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Using machine learning algorithms to evaluate the performance of electrocoagulation with membrane bioreactor (EC-MBR) for treatment of organic matters in domestic wastewater

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Abstract

An electrocoagulation with membrane bioreactor technique (EC-MBR) was developed to treat domestic wastewater and prevent membrane fouling. To support the new design, experiments were conducted on a few levels. The structure and distribution of organic matter removal utilizing the membrane are investigated using a laboratory-scale (EC-MBR) treatment of domestic wastewater. The study's goals were to assess the removal efficiency of organic matter (biological oxygen demand (BOD) and chemical oxygen demand (COD) in Al-Hawraa's wastewater, as well as its links to statistical indicators. It was chosen to sample and evaluate effluent from domestic wastewater using EC-MBR with operating temperature (25 0C), pH (7-8), DO (4-6) mg/L, beginning and final concentrations of BOD (184-6 mg/L), and COD (489-20 mg/L) using biological and electrochemical treatment procedures. According to the results, the organic matter removal efficiency may be calculated using the multilinear regression (MLR) and neural network (NN) models in the SPSS modeler. In addition, the results showed that the entire reactor had good BOD and COD maximum removal efficiencies of 96.7% and 95.9%, respectively. Finally, the highest accuracy of the MLR algorithm for COD and BOD is 99.6 for both, whereas the maximum accuracy of the NN algorithm for COD and BOD is 99.2 % and 99.1%, respectively. To choose the best algorithm for analysis and modeling the outcomes, a comparative study has been achieved to compare the results of two algorithms that used in this study. Therefore, for this study MLR algorithm was chosen.

Keywords: BOD, COD, removal, Al-Hawraa domestic wastewater, regression, neural network, spss modeler.

الخلاصة: لمعالجة مياه الصرف الصحي المنزلية ومنع تلوث الأغشية، تم تطوير تقنية التخثير الكهربائي مع المفاعل الحيوي الغشائي (EC-MBR). لدعم التصميم الجديد، أجريت التجارب على عدة مستويات. يتم فحص ونمذجة وتوزيع إزالة المواد العضوية باستخدام وحدة مختبرية من (MBR-EC) لمياه الصرف الصحي المنزلية. هدفت الدراسة إلى تقييم كفاءة إزالة المادة العضوية (الطلب البيولوجي على الأكسجين (BOD) والطلب الكيميائي للأكسجين (COD) في مياه الصرف الصحي بالحوراء، بالإضافة إلى ارتباطها بالمؤشرات الإحصائية. تمت المعالجة باستخدام نظام MBR-EC مع ظروف تشغيلية، درجة حرارة (٢٥ ° درجة مئوية)، ودرجة الحموضة (٧-٨)، و DO(٤-٦) مجم / لتر، والتركيزات الأولية والنهائية من BOD(١٨٤-٦ مجم / لتر)، و COD(٤٨٩-٢٠ ملجم / لتر) باستخدام إجراءات المعالجة البيولوجية والكهروكيميائية. ووفقًا للنتائج، يمكن حساب كفاءة إزالة المادة العضوية باستخدام الانحدار المتعدد (MLR) ونماذج الشبكة العصبية (NN) في برنامج SPSS. بالإضافة إلى ذلك، أوضحت النتائج أن المفاعل بأكمله كان له كفاءة إزالة جيدة من BOD و COD بلغت ٩٦.٧٪ و ٩٥.٩٪ على التوالي. أخيرًا، أعلى دقة لخوارزمية MLR لـ COD و BOD هي ٩٩.٦ لكليهما، في حين أن أقصى دقة لخوارزمية NN لـ COD و BOD هي ٩٩.٢٪ و ٩٩.١٪ على التوالي، لاختيار أفضل خوارزمية لتحليل ونمذجة النتائج. يجب مقارنة نتائج الخوارزميتين. لذلك تم اختيار خوارزمية MLR لهذه الدراسة.

1. INTRODUCTION

The gap between demand for clean water supplies and contaminated water arising from population growth, industrial activities and home sewage disposal has deepened. The problem of pollution in water sources has grown as a result of industrial activities, population growth, urban development, and advancement. As a result, instead of disposing of polluted water at a significant expense, it must be considered that cleaned water from polluted water is valuable and an essential supply of water. Domestic wastewater treatment has demonstrated excellent outcomes when biological activities are combined to physical or physio-chemical processes. In this regard, the electrocoagulation process EC with membrane bioreactor MBR has demonstrated its capacity to provide a wonderful solution for waste water recycling. [1,2].

Electrocoagulation (EC) is an electrochemical water treatment process used by a variety of industries. The process destabilizes and aggregates contaminant particles, ions such as heavy metals, and colloids, using an electrical charge to hold them in solution. The process traditionally utilizes an anode and a cathode, stimulated by a DC power source to destabilize the charges. This operation separates flocculated materials from water, allowing those materials to be removed, leaving clear water. [3,4]

Wastewater treatment using membrane bioreactors membrane bioreactors combine a suspended growth biological treatment technology, such as activated sludge, with membrane filtration equipment, such as low-pressure microfiltration (MF) or ultrafiltration (UF) membranes, for wastewater treatment. The membranes are utilized to separate solids from liquids, which is a crucial function. Secondary and tertiary clarifiers, as well as tertiary filtering, have typically been used in activated sludge plants to accomplish this. Vacuum (or gravity-driven) and pressure-driven MBR systems are the two most common varieties. Immersed vacuum or gravity systems are commonly used, with hollow fiber or flat sheet membranes inserted in the bioreactors or a later membrane tank. External to the bioreactor, pressure driven systems are in-pipe cartridge systems. [5]

