Journal of Hazardous Materials 192 (2011) 568–575

Contents lists available at ScienceDirect

Journal of Hazardous Materials

journal homepage: www.elsevier.com/locate/jhazmat

Modeling of membrane bioreactor treating hypersaline oily wastewater by artificial neural network

Ali Reza Pendashteh [a,b], A. Fakhru'l-Razi [a,*], Naz Chaibakhsh [c], Luqman Chuah Abdullah [a], Sayed Siavash Madaeni [d], Zurina Zainal Abidin [a]

[a] Department of Chemical and Environmental Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor D.E., Malaysia
[b] Environmental Research Institute, Iranian Academic Center for Education, Culture & Research (ACECR), Rasht, Iran
[c] Department of Chemistry, Faculty of Science, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor D.E., Malaysia
[d] Chemical Engineering Department, Razi University, Kermanshah, Iran

ARTICLE INFO

Article history:
Received 14 November 2010
Received in revised form 13 May 2011
Accepted 17 May 2011
Available online 23 May 2011

Keywords:
Membrane bioreactor
Artificial neural network
Hypersaline oily wastewater
Halophilic microorganisms
Modeling

ABSTRACT

A membrane sequencing batch reactor (MSBR) treating hypersaline oily wastewater was modeled by artificial neural network (ANN). The MSBR operated at different total dissolved solids (TDSs) (35,000; 50,000; 100,000; 150,000; 200,000; 250,000 mg/L), various organic loading rates (OLRs) (0.281, 0.563, 1.124, 2.248, and 3.372 kg COD/(m^3 day)) and cyclic time (12, 24, and 48 h). A feed-forward neural network trained by batch back propagation algorithm was employed to model the MSBR. A set of 193 operational data from the wastewater treatment with the MSBR was used to train the network. The training, validating and testing procedures for the effluent COD, total organic carbon (TOC) and oil and grease (O&G) concentrations were successful and a good correlation was observed between the measured and predicted values. The results showed that at OLR of 2.44 kg COD/(m^3 day), TDS of 78,000 mg/L and reaction time (RT) of 40 h, the average removal rate of COD was 98%. In these conditions, the average effluent COD concentration was less than 100 mg/L and met the discharge limits.

1. Introduction

Many industries generate billions of gallons of wastewaters containing organic matter and high concentrations of NaCl (>3.5%, w/v). For example, large volumes of oil contaminated wastewater are produced during extraction, transportation and refinery of crude oil [1]. Oilfield wastewater or "produced water" is the largest high salinity and oily wastewater generated during oil production activities. The salt, oil and grease (O&G) and total organic carbon (TOC) concentration of oilfield produced water varies from a few parts per thousand to that of saturated brine [2]; 2–565 mg/L; and 15–1500 mg/L, respectively [3].

Discharging untreated produced water can pollute surface and underground water and soil. The permitted O&G limits for treated produced water discharging from offshore facilities in the United States are 42 mg/L daily maximum and 29 mg/L monthly average [4]. To reduce the pollution load, many countries have implemented more stringent discharge limits. The monthly average discharge limits of COD and O&G of treated produced water prescribed by the Peoples Republic of China are 100 and 10 mg/L, respectively [5].

Some physical and chemical methods such as photo-electrocatalytic decontamination, hydrocyclones, coagulation and flocculation and membrane filtration have been investigated to remove hydrocarbons from oily wastewaters [6]. Generally, biological treatment of wastewater is the most cost-effective alternative when compared to other treatment technologies. However, the salinity of hypersaline wastewaters affects the metabolism of microorganisms in activated sludge systems due to plasmolysis whereas halophilic microorganisms are usually able to survive in hypersaline environments [7]. SBR is a promising biological treatment system because of its flexibility and ease of operation [8].

At high concentration of NaCl, microorganisms exhibit poor settleability and cause high turbidity of the SBR effluents [9]. A membrane coupled biological process as a separation step is able to retain microorganisms in the bioreactor [10]. Membrane bioreactor (MBR) has many advantages including high effluent quality, small footprint, high mixed liquor suspended solids (MLSS) concentration, good disinfection capability, and high volumetric loading [11].

Due to the rising concern about environmental issues, the control and proper operation of wastewater treatment plants to meet stringent effluent limitations have become very important.

* Corresponding author. Tel.: +60 3 89466304; fax: +60 3 86567120.
E-mail address: fakhrul@eng.upm.edu.my (A. Fakhru'l-Razi).

0304-3894/$ – see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.jhazmat.2011.05.052

