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Membrane Fouling Prediction for Wastewater Treatment in Membrane Bioreactor System by Using Ann Modeling

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Abstract
Membrane fouling has been seen as a big disadvantage of membrane technology. It declined the membrane filtration flux and affected the treatment efficiency of the wastewater treatment systems. Prediction of membrane fouling could provide a suitable solution for operation. In this work, an artificial neural network (ANN) is developed for predicting membrane fouling. The input variables included several parameters such as pH, ammonium, nitrate, and alkalinity. The obtained results show that pH and ammonium as the input variables were not satisfying to predict membrane fouling (with low correlation efficiencies of 0.606 and 0.794, respectively). The nitrate and alkalinity were performant for membrane fouling prediction (with correlation efficiencies of 0.974 and 0.875, respectively). Therefore, nitrate and alkalinity could be considered as two suitable inputs for artificial neural networks to predict TMP (transmembrane pressure). In conclusion, ANN could provide a good solution for predicting membrane fouling in MBR system. Application of ANN could support an alternative way to prevent the membrane fouling in the system.

Keywords
ANN; flux; fouling; membrane; wastewater

1. Introduction
Membrane filtration has been used in wastewater so far [1,2]. In this concept, membrane was submerged in a biological process to make a modern technology as membrane bioreactor (MBR) [2–5]. Membrane fouling is a big disadvantage for the application of membrane bioreactor (MBR) technology in treating wastewater [6,7]. Basically, several reasons could make membrane fouling, i.e. pore-clogging; colloidal particles; soluble compounds; cake layer; and biofouling [8,9]. Membrane fouling could be also affected by the design parameters and operational conditions, i.e. hydraulic retention time, air scouring, sludge retention time, sludge concentration, and permeate flowrate [1,10]. Membrane fouling could be controlled and reduced by several methods, such as physical ways (by applying a pretreatment to the influent, or aeration) [11]; chemical ways (i.e. using acids (H_2SO_4 or HCl) for inorganic scaling removal and/or using alkalines (NaOH or KOH) for microorganism removal) [12], or by modifying the mixed liquor in the MBR reactor [13]. Normally, physical or chemical methods were used to clean the membrane fouling. It would be important that if membrane fouling is predicted, it could suggest adjusting the operational conditions of MBR. Therefore, filtration time of membrane could be prolonged. So far, membrane fouling has been predicted by modeling. In a modeling, membrane fouling was simulated by several ways. For example, transmembrane pressure (TMP) has been predicted by numerous simulations. Besides, the permeate membrane flux has been predicted by mathematical models [14–16]. In addition, membrane fouling could be simulated by computational fluid dynamics [17,18]. Those modeling and simulations could provide an acceptable prediction of

membrane fouling. However, membrane fouling dependent on many factors, i.e. influent characteristics, design parameters, and operational conditions. Therefore, the prediction of membrane fouling could be faced with difficulties when those conditions were changed during operation.

It should be noted that artificial neural networks (ANNs) could be used as a good tool to predict membrane fouling [19]. In this ANN model, input parameters were used to put into a black box [7,20]. Therefore, the complex phenomenon of membrane fouling could be reduced [6,21]. For example, COD, NH_4 and PO_4 were predicted by the ANN using a single hidden layer [21,22]. However, in this study, this ANN did not predict membrane fouling. In addition, TMP (transmembrane pressure) and permeate membrane flux were not predicted as well.

Therefore, it would be interesting to develop a suitable ANN model to predict TMP (transmembrane pressure) which could be represented for membrane fouling in MBRs. In particular, in this study, many input variables, i.e. pH, NO_3, NH_4 and Alk have used ANN modeling on the target of membrane fouling.

2. Materials and Methods

2.1. Experimental System Operation

In this study, a small-scale anoxic-oxic membrane bioreactor (AO-MBR) was used. The total working volume of the system was 75 L (in which, 25 L for anoxic tank and 50 L for oxic tank) **(Figure 1)**.

In this system, the anoxic tank was placed before the oxic tank to carry out a function of the denitrification process. The oxic tank carried out two roles as the oxidation and nitrification processes. In particular, five flat sheet membranes were submerged in the oxic tank. The membrane characteristics included membrane pore size of 0.22 µm and the total membrane surfaces of 0.5 m^2. Membrane played an important role in increasing the sludge concentration in the system which could enhance the system's performance. During operation, the air was supplied into the oxic tank by an air compressor at a flowrate of 30 L/min. The air provided the oxygen for the biological processes, i.e. the oxidation and nitrification processes. A part of the mixed liquid containing nitrate from the oxic tank was recycled back to the anoxic tank for the denitrification process. A part of the treated wastewater in the oxic tank was taken out by membrane filtration. This was carried out by a peristaltic pump which was operated at a relatively constant membrane flux of 20 L/(m^2.h). A timer was used to adjust the operational time of the pump at a sequencing cycle of 10 min on and 2 min off. Membrane fouling was monitored by flow rate decreasing and transmembrane pressure (TMP) increasing.

