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Investigation and modeling of a hybrid petroleum refinery wastewater treatment system using neural networks

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ABSTRACT

This research was an effort to improve the performance of an activated sludge system by using biofilm carriers in the aeration basin of the system for treating petroleum refinery wastewater. Eventually, a granular activated carbon column was used in the last part of the treatment process. A neural network was employed to predict pollutants in the effluent and analyze the operating parameters. Overall treatment efficiencies of chemical oxygen demand (COD), turbidity, NH_3, and total suspended solids (TSS) removal were 93%, 94%, 94%, and 92%, respectively. The results indicated that the removal efficiencies of pollutants in our hybrid system were superior to conventional activated sludge systems. The training procedure of the neural network model was promising, and virtually an acceptable match was achieved between predicted values and experimental values. For all models predicting effluent COD, turbidity, NH_3, and TSS, the correlation coefficient was higher than 0.9, and the mean squared error approached zero. According to the analysis of input parameters, the influent concentration is the essential factor in the modeling of effluent characteristics.

Keywords: Petroleum refinery wastewater treatment; Activated sludge process; Biofilm carriers; Activated carbon; Neural networks; Prediction

1. Introduction

It is essential to collect and treat wastewater and then dispose of reclaimed wastewater without changing the ecosystem of the receiving environment to achieve a healthy and non-polluting environment [1]. Generally, conventional wastewater treatment systems are a combination of chemical, physical, and biological processes. Microorganisms are suspended in the bioreactor or are attached to carriers in biological wastewater treatment processes [2]. The hybrid treatment processes use both suspended and attached growth within the same reactor, and this is an economically attractive solution. Thus, they have several advantages over single processes [3].

The activated sludge process is fundamentally suspended growth biological wastewater treatment process in which a bacterial biomass suspension is responsible for the removal of pollutants [4]. The activated sludge process has been successfully used for treating various wastewaters with satisfactory removal efficiencies [5]. The focus of recently conducted studies regarding the application of the activated sludge processes in wastewater treatment is to decrease the cost of treatment and improve the performance. Tellez et al. [6] used a field continuous-flow activated sludge treatment system for removing petroleum hydrocarbons from Southwestern the United States oilfield generated produced water. Field-scale test results have indicated that an activated sludge treatment system

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can effectively remove total petroleum hydrocarbon from oilfield generated produced water to concentrations of 1.0 mg/L. Also, it has been reported that an activated sludge system has high performance in color removal from the cotton textile industry wastewater [7]. Aslan et al. [8] investigated the chemical oxygen demand (COD) removal for the edible oil wastewaters by an activated sludge system. The results showed that the system could remove approximately 80% of COD in 5 d.

While the performance of suspended growth processes in wastewater treatment is excellent, their capability can be improved by using packing materials or biofilm carriers in aeration basins [9]. Biofilm carriers are suitable for enhancing overloaded activated sludge plants and converting unused volumes into biofilm reactors [10]. The application of biofilm carriers in the aeration basin of activated sludge systems may improve the performance of these suspended growth treatment systems. Di Trapani et al. [11] used a hybrid biofilm/activated sludge pilot to investigate the organic removal efficiency of the pilot in different temperatures and values of the mixed liquor sludge retention time. The results indicated that the hybrid system could effectively treat municipal wastewater in low temperatures and with low mixed liquor sludge retention time values. Nutrient removal was investigated using a combined process with activated sludge and fixed biofilm by Su and Ouyang [12]. The results showed that the combination of packing materials and activated sludge systems can be successfully used for upgrading conventional activated sludge systems. Park and Lee [13] used an activated sludge system with a polyurethane fluidized bed biofilm for treating dyeing wastewater. COD removal in the pilot was promising in different organic loading rates. In another study, Gebara [14] used plastic nets inside the aeration tank of a conventional activated sludge process in a laboratory-scale model. The nets could improve biochemical oxygen demand (BOD_5) removal efficiency for synthetic wastewater.

This study aims to assess the removal efficiency of organic pollutants in petroleum refinery wastewater through the integration of attached and suspended growth by employing biofilm carriers in the aeration basin of an activated sludge system. Although biofilm carriers can improve the efficacy of biological wastewater treatment systems, the detachment of biomass from suspended biofilm carriers is a crucial issue among these systems. Hence, a suitable balance between detachment and growth forces is critical for the stability of biofilm attached growth systems [15]. High filling carrier ratios might result in biofilm detachment, which can decrease biomass concentration in biological reactors [16]. Furthermore, it is not economical to use high biofilm ratios as the aeration flux should be increased, which increases the cost of the biofilm process [17]. For this purpose, 50% of the aeration basin of the activated sludge system was filled with biofilm carriers. Additionally, a granular activated carbon column was used as a tertiary treatment system to meet the improved standards for the effluent of the wastewater treatment system. Based on our knowledge, this hybrid system for treating petroleum refinery wastewater has not been previously studied or reported in the literature.

On the whole, modeling can be used as a practical approach to monitor the changes over time of water and wastewater treatment systems and predict effluent quality parameters. Recently, artificial neural network (ANN) methods have been used for various areas of environmental issues such as wastewater and water treatment [18–20]. While wastewater treatment processes are pretty complicated, the improvements in intelligent methods make them possible to employ in the modeling of complex systems [21]. In this study, a multi-layer perceptron neural network (MLP-NN) was used to predict wastewater characteristics at the effluent of the petroleum refinery wastewater treatment system. The MLP-NN model is developed as a reliable predictive tool to monitor wastewater characteristics in the hybrid wastewater treatment system. Additionally, the importance of operating parameters is investigated in the modeling process by MLP-NN.