There are many researches studied the different type of wastewater treatment by MBR, the application of electro-technologies to existing biological treatment methods to assess the microbial populations in a bio-electrochemical reactor under a different operating conditions and at lower current densities, electric field that supplied greatly improve reported bacterial populations, growth rates, and chemical oxygen demand (COD) removal. The use of a direct current (DC) field has shown to be a feasible and innovative technique. This can be accomplished by incorporating electrocoagulation (EC) into the same reactor as the MBR. [7,8] a well as using the membrane as a cathode can be used to achieve this technique [9]. Direct applying of a DC field to the activated sludge reactor may be harmful to microbial activity [10]. One option is to employ the EC unit as a pre-treatment step before the MBR system to reduce direct microbial community interaction with the applied DC field. In this study, an electrocoagulation unit (EC-MBR process) was used as a pre-treatment for a municipal waste water treatment MBR, with the two reactor systems linked in a series and operating in continuous flow mode. In addition, electrode design and material, as well as the applied direct current field between the electrodes, have an impact on submerged membrane bioreactor treatment performance. The electrodes in the SMBR should be designed to allow for optimal aeration distribution while not obstructing mixed liquid circulation. [11]. To evaluate the effectiveness of water treatment units, artificial intelligence programs can be used with a variety of algorithms. The effectiveness of the treatment units is assessed by analysing the data that collect from treatment units. [12].

2. OBJECTVE AND PURPOSE

The main goal of the present study is to evaluate the performance of the MBR process combined with the EC process, using Multilinear regression (MLR) and neural network (NN) models in SPSS modeler, to remove BOD and COD that discharged in the domestic wastewater of Al Hawraa residential area.

The precise aims of the study are as follows:

1. Investigation of (EC–MBR) method to reduce the concentration of pollutants in domestic wastewater.
2. Make comparatave study between MLR algorithm and NN algorithm in this study via SPSS modeler in this study.

3. METHODOLOGY AND PROCEDURE

The methodology that followed in this study involved of the following tasks:

1. The domestic wastewater is collected at the Wasit governorate's AL-Hawraa residential quarter (HRQ).
2. EC-MBR system was run into two haydrulic retintion time HRT 12 hr and 24 hr, until getting of COD and BOD initial and final concentrations.
3. Multiple linear regression algorithm and neural network algorithm was established to select the best algorithm that can be used to analysis the results of COD and BOD.

4. MATERIALS AND METHODS

4.1 Case study description

Figure 1 shows the AL-Hawraa residential unit (HRU) in Wasit governorate, which contains around 5000 housing units, the number of schools is (8), one sports City, one health clinic, one rain station, and one wastewater plant. AL-Hawraa was erected on a 67-acre site at a total cost of (41) billion dinars.

The current analysis focuses on HRU municipal wastewater, assuming that each household has five persons and that the average wastewater for each is 80 percent of the water consumption [13], which is (400 L/person per day).

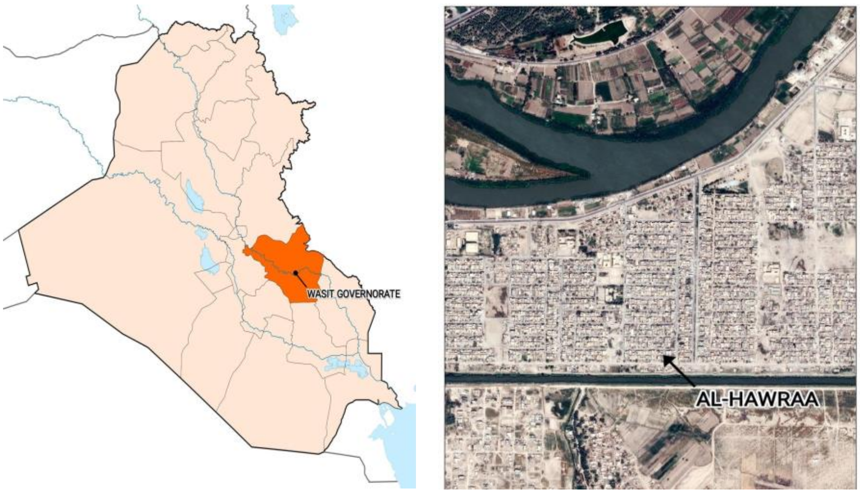


Figure 1 Location of Al-Hawraa residential unit in Wasit city (Wasit Sewer Division Directorate, GIS Division)

4.2 Data collection

In this study, data were collected from laboratory experiments that included the manufacture of an Electrocoagulation with Membrane Bioreactor and testing its efficiency in removing BOD and COD over time, as well as other environmental factors such as PO4 (mg/L), TSS (mg/L) and NO3 (mg/L) of Al-Hawraa residential unit. Data gathered from the pilot scale EC-MBR system that designed in this study to treat domestic wastewater. In data analysis, Excel 2019 software was used. The neural network (NN) and Multiple Linear Regression (MLR) algorithms was carried out using IBM SPSS modeler 18 software.

4.3 Experimental set-up

A pilot-scale EC-MBR with an effective volume of (0.008) m^3 was used in this investigation. As illustrated in Figure 2, the bioreactor's riser was immersed in a hollow fibre membrane module made of polyvinylidene fluoride (PVDF) (Made in Republic of Korea) with a pore size of (0.05) micron and a filtering area of (0.8) m^2.

Because the bacteria activity is at its highest level, the EC (with 0.003 m3 in volume) is operated twice a day for Hydraulic Retention Time (HRT 12) and once a day for (HRT 24) with electrodes running for five minutes. The water is pumped from the EC to the feeding tank and subsequently to the membrane after five minutes in the EC (which works continuously). The difference in flow rate is around (15-20 percent) and consider as measure of membrane fouling development. A perforated pipe inserted beneath the membrane module carries out the air, which is linked to a distributor in the feeding tank and another in the membrane module for aeration. One of the good elements of the reactor that linked to EC is the efficiency of the reactor in comparison to the typical economic cost.

