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Permeate Flux Measurement and Prediction of Submerged Membrane Bioreactor Filtration Process Using Intelligent Techniques

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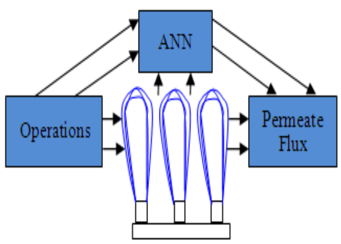
Graphical abstract



Abstract

Recently, membrane technology has become more attractive particularly in solid-liquid separation process. Membrane bioreactor (MBR) has found to be a reliable technology to replace the conventional activated sludge (CAS) process for water and wastewater treatment by adopting membrane filtration technology and bioreactor. However, numerous drawbacks arise when using membrane which includes high maintenance cost and fouling problem. An optimal MBR plant operation is needed to be determined in order to reduce fouling and at the same time reduce the cost of running the MBR. It is crucial to have a reliable MBR filtration prediction that can measure and predict the filtration dynamic performance especially the effect of fouling to the filtration and cleaning operations. With this prediction tool, suitable action can be taken to improve the operation in order to find the optimum setting of the filtration process. This paper presents the permeate flux measurement and prediction development for submerged membrane filtration process. Three input filtration parameters were used to predict the permeate flux in the filtration process. This work employed feed forward artificial neural network (FFNN) and radial basis function neural network (RBFNN) for the prediction purpose. The permeate flux prediction method was developed using operation settings such as aeration airflow, suction pump voltage and transmembrane pressure (TMP) under schedule relaxation condition. The result shows that FFNN method gives better performance compared with RBFNN method in terms of accuracy and reliability.

Keywords: Membrane filtration process; soft sensor; FFNN; RBFNN

■1.0 INTRODUCTION

Membrane bioreactor (MBR) is recognized as the best alternative solution for conventional activated sludge (CAS) system for wastewater treatment. This technology is capable to give better treatment of influent either from industrial or domestic waste water treatment. Membrane filtration system is one of the key successes in any MBR system. Several configurations of MBR and membrane filtration system are developed to optimize the biological part and the filtration system. Membrane filtration system is not just used in bioreactor, but it is also widely used in solid liquid separation process in many industries such as chemical, food technology, and agriculture. The implementation of membrane filtration system for any filtration system application is it must consider its strengths and weaknesses in terms of quality, efficiency and operation cost. The successful operation of this technology is measured from its filtration performance.

Membrane filtration system still struggles from many issues such as fouling and energy efficiency [4][5][6][7]. 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 [8]. 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 or soft sensor technique for membrane filtration system is crucial in order to improve the performance of the membrane filtration system in MBR plant[1][2][8]. With this prediction model it can help the plant operator to predict the filtration performance under different operation settings.

Membrane filtration system is influenced by many factors including membrane physical cleaning operations[9][10]. Apart from that membrane filtration permeates flux also affected with the influent concentration [11], transmembrane pressure (TMP) [12] and other influent properties. The complexity of the membrane filtration process causes the development of the filtration prediction tool to be very difficult. In literature, there are several techniques which can be adopted to represent the filtration system such as mechanistic/mathematical model and the artificial intelligent technique such as fuzzy, artificial neural network (ANN), and support vector machine. However, the application of ANN is

widely used in the membrane filtration prediction because of its accuracy and reliability in prediction nonlinear dynamic system.
In the Submerged MBR (SMBR), Geissler *et al.* [13] developed two models which are semi empirical model and empirical ANN based model for permeate flux modeling in submerged capillary MBR. The ANN model was based on Elman neural network structure to predict the permeate flux. Nine inputs were used in the model and the inputs were TMP, rate of transmembrane pressure change, TMP during backwash, filtration cycle length, backwash cycle length, solid retention time (SRT), total suspended solids (TSS), temperature and oxygen decay. Results showed both of the models can give very good results. In addition, the semi empirical model required small input variables compared to ANN. However, ANN gave high accuracy with the average error of 2.7%.