2. Materials and methods

2.1. Wastewater characteristics

The pilot plant was located in the Tehran Oil Refining Company in the city of Tehran, Iran. The influent of our hybrid treatment system was actual petroleum refinery wastewater from the Tehran refinery wastewater treatment plant. Analyses of the influent to the pilot were performed for four months before designing the pilot plant. The maximum values indicated that the raw wastewater characteristics were roughly in the range of petroleum wastewaters which had been treated by other activated sludge systems [11–14]. The effluent of the dissolved air flotation (DAF) unit in the refinery wastewater treatment plant was used as raw wastewater. The maximum, minimum, and average values of the influent characteristics are given in Table 1.

2.2. Pilot plant

The hybrid activated sludge system consisted of a feeding tank, an aeration basin, which was filled with Kaldnes type 2 carriers, a settling tank, and an activated carbon column for tertiary treatment (Fig. 1). The configuration of the pilot plant is given in Table 2. The feeding tank was made of plastic and was 1.5 m above the ground level to

Table 1
Petroleum refinery wastewater characteristics

Parameter	DO (mg/L)	Oil (mg/L)	NH_3 (mg/L)	TSS (mg/L)	TDS (mg/L)	BOD_5 (mg/L)	COD (mg/L)	pH	Tu (NTU)
Maximum	1.5	87	15	67	2,000	80	280	8.2	29.9
Average	0.85	55	9	47.5	1,681	55	200	7.6	23.8
Minimum	0.2	23	3	28	1,362	30	120	7.1	17.7

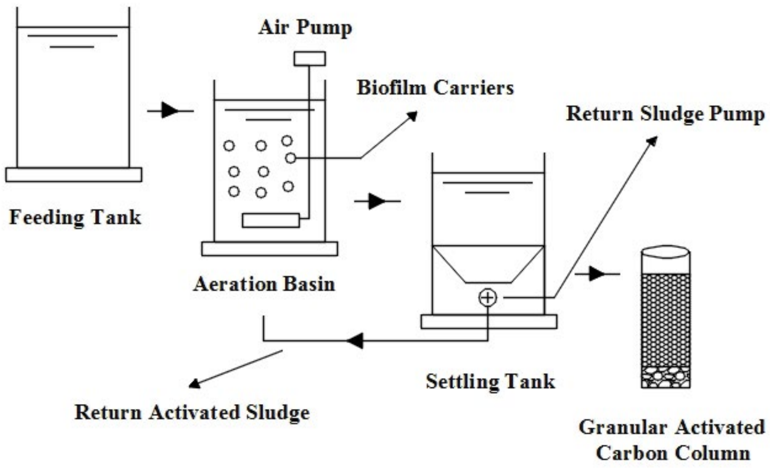

Fig. 1. Configuration of the pilot plant and the process used in this study.

Table 2
Configuration of pilot plant

	Length (cm)	Width (cm)	Height (cm)	Radius (cm)	Volume (L)
Feeding tank	–	–	96	32	300
Aeration basin	35	35	40	–	50
Settling tank	30	16	25	–	12
Activated carbon column	–	–	75	16	60

establish a continuous flow. About 50% of the aeration basin with a volume of 0.05 m^3 was filled with biofilm carriers. Table 3 presents the characteristics of Kaldnes type two carriers used in this study. Fig. 2 shows the photos of biofilm carriers before and after usage in the wastewater treatment system and biofilms in the aeration basin. An air compressor supplied airflow to the wastewater treatment system through diffusers lying on the bottom of the aeration basin to provide oxygen for the aeration basin and also ensure mixing in the reactor. Four aquarium heaters were used with temperature variations of 25°C–35°C to maintain the temperature at 30°C. The Plexiglas settling tank had a trapezoidal shape part since this can help sludge and suspended solids settle quickly. A pump was put in the bottom of the settling tank to return settled sludge to aeration basin with a specific flow. A cylindrical tank was used to build the granular activated carbon column. A 20 cm layer of gravel with two parts was placed at the bottom of the granular activated carbon column to allow drainage, and a layer of sand was added above the gravel layer to support the granular activated carbon and prevent it from escaping through the drainage layer. The main layer of the granular activated carbon column consisted of new granular activated carbon. The specification of granular activated carbon is given in Table 4.

Table 3
Characteristics of Kaldnes type 2 carriers used in this study

Parameter	Value
Length (mm)	13 ± 2
Diameter (mm)	30
Color	White
Material	HDPE
Hole numbers	4
Weight per m^3 (kg)	110 ± 3
BOD_5 oxidation efficiency ($gBOD_5/m^3$ d)	6,000
Specific surface area (m^2/m^3)	460

2.3. Operating conditions

After adding biofilm carriers to the aeration basin (50% of the basin, which is equal to 25 L), half of the effective volume of the aeration basin was filled with return activated sludge of the aeration basin unit of the petroleum refinery wastewater treatment plant. Mixed liquor suspended solids (MLSS), mixed liquor volatile suspended solids (MLVSS), and pH for return activated sludge were 1,234 mg/L, 339 mg/L, and 7, respectively. The remaining volume was filled with wastewater passed through the DAF unit. Activated sludge and wastewater were daily added to the aeration basin to provide organics and nutrients required for the growth of microorganisms. This process had been done 25 times before we started pilot testing. In other words, 25 cycles of treatment had been done during the operational period. During the adaptation phase, the temperature varied from 25°C to 35°C, and the pH was between 6.5 and 8.5. It was observed that after 7.5 h aeration in the