Higher capital and operational expenses that owing to membrane cleaning and replacement, as well as high energy prices, are reprecented the disadvantages of this reactor. Additionally, extra chemicals may be necessary to boost the settling rate of waste sludge in the system. On the other hands, there are some benfits of the reactor such as High-quality effluent, greater volumetric loading rates, shorter hydraulic retention periods (HRT), reduced sludge generation, and the possibility of simultaneous nitrification/denitrification in a lengthy solid retention time.

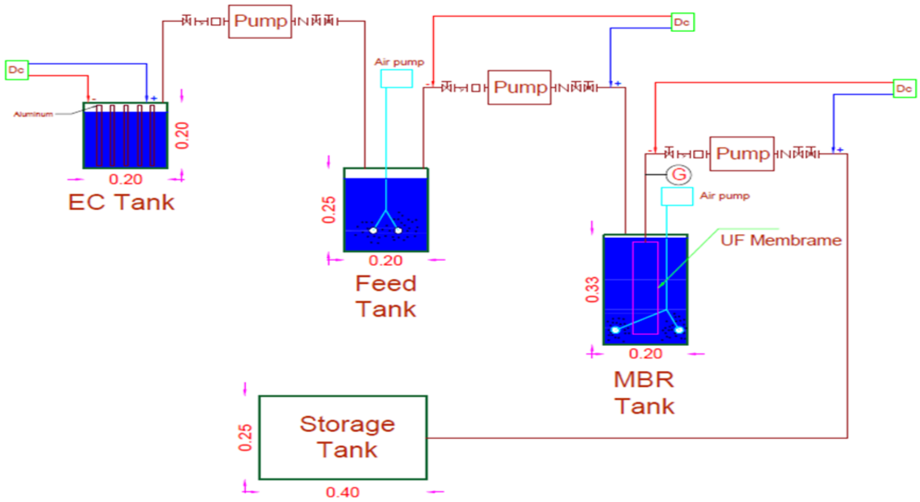


Figure 2 A pilot-scale EC-MBR.

5. RESULTS AND DISCUSSION

5.1 COD AND BOD Removal

Domestic wastewater treatment was investigated under two different HRT perioeds (12 and 24 hours), and two removals were achieved in the current study, with the first removal in the electrocoagulation tank and the second removal by the membrane bioreactor, and the overall removal of organic matter at the end of the system (BOD and COD).

Because a free anodic appears in the EC reactor and interferes with charged double layers after a time of adaption, the removal in mixed liquor was improved. Figures 3 and 4 show the temporal patterns of COD and BOD concentrations (influent and effluent) and their total removal effectiveness for 12 and 24 hours, respectively.

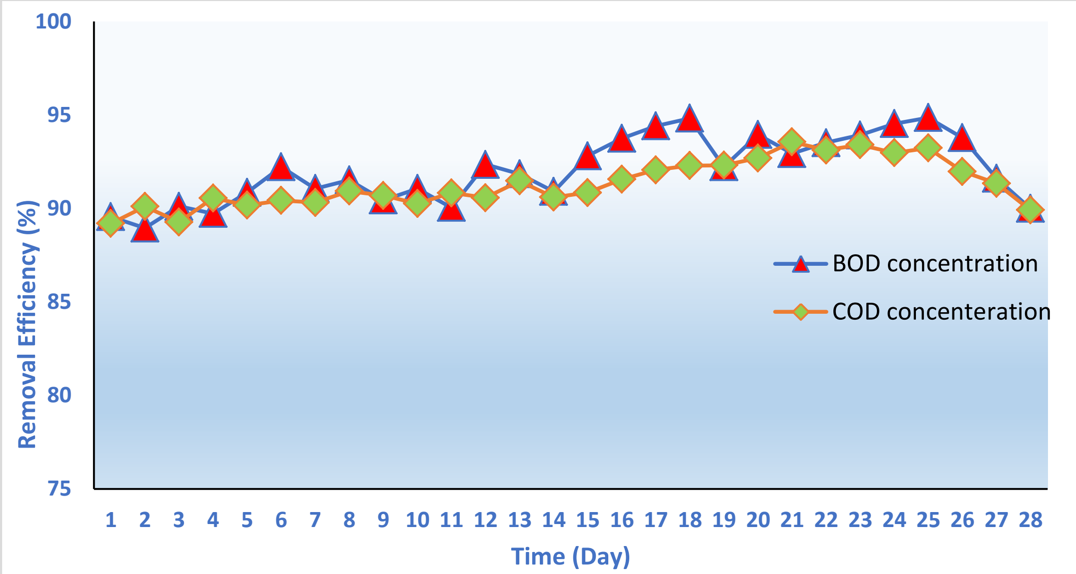


Figure 3 The COD and BOD overall removal efficiency at HRT 12 hrs.

