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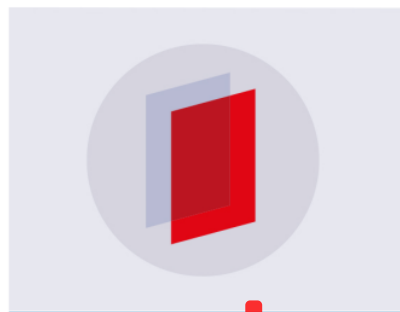
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Artificial Neural Network (ANN) for Optimization of Palm Oil Mill Effluent (POME) Treatment using Reverse Osmosis Membrane

Muhammad Said¹, Muneer Ba-Abbad², Siti Rozaimah Sheik Abdullah³, Abdul Wahab Mohammad⁴

¹Department of Chemistry, Faculty of Mathematics and Science, University of Sriwijaya, Indralaya 30662, Sumatera Selatan, Indonesia

²Department of chemical Engineering, Faculty of Engineering and Petroleum, Hadhramout University of Science & Technology, Mukalla, Hadhramout, Yemen

³Centre for Sustainable Process Technology (CESPRO), Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia

⁴Department of Chemical and Process Engineering, Faculty of Engineering and Built Environment, University kebangsaan Malaysia, 43600, Bangi Selangor

E-mail: saidusman2011@gmail.com

Abstract. The treatment of palm oil mill effluent (POME) by Reverse Osmosis (RO) membrane was achieved experimentally. The biological oxygen demand (BOD), chemical oxygen demand (COD) and Color as final response of POME treatment process were selected. However, main influence factors on POME treatment process as concentration, transmembrane pressure and pH were tested on responses. The experimental results of responses were compared to the prediction by applying of Artificial Neural Network (ANN) as a simulation technique to create model of the process. Higher validation of ANN model was found for COD, BOD and Color which the prediction values very close compared to experimental result. The COD removal was investigated as a major affect factor in experiments. The best removal of COD was obtained at lower of POME concentration, pH, transmembrane pressure and time of contact. Therefore, these results showed that appreciate model created by ANN for POME treatment process which contributed easily to apply in industrial filed as future application.

Keyword : POME, RO, ANN, Pollutant removal

1. Introduction

Malaysia is one of the largest palm oil producers in the world with a total crude palm oil (CPO) production of 17.56 million tons per year. The CPO production always increases every year which means the increase in wastewater, called palm oil mill effluent (POME). POME is a hazardous liquid as wastewater that comes out of the discharge pipe at a temperature of 80-90oC which contains high biological oxygen demand (BOD) of 25 g/L, chemical oxygen demand (COD) of 53.6 g/L, Total suspended solids (TSS) of 19 g/L and low pH of 3.5-4.0 [1].

In the last decade, the application of membrane technology in POME treatment has been growing. Initiated by Said et al. [2], which investigate the pretreatment methods followed by membrane ultrafiltration and the performance shows more than 90% removal of total nitrogen, suspended solids, turbidity and color. Ahmad et al. [3] used combination treatment of coagulation and adsorption equipped by membrane UF and RO. From the investigation, the odor and color as well as the solid suspension (SS) and turbidity under different conditions almost removed. Yejian and Li [4] has been applied the biological system combine with membrane UF and RO which at the end of process, clear water was produced and could be used as boiler feed water. Other researcher, recently not only succeeded to removed the pollutant but also investigation of cleaning of membrane using chemical [5].

Since the success of a membrane filtration process depends on the relationship between many factors, the modeling has many problems difficultly solved by simple mathematical equations.



Therefore, there are alternative ways to solve the problem using the existing data with assistant a sophisticated tool. The conventional mathematical models which applied to estimate the parameters of cross flow filtration have limitations and disadvantages. For example, linear models have not provided a satisfactory description of the actual processes when occurring as a nonlinear process. Main disadvantage of the conventional model is difficult to eliminate confounding factors or noise that usually appeared in the filtration process which have negative affected on final result [6]. Therefore, artificial neural network (ANN) have been applied to solve this problem as new tool that can be constructed the experimental results to predict the performance of the membrane system.