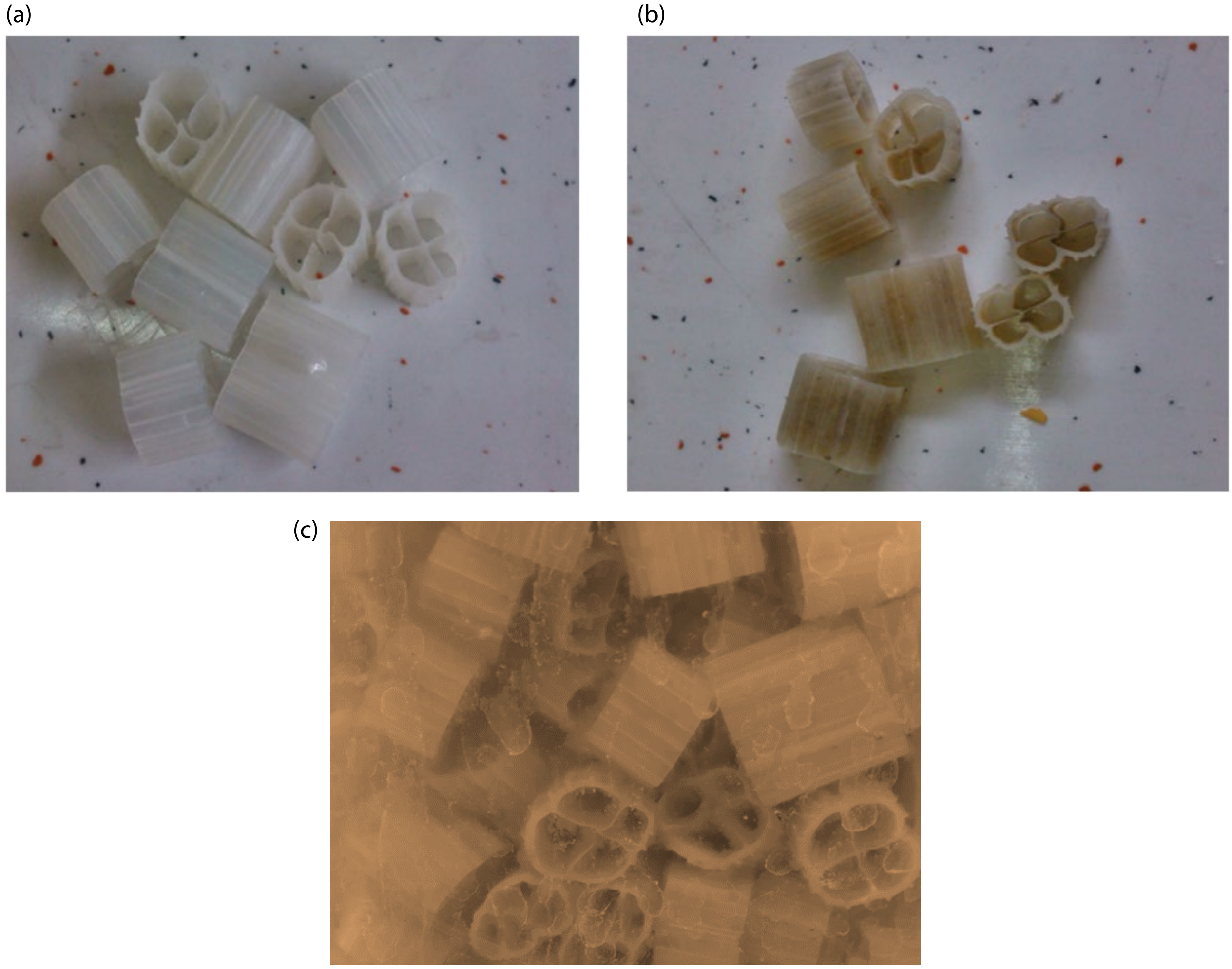

Fig. 2. Biofilm carriers before and after usage in the system (a and b) and in the aeration basin (c).

Table 4
Specification of granular activated carbon

Parameter	Value
Appearance	Black granular
Moisture	Maximum 10%
Ash	Maximum 5%
pH	6.5–10
Hardness	Minimum 85%
Bulk density (kg/m^3)	650 ± 50
Surface area (m^2/gm)	500

aeration basin, the COD removal rate decreases because of the decline in the concentration of MLVSS. This decline can be attributed to the decrease in the food to microorganism ratio and death of microorganisms in the aeration basin, which increases COD concentration. Also, according to the dimensions of the settling tank and inlet wastewater flow rate, settling time in the activated sludge system was 2.5 h. Therefore, 10 h optimum was chosen for the whole hybrid treatment system as the optimum hydraulic retention time. Settling tank and the granular activated carbon column were added to the system after the adaptation phase. Petroleum refinery wastewater was added to the feeding tank by a pump; wastewater samples were collected to measure the influent wastewater characteristics. The aeration basin was filled with 50% carriers, and after that raw wastewater with approximately 80 mL/min flow rate was discharged into the aeration basin. Afterward, the treated wastewater from the settling tank passed through the granular activated carbon column for tertiary treatment.