Another SMBR application of ANN model was demonstrated by [14] in the application of flat sheet SMBR system for wastewater treatment application. The ANN model represented the backwash effect to the permeate flux. Several backwash intervals were tested to the flat sheet filtration. The multilayer neural network was used to model the system with backwashed interval, and filtration interval was used as an input to the model and flux is the output of the model. Work by [15] presented ANN model for effluent quality for SMBR treating cheese whey wastewater. The model is used to predict chemical oxygen demand (COD), ammonia, nitrate and total phosphate concentrations.

Submerged membrane flocculation hybrid systems for synthetic wastewater treatment filtration model was developed by [16] using different types of neural network structure. Multilayer perceptron neural network (MLPNN), radial basis function neural network (RBFNN) and general regression neural network (GRNN) were compared in terms of their performance for the modeling result. The inputs of the model were coagulation dose and filtration time, while the outputs of the model were the TMP, permeate pH and permeate DOC. All three ANN structure provided good prediction of the TMP profile during the filtration process.

In this work, the feed forward neural network (FFNN) and RBFNN were compared in terms of their reliability and accuracy for permeate flux prediction in SMBR filtration application. This paper is organized as follows: Section 2 presents the method used for the permeate flux prediction. Section 3 discusses the experiment setup, permeate measurement, data set used for training and testing procedure. Section 4 presents the results obtained and analysis for each method. Finally section 5 concludes the findings of this work.

2.0 METHOD

2.1 Feed Forward Neural Network (FFNN)

In this work, the FFNN was used to predict the flux. The FFNN structure is represented by multilayer network starting from the first layer in which the neuron received input from external input. The next layer is connected by each of the neuron from the previous layer. This network will be connected until the final (output) layer neuron. Figure 1 presents the basic feed forward neural network structure. In this work, the network is trained using back propagation Levenberg-Marquardt (LM) algorithm.

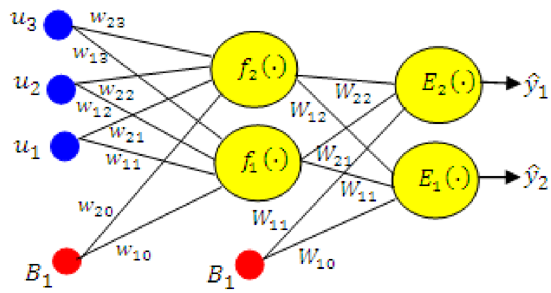


Figure 1 Feed Forward neural network structure [17]

This network can be represented by Equation (1).

$$\hat{y}_1(t) = E_i \left[\sum_{j=1}^{n_h} W_{ij}\, f_j\ \left(\sum_{l=1}^{n_\varphi} w_{ij} + w_{j0}\right) + W_{i0}\right] \quad (1)$$

Where $\hat{y}_i(t)$is the prediction output. F_i is the function of the network, φ is the input vector, W_{ij} and w_{ij} represent the network connection layer weights and biases.

2.2 Redial Basis Function Neural Network (RBFNN)

The RBFNN is almost similar in structure with the FFNN structure. The main difference in the RBFNN is the neuron is based on Gauss function. The structure of RBFNN is presented in Figure 2 below.

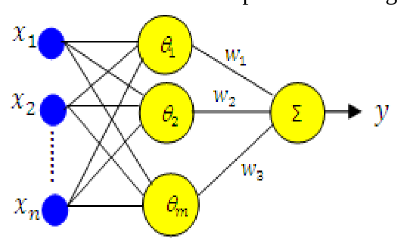


Figure 2 RBF neural network structure

The RBFNN structure can be represented by Equation (2)[18].

$$y(t) = \sum_{i=1}^{i} w_i\, \theta_i(t), \quad (2)$$

i= 1, 2, 3…k

Where, the output of the hidden layer is given by Equation (3).

$$\theta_i\,(t) = e^{\left(\frac{\|x(t)-c_i\,(t)\|^2}{\psi_i^2}\right)} \quad (3)$$

x is the input vector, c is the center of the hidden node, k is the number of hidden nodes and ψ is the width of hidden node. w is the weight number of output layer. y indicates the output of the network.