Generally, ANN is technique inspired by biological neuron processing consist of three layers. The first layer is called the input layer which is the variables conditions of the experiment, in the middle there is a hidden layer where acts as feature predictors with more than one hidden layer and last layer is the output layer which is the target of an overall process. In turn, hidden nodes responses are weighted by the connections between the hidden and output layer which forwarded to nodes of the output layer [7].

Extensive research has been conducted to determine the capability of ANN to explain the membrane system phenomena. For example, ANN has been applied by many researchers to explain the membrane fouling [8-10], and also to predict the parameter to produce high water quality [11-14].

In this study, a feed-forward network was proposed. The input layer consists of four variables as concentration, transmembrane pressure, pH as well as time and the output layer contains four variables also as COD, BOD, TSS and Color. The objective of this study is to develop a neural network model to estimate the performance in POME parameters removal as COD, BOD, TSS and Color with compared to actual value of experiment.

2. Materials And Methods

2.1 Materials

For this study, a POME was collected from one of palm oil mill in Carey Island in Malaysia, and preserved in PVC containers at a temperature lower than 4°C. The sample was analyzed using DR/2010 portable data logging spectrophotometer (HACH, USA), covering the biological oxygen demand (BOD), chemical oxygen demand (COD), Total suspended solids (TSS), and Color. All the chemicals, required for the characterization of COD and BOD were supplied by HACH Chemical. Firstly, POME was treated with adsorption and ultrafiltration to remove large particles. Furthermore, POME was treated by RO membranes as final stage. The characteristic of POME was listed in Table 1.

Table 1 Characteristic of raw sample of POME

No.	Parameters	Content value
1.	BOD (mg/L)	174.67
2.	COD (mg/L)	244.67
3.	TSS (mg/L)	7
4.	Color (PtCo)	1263.33
5.	Turbidity (NTU)	43.57

The cross flow filtration set was equipped with adsorption, UF and RO membrane. The Montmorillonite was chosen as the adsorbent materiel. The hollow fiber made from Polysulphone for ultrafiltration while RO membrane used tubular type (RE-2012 LPF) from Woongjin, Korea. The pH of POME sample was adjusted by additional of NaOH and HCl solutions. All chemicals were supplied by Friendemann Schmidt Chemicals.

2.2 Methods

2.2.1 Experimental procedure

A 10-liter of POME sample was feed to adsorption column and fall drop by drop using the dosing pump with concentration variation of 10 to 90%. The product was collected at the bottom of the column and analyzed the content. The product was sent to feed sample tank of membrane module with analyzed. The first stage, POME was treated by UF membrane and continued with RO membrane. Permeate from UF was also analyzed the content and considers a simultaneously as the feed sample for RO membrane process. For the adsorption and UF membrane treatment stage, the sample was collected and analyzed for interval time of 1 hr. Furthermore, the samples pass through the RO membrane. Permeate was collected and retentate was recycled to feed sample tank. This process continues for 6 hrs and collected sample analyzed for every 2 hrs. A transmembrane pressure was varied between 0.5 to 2.5 kPa while the pH from 3 to 11 adjusted.

The product accumulates in basins that equipped with balance weight and connected to computer and recorded automatically every 1 min for 6 hrs. The results of all parameters were compared to the predict value from ANN calculation. The difference between actual and predict value as error of the process was recorded.