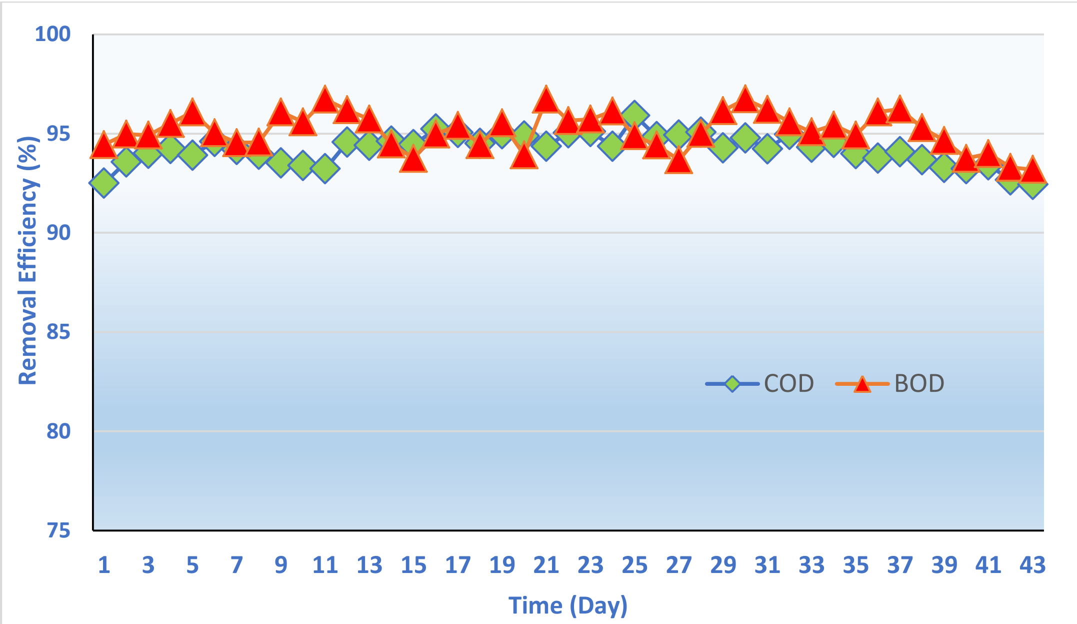


Figure 4 The COD and BOD overall removal efficiency at HRT 24 hrs

The overall reactor showed good COD and BOD removal efficiency across the testing period at HRT = 12 h, with a high removal percentages of (93.56% and 94.86%, respectively), as well as (95.91% and 96.4%) at HRT = 24 hr. The total removal efficiency for COD was achieved with a final effluent concentration of 20 mg/L and for BOD with a final effluent concentration of 6 mg/L [14].

Some researches has found that the MBR process removes more COD and BOD than the current study, which has been attributed to low quantities of biodegradable organic matter in wastewater and the presence of scarcely degradable chemicals [15].

5.2 Data analysis

The SPSS Modeler application is a widely used program for describing variables and parameters. Also SPSS is a statistical program with a number of tools and lists that may be generated from data input. The data is then analysed and generalized using neural network (NN) and Multiple Linear Regression (MLR) algorithms, and we may select the optimal technique for data analysis [16].

5.2.1 Multiple linear regression model (MLR)

The regression approach is utilized as a linear connection between dependent and independent variables to approximate the link between a single defined predictor variable (removal efficiency of COD and BOD) [17]. The parameters are used as independent variables in the MLR linear equation to construct the classification functions as follows:

$$Y_i = constant\ (B_\circ) + a_1 x_1 + a_2 x_2 + \cdots + a_n x_n \tag{1}$$

The independent variables are indicated by x, and the dependent variables are denoted by y. For I = 1, the classification function is indicated by (Y i) (a number of condition classes), the classification coefficients are denoted by (ai), and the offset is given by (a constant value).

Result of COD and BOD for HRT 12 hr and 24 hr;

The accuracy model represents the strength of the model, i.e., the removal efficiency relative to the concentration of the electrocoagulation process and the membrane bioreactor and the time of the treatment process. The assessment of model shows some indicators that can be used to evaluate the model such as, maximum error, minimum error and linear correlation. The prediction model The prediction model It reflects the data distributed on the general regression line, with the more data lying on the regression line, the model be better (strong).

For COD at HRT 12 hr:

Model Summary

Target	Total Removal
Automatic Data Preparation	On
Model Selection Method	Forward Stepwise
Information Criterion	-119.954

The information criterion is used to compare to models. Models with smaller information criterion values fit better.

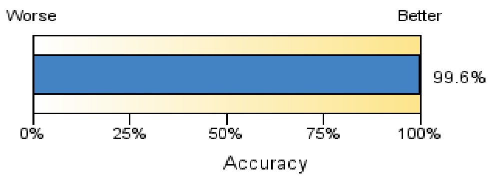


Figure 5 The accuracy of MLR for COD at HRT 12 hr.

Minimum Error	-0.237
Maximum Error	0.242
Mean Error	-0.0
Mean Absolute Error	0.082
Standard Deviation	0.106
Linear Correlation	0.998
Occurrences	28

Figure 6 Assessment of MLR model.

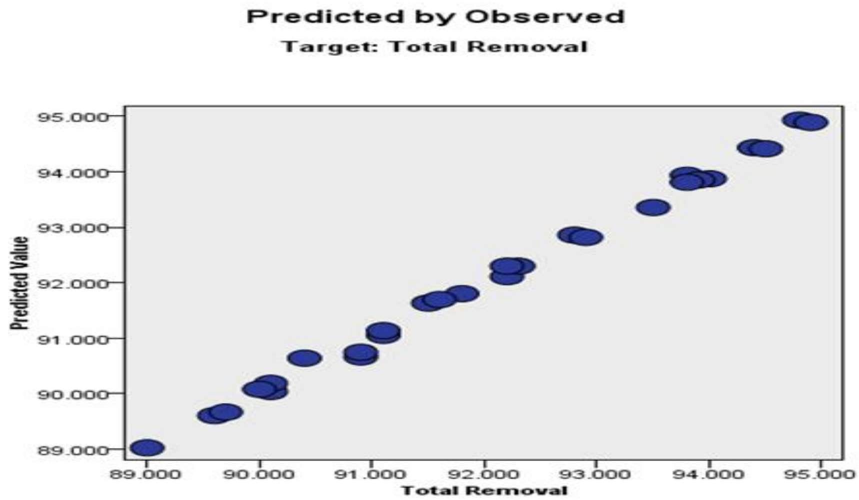


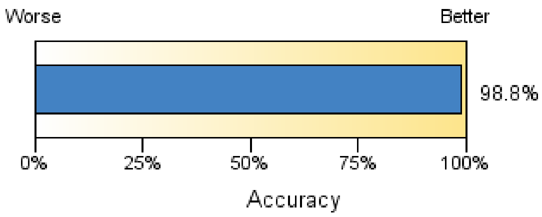
Figure 7 The prediction model for COD at HRT 12 hr.