2.4. Analytical method

Temperature, turbidity, pH, oil, COD, BOD_5, dissolved oxygen (DO), total suspended solids (TSS), MLSS, MLVSS, ammonia (NH_3), and total dissolved solids (TDS) were measured in this study. The temperature and the pH were measured by a digital pH meter. Turbidity was measured by PC CECKIT Loviband, and TDS was measured by AZ8371. A spectrophotometer (Loviband Laboratory Spectrophotometer) was used to measure COD and NH_3 at the petroleum refinery wastewater treatment plant laboratory. TSS, MLSS, DO, BOD_5, Oil, and MLVSS were measured according to standard methods [22].

2.5. NN-based model development

Overall, neural networks (NNs) are inspired by biological neural networks, and they are also computing systems [23]. Moreover, the NNs try to project a relationship between outputs and inputs of each network only by considering examples from the training data set and without being programmed with any task-specific rules. NNs are appropriate for solving the problem of the mapping from one set to another due to their ability of well nonlinear mapping; hence, this is one of the most important advantages of NNs [24]. The NNs commonly consist of many artificial neurons operating in parallel, and the connections among neurons determine the function of the network [25]. A neuron is a computational processor; this has a transfer function that is used to weight inputs, and the result is the output of the neuron. A single-layer neural network cannot detect the relationship between the number outputs and inputs of the network; therefore, a MLP is used for building the NN models. An MLP-NN with three layers, including an input layer, a hidden layer with 15 neurons, and an output layer, was used in this study. In this study, the single-output MLP-NN, implemented with M neurons in the hidden layer, can be expressed by Eq. (1):

$$y(w,x)=\phi_{\text{out}}\left(\sum_{i=1}^{M}\left(W_{i,\text{out}}\times x_{\text{ih}}\right)+b_{\text{out}}\right) \quad (1)$$

where $W_{i,\text{out}}$ is the weight between the ith neuron in the hidden layer and the output neuron, ϕ_{out} is the transfer function of the output layer, b_{out} is the bias of output neuron, and x_{ih} is the output of each neuron in the hidden layer, and this is calculated by Eq. (2):

$$x_{\text{ih}}=\phi_{h}\left(\sum_{i=1}^{N}\left(W_{i,n}\times x_{i}\right)+b_{n}\right) \quad (2)$$

where ϕ_h is the transfer function of the hidden layer, N is the number of inputs, b_n is the bias of nth neuron in the hidden layer, $W_{i,n}$ is the weight between the ith input and the nth neuron in the hidden layer, and x_i is the ith input.

Fig. 3 shows the architecture of the MLP-NN used in the study for the prediction of effluent wastewater characteristics. Seven parameters, including influent COD, BOD_5, TSS, NH_3, Do, pH, and turbidity, were used as inputs of the MLP-NN to predict effluent COD, turbidity, NH_3, and TSS. Table 5 shows the characteristics of input and output variables in the NN modeling process. Through a random data division, the data set was divided into three sets, 70% for training, 15% for testing, and 15% for validation of the MLP-NN model. In this study, the Levenberg–Marquardt algorithm was used for training the MLP-NN model. The performance of the MLP-NN model in predicting effluent COD, turbidity, NH_3, and TSS was measured using mean squared error (MSE) and correlation coefficient (R).

3. Results and discussion

3.1. Changes of pH and MLSS

During the treatment process, pH was monitored because of its effect on the treatability of wastewater in physical/chemical and biological treatment processes [26]. pH was observed in the treatment process, and pH values varied from 7 to 8.5. Therefore, the treatment system and microorganisms did not experience any shock during the treatment process. MLSS was significant due to its influence

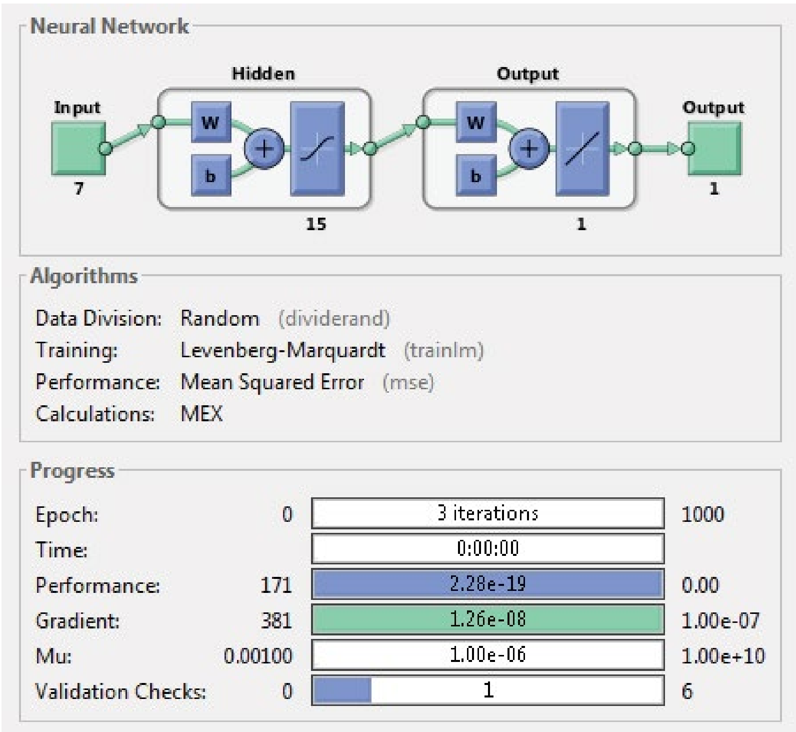

Fig. 3. Architecture of MLP-NN model for the prediction of effluent COD, turbidity, NH_3, and TSS.