2.2.2 Artificial neural Networks (ANN)

An ANN consists of a set of connected cells known as the neurons. The number of neurons in the input and output layers is given respectively, by the number of input and output variables of the process. An additional bias input was added to the weighted sum for increasing or decreasing the net input to the activation function. The term of networks architecture is tandem with learning algorithm that using to train the networks. Generally, ANN architecture is consists of two activation functions, i.e. feed forward and feedback. One of important aspect in ANN is learning process as initial step. The learning process uses to predict the output which it having the minimum difference compared to the actual value. This disparity between actual and predict values of output is error of output over the target. Learning process consists of three learning algorithm, Back propagation, Quasi-Newton and Lavenberg-Marquardt. Majority of networks architectures use feed-forward networks where it processes the input data using error back-propagation algorithm.

In this study, the back propagation algorithm was trained using MATLAB 7.11.0.584 Neural Network Toolbox (R2010) from the Math Works, Inc. Four conditions of operating condition were applied in the RO membrane stage: concentration of POME (10%, 50% and 90% by volume), pH of solution (3.0, 7.0, and 11.0), transmembrane pressure (0.50 kPa, 1.50 kPa, 2.50 kPa) and time to collect sample (2.0 hr, 4.0 hr, 6.0 hr). The concentration and pH of POME were applied since the pretreatment step (on adsorption and UF membrane) and the others special for RO membrane. All experiments were conducted at different set of conditions and repeated for minimum two times. Thus, 81 runs of experimental conditions were made to conduct the optimization of RO membrane process.

3. Results and Discussions

3.1 Proposed of ANNs architecture

The important step in ANN is to determine the number layer that has specific number of neuron for each layer, which used to train the network optimally [15]. A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons uses to fit multi-dimensional mapping problems well and given consistent data and enough neurons in hidden layer. Figure 1 shows the correlation of hidden neurons number and MSE. The optimization of neural network was determined based on the mean squared error (MSE) and the coefficient of determination (R^2). The number of hidden neuron that gives the smallest MSE is the best number of neurons. Hence, 6 neurons were chosen as the hidden neuron to optimize the neural network.

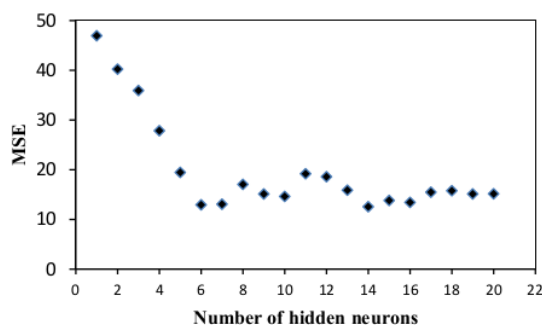


Figure 1. Correlation of neurons and MSE Number

In this study, the input data were applied a concentration, pH of POME, transmembrane pressure and time to collect sample. The input data were used to predict the BOD, COD and Color removal after treatment with RO membrane. The neural network was performing using back propagation algorithm. The architecture of a single hidden layer and an output layer was shown in figure 2.

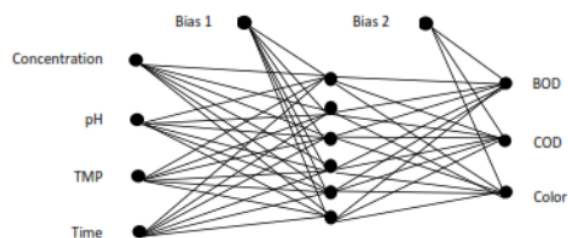


Figure 2. The architecture of ANNs

3.2 Neural network training

The relationship between the results from experimental data and ANN predictions of COD, BOD and Color removal are presented in figure 3. Plot distribution shows that predictive capability between the values of experiment and predicted quite satisfactory with slope line closed to 1. It is seen that the predicted value by neural network almost similar to the experimental data. The R^2 found to be more than 0.9 for all parameter of COD, BOD and Color removal which indicated the higher accuracy of the ANNs.

Some literature shows the similar trend of accuracy as Elmolla [16] obtained 0.997 for removal of COD, Hamzaoui [12] reached 0.9913 for removal of COD, Ghandehari [17] produced 0.9965 for removal of BSA and Bhatti [18] was reached to 0.982 for removal copper.