For COD model at HRT 24 hr:

Model Summary

Target	Total Removal
Automatic Data Preparation	On
Model Selection Method	Forward Stepwise
Information Criterion	-210.771

The information criterion is used to compare to models. Models with smaller information criterion values fit better.



Minimum Error	-0.208
Maximum Error	0.13
Mean Error	0.0
Mean Absolute Error	0.064
Standard Deviation	0.081
Linear Correlation	0.994
Occurrences	43

Figure 8 The accuracy model of MLR for COD at HRT 24 hr.

Figure 9 Assessment for MLR model.

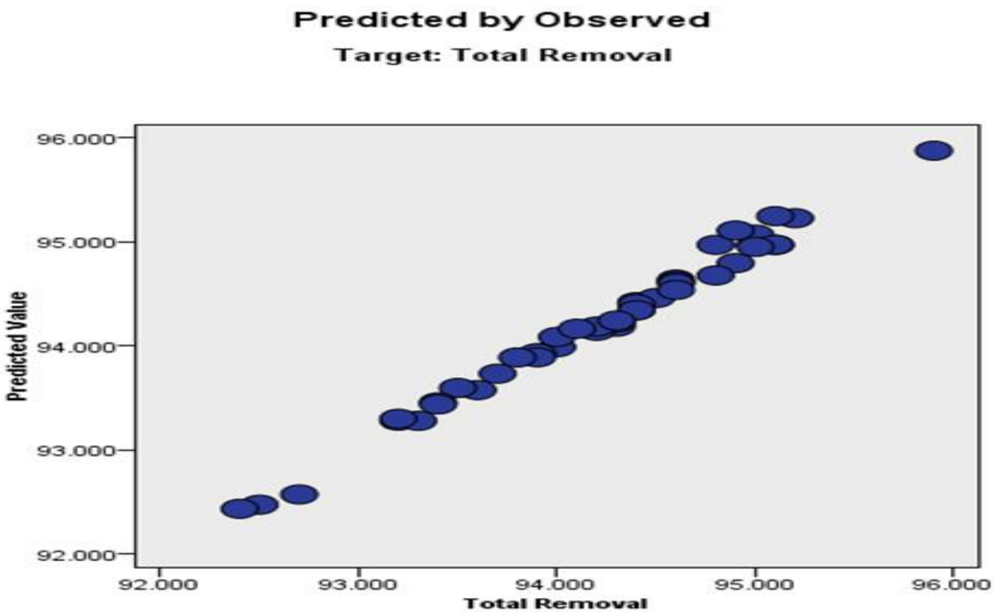


Figure 10 The prediction model for COD at HRT 24 hr.

For BOD model at HRT 12 hr:

Model Summary

Target	Total Removal
Automatic Data Preparation	On
Model Selection Method	Forward Stepwise
Information Criterion	-119.954

The information criterion is used to compare to models. Models with smaller information criterion values fit better.

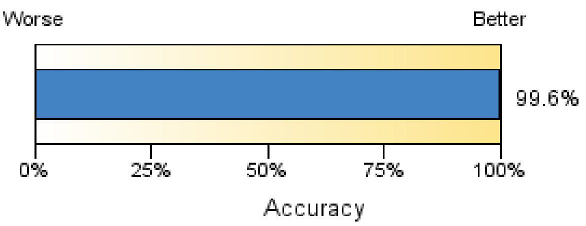


Figure 11 The accuracy of MLR model for BOD at HRT 12 hr.

Minimum Error	-0.237
Maximum Error	0.242
Mean Error	-0.0
Mean Absolute Error	0.082
Standard Deviation	0.106
Linear Correlation	0.998
Occurrences	28

Figure 12 Assessment of MLR model.

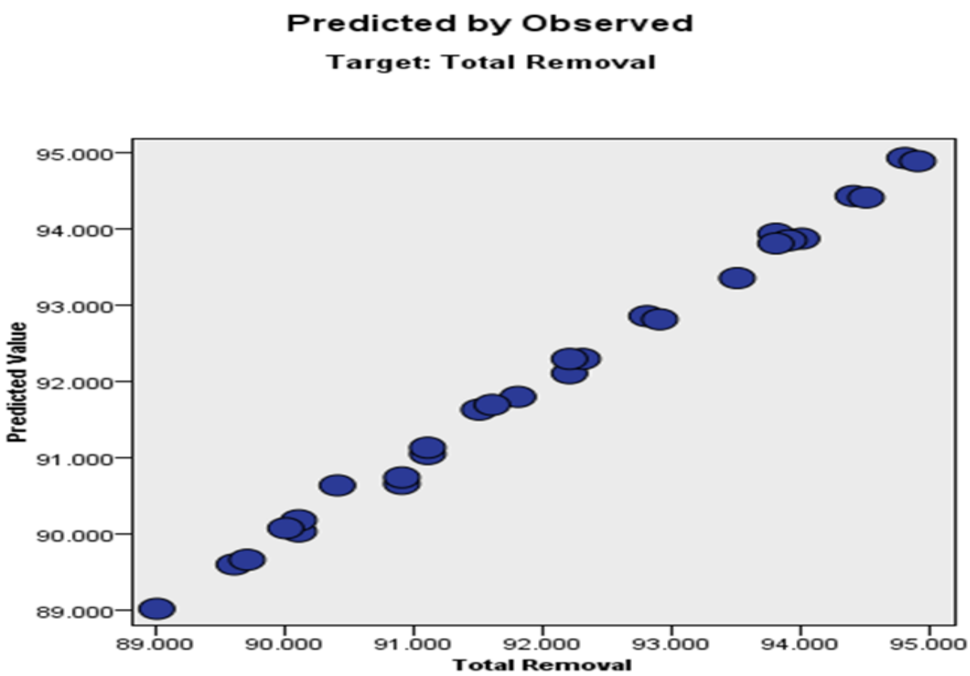


Figure 13 The prediction model for BOD at HRT 12 hr.