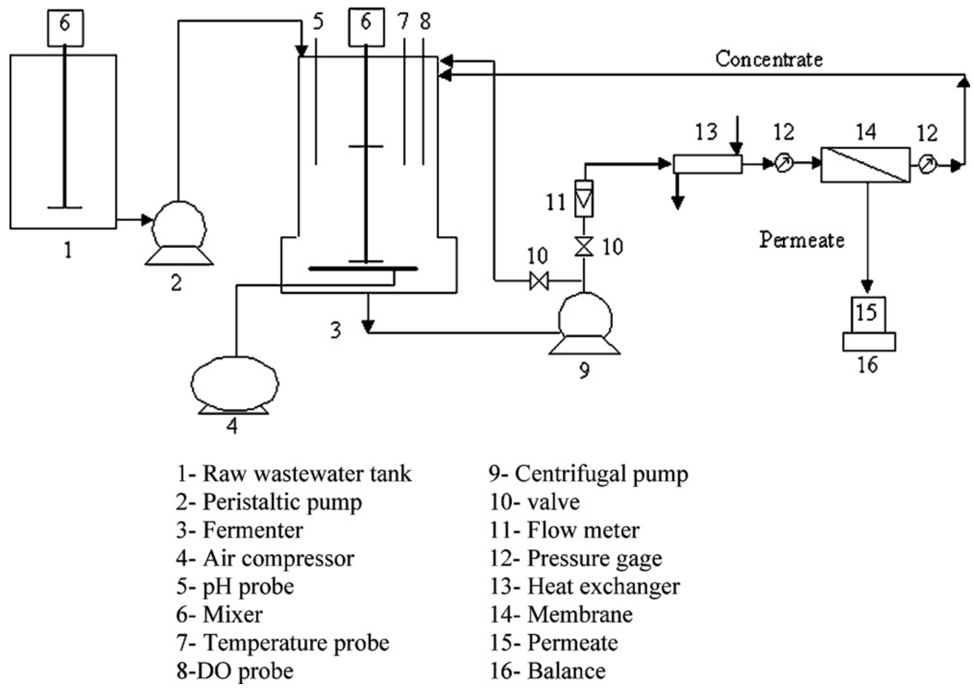

Fig. 1. Schematic of experimental setup.

Treatment process models are essential tools to assure proper operation and better control of wastewater treatment plants [12]. The ability of artificial neural networks (ANNs) in the modeling of complex systems that have nonlinear characteristics has made them the most popular tool for modeling of biological processes [13].

In recent years, ANNs have been used for monitoring [14], controlling [15], classification [16] and simulation [17–19] of activated sludge processes of wastewater treatment plants. In the literature to date, a limited number of applications of ANNs have been made to MBRs for modeling of a plant operation [20,21]. Geissler et al. [20] used an ANN model to predict the filtration performance in a submerged capillary hollow fiber membrane treating municipal wastewater. Cinar et al. [21] have also proposed an ANN model for a submerged MBR treating cheese whey and evaluated its performance at different sludge residence time (SRT).

Up till now, there have been only few investigations on treating produced water by MBRs. Furthermore, no attempt has been made on the modeling of the produced water treatment systems.

In this study, ANN was used to model the performance of a membrane sequencing batch reactor treating hypersaline oily wastewater at different organic loading rate (OLR), reaction time (RT) and total dissolved solid (TDS) in order to predict the effluent characteristics to meet the effluent discharge standards.

2. Materials and methods

2.1. Experimental setup

A 5-L fermenter (Biostat-B.Braun Biotech International, Melsungen, Germany) was used as the SBR (Fig. 1). Dissolved oxygen (DO), pH, temperature, aeration, and agitation were microprocessor controlled. Aeration was provided by using an air compressor and a sparger. The synthetic wastewater was fed by a peristaltic pump (Peristaltic pump model: Watson-101U/R, Watson-Marlow, UK). Mixed liquor was pumped through two tubular crossflow ultrafiltration (UF) membrane modules (MIC-RO 240, PCI membrane systems, UK) and recycled back to the bioreactor. The microorganisms separated by the membranes were returned to the bioreactor. Permeate flux was measured gravimetrically with an electronic balance (Tanita KD-200, Tanita Corporation, Tokyo, Japan). Table 1 shows the UF characteristics and the membrane sequencing batch reactor (MSBR) operating conditions.

2.2. Synthetic wastewater preparation

In order to determine the response of the MSBR system under controlled conditions, synthetic wastewater was used during the whole study. Based on halophilic medium proposed by other researchers [7,22], produced water was simulated. The synthetic produced water composition (TDS of 35,000 mg/L) in mg/L is shown in Table 2.

For TDS concentrations of 50,000, 100,000, 150,000, 200,000, and 250,000 mg/L, NaCl was added at concentration of 46,000, 96,000, 146,000, 196,000, and 246,000 mg/L, respectively. The composition of the wastewaters gave a C/N/P ratio of approximately 100/10/1 by adding NH_4Cl and KH_2PO_4. The pH was adjusted to 7 using NaOH. All of the chemicals used in this study were of technical grade. Crude oil was collected from Malaysia oilfields (Petronas BCOT, Sarawak). Synthetic produced water was prepared in a homogenizer (KIKA labortechnik, Staufen, Germany)

Table 1
UF characteristics and the MSBR operating conditions.

UF (FP200)	Material	Polyvinylidene difluoride (PVDF)
	Tube diameter	1.25 cm
	Length	30 cm
	Molecular cut-off weight (MWCO)	200,000 Dalton
	Membrane area	0.012 m^2
MSBR operating conditions	Agitation speed	300 rpm
	DO	3 mg/L
	Crossflow velocity	2 m/s
	Temperature	30 °C
	Transmembrane pressure	2 bar

Table 2
Chemical composition of the synthetic produced water.

Chemical	NaCl	$CaCl_2 \cdot 2H_2O$[a]	KCl	$MgCl_2 \cdot 6H_2O$[b]	$NaHCO_3$	NH_4Cl	KH_2PO_4
mg/L	31,173	60	2,000	50	800	860	99

[a] Excluding the water of crystallization: 45 mg/L.
[b] Excluding the water of crystallization: 23 mg/L.

by mixing salts and crude oil in a 5-L propylene container for 24 h (2400/min) to achieve equilibrium between the oil and water phases [23]. Biochemical oxygen demand (BOD), COD and O&G of synthetic produced water (1 mL oil/L) were 645, 2250 and 350 mg/L, respectively.

2.3. Culture selection

Hypersaline soil from Morib onshore in Malaysia served as a source of halophilic microorganisms. Isolation of microorganisms capable of degrading crude oil in the hypersaline-produced water began by placing approximately 6 g of soil into 200 mL of synthetic produced water (1 mL oil/L and TDS of 35,000 mg/L). After 15 days of mixing on a shaker table (150/min, 30 °C), a 2 mL sample of the mixture was transferred to a fresh medium. After the three steps, the resulting mixture was free of soil [7]. The culture was transferred monthly to fresh medium for six months [22,24].