2.3 Data Structure

In this work, the nonlinear autoregressive with exogenous input (NARX) is used for the flux prediction. This structure employed past input and past output data to predict the current output. This method is more suitable for time series prediction. The general equation of NARX is given in Equation (4)

$$\hat{y}_i(t) = f_i(y_1(t-1), \ldots, y_1(t-n^i_{y_1}), \ldots, y_{na}(t-1), \ldots, y_{na}(t - n^i_{y_{na}})), (u_1(t-1), \ldots, u_1(t-n^i_{u_1}), \ldots, u_{nb}(t - 1), \ldots, u_{nb}(t-n^i_{u_{nb}})) + e_i(t) \quad (3)$$

Where $i=1, 2 \ldots na$

$\hat{y}(t)$ is the predicted output. $y(t+1 \ldots n^i_{y1})$ and $u(t+1 \ldots n^i_{u1})$ is the past input and past output lag respectively. *na* is the number of output and *nb* is the number of input. *e(t)* is the residual and *f* represents the nonlinear function of the structure.

2.4 Performance Evaluation

In this work the performance of permeate flux prediction for all methods was based on three criteria which are correlation coefficient (R^2), mean square error (MSE) and mean absolute deviation (MAD). The equations of MSE and MAD are given in Equation (5) and (6) respectively.

$$MSE = \frac{\sum |\hat{y}_i - y_i|^2}{N} \quad (5)$$

Where y_i is the predicted value and y_i is the actual value from the measurement data and N is the number of data point.

$$MAD = \frac{\sum |x_i - \bar{x}_i|}{N} \quad (6)$$

Where x_i is the predicted value and the $\bar{x}_i$is the mean of the predicted value.

■3.0 EXPERIMENTAL SETUP

The experiments were carried out in three double-walled cylindrical column bioreactors working volume of 20 L palm oil mill effluent (POME) taken from Sedenak Palm Oil Mill Sdn. Bhd. in Johor, Malaysia. The working temperatures for the bioreactors were at 27 ± 1 °C. The plant was operated with 90 second permeate and 30 second for relaxation period. The airflow rate is maintained around 8 SLPM at the first half of the experiment while the second half of the experiment the airflow was lowered down to about 5 SLPM. Figure 3 shows the pilot plant setup for the experiment. The data plant was controlled and monitored using National Instruments, Labview 2009 software with NI USB 6009 interfacing hardware.

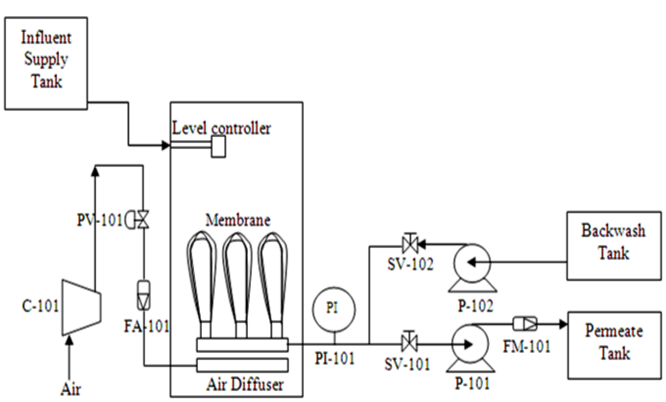


Figure 3 Schematic diagram of the submerged MBR

Table 1 shows the list of instruments used in the pilot plant development.

Table 1 List of instruments/parts

Tag No	Description
C-101	20L 2HP Air compressor
PV-101	Proportional Valve
FA-101	Airflow Sensor
PI-101	Pressure Transducer
SV-101	Solenoid Valve Permeate Stream
SV-102	Solenoid Valve Backwash stream
P-101	Peristaltic Pump
P-102	Diaphragm Pump
FM-101	Liquid Flow Meter
Membrane	Hollow Fiber Membrane

In this work, Polyethersulfone (PES) material with approximately 80-100kda pore size membrane was used in the filtration system.

