Dynamic Model Development for Submerged Membrane Filtration Process Using Recurrent Artificial Neural Network with Control Application

Zakariah Yusuf[1], Norhaliza Abdul Wahab[2*], Shafishuhaza Sahlan[3]

[1]Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Malaysia
[2]Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Malaysia
[3]Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Malaysia

* corresponding author: aliza@fke.utm.my

Abstract

Modeling of membrane filtration process is challenging task because it is involves many interactions from biological and physical operation behavior. Membrane fouling in filtration process is too complex to understand and to derive a robust model is not possible. The aim of this paper is to study the potential of neural network based dynamic model for submerged membrane filtration process. The purpose of the model is to represent the dynamic behavior of the filtration process therefore suitable control strategy and tuning can be developed to control the filtration process more effectively. In this work, a recurrent neural network (RNN) structure was employed to perform the dynamic model of the filtration process. The random step was applied to the suction pump to obtained the permeate flux and Transmembrane Pressure (TMP) dynamic. The model was evaluated in term of $\%R^2$, root mean square error (RMSE,) and mean absolute deviation (MAD). Proportional integral derivative (PID) controller was implemented to the model for different control strategies and several tuning gains were tested for the effective filtration control. The result of proposed modeling technique showed that the RNN structure is able to model the dynamic behavior of the filtration process below critical flux condition. The developed model also can be a reliable assistance for the control strategy development in the filtration process

Keywords: Membrane; Filtration; Model; Control

Introduction

Membrane bioreactor (MBR) is recognized as the best alternative solution for conventional activated sludge (CAS) system for wastewater treatment. The main different between MBR and conventional system is the application of membrane filtration that able to produce better effluent quality compared with conventional system. Membrane filtration system still struggles from many issues such as fouling and energy efficiency [1][2] [3]. Fouling can be defined as undesirable of the accumulation of matter such as colloidal, particulate, solute materials, microorganism, cell debris on the membrane during filtration process [4]. Fouling can lead to membrane clogging where the membrane pore will be blocked by solid material. When this phenomenon occurs, the Transmembrane Pressure (TMP) will be risen or permeate flux will be declined and if this situation cannot be controlled it will lead to the membrane damage. The development of a reliable prediction model for membrane filtration system is crucial in order to improve the performance of the membrane filtration system in MBR plant[5][6][8]. This prediction model can help the plant operator to predict the filtration performance under different operation settings and suitable control strategies can be developed to enhance the filtration process in term of quality and cost.

Several works have been done to model the filtration system using mechanistic model and black box model. However, the mechanistic model is very complex and involved many parameters to tune. The black box model like artificial neural network (ANN) have showed great potential in membrane filtration process modeling such as [8], [9] and [10]. This work proposes recurrent type of ANN structure to model the membrane filtration process for controller design application.

Methods

Data Collection

The data set is collected from the membrane bioreactor pilot plant located in Process Control Lab, Faculty of Electrical Engineering, Universiti Teknologi Malaysia (UTM). Random steps input were given to the suction pump to stimulate the dynamic behavior of the process. Figure 1 shows the plant schematic diagram while figure 2 shows the data collected from the pilot plant. The experiments were carried out in single tank submerged membrane bioreactors, with working volume of 20 L Palm Oil Mill Effluent (POME) taken from Sedenak Palm Oil Mill Sdn. Bhd. in Johor, Malaysia. The aeration during filtration is set around 6 to 8 standard litter per minute (SLPM). The input of the filtration is the voltage of the permeate pump, mean while the flux and TMP are the measurement outputs.

