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Treatment of Bilge Water by Membrane Bioreactor and Prediction of Effluent Characteristics by Artificial Neural Network

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Keywords

Bilge water,
Membrane bio-reactor,
Oily-saline wastewater.

Abstract

The purpose of this study is to investigate the treatment of bilge water by membrane bioreactor. The highest value of COD removal, turbidity, TDS, TSS and color at HRT of 48 h are of 91.96, 99.85, 97.48, 100 and 100%, respectively. Also, the neural network was used to predict membrane bioreactor effluent. Multilayer perceptron was used, which showed a great fit. For TCOD, the best algorithm was Levenberge-marquardt with mean R and MSE of 0.9962 and 2.8179, respectively and for turbidity, the Levenberge-marquardt algorithm with mean R and MSE was 0.9734 and 0.00092, respectively.

1. Introduction

Bilge water consists of seawater, oily fluids, lubricants, detergents, and other similar wastes. The main sources of bilge water in a vessel include engines, boilers, evaporators and related auxiliary systems, equipment and associated components, machines and other operations. the characteristics of bilge water is different among vessels. Furthermore, the salinity of bilge water is varied where many problems are generated for biological treatment [1, 2]. The production of bilge water in the U.S.A. is predicted to be millions of cubic meters per year. cruise ships, generate about 1800-7200 m3 per day [3]. It has been estimated that bilge water, a serious oily pollutant resource, includes 20% of oily wastewater discharged through channels into the oceans around the world [4]. Also, wastewater can contaminate the soil because of heavy metals which cause several problems such as, the loss of ecosystems, the deterioration of food chain, polluted water resources, economic damage, and human and animal serious health problems etc [5].

There are several treatment methods including biological, chemical and physical processes [6]. But biological process is the most popular one due to its high performance [7-9]. Membrane separation processes such as nanofiltration (NF), ultrafiltration (UF) and reverse osmosis (RO) are used to purify a wide variety of industrial and municipal wastewater [10-13]. As a very efficient process, ultrafiltration process was favorable for using in the studies because of its low expense energy and high efficiency [14].

The aerobic microbial consortium was treated through 3 pilot (200 L) Moving Bed Biofilm Reactors (MBBRs) under filling fractions of 10%, 20% and 40% and then treated actual bilge water during 165 days under 36 h HRT. The MBBR having a filling fraction of 40% caused the highest COD reduction (60%) rather than the operation of the MBBRs with a filling fraction of 10% and 20%. [2]. Hybrid up-flow anaerobic sludge blanket (HUASB) bio-reactor for treating dilute bilge water. Eventually the efficiency of COD removal reached into 75% with the HRT of 8 h and OLR of 0.6 g COD/l day [8]. Artificial neural networks which is an authentic method, can be applied to predict the performance of wastewater treatment processes [15-17].

In this paper, the pilot study of bilge water was investigated by membrane bioreactor in order to find the best condition. Also, MLPANN was applied for estimating the performance of biological treatment of bilge water through different retention times. The operating parameters included total chemical oxygen demand and turbidity applied in a system.

2. Material and Methods

2.1. Characteristics of Synthetic Bilge Water

Bilge water was sampled several times from the ships in order to obtain the most certain characteristics of bilge water. Collection and maintaining the samples were done according to the standard methods for water and wastewater. The oil and surfactants are the main pollutants of bilge water. In order to synthesize the bilge water, the seawater was mixed

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with used oil prepared from ships' engine and also sodium dodecyl sulfate (sds) was added as surfactant in order to emulsify the oil in seawater. O&G concentration of real bilge water was 440 mg/l. The main characteristics of bilge water are suggested in Table 1.

Table 1. Characteristic of synthetic bilge water

Characteristic	Number	Value
pH	28	6.8-7
COD	28	908 ± 8
BOD	14	425 ± 20
O&G	14	449 ± 12
Turbidity	28	123 ± 4
Phosphate	28	5 ± 1
TDS	28	15084 ± 396

2.2. Experimental Setup

The influent of membrane reactor was transferred from feed tank into bioreactor through a peristaltic pump. The working volume of bioreactor was of 1.4 L equipped by diffusers for supplying air. The surplus sludge was monitored through a peristaltic pump. A programmable logic controller was applied in order to control the pumps.