Table 5
Characteristics of the measured variables in the NN modeling process

Input variable	Value	Output variable	Value
Influent concentration		Effluent concentration	
COD (mg/L)	140–260	COD (mg/L)	6–20
Turbidity (NTU)	19.4–28.2	Turbidity (NTU)	0.02–2.9
NH_3 (mg/L)	3.2–4.6	NH_3 (mg/L)	0.08–0.46
TSS (mg/L)	38.7–51	TSS (mg/L)	0.3–7.5
BOD_5 (mg/L)	38–67.6	BOD_5 (mg/L)	2.1–7.4
DO (mg/L)	0.2–1	DO (mg/L)	3.2–3.8
pH	7.5–8	pH	7.6–8

on the treatment and settleability, hence, the activity of microorganisms within our treatment system was monitored by measuring MLSS [27]. MLSS during the aeration stage in the activated sludge system was constant, and that indicated that the biological wastewater treatment system was stable.

3.2. COD removal efficiency

Fig. 4 shows the changes of COD concentration in the petroleum refinery wastewater and also the removal efficiencies after the activated sludge system with biofilm carriers and the granular activated carbon column. The influent COD concentration in the raw petroleum refinery wastewater was about 193 ± 50 mg/L, which decreased to 12.5 ± 8 mg/L in the effluent (lower than the standard limit of 60 mg/L by U.S. EPA) [28]. In Fig. 4, the standard deviation for raw wastewater, effluent after the activated sludge system, and effluent after the granular activated carbon column are 40.7, 9.0, and 5.3, respectively. The average COD removal efficiency after the activated sludge system with carriers was 87%, and the removal efficiency increased to 93% after the granular activated carbon column. The results of this study indicate that the activated sludge system with biofilm carriers in the biological reactor, and granular activated carbon is effective in terms of COD removal. The microorganisms in our hybrid system (suspended/attached growth), have a higher ability to remove organic carbon than an activated sludge system with the single suspended growth process [29]. The integrated petroleum refinery wastewater treatment system showed higher COD removal efficiency as compared with a conventional activated sludge process coupled with an immobilized biological filter utilized by Tong et al. [30] with a removal efficiency of around 64% in the treatment of heavy oil wastewater. Additionally, COD removal in our hybrid system is higher than a hybrid oil refinery wastewater treatment system, which consisted of a moving bed biofilm reactor (MBBR) and a slow-rate sand filter [31]. In another study, Shokrollahzadeh et al. [32] used an activated sludge system to treat petrochemical wastewater, and that system's COD removal efficiency was lower than our hybrid system. Our hybrid wastewater treatment system also performed better, in terms of COD removal, than an aerated baffled reactor, which was coupled with an aerated biological filter [33].

3.3. TSS removal efficiency

The changes of TSS concentration and TSS removal efficiencies after the activated sludge system with biofilm carriers and the granular activated carbon column are shown in Fig. 5. Settling tank of the activated sludge system and the granular activated carbon column are the two main steps of TSS removal in the hybrid wastewater treatment system. The average influent TSS concentration of 45 ± 5 mg/L decreased to 31 ± 3 mg/L after the settling tank and then decreased to 3.4 ± 1 mg/L in the effluent, which shows TSS removal efficiency of 92% for the hybrid system. In Fig. 5, the standard deviation for raw wastewater,

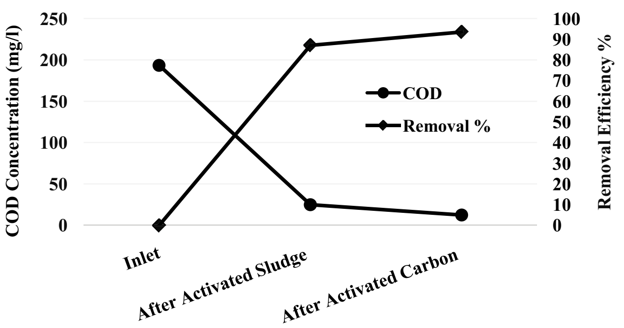

Fig. 4. COD concentration and removal efficiencies in the hybrid system.

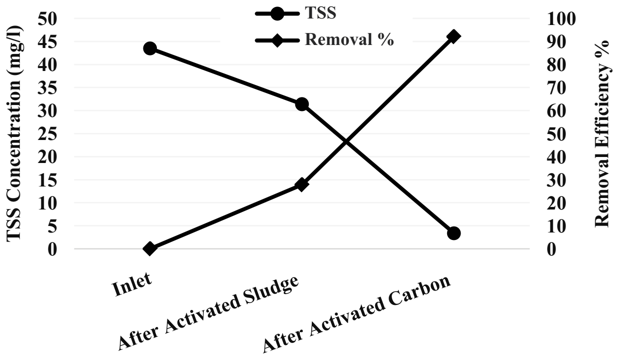

Fig. 5. TSS concentration and removal efficiencies in the hybrid system.

effluent after the activated sludge system, and effluent after the granular activated carbon column are 4.8, 3.8, and 2.4, respectively. The results showed that the integrated system is effective for TSS removal in petroleum refinery wastewater. The hybrid system demonstrated a higher TSS removal efficiency in comparison to conventional activated sludge systems. In a study, Gasim et al. [34] used extended aeration activated sludge system for petroleum refinery wastewater treatment; the maximum TSS removal efficiency was 71%. The 92% TSS removal efficiency of our hybrid system is higher than the 65% TSS removal efficiency of a system developed by Ahmed et al. [35] in another study. The system was composed of three different configurations of sequencing batch reactors. In another study, Xie et al. [36] used an aerated biological filter process for the treatment of slightly polluted wastewater in an oil refinery. TSS removal efficiency was 83%, which is lower than TSS removal in our hybrid system. Comparing our results with Perez et al. [37], who applied an anaerobic thermophilic fluidized bed in the treatment of cutting-oil wastewater, our hybrid system is more effective than that system regarding TSS removal.