For BOD model at HRT 24 hr:

Model Summary

Target	Total Removal
Automatic Data Preparation	On
Model Selection Method	Forward Stepwise
Information Criterion	-181.348

The information criterion is used to compare to models. Models with smaller information criterion values fit better.

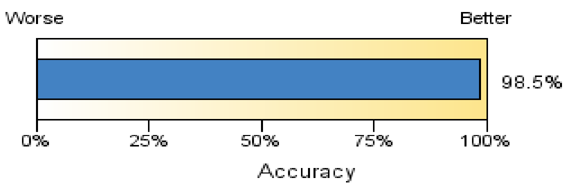


Figure 14 The accuracy of MLR model for BOD at HRT 24 hr.

Minimum Error	-0.305
Maximum Error	0.277
Mean Error	-0.0
Mean Absolute Error	0.084
Standard Deviation	0.111
Linear Correlation	0.993
Occurrences	43

Figure 15 Assessment of MLR model.

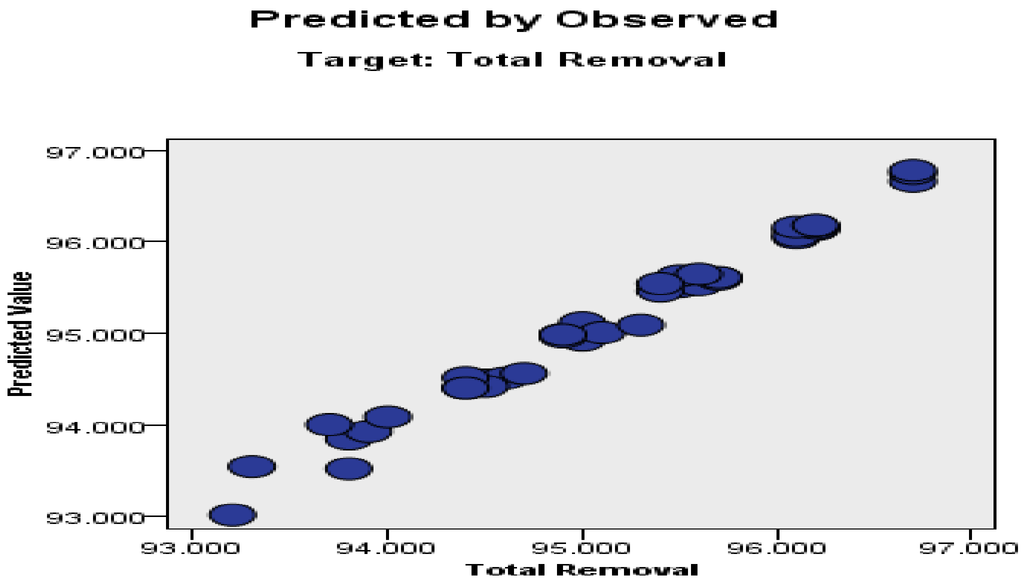


Figure 16 The prediction model for BOD at HRT 24 hr.

5.2.2 Neural Network model (NNM)

The SPSS class of machine learning (ML) includes neural networks (NN). Neural Networks employ many layers of neurons to enter data into the network, then send it to a hidden layer for prediction. The difference between the goal and predicted numbers is used to compute the error [18].

Result of COD and BOD for HRT 12 hr and 24 hr

The prediction model It reflects the data distributed on the prediction line, with the more data lying on the predction line, the model be better (strong).

For COD at HRT 12 hr:

Model Summary

Target	Total Removal
Model	Multilayer Perceptron
Stopping Rule Used	Error cannot be further decreased
Hidden Layer 1 Neurons	1

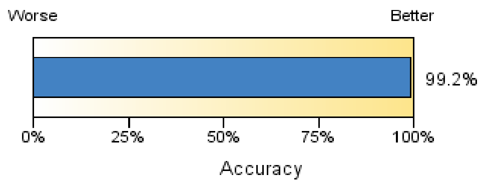


Figure 17 The accuracy of NN model for COD at HRT 12 hr.

Minimum Error	-0.275
Maximum Error	0.219
Mean Error	-0.002
Mean Absolute Error	0.09
Standard Deviation	0.113
Linear Correlation	0.996
Occurrences	28

Figure 18 Assessment of NN model.

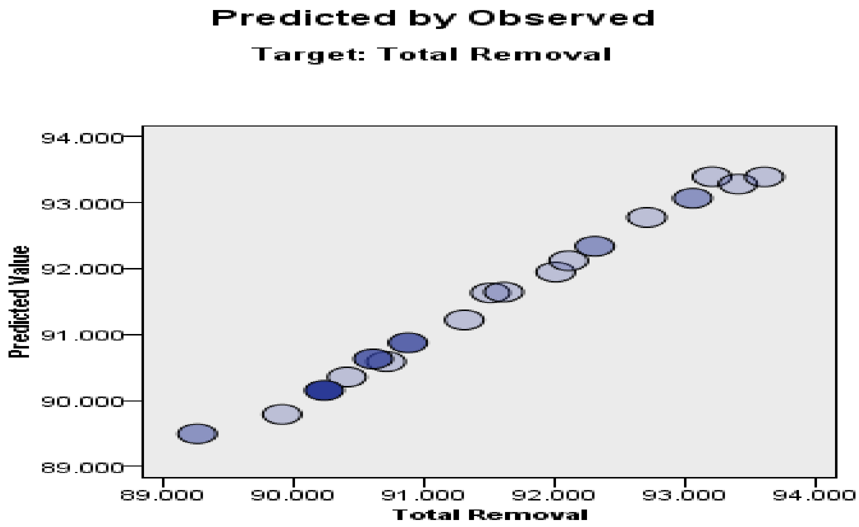
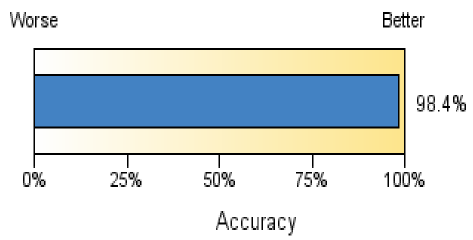


Figure (19): The prediction of NN model for COD at HRT 12 hr.