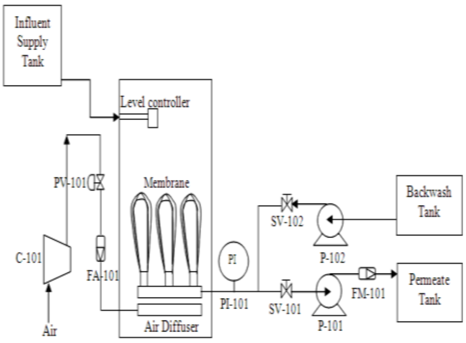

Figure 1: Plant Schamatic

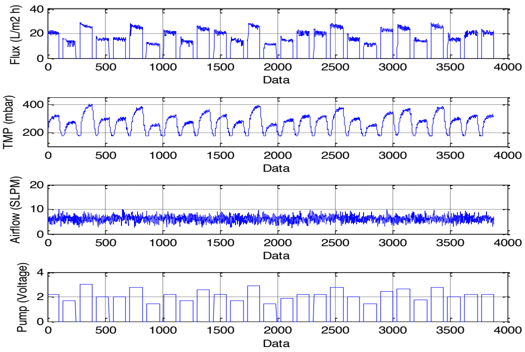

Figure 2: Experimental data

Model Development

The model was developed using Recurrent Neural Network (RNN) structure. The data are divided in to training and testing data sets. The model is validated using three evaluation techniques such as $\%R^2$, root mean square error (RMSE) and mean absolute deviation (MAD).

Controller Application

In this work, standard proportional integral derivative (PID) controller was applied to control the filtration system. Two control strategies are applied in the simulation work using the developed model. The first strategy is the permeate flux set point control and the second strategy is TMP cycle control.

Results and Discussion

The training result showed an acceptable result for both flux and TMP. The evaluations of the model performances indicate more than 98% R^2 for the training dataset with RMSE and MAD value at 1.9882 and 5.0874 respectively. Flux model training result shows reliable prediction where the model able to predict flux decline in the cycle. The $\%R^2$ achieved 95.3144%, RMSE is 3.9530 and MAD is 0.9683.Table 1 presents RNN training performance.

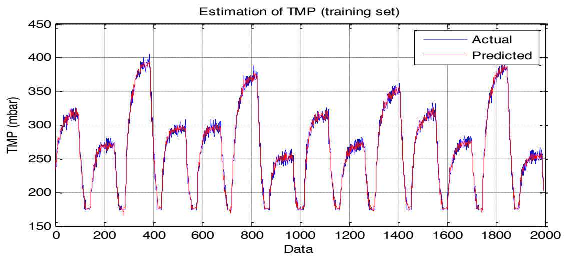

Figure 3: TMP model training result

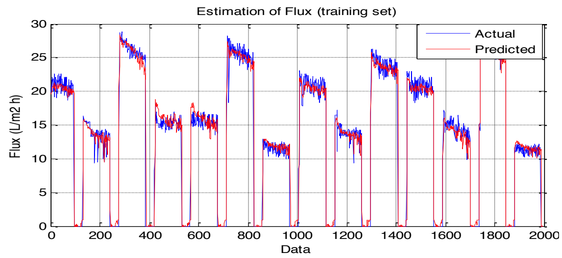

Figure 4: Permeate flux traning result

Table 2. TMP Modeling Peformance

Column1	Training	Testing
%R^2	98.8779	98.4648
RMSE	1.9882	2.0336
MAD	5.0874	5.6204

Testing result of the RNN model indicates reliable prediction result using the testing data set. TMP testing result showed more than 98% of R^2. 1.988 of RMSE and 5.0874 of MAD. The testing result for flux also gave an acceptable performance. Table 2 shows the model testing performance.

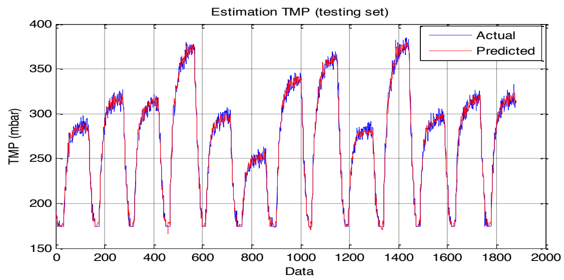

Figure 5: TMP model testing result

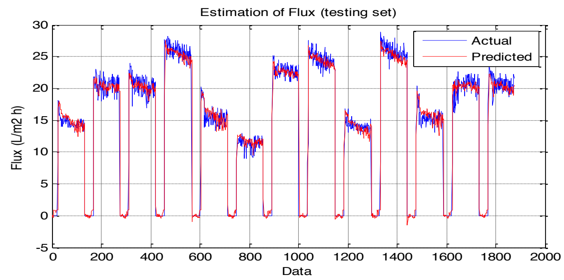

Figure 6: Permeate flux testing result

Table 2. Permeate Flux Modeling Peformance

Column1	Training	Testing
%R^2	95.3144	94.9799
RMSE	3.9530	4.1357
MAD	0.9683	1.0298