2.3. Pilot Startup

In this research, the microorganisms adapted to oily wastewater having either high salinity was provided in order to treat bilge water. The process of microorganism growth and adaptation to bilge water was conducted for 4 weeks. Then it was transferred into the pilot. Membrane bioreactor with ultrafiltration membrane has an effective volume of 1.4 L. MLSS reaches into 7960 mg/l. In this bioreactor, the membrane is located vertically. HRT of 24 h and 48 h was applied in order to find the optimum condition.

2.4. Experimental Setup

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2.5. Analytic Method

The sample analyses were defined according to the APHA standard methods [18] for measuring total COD, mixed liquor suspended solid, fat, oil and grease and phosphate. TCOD was measured through thermo-reactor. The concentrations of Phosphate were estimated through spectrophotometer. Turbidity was also estimated through a turbidity meter. The samples of COD were defined through Freire and Sant'Anna method due to high concnetration of chloride [19, 20].

2.6. Model Developments

Operational data of primary studies about bilge water treatment was used to train network. In order to train networks, some learning algorithms were used. MLPANN was applied to predict the operation of system. it included an input layer of three nodes consisting COD, TU, and HRT, a hidden layer with some nodes for obtaining the best model and output layer with two nodes of COD and TU. The structure of neural network is suggested in Figure 1. ANN which works in parallel consisting neural cells, a single computing processor having two summing function and transfer function [21, 22].

Several networks were used for finding the best transfer function for hidden and output layer. When MSE reached under ep=0.1, or after 1000 iteration step, the network stopped working. The proper transfer function for hidden and output layers were tansig and purelin, respectively.

Of all data, 70% was used for training the networks and 15% was used for testing the networks. In a set of validation data, 15% of data was used for evaluating the function of network through training.

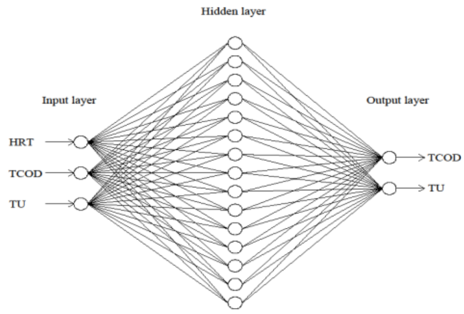

Figure 1. The structure of neural network

2.7. Models Verification

R^2 and mean square error (MSE) between the predicted values of the network and the experimental values were used to estimate the function of models which were computed through Eqs. (1) and (2), respectively [23, 24].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i^* - y_p^{(i)})^2}{\sum_{i=1}^{n}(y_i^* - \bar{y})^2} \quad (1)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_p^{(i)} - y_i^*)^2 \quad (2)$$

where $\bar{y}$ is the average of y over the n data, and $y_i^*$and $y_p^{(i)}$ are the ith target and predicted responses, respectively.

3. Results and Discussion

3.1. Reduction of COD, TU and O&G

COD, turbidity and O&G removal rate are among the most important functional parameters describing organic matter removal. In the first stage, OLR of 0.58 kgCOD/(m^3d) with HRT of 24 h, the minimum COD and turbidity concentration were obtained as 80 mg/l and 0.1 NTU and the maximum COD was 137 mg/L during the first period. In the second stage, retention time increased into 48 h where OLR was 0.29 kgCOD/(m^3d). The least COD and turbidity concentration were 51 mg/L and 0.1 NTU. The highest COD concentration was 80 mg/l through this study. O&G concentration in this test was lower than 10 mg/l. The ability of MBR was more than other conventional activated sludge systems. For treating produced water, MBR could remove chemical oxygen demand (COD), total organic carbon (TOC) and oil and grease (O&G) removal efficiencies up to 90.9%, 92% and 91.5%, respectively at HRT of 20 h [19].

Removal efficiency caused by Membrane Separation was measured through dividing the concentration of removed

COD in supernatant. Total removal efficiency is a combination of biological and membrane separation processes. Membrane process mostly separates some pollutants and microorganisms from biological treated wastewater (14%) and balances instability of bioreactor.

3.2. Oil Concentration and MLSS

MLSS concentration increased from 900 mg/l to 7960 mg/l during 30 days. Then, it was monitored for the final value in order to assess bilge water treatment operation. The oil in the synthesized wastewater was of 449.85 mg/l.