3.4. NH_3 removal efficiency

The influent NH_3 concentration in the raw wastewater was about 4 ± 0.5 mg/L, which decreased to 0.26 ± 0.2 mg/L in the effluent. The average ammonia removal efficiency after the activated sludge system with biofilm carriers was about 90%, and the removal efficiency increased to about 94% after the granular activated carbon column. The standard deviation for raw wastewater, effluent after the activated sludge system, and effluent after the granular activated carbon column are 0.5, 0.2, and 0.1, respectively. The results of this study indicate that the hybrid system with biofilm carriers in the aeration basin, and the granular activated carbon column is efficient in terms of NH_3 removal. Mirbagheri et al. [38] used an activated sludge contact stabilization process to treat petroleum refinery wastewater; NH_3 removal efficiency in our hybrid system is higher than that system. In another study, Zhidong et al. [39] used a submerged membrane bioreactor for oil refinery wastewater treatment; NH_3 removal in that research was approximately analogous to our research, but they used membranes, and they were confronted with membrane fouling problem which is an obstacle in these kinds of treatment systems [40]. Cao and Zhao [41] used an MBBR for treating petrochemical wastewater. The 94% NH_3 removal efficiency of our hybrid system is higher than the approximately 80% NH_3 removal efficiency of that wastewater treatment system. Hamoda and Al-Haddad [42] evaluated the performance of a fixed-film reactor for treating petroleum refinery wastewater. NH_3 removal in that wastewater system was lower than our hybrid system.

3.5. TDS and turbidity removal efficiencies

The TDS concentration in the influent wastewater was 1,610 ± 200 mg/L and decreased to 950 ± 100 mg/L in the effluent. The TDS removal efficiency after the activated sludge system with biofilm carriers and the granular activated carbon column was approximately 41%. The standard deviation for raw wastewater and effluent after the granular activated carbon column are 249.7 and 82.8, respectively. The results of TDS removal in our hybrid petroleum refinery wastewater treatment system indicated that the system was effective for TDS removal. In a study, Salahi et al. [43] used polymeric membranes for the treatment of oily wastewater. TDS removal in that study was 31.6%, which is lower than TDS removal in our hybrid system. Noshadi et al. [44] evaluated the performance of an ultrafiltration (UF) wastewater treatment system for treating petroleum refinery wastewater. Forty-one percent of TDS removal in our hybrid system is higher than 23% TDS removal in that system. In another study, Aziz et al. [45] reported TDS removal efficiency of approximately 20% for a sequencing batch reactor system in the best conditions. TDS removal in that wastewater treatment system is lower than TDS removal in our hybrid system.

The hybrid system indicated high performance in terms of turbidity removal mainly because of the settling tank and the granular activated carbon column. The average turbidity of the oil refinery wastewater was 24 ± 5 NTU, which decreased to 11.5 ± 2 and 1.5 ± 1 NTU after the settling tank and the granular activated carbon column, respectively. The standard deviation for raw wastewater, effluent after the activated sludge system, and effluent after the granular activated carbon column are 3.5, 1.6, and 0.9, respectively. The turbidity removal efficiency was approximately 94% at the end of the integrated petroleum refinery wastewater treatment system. The results of this study showed that the integrated system is efficient for the removal of turbidity in wastewater with higher efficiencies than other kinds of hybrid wastewater treatment systems [46]. In a study, Velioĝlu et al. [47] used an activated sludge system for treating olive oil-bearing wastewater; turbidity removal in that system was lower than our hybrid system. The average turbidity removal in our hybrid system is higher than the average turbidity removal of a batch electrochemical reactor, which was used by Körbahti and Artut [48] for treating bilge water. In another study, Pendashteh et al. [49] used a sequencing batch reactor for treating produced water. The average turbidity of the effluent in that wastewater treatment system was higher than the average turbidity of the effluent in our hybrid system.

3.6. Oil removal efficiency

The influent oil of 44 ± 10 mg/L after the hybrid petroleum refinery wastewater treatment system deceased to 8 ± 5 mg/L. The oil removal efficiency was approximately 82% at the end of the integrated petroleum refinery wastewater treatment system. The standard deviation for raw wastewater and effluent after the granular activated carbon column are 8.2 and 5.9, respectively. The results indicated that the hybrid system is effective in oil removal from petroleum refinery wastewater. The oil removal efficiency of our integrated system is higher than an oil refinery wastewater treatment system, which was used by Otadi et al. [50]. That system consisted of a DAF system, an activated sludge system, and a clarifier. Oil removal in our hybrid system is higher than oil removal in a system, which was used by Dumore and Mukhopadhyay [51]. Comparing our results with the findings of Wang et al. [52], who applied an up-flow anaerobic sludge bed (UASB) reactor for treating heavy oil refinery wastewater and achieved the oil removal efficiency of up to 72%, our hybrid activated sludge system is more efficient. Sekman et al. [53] used electrocoagulation for treating oily wastewater. Oil removal in that system is lower than oil removal in our system.