The development of ANN model included two steps as a training and validation. For the treatment with RO membrane, a total number of 324 experimental data were created. About 243 data apply for training and 81 data for rest for validation of proposed ANN model.

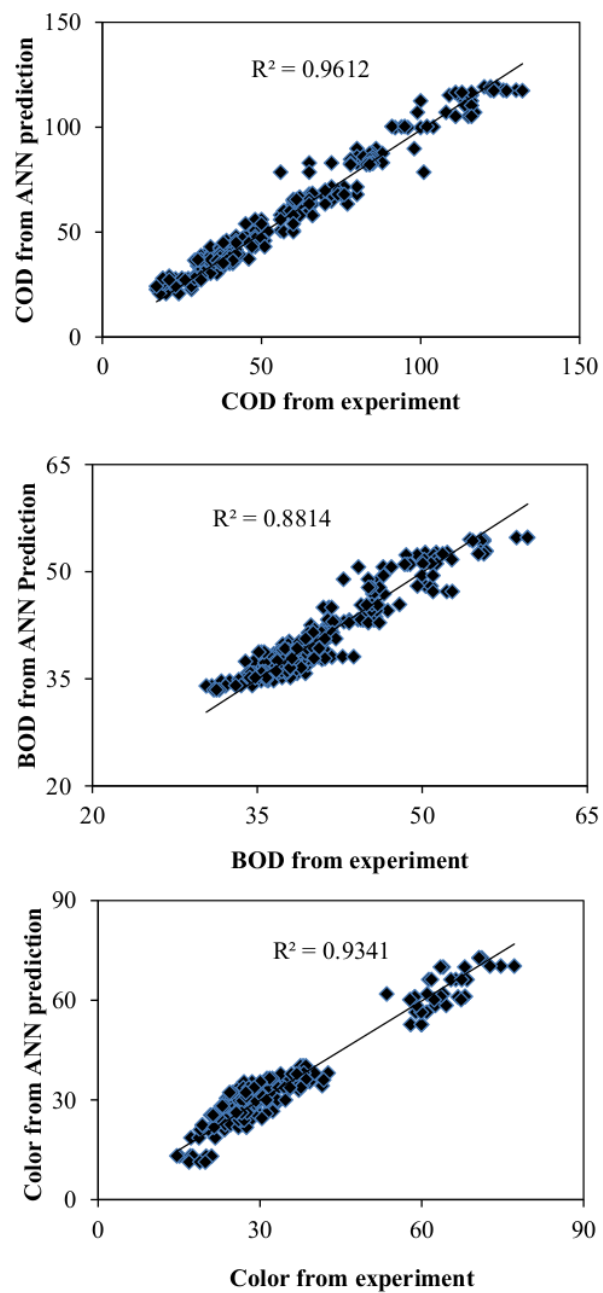


Figure 3. Correlation between experimental data and predicted value of (a) BOD, (b) COD, (c) Color

3.3 Neural network model

Neural network with six neurons in each hidden layer and four inputs are used to propose the simulate model of COD, BOD and color. Therefore, the ANN model is applied according to Equation (1):

$$Y = \sum_{n=1}^n \left\{ W_{0(n,l)} \left[\frac{2}{1 + \exp(-2(\sum_{m=0}^n (W_{i(n,m)} \ln_{(m)} + b_{1(n)})) - 1)} \right] \right\} + b_{2(l)} \quad (1)$$

where Y is the parameter forecast of COD, BOD and color, n is the number of hidden neurons, m is the number of inputs, l is the linear output, W_i and b_l is the weight and the bias in the input layer to the hidden layer, W_o and b_2 are the weights and biases in the hidden layer to the output layer. Hyperbolic tangent "TANSIG" (which is a function of the transition) is selected for the mapping of input to hidden layers while pure linear transfer function "secretary" for mapping hidden layer to the output layer. Weight bias circuit and connected to the removal of COD, BOD and color are described in Table 2 and 3.