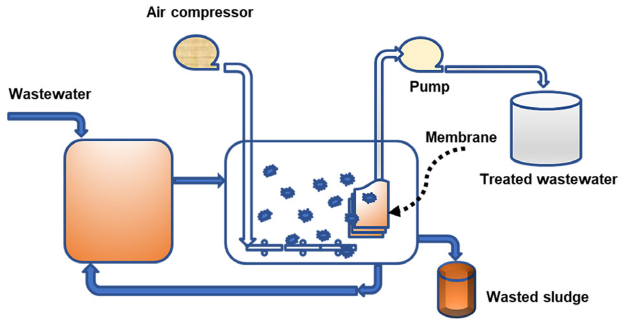

Figure 1: Schematic diagram of small-scale AO-MBR system.

2.2. ANN Modeling Development

In this work, the input variables (such as pH, NO_3, NH_4 and Alk) were selected for ANN model to predict the variation of transmembrane pressure which could be represented for membrane fouling. It should be noted that the above parameters in the different tanks (influent, anoxic, oxic, effluent) in the MBR system. Therefore, they were combined with "-in" which means "influent", "-an" which means "anoxic", "-mbr" which means "MBR" and "-eff" which means "effluent." Each parameter was used as input variable for the prediction of TMP variation. The structure of the developed ANN is represented on **Figure 2**.

Figure 2 shows that each couple of a weight (w) and a bias (b) was connected to a node (called a neuron). All of them were summed to form the weighted input variables. The output (i.e. y_i) was obtained from the i-th neuron of a defined layer. It was a function of a corresponding input (i.e. x_j). This input was come from the j-th neuron of the previous layer. A weight (i.e. w_ij) was entered in this neuron. The weight is used as an interconnection between the neural "i-th" and "j-th" of the previous layer. It was also connected with the bias (b_i) and activation function (Eq. **(1)**).

$$y_i = f(b_i + \sum_{j=1}^{n} x_j \times w_{ij}) \tag{1}$$

The prediction of outputs from the ANN model with the measured target outputs was controlled by a mean squared error (MSE) (Eq. **(2)**). It should be noted that MSE was used as a risk function that evaluates the quality of predicted results.

$$MSE = 1/N \sum_{i=1}^{N} (Y^{(i)} - Y_t^{(i)})^2 \tag{2}$$

In which, $Y^{(i)}$ and $Y_t^{(i)}$ are the predicted and target outputs at the i-th of the total N data.

2.3. Analysis Methods

During the study, the parameters were measured and analyzed. The filtrate was obtained by using a membrane of 0.45 µm pore size. In this work, filter paper of GD/X PVDF (Whatman) was used. pH was measured with a pH meter (Hach HQD Portable Meters, USA). Nitrate was analyzed by Standard Methods (Test Method D992). The ammonia was determined with the ion-selective electrode method by using a Thermo Orion, Model 95-12. Permeate membrane flow rate was measured with a flow rate meter. Membrane fouling as TMP (transmembrane pressure) was obtained by reading the number of pressure that appeared on the gauge meter.

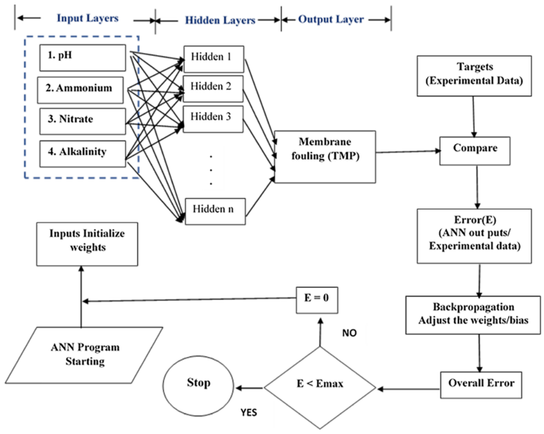

Figure 2: A structure of artificial neural network modeling.