2.4. Startup of the SBR

The SBR was inoculated with the isolated microorganism's culture. After inoculation, the bioreactor was operated with synthetic produced water to increase the biomass concentration to 1000 mg/L. The reactor was operated at different operating conditions and the temperature was kept constant at 30 °C. The operation mode was 12, 24, and 48 h cycles. The 24 h mode cycle consisted of three stages: 1 h of feeding time, 20 h of reacting time, and 3 h of decanting time. In the last stage, 2.5 L permeate was withdrawn from the bioreactor. In this study, the membrane chemical cleaning (NaOCl 0.5%, w/v, and HCl 0.5%, w/v) and sonication was carried out when flux declined to a value almost 40 L/(m^2 h). After the cleaning, the decanting time was reduced to 1.5 h.

2.5. Effect of OLR, TDS and RT

In this experiment, OLR was increased in a stepwise mode in different stages. Characteristics of the raw wastewater at different stages are presented in Table 3. The possible adverse effects of salt concentration on microbial activity were studied where biological treatment of synthetic produced water was conducted over different TDS levels (50,000, 100,000, 150,000, 200,000 and 250,000 mg/L). In order to study the effect of RT on the MSBR-product quality, the fermenter was started up again as in the previous section and three cycle times of 12, 24, and 48 h (corresponding to hydraulic residence time (HRT) of 24 h, 48 h, 96 h) were studied.

2.6. Oil in mixed liquor

In order to measure the accumulation of undigested crude oil in the activated sludge, extraction of hydrocarbons from bioreactor mixed liquor samples were performed by shaking 5 mL sample and 10 mL dichloromethane vigorously for 10 min. The extracts were filtered through anhydrous sodium sulfate to remove water. The samples were filtered through a 0.45-μm pore size Teflon membrane. Then the samples were dried and weighed on an analytical balance [25].

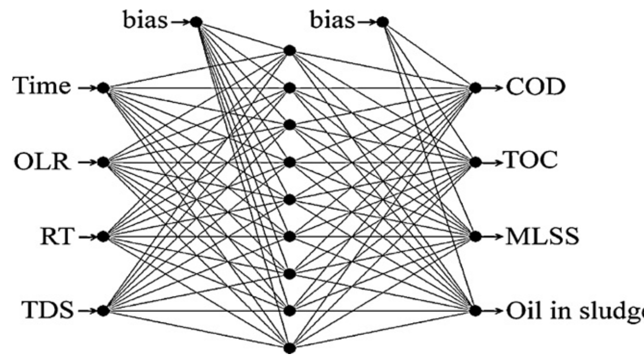

Fig. 2. Structural organization of the neural network used for the estimation of effluent characteristics.

2.7. Analytical methods

Since the chloride concentration was high, the COD of the samples was determined according to the Freire and Sant'Anna [26] method. MLSS, mixed liquor volatile suspended solids (MLVSS), and O&G were determined according to the standard methods [27]. The TOC was measured by a TOC analyzer (Shimadzu, Kyoto, Japan).

2.8. Model development

A software package of NeuralPower version 2.5, CPC-X Software, USA, was applied in this study. A set of 193 operational data from the synthetic produced water treated with the MSBR was used to train the network.

Multilayer normal feedforward neural network was used in order to predict the performance of the MSBR treating the synthetic produced water. The networks were trained by different learning algorithms (incremental back propagation, IBP; batch back propagation, BBP; Levenberg–Marquardt algorithm, LM; genetic algorithm, GA; and quickprob, QP). The developed network consisted of three layers including input layer that comprised four nodes, which were experiment day, RT, OLR and TDS; one hidden layer consisting of several nodes, which were varied to obtain the best model and the output layer that had four output nodes (which were TOC, COD, oil in sludge and MLSS). The structure of the proposed ANN used for prediction of the effluent characteristics is shown in Fig. 2.

The transfer function determines the input–output behavior and adds nonlinearity and stability to the network [28]. The transfer function of the hidden and output layers (sigmoid, hyperbolic tangent function, gaussian, linear, threshold linear and bipolar linear) was iteratively determined by developing several networks. The best transfer function for the hidden layer was found to be hyperbolic tangent (tanh) function while the best transfer function for the output layer was a sigmoid one. Each network was trained until the network average root mean squared error (RMSE) was minimum and coefficient of determination (R^2) was equal to 1. Other parameters for network were chosen as the default values of the software (learning rate = 0.1 and momentum = 0.4).

The weights were initialized with random values and adjusted in order to minimize the network error. A second set of validation data was used to evaluate the quality of the network during training. In

Table 3
Synthetic oily wastewater characteristics at different OLR, TDS and RT.