3.1 Filtration Measurement

The TMP during filtration was measured using WIKA pressure transducer ranging from -1 to 1.5 bar. The permeate flux of the filtration was measured using RS 508-2704 flow sensor range from 0.05 to 10 liter per minute (LPM). The permeate flux equation is given by Equation (7).

$$J = \frac{V}{At} \quad (7)$$

Where J is the permeate flux in (l/m^2 h), V is the volume flow rate in litter and t is the time (h). The airflow was measured using Honeywell airflow sensor AWM5104V ranging from 0 to 20 standard liter per minute (SLPM) while the Watson Marlow peristaltic pump is used for permeate suction. Figure 4 shows the data collected from the experiment.

From the data it can be observed that the permeate flux has an impact with the plant operation which are airflow rate, pulsating and TMP. Figure 5 shows the comparison between the permeate flux at high and low airflow rate. At the high airflow rate setting, permeate flux is higher than at the low airflow rate setting. The flux slope for each cycle also shows that the decrement of flux is much faster in high TMP at the low airflow rate compared to high airflow rate.

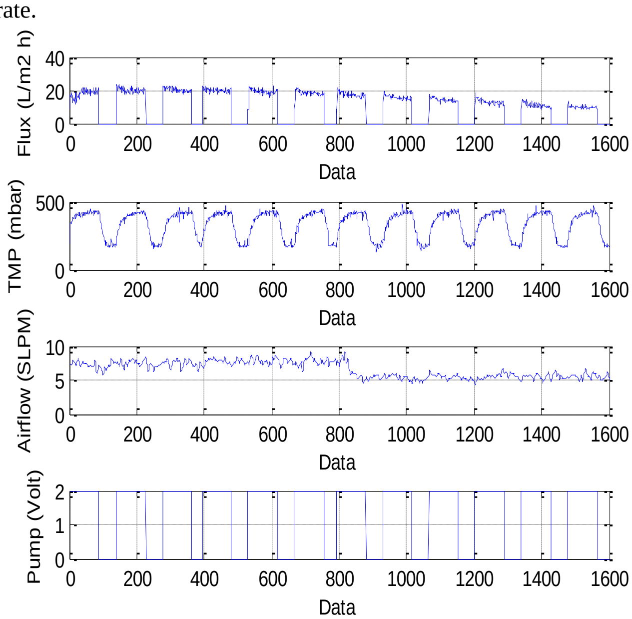


Figure 4 Data from filtration experiment

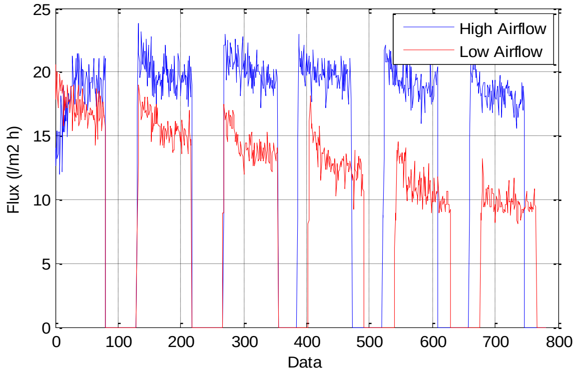


Figure 5 Comparison flux flow at low and high airflow rate

3.2 Data Preparation

The data collected in Figure 3 was divided into three blocks M1, M2 and M3. The first block was taken in the middle of the data where this block included the transition between high to low airflow rate and this data was used in the training of the neural network. Figure 6 shows the M1 for training data set.