3.7. NN-based prediction of effluent characteristics

In this study, various network architectures with neurons at the hidden layer were tested to predict COD, turbidity, NH_3, and TSS. The three-layer MLP-NN was chosen to keep the network as simple as possible after a lot of preliminary experiments for each output. Whereas using more hidden neurons in the neural networks might improve the performance, employing too many neurons may result in over-fitting, which undermines the generalization capacity of the model [54]. Therefore, MLP-NN with three layers and 15 neurons in the hidden layer brought about higher accuracies for most of the tested architectures and the effluent characteristics. Optimal architecture is essential for training the algorithm with appropriate speed and short simulation time for particular network performance [55]. The training procedure of the MLP-NN model was promising for the prediction of effluent COD, turbidity, NH_3, and TSS. The results of the prediction for the four effluent characteristics using the MLP-NN algorithm are shown in Fig. 6. The results of the different data almost showed a perfect match between experimental values and predicted values for the effluent COD, turbidity, NH_3, and TSS. The results of this study confirm the high generalization capability of the MLP-NN algorithm, and this has been reported in some studies [19,56].

Fig. 7 shows the regression lines for the MLP-NN model predicting effluent COD, turbidity, NH_3, and TSS based on the train and all data sets. The high correlation of predicted values with experimental values is confirmed by the results. The *R* values for the MLP-NN model predicting effluent COD were 1 and 0.973 based on the train and all data sets. The MSE values for the prediction of effluent COD based on the train and all data sets were 2.8e-08 and 0.221, respectively. For the prediction of effluent turbidity using MLP-NN, the *R* values were 1 and 0.998, respectively. The MSE values for the MLP-NN predicting effluent turbidity were 5.5e-08 and 0.008 based on the train and all data sets. The *R* values for the MLP-NN model predicting effluent NH_3 were 0.948 and 0.925 based on the train and all data sets. The MSE values in the prediction of effluent NH_3 based on the train and all data sets were 2.8e-03 and 2.7e-03, respectively. For the prediction of effluent TSS using MLP-NN, the *R* values were 0.982 and 0.948, respectively. The MSE values for the

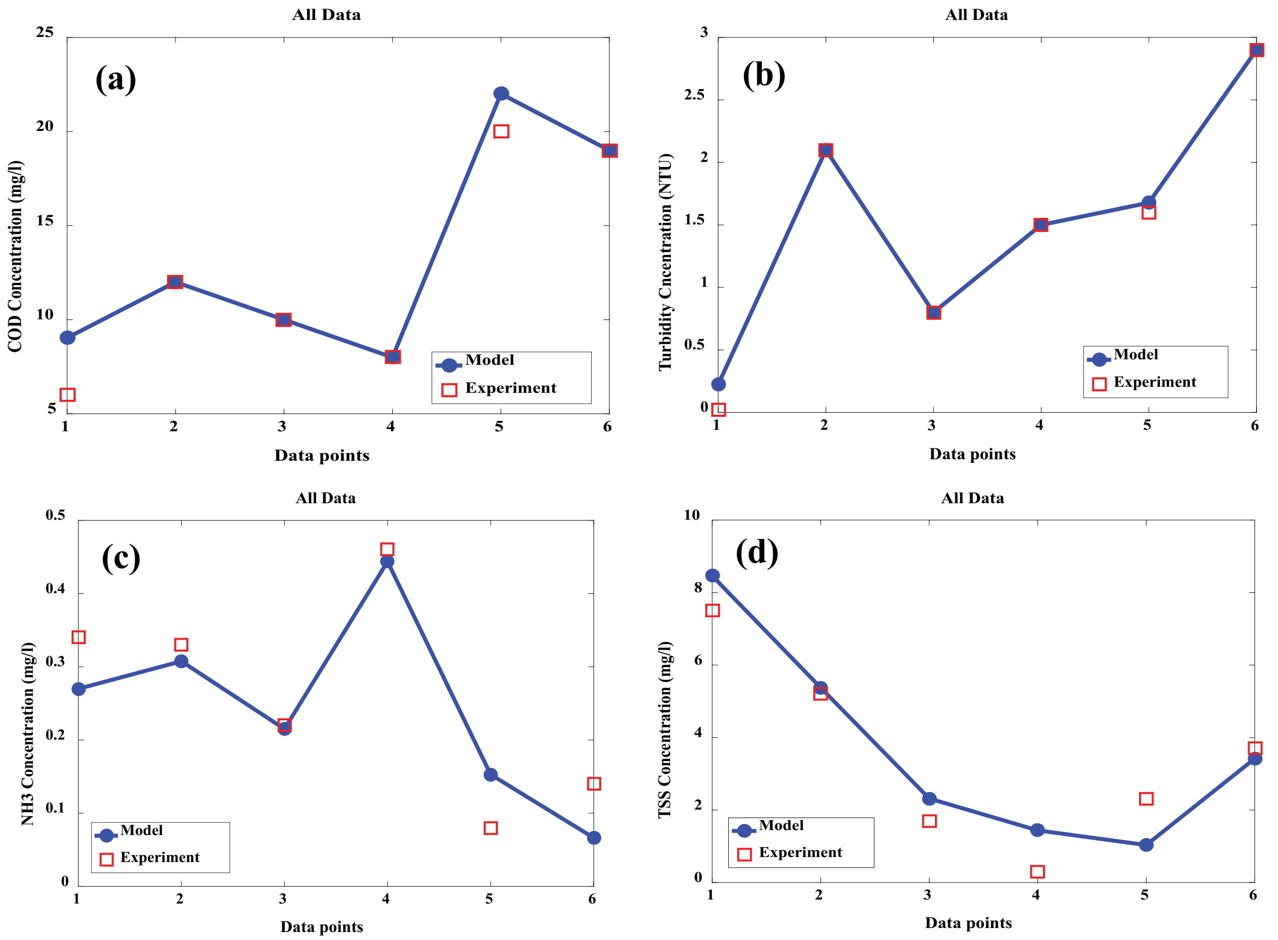

Fig. 6. Prediction of (a) effluent COD, (b) effluent turbidity, (c) effluent NH_3, and (d) effluent TSS using MLP-NN model.