Table 2. Weights and biases for the ANN model to describe the COD, BOD and color removal

Neuron	W_i				b_1
	Concentration (%)	pH	Trans Membrane Pressure (bar)	Time (hr)	
1	-1.6418	1.0695	-3.8884	-0.044911	3.5633
2	-4.0443	5.3732	0.25598	2.0763	0.84903
3	1.2197	1.1371	-0.31881	-0.0027809	-1.4653
4	3.5744	6.5205	2.0026	0.094434	6.8339
5	1.531	-0.95662	0.11425	-0.01517	-1.0172
6	-4.5128	5.621	0.13695	0.33648	0.64359

Table 3. Output of COD, BOD and color removal

Output	$W_{o(1,1)}$	$W_{o(1,2)}$	$W_{o(1,3)}$	$W_{o(1,4)}$	$W_{o(1,5)}$	$W_{o(1,6)}$	b_2
COD	-0.080188	-0.16399	0.029091	0.029091	1.0826	0.51319	0.27136
BOD	-0.27865	-0.30863	-0.66178	-0.32838	1.3025	0.70999	0.15934
Color	0.39307	-0.20635	-2.16	-0.55507	3.0361	0.96809	-0.3892

3.4 Prediction of COD, BOD and color removal

The ANN model is validated by independent data and the experimental data with simulated results are shown in figure 4. It is seen that the COD and Color values are increased while BOD relative constant. This result was not surprising because at the beginning of the sequence experiment, the lowered concentration of POME as 10 % was used and then further increased to 50 and 90%. An increasing of concentration means increased the organic and impurities particle in POME. Despite of RO membrane showed a good ability to filter particles, but the RO membranes were very sensitive to particle size. If the particles contains in the solution, a great shape and rough rapidly caused membrane fouling and it reduced the ability of the membrane.

In addition, the fluctuation of curve was influenced by differences of pH values from 3 to 11. When pH below than 5.05, the POME was more positively charged and the particles were attracted to the membrane and enter the pores and trapped. The trapped particle shows difficulty to pass through the membrane, where the particles contain a variety of organic molecules was observed. This mechanism caused to value of parameters in the permeate decrease. In general, RO membranes succeed to remove pollutants in POME which is characterized by impairment of BOD, COD and color value. These finding showed similar results compared other previous studies [11, 16, 19-21]