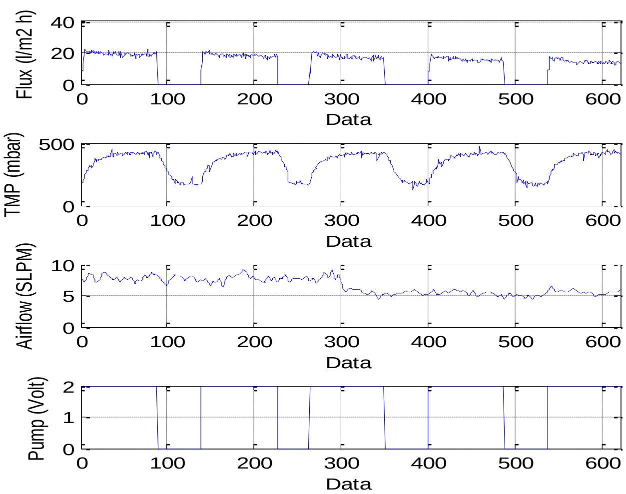


Figure 6 M1 data set

M2 is the first block for the testing data set. This data set was taken from the high airflow filtration. Figure 7 shows the M2 data set.

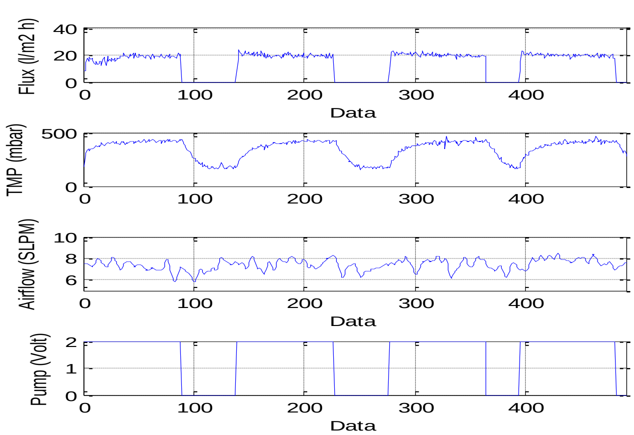


Figure 7 M2 data set

M3 is the second block for the testing data set. This data set was taken from the low airflow filtration. Figure 8 shows the M3 data set.

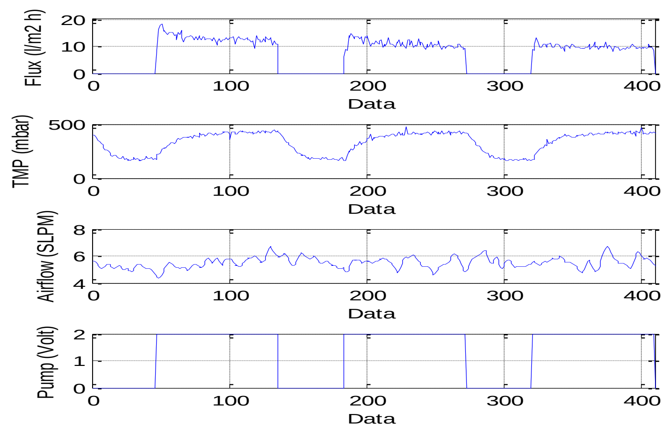


Figure 8 M3 data set

4.0 RESULTS AND DISCUSSION

The training result using M1 data set for permeate flux prediction shows a satisfactory performance from both methods used. Figure 9 shows the comparison of M1 data set, which was used for training of the network. In terms of the evaluation performance, both methods gave almost similar performance which FFNN and RBFNN were able to match the flux decline and its slope for each cycle at high and low airflow rate. This performance can be proven by the evaluation criterion used where %R^{2}, MSE and MAD showed almost similar result with the FFNN and RBFNN score 94.1% and 94.2% respectively for R^2. MSE performance is 0.0077 and 0.0076 while MAD is 0.0422 and 0.0424.