3.3. The Effect of HRT on Turbidity and COD Removal

In biological wastewater treatment, retention time (HRT) is an important functional parameter. Figure 2 and 3 suggest the effect of retention time for removing the polutants from bilge water. The maximum efficency of COD removal was obtained in the highest HRT. In 48 h retention time, average effluent COD concnentration was lower than 60 mg/l. It could be concluded that in lower retention time, enhancement of COD in the effluent may be attributed to insufficient contact time in the system.

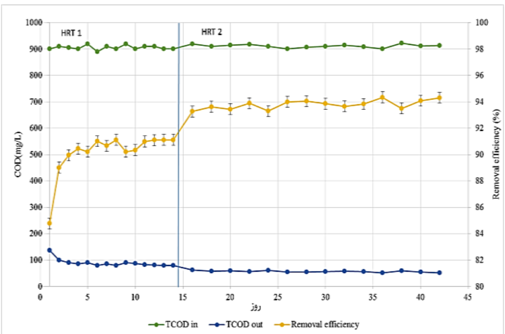

Figure 2. Membrane bioreactor operation for COD removal

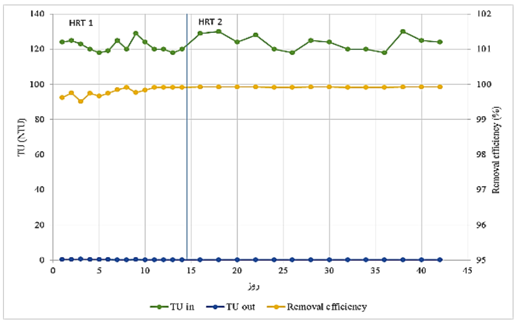

Figure 3. Membrane bioreactor operation for turbidity removal

3.4. Effluent SS

In a membrane bioreactor system, membranes are the main devices for separating liquid from solids. During the experiment, no SS was observed in MBR effluent. Therefore, the final effluent just includes dissolved pollutant available in the system. SS removal efficiency was remained as 100% suggesting very efficient separation of ultrafiltration membrane.

3.5. Turbidity Removal Efficiency

Turbidity of crude bilge water was high and it was varied from 118 to 130 NTU during the experiments. The effluent turbidity was always lower than 1 NTU due to the great ability in membrane separation.

3.6. Feed to Microorganism Ratio (F/M)

In this study, the values of F/M were of 0.036-0.0743 kgCOD/KgMLSS.d which are lower than F/M ratios obtained by Pendashteh et. al for treating the oily synthesized wastewater in a membrane bioreactor with OLR of 0.62 kgCOD/KgMLSS.d [19].

3.7. ANN

Prediction of COD and turbidity of bilge water treatment were done by MLPANN. Operation of a network algorithm depends on data features, number of neurons and problem complexity [25].

This model was trained with 9 different algorithms for predicting the effluent of treatment process (Table 3). The best algorithm for COD was obtained to be Levenberge-marquardt with average R and MSE of 0.9962 and 2.8179 mg/L, respectively. Also for turbidity, Levenberge-marquardt algorithm was the best with average R and MSE of 0.9734 and 0.00092, respectively. After 1000 iteration step, according to the obtained R for all parameters, TCOD had highest value of R in Levenberge-marquardt compared to the turbidity. Other algorithms such as CGF and SCG suggest an appropriate function.

Various transfer functions were used for the hidden and output layers by error and trial method. Tangsig was the best transfer function for hidden layer and pure line was the best transfer function of output layer.

Figure 4 (A and B) suggest the effluent characteristics in membrane bioreactor predicted by MLPANN. Input turbidity was low, so the system could remove turbidity highly in both stages. There is high correspondence between experimental and predicting data of all parameters and the obtained results suggest that MLPANN is a suitable model for predicting turbidity and TCOD.