For COD at HRT 24 hr:

Model Summary

Target	Total Removal
Model	Multilayer Perceptron
Stopping Rule Used	Error cannot be further decreased
Hidden Layer 1 Neurons	2



Minimum Error	-0.216
Maximum Error	0.376
Mean Error	-0.006
Mean Absolute Error	0.064
Standard Deviation	0.096
Linear Correlation	0.992
Occurrences	43

Figure 20 The accuracy of NN model for COD at HRT 24 hr.

Figure 21 Assessment of NN model.

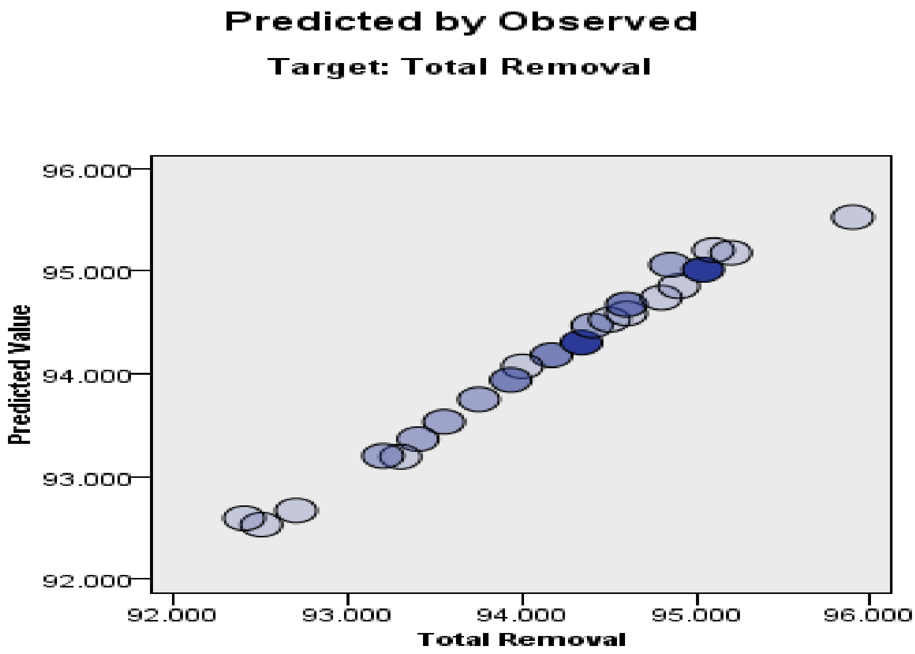


Figure 22 The prediction of NN model for COD at HRT 24 hr.

For BOD at HRT 12 hr:

Model Summary

Target	Total Removal
Model	Multilayer Perceptron
Stopping Rule Used	Error cannot be further decreased
Hidden Layer 1 Neurons	1

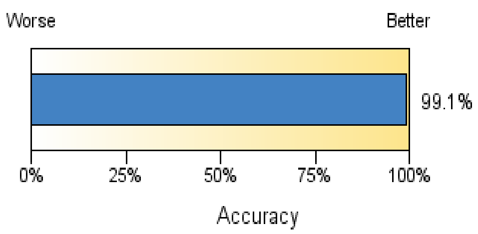


Figure 23 The accuracy of NN model for BOD at HRT 12 hr.

Minimum Error	-0.531
Maximum Error	0.333
Mean Error	-0.022
Mean Absolute Error	0.117
Standard Deviation	0.168
Linear Correlation	0.996
Occurrences	28

Figure 24 Assessment of NN model.

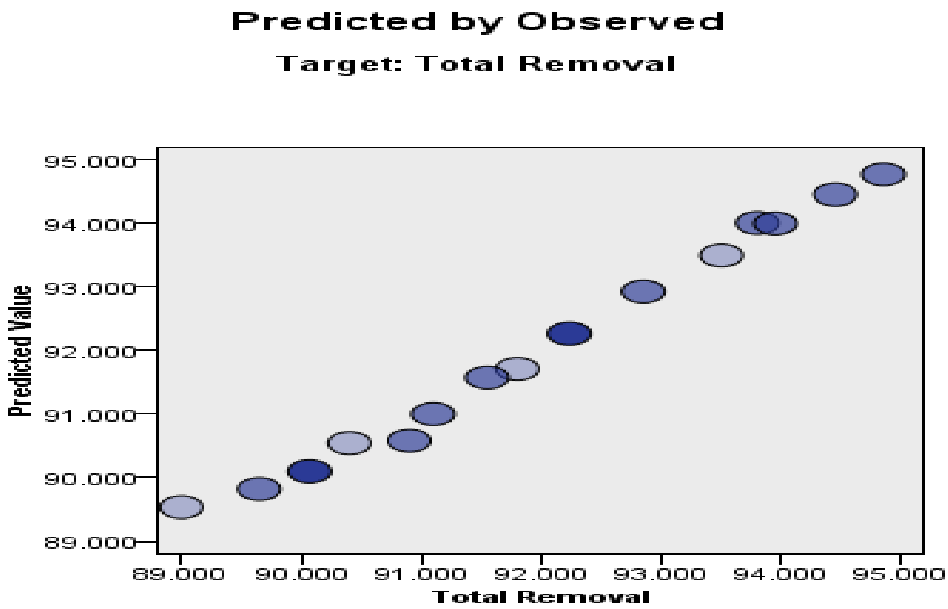


Figure 25 The prediction of NN model for BOD at HRT 12 hr.