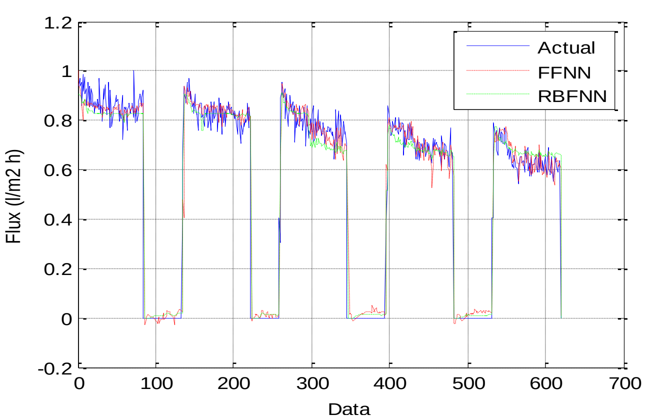


Figure 9 Training using M1 data set

Figure 10 shows the residual for the training using M1 data set. Only small deviations can be observed from both methods.

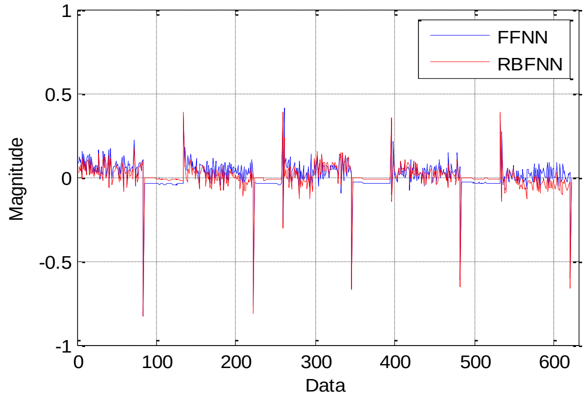


Figure 10 Training residuals using M1 data set

The first testing procedure was taken from M2 data set where this data is taken from the high airflow rate data set. This data has small decline of permeate flux for every next cycle. From the observation, both of the methods were able to predict the slope and the small flux reduction in the cycle. The % R^2 for the FFNN and RBFNN are 93.5 and 93.7%, while the MSE are at the 0.01 and 0.0096 respectively. The MAD score is 0.0513 for FFNN and 0.0496 for RBFNN. Figure 11 shows the comparison between FFNN and RBFNN.

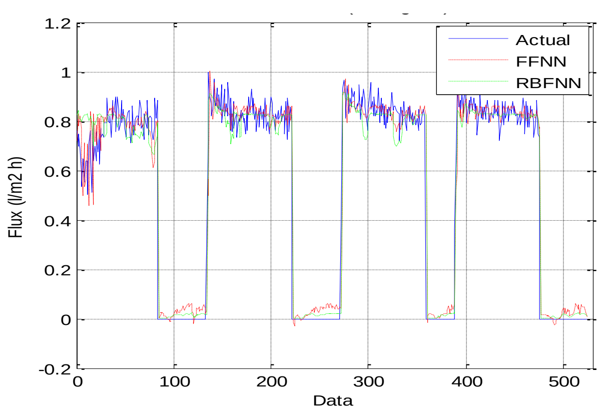


Figure 11 Testing using M2 data set

Figure 12 shows the residual for the testing using M2 data set. Almost similar deviations can be observed from both of the methods.

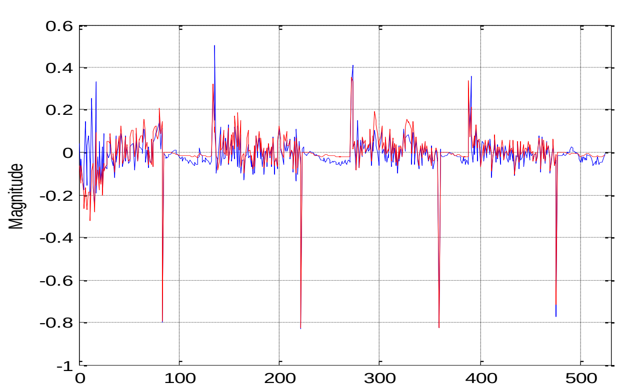


Figure 12 Testing residuals using M2 data set

M3 data set was taken from the low airflow side. This data shows fast permeate flux decline in every cycle. The validation using these data sets shows different performance from each method. The FFNN gives more accurate and reliable prediction compared with the RBFNN technique. Figure 13 shows the comparison of both methods with the actual data. From the figure it can be seen that RBFNN predicts higher than the actual data while the FFNN and follow the reduction trend of the permeate flux. *%*R^2 for both techniques shows FFNN score almost 93% while only 79.5% scored by the RBFNN method. For the MSE criteria, FFNN gives 0.0069 while the RBFNN with 0.02. The MAD criteria show 0.0406 achieved by the FFNN while the RBFNN shows poor performance with 0.0884 for this criteria evaluation.