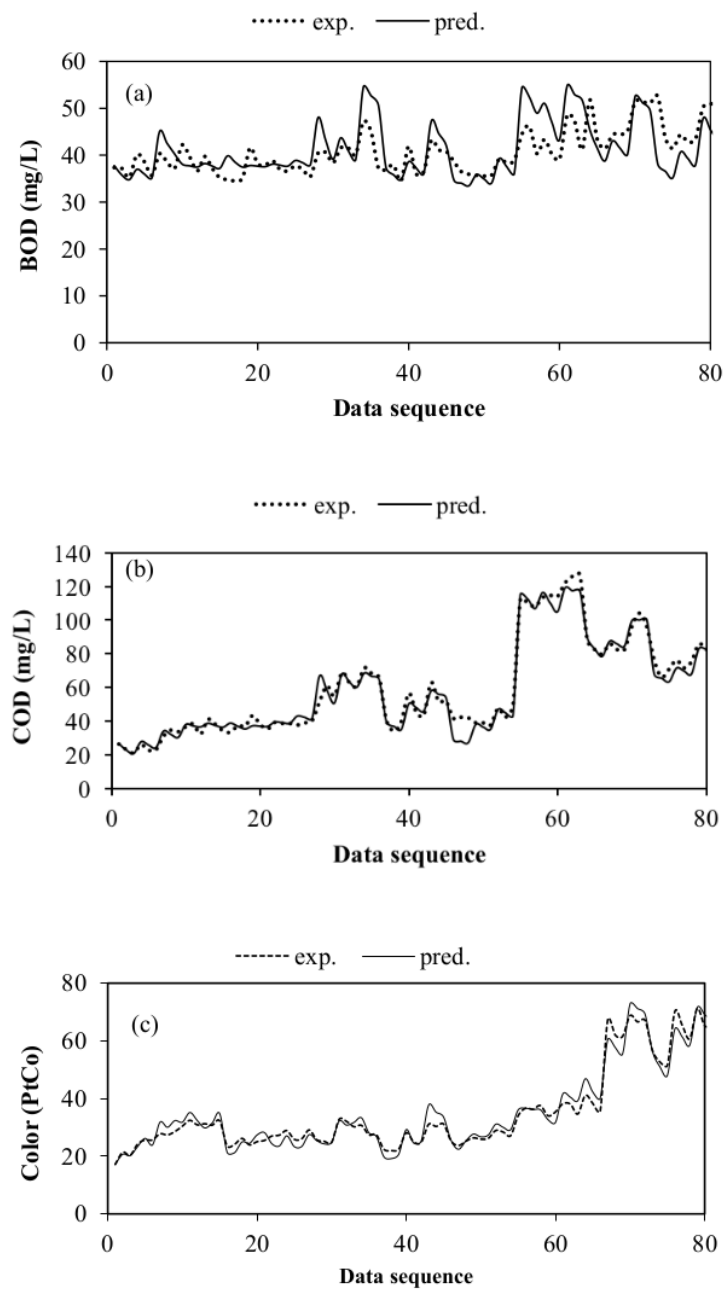


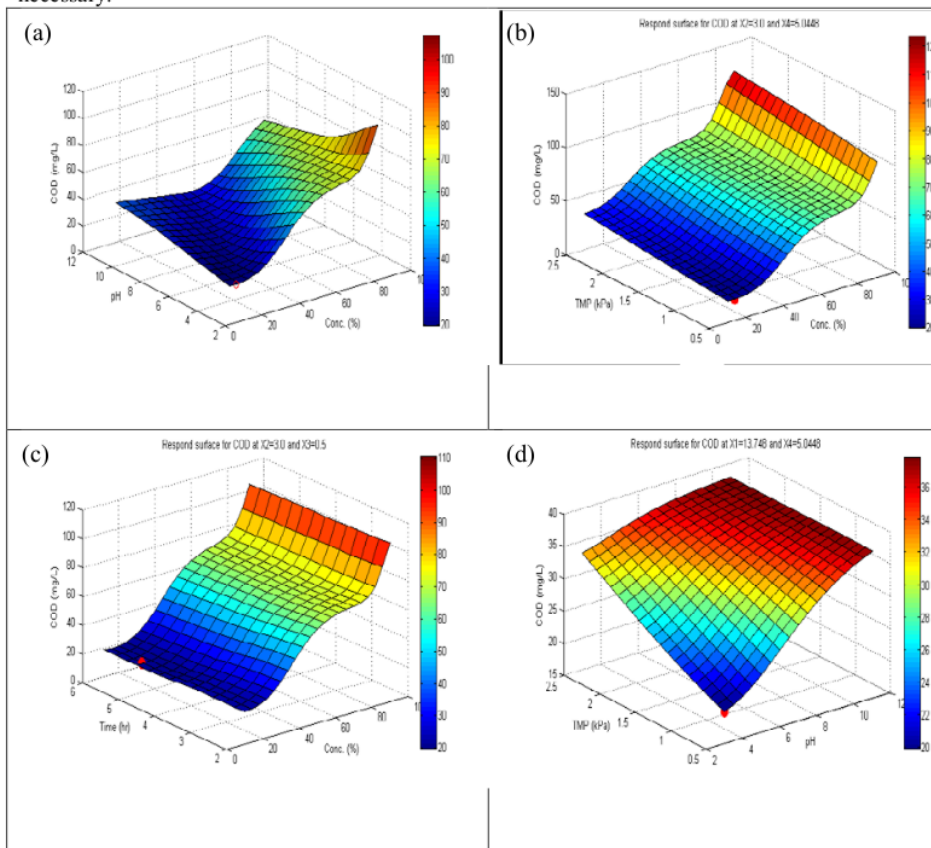
Figure 4. The prediction values by ANN model for (a) BOD, (b) COD, (c) Color