3. Results and Discussion

3.1. Membrane Fouling Prediction by pH

In this work, pH values in different positions (pH_{in}, pH_{an}, pH_{mbr}, and pH_{eff}) of the AO-MBR system were measured. The obtained results were presented in **Figure 3**. As seen in **Figure 3**, the performance of ANN obtained from 4 pH input variables was relatively low, the testing correlation efficiency was only about 0.524. Among 4 pH input variables, pH_{an} (in anoxic tank) and pH_{mbr} (in MBR tank) showed the highest performances for prediction on membrane fouling. The overall correlation coefficiency was obtained at 0.606. It should be noted that membrane filtration performance was strongly affected by membrane fouling. Several factors in the influent and the system, such as pH in the bioreactor could also affect the membrane fouling during operation [23,24]. So far, several inputs, i.e. COD, ammonia, nitrate, and phosphates have been used to predict membrane fouling by the ANN model. pH is an important parameter which affects strongly to the biological processes in the reactors. However, pH has not been considered to use as an input in that work. Therefore, it is necessary to test pH as input variables with the ANN for membrane fouling prediction. However, the obtained results show that the correlation coefficiency is not high enough to predict membrane fouling based on the pH input variables [20].

3.2. Membrane Fouling Predicted Based on NO_3

Nitrates (NO_3) in the different positions (i.e. in the influent, in anoxic tank, in MBR, and in the effluent) were monitored. **Figure 4** shows the variation of measured and predicted NO_3. The obtained results show that the testing correlation efficiency was reached at a relatively high value of 0.873. The concentration of NO_3 in each position in the AO-MBR could have a great effect on predicting the TMP variation. In fact, membrane fouling could have a positive on nitrification. This is due to ammonium oxidation bacteria being retained in the MBR tanks at high concentrations [16,24]. Actually, a combination of NO_3 from all positions could enhance slightly the correlation efficiency. In particular, when $NO_{3\text{-}mbr}$ and $NO_{3\text{-}eff}$ were used for the input variables, the overall correlation efficiency could enhance up to over 0.974.

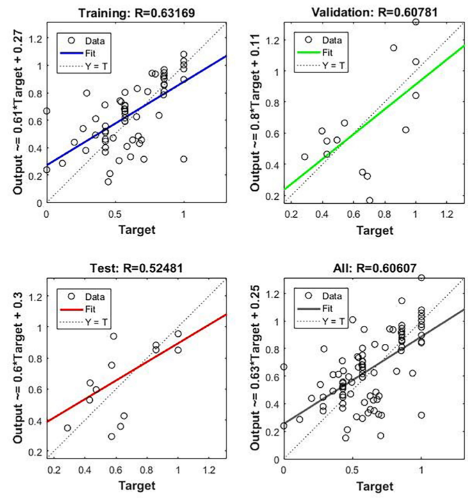

Figure 3: Correlation efficiency of pH for TMP (transmembrane pressure) prediction.

3.3. Membrane Fouling Predicted Based on NH_4

NH_4 measured from different positions of the AO-MBR was also used as input variables for predicting the TMP variation. **Figure 5** shows the measured and predicted results of TMP by time.

The testing correlation efficiency of the ANN in this was low, only about 0.669. A combination of NH_4 in all positions of the AO-MBR could not enhance the correlation efficiency of the ANN. The overall correlation efficiency was about 0.794. The obtained correlation efficiency was higher than that obtained from pH variables, but it was much lower when compared with that obtained from NO_3 variables. Based on the obtained correlation efficiency, it seems that the prediction of membrane fouling was not strongly dependent on the NH_4 in AO-MBR. It should be noted that membrane fouling could be significantly affected by operational conditions. The influent parameters such as ammonium could also affect membrane filtration [20,25]. The obtained results show that using ammonium as the input variable was not satisfying to predict membrane fouling. It was reported that membrane fouling was found not to depend on ammonium [9]. Therefore, ammonium was not recommended to be used for predicting membrane fouling [7].

3.4. Membrane Fouling Predicted Based on Alkalinity

Alkalinity (Alk) in several positions (i.e. influent, anoxic, MBR, effluent) of the AO-MBR was analyzed. The measured Alk was used as the input variable for the ANN to predict the TMP variation. The obtained results were presented in **Figure 6**. In this case, the testing correlation efficiency was reached at a relatively high value of 0.898. Interestingly, the alkalinity in the anoxic, MBR, and effluent (Alk_{an}, Alk_{mbr}, and Alk_{eff}) could provide the highest validation correlation efficiency, up to 0.875. A combination of Alk_{mbr} and Alk_{eff} could give a relatively high correlation efficiency at about 0.902 for training). Based on the obtained results, a combination of alkalinity in different positions in the AO-MBR could be a good input variable for ANN to predict membrane fouling at high correlation efficiency. It was reported that the ANN input variables were very important to predict membrane fouling [7,21].