	Time (day)	mL oil/L	Hydrocarbon (mg/L)	COD (mg/L)	RT	OLR (kg COD/(m^3 day))	O&G (mg/L)	TOC (mg/L)[a]	TDS (mg/L)
Effect of OLR	1–15	0.25	204.5	562.5	20	0.281	87.5	137	35,000
	16–30	0.5	409	1,125	20	0.563	175	275	35,000
	31–45	1	818	2,250	20	1.124	350	550	35,000
	46–60	2	1,636	4,500	20	2.248	700	1,100	35,000
	61–75	3	2,454	6,750	20	3.372	1,050	1,650	35,000
Effect of TDS	76–90	1	818	2,250	20	1.124	350	550	50,000
	91–105	1	818	2,250	20	1.124	350	550	100,000
	106–120	1	818	2,250	20	1.124	350	550	150,000
	121–135	1	818	2,250	20	1.124	350	550	200,000
	136–150	1	818	2,250	20	1.124	350	550	250,000
Effect of RT	151–165	1	818	2,250	20	1.124	350	550	35,000
	176–180	1	818	2,250	8	1.124	350	550	35,000
	181–195	1	818	2,250	44	1.124	350	550	35,000

[a] Calculated.

addition, the performance of the trained network was estimated based on the accuracy of the network on the test dataset which was unseen by the developed network during training. For optimization of the conditions, GA was used. GA is an adaptive search algorithm based on the principles of biological evolution, such as natural selection and genetic inheritance. In the GA, each solution to a given problem is encoded as a chromosome, which evolves over time towards a better solution. Some of the advantages of GA over the conventional optimization methods are short calculation time, flexibility, robustness and high convergence property [29]. The use of GA requires the choice of a set of operational parameters such as population size, mutation rate and crossover rate. In this study, the GA parameters were set at the default values of the software.

2.9. Verification of the model

The performances of the ANN models were measured by R^2 and RMSE between the predicted values of the network and the experimental values, which were calculated by Eqs. (1) and (2), respectively.

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

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_p^{(i)} - y_i^*)^2} \tag{2}$$

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. Artificial neural network modeling of the MSBR

The goal of iterative neural network training is to update the networks' weights to minimize the difference between the network output and the desired output. Various feedforward neural networks (FNNs) were trained using different learning algorithms for the estimation of the characteristics of the synthetic produced water treated by the MSBR. The best algorithm was found to be BBP with an average R^2 of 0.97339 and RMSE 89.385. The learning was completed after 10,000 iteration steps.

Back propagation (BP) is a commonly used algorithm that searches for the minimum of error function in weight space using the method of gradient descent [30]. Each iteration in BP involves two phases: forward activation with the computation of error, and backward propagation of the computed error to modify the weights [31]. The difference between BBP and standard BP learning algorithm lies in timing of the weight update. The weight update of the standard BP is performed after each single input data while for the BBP, the update step with accumulated weight changes is performed after full presentation of all training patterns [32]. In fact, the BBP is smoother in converging compared to that of the standard BP and is best suited for nonlinear regression [33]. In order to minimize the total error of the network trained by BBP, the weights are adjusted according to the following equation [34,35]:

$$\Delta w_{ji}(n) = -\eta \times \frac{\partial e}{\partial w_{ji}} + a \times \Delta w_{ji}(n-1) \tag{3}$$

where e is error function being minimized, w_{ji} is a generic weight in the network, α is a momentum factor, η is the learning rate or step size parameter and n and $n-1$ are two successive iterations.

Because gradient decent usually slows down near minima, so the Levenberg–Marquardt (LM) method can be used to obtain faster convergence. LM is a blend of simple gradient descent and the Gauss–Newton method. The algorithm for parameter updating is presented by the following equation:

$$\Delta w = -[J^T J + \mu I]^{-1} J^T \varepsilon \tag{4}$$

where $\varepsilon = [e_1\ e_2\ \ldots\ e_P]^T$ is the error vector. μ is a positive constant, I is the identity matrix and J is the Jacobian matrix given by:

$$J = \begin{bmatrix} \frac{\partial e_1}{\partial w_1} & \frac{\partial e_1}{\partial w_2} & \cdots & \frac{\partial e_1}{\partial w_N} \\ \frac{\partial e_2}{\partial w_1} & \frac{\partial e_2}{\partial w_2} & \cdots & \frac{\partial e_2}{\partial w_N} \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \frac{\partial e_P}{\partial w_1} & \frac{\partial e_P}{\partial w_1} & \cdots & \frac{\partial e_P}{\partial w_N} \end{bmatrix} \tag{5}$$

LM has found to be the fastest method for training moderate-sized feedforward neural networks, where the training rate is 10 to 100 times faster than the usual gradient descent backpropagation method [36]. However, when the number of network weights is large, the requirement for computation and memory becomes significant. Since in LM algorithm, inversion of square matrix $J^T J + \mu I$ is involved thus a large memory space is required to store the Jacobian matrix and the Hessian matrix ($J^T J$) along with inversion of approximated Hessian matrix in each iteration [34]. In this study, LM showed considerable thrashing (rise and fall in error rate), which slowed the conversion. This problem could be due to the large memory overheads. Therefore, BBP was selected as the best algorithm for training the network.

Convergence rate and complexity of a model strongly depends on the type of transfer function applied [37]. The best transfer