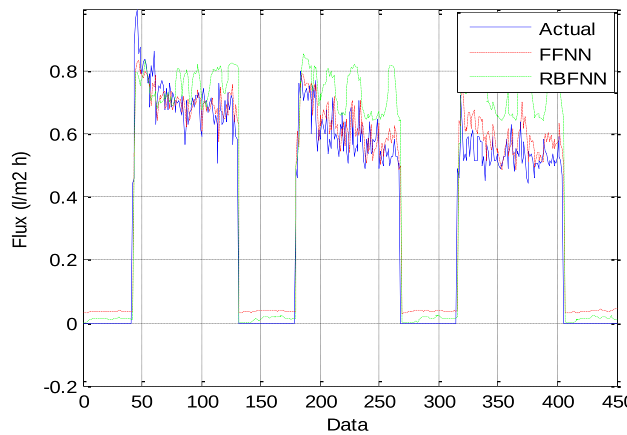


Figure 13 Testing using M3 data set

Figure 14 shows the residual for the testing using M3 data set. From the figure, it shows that FFNN gives better performance compared with the RBFNN with smaller deviations.

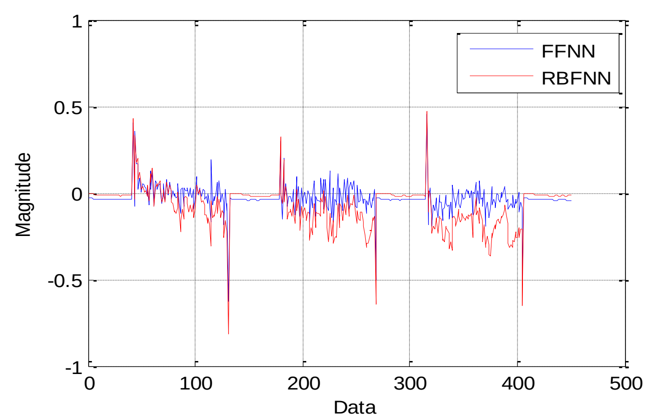


Figure 14 Testing residuals using M3 data set

Table 2 presents the performance evaluation for both methods in the training and testing using all data sets.

Table 2 Performance evaluation

Data/Method	%R^2	MSE	MAD
M1/ FFNN (Training)	94.1036	0.0077	0.0422
M1 /RBFNN (Training)	94.2249	0.0076	0.0424
M2/ FFNN (Testing)	93.5030	0.0100	0.0513
M2 /RBFNN (Testing)	93.7467	0.0096	0.0496
M3 /FFNN (Testing)	92.9708	0.0069	0.0406
M3/ RBFNN (Testing)	79.5611	0.0200	0.0884

■5.0 CONCLUSION

This paper has presented the measurement and prediction of permeate flux in the submerged membrane bioreactor filtration using FFNN and RBFNN. The filtration process was done using hollow fiber membrane with palm oil mill effluent as an influent in the bioreactor. In this work, data sets were divided into three blocks (M1, M2 and M3) where the training blocks were taken in the changing state from high to low aeration airflow rate. Both of the methods were able to give good prediction in the training and testing result for the M2 data (low aeration). However, the FFNN was more reliable and accurate for the permeate flux prediction using M3 data set. This makes the FFNN able to predict well in both high and low aeration airflows.The experiment also showed that the permeate flux at the low aeration airflow is faster to decline compared to the high aeration airflow.

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