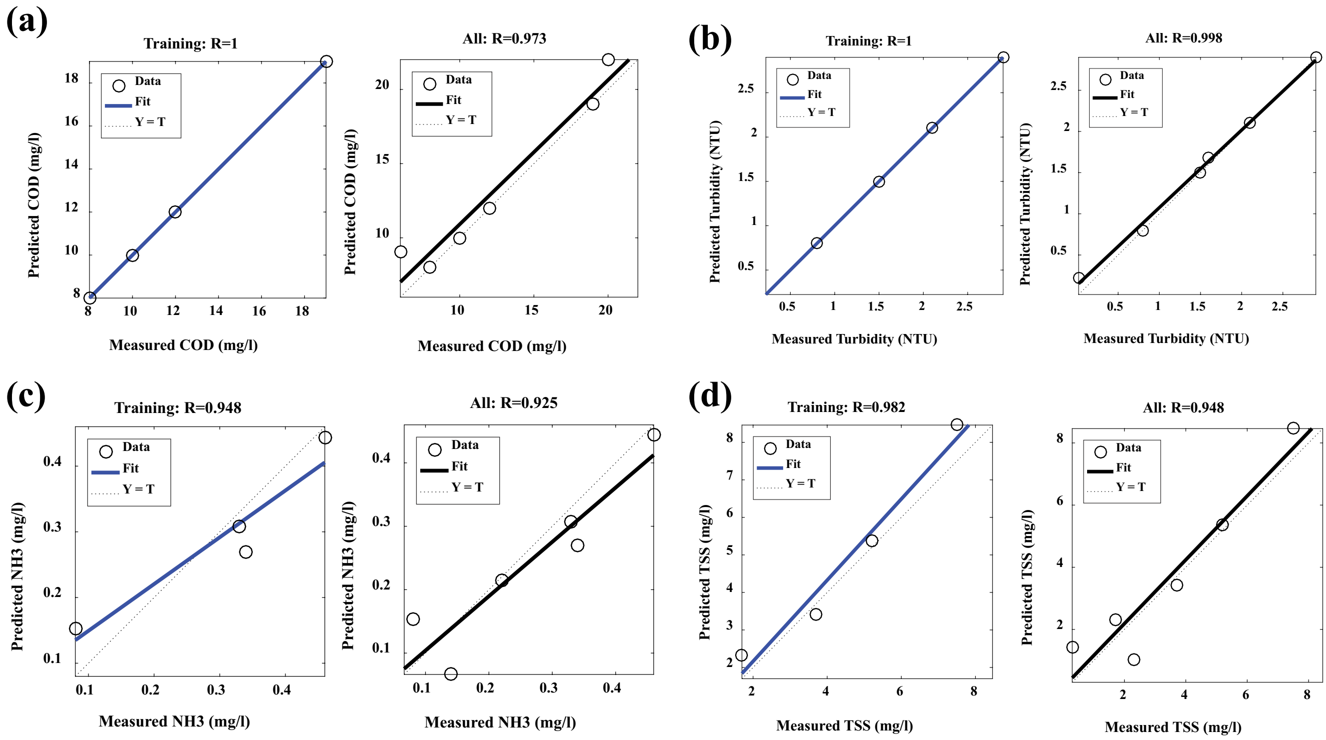

Fig. 7. Regression plots for the MLP-NN models predicting (a) effluent COD, (b) effluent turbidity, (c) effluent NH_3, and (d) effluent TSS.

MLP-NN predicting effluent TSS were 0.353 and 0.718 based on the train and all data sets. The results of our modeling for the prediction of effluent characteristics using MLP-NN show higher accuracies than previously developed models [57,58]. The optimal architecture of the MLP-NN model in this study was found to be reliable because the error based on the train and all data sets approached zero for effluent COD, turbidity, NH_3, and TSS.

4. Conclusion

In this study, an activated sludge system was coupled with biofilm carriers, and a granular activated carbon column was used at the end of the wastewater treatment process to improve the performance of petroleum refinery wastewater treatment. To make a tradeoff between suspended growth and attached growth, 50% of the aeration basin of the activated sludge system was filled with biofilm carriers. With the HRT of 10 h, COD, turbidity, NH_3, and TSS removal efficiencies were 93%, 94%, 94%, and 92%, respectively. In our hybrid wastewater treatment system, the removal efficiencies were higher than as compared to conventional activated sludge systems and MBBRs. The application of a granular activated carbon column as a post-treatment step after the biological wastewater treatment is a promising technology for wastewater reclamation and reuse in countries, which are plagued with the water crisis. The results of our hybrid system indicate that NN is a practical modeling approach for the prediction of wastewater characteristics. According to the findings, MLP-NN is a capable tool to monitor the characteristics of the effluent wastewater.

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