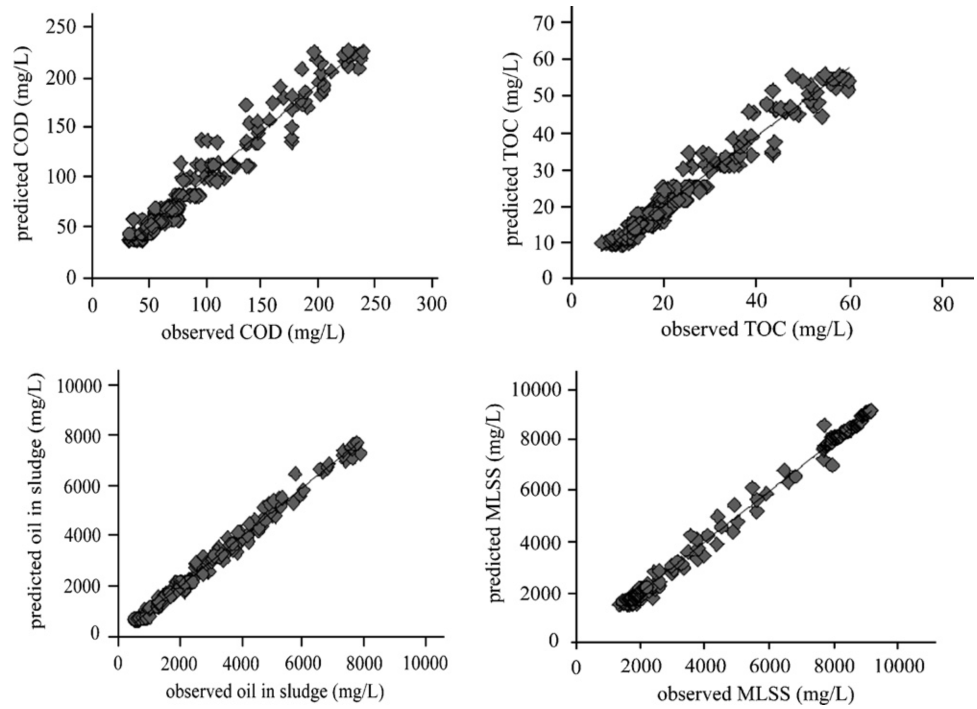

Fig. 3. Correlation between the experimental data and predicted values of the ANN model used for prediction of COD, TOC, MLSS, and oil in sludge.

function can be selected easily by trial and error. In this research, among all employed transfer functions for hidden layers, tanh showed a better performance. The output layer contains sigmoid transfer function which produces a continuous value in the 0–1 range.

Finding the optimal number of neurons in hidden layer(s) is crucial for processing capability of the network and accuracy of developed models [38]. Too few hidden neurons limit the ability of the network to model the process whereas excessive hidden neurons lead to poor generalization for untrained data [31]. Although several approximation methods for determining the number of neurons in hidden layers are presented, the optimal number of neurons is usually determined by trial and error [39]. In this study, the optimum number of neurons was chosen on the base of R^2 and RMSE of the network. In order to find optimum number of neurons, six different 4-x-4 architectures (x changes from 6 to 11) were used. The optimum number of hidden neurons was found to be 9. Table 4 presents the corresponding average R^2 and RMSE for the network trained with BBP with respect to the training data when the number of neurons is varied. Correlation between the experimental data and the predicted values of the final trained ANN model with 9 hidden neurons is shown in Fig. 3. The scatter plots show that for all the four parameters, the predictive capability was satisfactory and the linear adjustment between actual and predicted values gives almost a slope equal to 1.

Table 4
Modeling error with respect to training data.

Model	Average R^2	Average RMSE
4-6-4	0.97024	113.450
4-7-4	0.97330	91.458
4-8-4	0.97347	90.729
4-9-4	0.97339	89.385
4-10-4	0.97299	93.859
4-11-4	0.96504	206.090

3.2. Variation of effluent parameters at different stages

Fig. 4 shows the effluent characteristics variations at different experimental stages. In this study, the effect of OLR was investigated at the cycle time of 24 h. During the experiment, OLR was increased from 0.281 to 3.372 kg COD/(m^3 day) corresponding to the influent COD and TOC concentrations from 562.5 to 6750 and 137 to 1650 mg/L, respectively (Fig. 4a and b). At the lowest OLR of 0.281 kg COD/(m^3 day), minimum effluent COD and TOC concentrations were observed. With an increase in the COD concentration from 562.5 to 6750, the average COD concentration of the effluent increased from 37.9 to 184.3 mg/L. According to Fig. 4b, at the TDS concentration lower than l00,000 mg/L, the permeate COD concentration was less than 100 mg/L. At higher TDS, the COD increased and reached the maximum COD value of 238 mg/L at the highest TDS.

It was observed that MLSS concentration increased from 1560 mg/L to 7950 mg/L during 75 days and the oil concentration in the sludge increased from 571 mg/L to 6005 mg/L (Fig. 4c and d). The decreasing trend of concentration of the oil trapped inside the sludge flocs was observed when TDS was less than 100,000 mg/L, and it was increased at higher TDS. It may be concluded that salinity can reduce the biological degradation rate of hydrocarbons. The isolated microorganisms played significant role for biodegradation of hydrocarbons. In this study, bacteria of the genera *Pseudomonas*, *Ochrobactrum*, *Corynebacterium* and *Bulkhorderi* were identified. Identification of the isolated microorganisms was explained in detail elsewhere [9].

At RT of 44 h, the average UF-permeate COD and TOC concentrations were lower than 48 and 12 mg/L, respectively. It may be concluded that, short contact time between microorganisms and food affects biodegradation of organic matter. The results also showed that higher RT affects oil concentration in sludge. At RT of 8 and 20 h, accumulation of crude oil was observed up to 2110 mg/L and it was decreased to 1321 mg/L at the highest RT. This indicated that although the removal efficiency of the organic matters at lower RT was acceptable, the high concentration of oil trapped