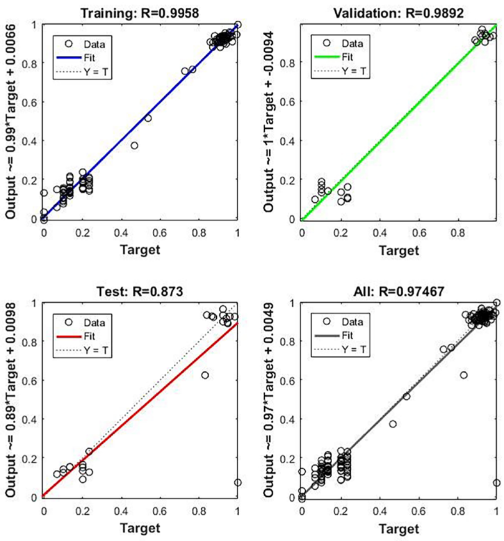

Figure 4: Correlation efficiency of NO_3 for TMP (transmembrane pressure) prediction.

4. Conclusions

Membrane filtration helps enhance the quality of treated wastewater. However, during operation, membrane fouling could reduce the flux and hence reduce the system performance. Therefore, the reduction of membrane fouling is an important action for the development of membrane technology in wastewater treatment. Especially, the prediction of membrane fouling could help to provide a suitable operational procedure. In this study, the prediction of membrane fouling in the AO-MBR was carried out by developing the ANN. Based on the obtained results, it could be concluded that pH and NH_4 as the input variables were not satisfying to predict membrane fouling. The correlation efficiencies were only 0.606 and 0.794, respectively. The NO_3 and Alk were performant for membrane fouling prediction (with correlation efficiencies of 0.974 and 0.875, respectively). The prediction of TMP (transmembrane pressure) or membrane fouling in the AO-MBR by the ANN could be good potential. However, enhancement of the membrane fouling predicted by the ANN should be further studied by optimization of the developed ANN to increase the correlation efficiency. In particular, optimizing the ANN structure would be carried out by involving a continuous change in the number of hidden layers and the number of neurons and thus the number of activation functions, along with the learning algorithm.

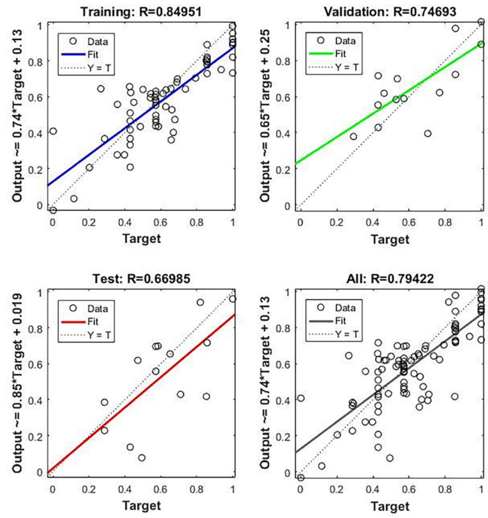

Figure 5: Correlation efficiency of NH_4 for TMP (transmembrane pressure) prediction.

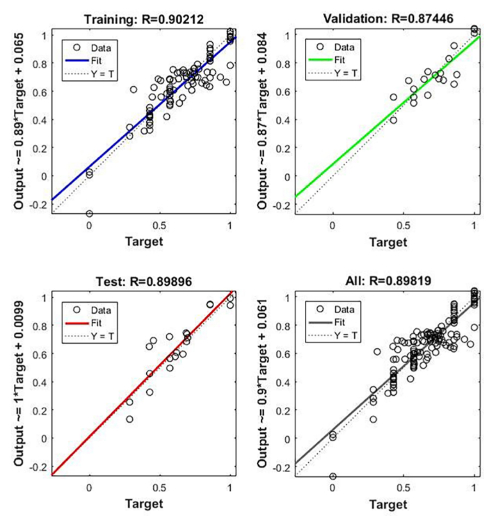

Figure 6: Correlation efficiency of Alkalinity for TMP (transmembrane pressure) prediction.

Supplementary Materials

The data used for the artificial neural network model in this study could be found in the **Supplementary Materials**.

Authors' Contributions

Khac-Uan Do: Data analysis and writing. Xuan-Quang Chu: Experiment, editing, drafting, and communication. Hung-Thuan Tran: Sample collection and experiment.

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Materials Technology, National Center for Technological Progress.

Data Availability

The data supporting the findings of this study are available in the figures within the article.

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Conflicts of Interest

The authors declare that there are no conflicts of interest.

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