For BOD at HRT 24 hr:

Model Summary

Target	Total Removal
Model	Multilayer Perceptron
Stopping Rule Used	Error cannot be further decreased
Hidden Layer 1 Neurons	1

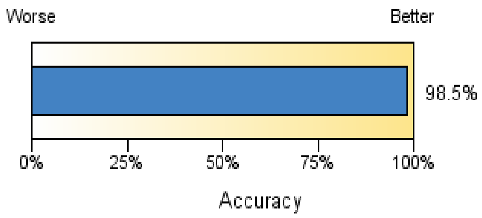


Figure 26 The accuracy of NN model for BOD at HRT 24 hr.

Minimum Error	-0.257
Maximum Error	0.256
Mean Error	-0.017
Mean Absolute Error	0.084
Standard Deviation	0.113
Linear Correlation	0.993
Occurrences	43

Figure 27 Assessment of NN model.

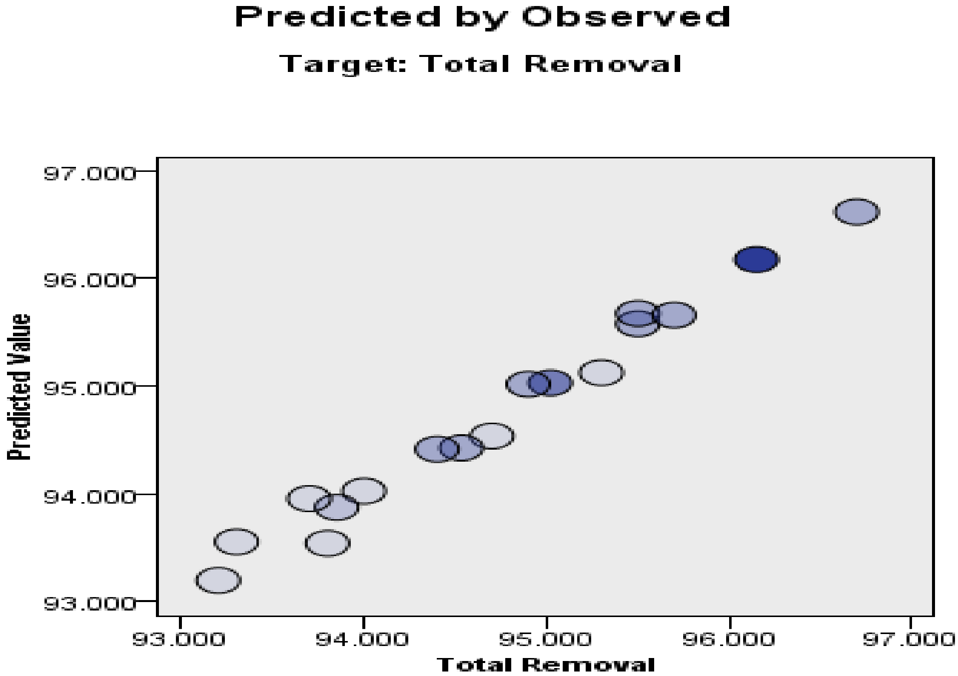


Figure 28 The prediction of NN model for BOD at HRT 24 hr.

by using these two algorithms to analysis and modeling of COD and BOD removals at two HRT periods as this will allow to make a comparative between MLR and NN as illustrated in Table (1)

Table 1 Results of MLR and NN algorithms for COD and BOD removals

Algorithms	Parameters	Accuracy %	Linear correlation %
MLR	COD at HRT 12 hr.	99.6	99.8
	COD at HRT 24 hr.	98.8	99.4
	BOD at HRT 12 hr.	99.6	99.8
	BOD at HRT 24 hr.	98.5	99.3
NN	COD at HRT 12 hr.	99.2	99.5
	COD at HRT 24 hr.	98.4	99.2
	BOD at HRT 12 hr.	99.1	99.6
	BOD at HRT 24 hr.	98.5	99.3

The comparison of results of the two algorithms shows that the MLR accuracy percentage for COD and BOD is around 99.6 % and the linear correlations for COD and BOD is around 99.8% for both. For the neural network, the model accuracy for COD and BOD is around 99.2% and 99.1% and the linear correlations for COD and BOD is around 99.5% and 99.6%.

The optimum method to utilize in this study for the given results is the multiple linear regression technique.

6 CONCLUSIONS

The following conclusions can be drawn from the current study;

Consistent filtration was accomplished during the course of a 43-day operation of a pilot-scale EC-MBR for domestic wastewater treatment, due to effective membrane fouling management, and the following results were reached:

The overall reactor showed a high COD and BOD removal efficiency across the testing period at HRT = 24 hr, with a maximum of 95.91% and 96.7%, respectively, as well as to (93.56% and 94.86% at HRT = 12 hr). The total removal efficiency for COD was achieved with a final effluent concentration of 20 mg/L and for BOD with a final effluent concentration of 6 mg/L. The use of statistical indicators gives positive results in the MLR and NN models, with expellant accuracy for both algorithms: MLR gives us good accuracy of 99.6%, and NN algorithm offers us good accuracy of 99.2%. According to obtained results, the best algorithm for this study is the MLR algorithm. MBR electrocoagulation is used to increase the removal of organic compounds from coagulated surfaces and to give the system more activity.

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