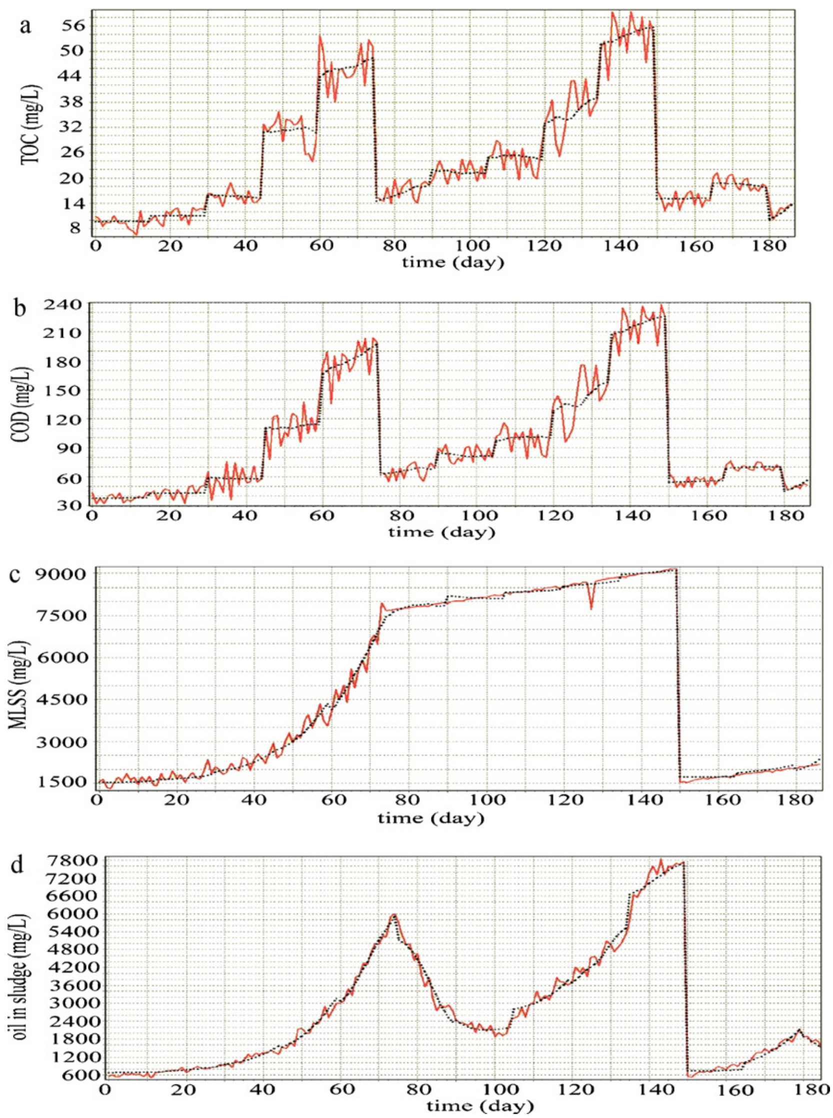

Fig. 4. Actual and predicted effluent variations: (a) TOC, (b) COD, (c) MLSS and (d) oil in sludge (predicted ___, actual ......).

inside sludge flocs might influence the treatment system at longer time, so a higher HRT could provide a sustained treatment system.

It should be mentioned that at RT of 8 h, the accumulation of 370 mg of crude oil in the sludge was observed in comparison with the total of 4090 mg of crude oil fed into the bioreactor per day. At RT of 44 h, the decreasing trend proved the ability of the microorganisms to degrade crude oil. It was also inferred that no toxic or non-biodegradable compounds had accumulated in the bioreactor [40].

From Fig. 4, a good correlation can be observed between actual data and values predicted by the model. The network performance was also investigated with respect to validating, and testing datasets. The R^2 and RMSE for validating dataset were 0.99795 and 0.460326, respectively, while for the testing data set, R^2 was 0.99499 and RMSE was 0.622540. The results show that the developed BPP network is properly capable of learning the relationship between the input and output parameters and therefore could be employed in the further part of the study.

3.3. Effect of parameters

The importance of the parameters was obtained by summing the absolute weights of the connections from the input neurons to all neurons in the hidden layer. The operative variables affected the effluent characteristics with an order of contribution OLR > RT > TDS. As shown in three dimensional plots obtained by ANN analysis, all the variables had significant effect on the treatment efficiency (Fig. 5). Fig. 5a shows the effect of OLR and TDS and their interaction on COD of the effluent. As shown in the figure, minimum COD was achieved when TDS and OLR were at the lowest values. Similar trend was achieved for TOC (Fig. 5b).

Fig. 5c shows the effect of OLR and RT and their interaction on the oil in sludge. Minimum accumulation of oil in sludge was achieved when RT was 34 h. Therefore, for sustainable operating of the system and to prevent the accumulation of trapped hydrocarbons inside bioreactor sludge, the bioreactor RT should be longer than 34 h. In this research, it was observed that during whole experiment, O&G concentration was less than 5 mg/L, so based on EPA limit [4], the treated wastewater can be discharged into the sea and it also can be used to re-inject into oil-wells to enhance oil recovery [41].

3.4. Optimization of the effluent COD for discharging to environment

Based on the most stringent discharge limits, COD should be less than 100 mg/L for discharging to sea [5]. Table 5 shows some

Table 5
Some optimum conditions for obtaining a COD less than 100 mg/L.

Input variable			Output	
OLR (kg COD/(m^3 day))	TDS (mg/L)	RT (h)	Predicted COD (mg/L)	Actual COD (mg/L)
2.44	78,000	40.4	100.2	95.3
0.9	164,000	8	98.2	92.4
0.281	56,500	11.6	42.2	48.5

optimum conditions for obtaining a COD less than 100 mg/L. It can be seen that the system is able to treat the wastewater at high OLR of 2.44 (kg COD/(m^3 day) and TDS of 78,000 mg/L during 40.4 h. At higher TDS, lower concentration of organic matter should be fed to the bioreactor. In this part, a good correlation between the actual and predicted values with a R^2 value of 0.9822 was obtained.

Generally, based on the optimization results, in order to control the effluent characteristics to meet discharge standard limits, influent wastewater can be pretreated chemically when initial TDS is low and initial OLR is high. In addition, when initial OLR is low and initial TDS is more than 100,000 mg/L, the raw wastewater can be diluted to reduce inhibition effect of NaCl.