3.5 The 3D plot of COD removal

In this study, only a 3D plot for COD removal was investigated due to COD a major affect factor in experiments. Plot 3D for COD removal shows the effect of interaction with two variables of final results as given in figure 5.

The successfulness of COD removal was characterized by a decrease in COD value at the outlet of the reverse osmosis membrane. The negative effects on COD removal was observed when the pH at greater than 5.0. The same sequence happening, when the concentration of POME and transmembrane pressure were increased. These results attributed due to a smaller concentration of POME which least impurity content in POME solution beginning indicator of the final COD. In addition, lower pH value leads to changes in impurities surface which was resulted the more negative charge of both impurity and membrane surfaces. The similarity of these charges made a more hydrophilic nature of the membrane which the dirt not stick to surface of membrane and permeate flow rate was increased. According to these results, to improve COD removal by diluting the concentration of POME and lowering the pH was observed.

Furthermore, the implementation of low operating pressure, ranging from 0.5-1.0 kPa and long contact time were found to be an important factors removal COD of POME. However, in general by applying a low transmembrane pressure and long contact time was made the filtration process of impurities by the membrane become maximal. However, filtration POME for a long time also causes the short lifetime of the membrane which important to clean the membrane within the process necessary.



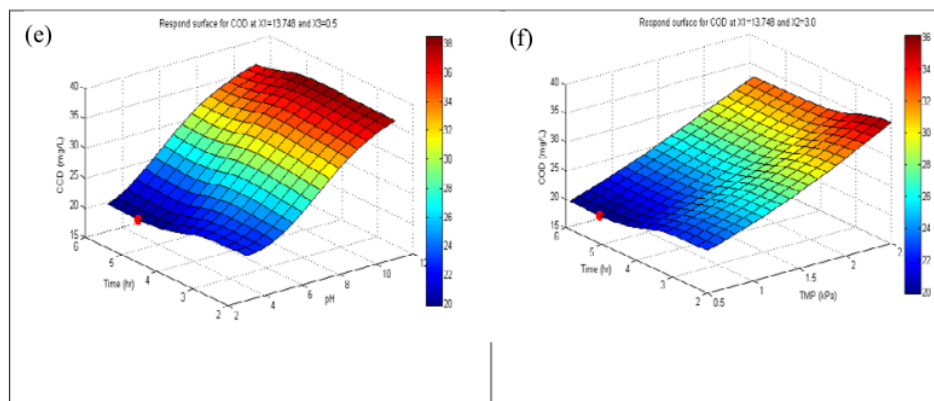


Figure 5. Plot 3D of the optimum for COD removal: a) effect of concentration and pH, b) effect of concentration and transmembrane pressure, c) effect of concentration and time, d) effect of pH and transmembrane pressure, e) effect of pH and time, f) effect of transmembrane pressure and time

4. Conclusion

In this study, the palm oil mill effluent (POME) treatment by Reverse Osmosis (RO) membrane was tested successfully. The factors of concentration, transmembrane pressure and pH on the final results of BOD, COD and Color were investigated. All predicted results by artificial neural network (ANN) were close to experimental results which confirm high accurate model produced to simulate the filtration process. These results indicate that artificial neural network (ANN) appreciated method to develop of filtration process using the membrane for waste water treatment in future.

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