The PID controller applied on the model shows that the capabilities of this controller to control permeate flux at the desired set point without facing flux decline that usually occur in the open loop control. Figure 7 shows the PID controller performance for permeate flux regulation. However, in Figure 7 the TMP shows increments from cycle to cycle that shows the fouling phenomena. Fouling is expected to occur in the membrane filtration process. With the assistant of this model further action can be performed, for example operator can schedule the back wash cleaning accordingly in the process.

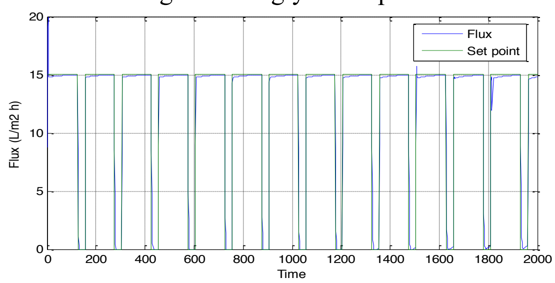

Figure 7: PID result for permeate flux control

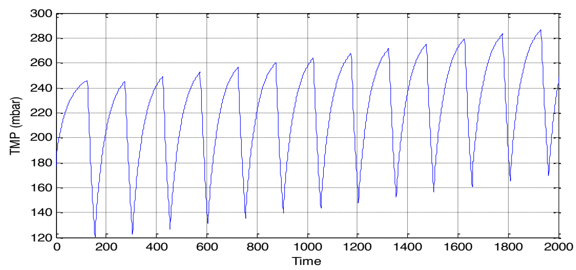

Figure 8: Effect of the controller performance to TMP

The TMP control strategies showed that the PID control is able to control the TMP at the desired set point. In this control strategy fouling will make the flux to decline in the cycle and as the filtration cycle increase. Figure 9 shows the TMP control result while Figure 10 shows the flux decline during filtration process.

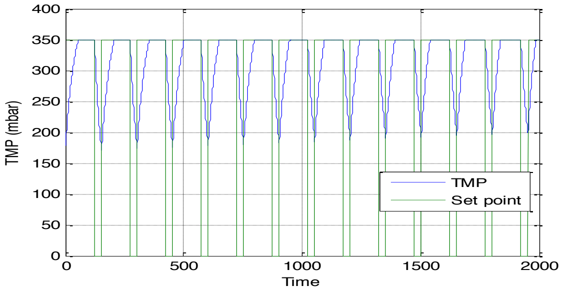

Figure 9: PID result for TMP control

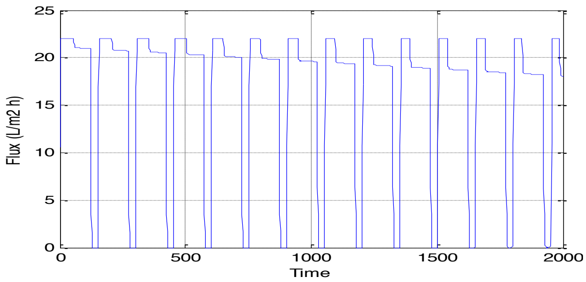

Figure 10: Effect of the controller performance to permeate flux

Conclusion

This work proposes RNN modeling technique to model the membrane filtration system. From the result, it showed that this technique able to model the dynamic of submerged membrane filtration. The training and testing result showed a good agreement between actual and predicted data. The model is very useful to facilitate plant operator in designing suitable control system. In this paper basic PID controller is applied to demonstrate application of the model in control system development. In the permeate flux control the controller is able to control the flux at the desired set point, however the TMP is increase because of the fouling. Similar result found in TMP controller, where the controller is able to maintain the TMP with decline of flux was observed. Suitable control strategy must be obtained in order to obtain effective filtration with most effective cost.

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