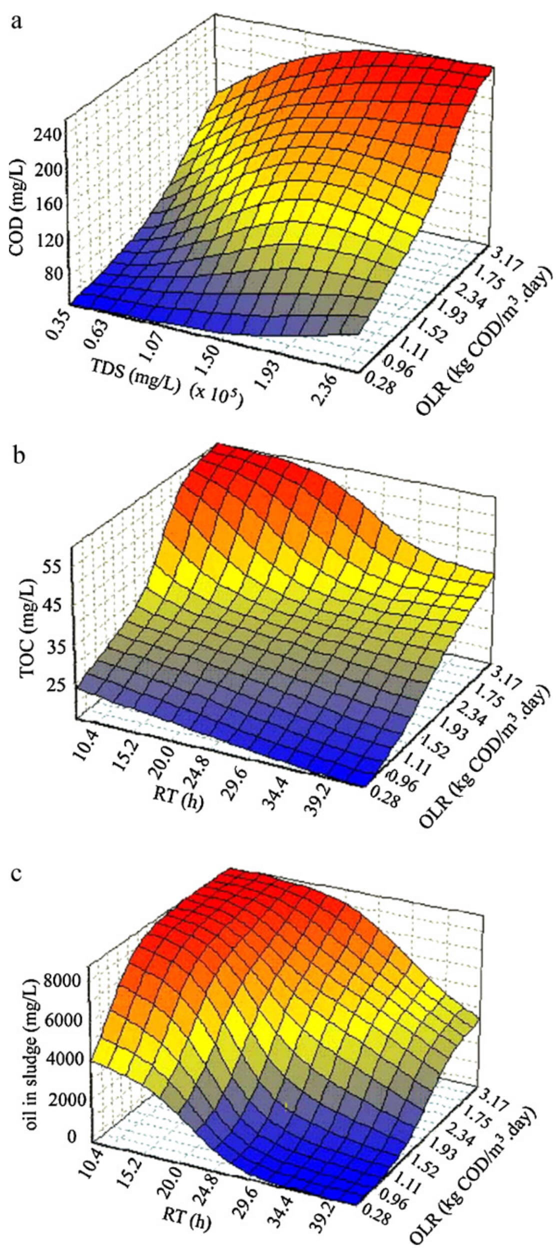

Fig. 5. Three dimensional plot showing the effect of individual parameters and their mutual interactions on the characteristics of oil in sludge, COD and TOC.

4. Conclusions

A membrane sequencing batch reactor inoculated with isolated halophilic microorganisms was used for the treatment of hypersaline oily wastewater. The training of an artificial neural network with operational data from the MSBR has been successful. The results of this study show that ANN-GA can easily be applied to evaluate the performance of a membrane bioreactor even though it involves the highly complex physical and biochemical mechanisms associated with the membrane and the microorganisms.

Acknowledgement

The authors are grateful to the Universiti Putra Malaysia (UPM) for supporting this work under the research grant RUGS No. 05/01/07/0158RU.

References

[1] M.P. Diaz, K.G. Boyd, S.J.W. Grigson, J.G. Burgess, Biodegradation of crude oil across a wide range of salinities by an extremely halotolerant bacterial consortium MPD-M, immobilized onto polypropylene fibers, Biotechnol. Bioeng. 79 (2002) 145–153.
[2] J.M. Neff, Bioaccumulation in Marine Organisms: Effects of Contaminants from Oil Well Produced Water, Elsevier Science Publishers, Amsterdam, 2002.
[3] P.J.C. Tibbetts, I.T. Buchanan, L.J. Gawel, R. Large, A comprehensive determination of produced water composition, in: J.P. Ray, F.R. Engelhardt (Eds.), Technological/Environmental Issues and Solutions, Plenum Publishing Corp, New York, 1992, pp. 97–113.
[4] USEPA, http://www.epa.gov.
[5] G.T. Tellez, N. Nirmalakhandan, J.L. Gardea-Torresdey, Performance evaluation of an activated sludge system for removing petroleum hydrocarbons from oilfield produced water, Adv. Environ. Res. 6 (2002) 455–470.
[6] A. Fakhru'l-Razi, A.R. Pendashteh, A. Luqman Chuah, A.B. Dayang Radiah, S.S. Madaeni, Z.A. Zurina, Review of technologies for oil and gas produced water treatment, J. Hazard. Mater. 170 (2009) 530–551.
[7] C.R. Woolard, R.L. Irvine, Treatment of hypersaline wastewater in the sequencing batch reactor, Water Res. 29 (1995) 1159–1168.
[8] S. Venkata Mohan, N. Chandrashekara Rao, K. Krishna Prasad, B.T.V. Madhavi, P.N. Sharma, Treatment of complex chemical wastewater in a sequencing batch reactor (SBR) with an aerobic suspended growth configuration, Process Biochem. 40 (2005) 1501–1508.
[9] A.R. Pendashteh, A. Fakhru'l-Razi, A. Luqman Chuah, A.B. Dayang Radiah, S.S. Madaeni, Z.A. Zainal, Biological treatment of produced water in a sequencing batch reactor by isolated halophilic microorganism consortium, J. Environ. Technol. 31 (2010) 1229–1239.
[10] I.J. Kang, C.H. Lee, K.J. Kim, Characteristics of microfiltration membranes in a membrane coupled sequencing batch reactor system, Water Res. 37 (2003) 1192–1197.
[11] P. Le-Clech, V. Chen, T.A.G. Fane, Fouling in membrane bioreactors used in wastewater treatment, J. Membr. Sci. 284 (2006) 17–53.
[12] D. Guclu, S. Dursun, Artificial neural network modelling of a large-scale wastewater treatment plant operation, Bioprocess Biosyst. Eng. 33 (2010) 1051–1058.
[13] J.S. Almeida, Predictive non-linear modeling of complex data by artificial neural networks, Curr. Opin. Biotechnol. 13 (2002) 72–76.
[14] S.H. Hong, M.W. Lee, D.S. Lee, J.M. Park, Monitoring of sequencing batch reactor for nitrogen and phosphorus removal using neural networks, Biochem. Eng. J. 35 (2007) 365–370.
[15] G.M. Zeng, X.S. Qin, L. He, G.H. Huang, H.L. Liu, Y.P. Lin, A neural network predictive control system for paper mill wastewater treatment, Eng. Appl. Artif. Intell. 16 (2003) 121–129.

