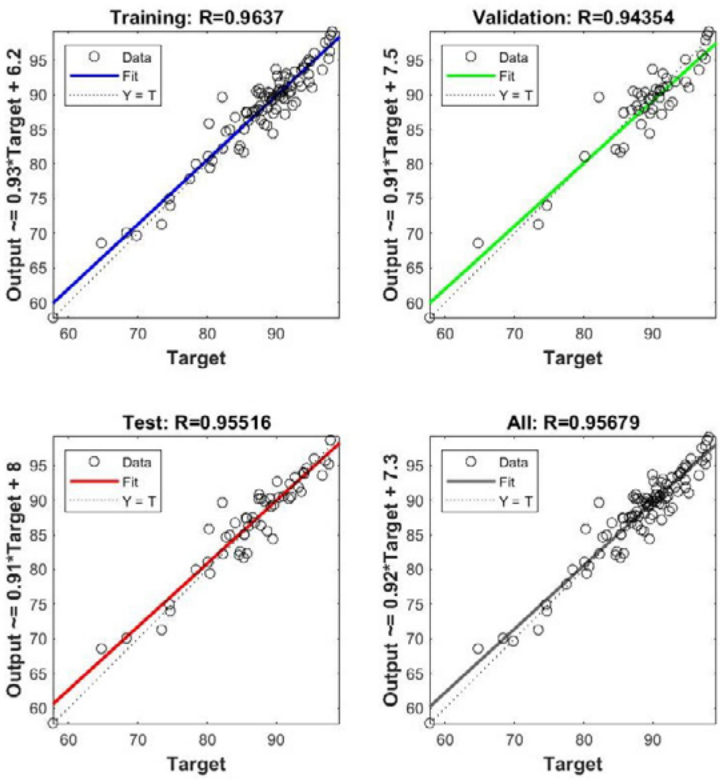

Figure 10. Training, validation and testing regression for the Levenberg–Marquardt algorithm for COD removal.

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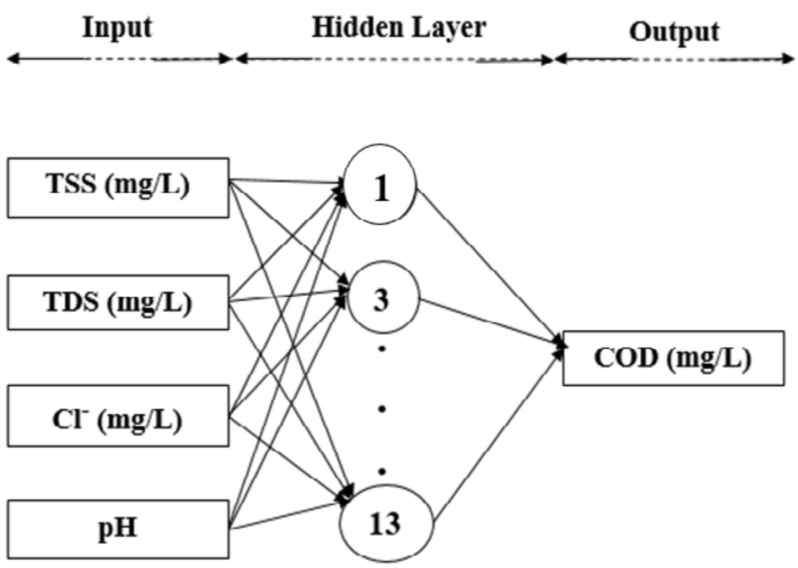

Figure 11. The architecture of the ANN model for the prediction of COD removal.

CONCLUSION

The results of the ANNs modelling for the prediction of BOD, and COD provided several advantages over the traditional calculation methods. The models were accurately able to determine the removal efficiency of the BOD, and COD of Al-Rustumiya WWTP by the use of raw dataset. The developed models can be considered as simple, fast, and most accurate determination tools. This proved that the developed MLP network trained with backpropagation incorporated with Levenberg–Marquardt algorithm was adequate in predicting the performance of Al-Rustamiya WWTP. For BOD and COD, the best results were obtained with 13 neurons at 3.09 MSE and 0.96 R for BOD and 4.28 MSE and 0.95 R for COD.

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CONFLICT-OF-INTEREST STATEMENT

The authors declare no conflict of interest for this research

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