Table 3. Comparison of different algorithms

Description	Algorithm	Output parameters			
		TCOD		Turbidity	
		R	MSE	R	MSE
Levenberg-Marquardt	Trainlm	0.9962	2.8179	0.9734	0.00092
BFGS Quasi-Newton	Trainbfg	0.9921	5.8906	0.9100	0.0030
Resilient Conjugate gradient	Trainrp	0.9919	6.0720	0.9293	0.00238
Scaled Conjugate Gradient	trainscg	0.9922	5.8786	0.9098	0.0030
Conjugate Gradient With Powell/Beale Restarts	traincgb	0.9912	6.6376	0.9133	0.00295
Fletcher-Powell Conjugate Gradient	traincgf	0.9928	5.5721	0.9098	0.0030
Polak-Ribiére Conjugate Gradient	traincgp	0.9911	6.8626	0.9107	0.00297
One Step Secant	trainoss	0.9898	7.9298	0.9086	0.00305
Variable Learning Rate Backpropagation	traingdx	0.9894	7.8992	0.9028	0.00322

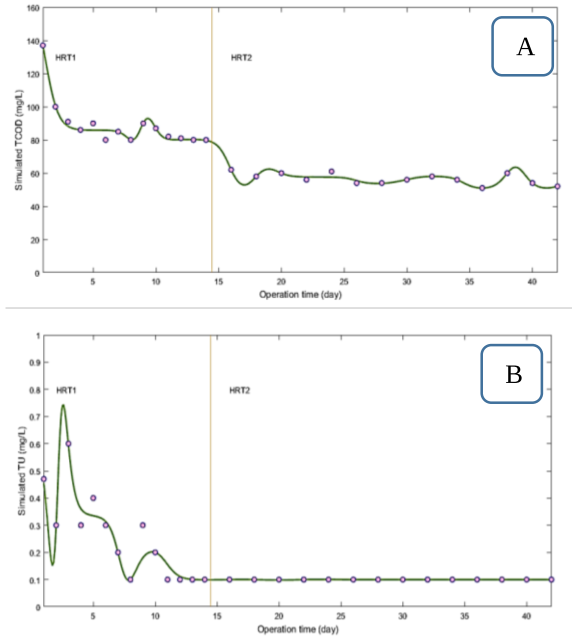

Figure 4. Prediction of TCOD and turbidity by MLPANN. A) TCOD, B) Turbidity

Figure 5 suggests correlation of training data set and test model of final MLPANN with 15 hidden neurons. This model presents a suitable performance in predicting the effluent characteristics. Validation ad testing data for predicting the effluent reaches into more than 95%. The plots indicate a good fit between the predicted values and experimental values for TCOD and TU with R of 0.99625 and 0.97342, respectively.

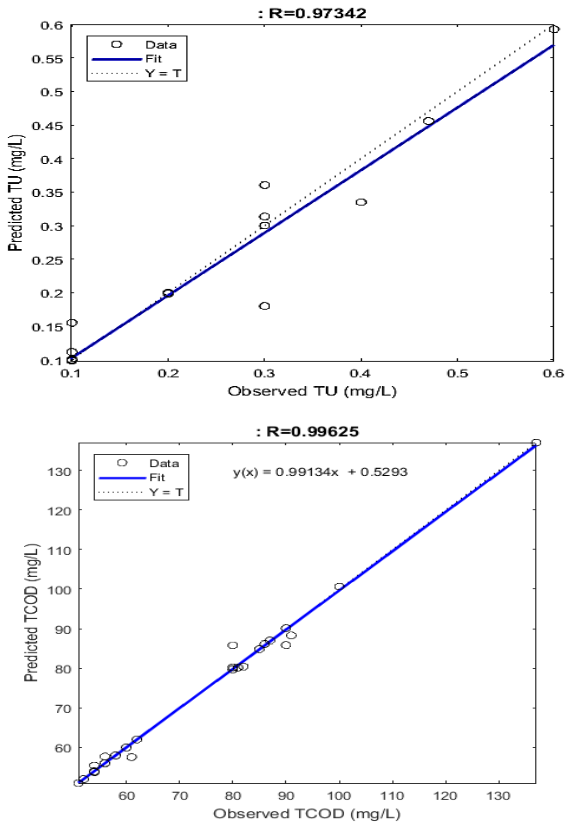

Figure 5. Regression plots of predicted and experimental data

10. Conclusions

The highest value of COD removal, turbidity, TDS, TSS and color under the optimum condition in membrane bioreactor process are of 91.96, 99.85, 97.48, 100 and 100%, respectively.

Neural network was used for predicting membrane bioreactor effluent after studying pilot from neural network. Multilayer perceptron was used which showed high correlation. For TCOD, the best algorithm was Levenberge-marquardt with average R and MSE of 0.9962 and 2.8179, respectively. For turbidity, also Levenberge-marquardt algorithm has been the best with average R and MSE of 0.9734 and 0.00092, respectively.

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