[16] O. Cinar, New tool for evaluation of performance of wastewater treatment plant: artificial neural network, Process Biochem. 408 (2005) 2980–2984.
[17] J.C. Chen, N.B. Chang, W.K. Shieh, Assessing wastewater reclamation potential by neural network model, Eng. Appl. Artif. Intell. 16 (2003) 149–157.
[18] B. Raduly, K.V. Gernaey, A.G. Capodaglio, P.S. Mikkelsen, M. Henze, Artificial neural-networks for rapid WWTP performance evaluation: methodology and case study, Environ. Modell. Softw. 22 (2007) 1208–1216.
[19] D. Hanbay, I. Turkoglu, Y. Demir, Prediction of chemical oxygen demand (COD) based on wavelet decomposition and neural networks, Clean 35 (2007) 250–254.
[20] S. Geissler, T. Wintgens, T. Melin, K. Vossenkaul, C. Kullmann, Modelling approaches for filtration processes with novel submerged capillary modules in membrane bioreactors for wastewater treatment, Desalination 178 (2005) 125–134.
[21] O. Cinar, H. Hasar, C. Kinaci, Modeling of submerged membrane bioreactor treating cheese whey wastewater by artificial neural network, J. Biotechnol. 123 (2006) 204–209.
[22] B. Peyton, T. Wilsona, D. Yonge, Kinetics of phenol biodegradation in high salt solutions, Water Res. 36 (2002) 4811–4820.
[23] B. Tansel, J. Regula, R. Shalewitz, Treatment of fuel oil and crude oil contaminated waters by ultrafiltration membranes, Desalination 102 (1995) 301–311.
[24] G. Thouand, P. Bauda, J. Oudot, G. Kirsch, C. Sutton, J.F. Vidalie, Laboratory evaluation of crude oil biodegradation with commercial or natural microbial inocula, Can. J. Microbiol. 45 (1999) 106–115.
[25] J.C. Bertrand, M. Bianchi, M.A. Mallah, M. Acquaviva, G. Mille, Hydrocarbon biodegradation and hydrocarbonoclastic bacterial communities composition grown in seawater as a function of sodium chloride concentration, J. Esp. Mur. Biol. Ecol. 168 (1993) 125–138.
[26] D.D.C. Freire, G.L. Sant'Anna Jr., A proposed method modification for the determination of COD in saline waters, Environ. Technol. 19 (2002) 243–247.
[27] APHA, AWWA, WEF, Standard Methods for Examination of Water and Wastewater, 21st ed., American Public Health Association, Washington, DC, 2005.
[28] B.G. Liptak, Instrument Engineers' Handbook: Process Control and Optimization, CRC Press, FL, 2006.
[29] E. Franco-Lara, H. Link, D. Weuster-Botz, Evaluation of artificial neural networks for modelling and optimization of medium composition with a genetic algorithm, Process Biochem. 41 (2006) 2200–2206.
[30] R. Rojas, Neural Networks: A Systematic Introduction, Springer-Verlag Berlin Heidelberg, New York, 1996.
[31] I.A. Basheer, M. Hajmeer, Artificial neural networks: fundamentals, computing, design, and application, J. Microbiol. Methods 43 (2000) 3–31.
[32] J. Mira, Artificial Neural Nets Problem Solving Methods, Springer-Verlag Berlin Heidelberg, New York, 2003.
[33] T.W.S. Chow, S.Y. Cho, Neural Networks and Computing: Learning Algorithms and Applications, Imperial College Press, Singapore, 2007.
[34] N. Ye, The Handbook of Data Mining, Lawrence Erlbaum Associates, Inc., Publishers, Mahwah, New Jersey, USA, 2003.
[35] Z. Zainuddin, N. Mahat, Y. Abu Hassan, Improving the convergence of the backpropagation algorithm using local adaptive techniques, Int. J. Comput. Intell. 1 (2002) 79–82.
[36] E. Al-Daoud, A comparison between three neural network models for classification problems, J. Artif. Intell. 2 (2009) 56–64.
[37] W. Duch, N. Jankowski, Survey of neural transfer functions, Neural Comput. Surv. 2 (1999) 163–212.
[38] J. Kamruzzaman, R. Begg, R.A. Sarker, Artificial Neural Networks in Finance and Manufacturing, Idea Group Publishing, PA, 2006.
[39] M. Islam, X. Yao, K. Murase, A constructive algorithm for training cooperative neural network ensembles, IEEE Trans. Neural Netw. 14 (2003) 820–834.
[40] W. Scholz, W. Fuchs, Treatment of oil contaminated wastewater in a membrane bioreactor, Water. Res. 34 (2000) 3621–3629.
[41] J. Veil, M.G. Puder, D. Elcock, R.J.J. Redweik, A white paper describing produced water from production of crude oil, natural gas, and coal bed methane, www.netl.doe.gov/publications/oil_pubs/prodwaterpaper.pdf, 2004.