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Proposing a new fouling index in a membrane bioreactor (MBR) based on mechanistic fouling model

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ABSTRACT

Membrane fouling is the most serious problem in membrane bioreactor (MBR) process, which is restricting the widespread application of MBRs in wastewater treatment processes. In recent years, several studies on the precise diagnosis and prediction of the membrane fouling have been carried out to obtain an efficient operation of MBRs. The aims of this study are 1) to predict the membrane fouling and to determine the chemical cleaning interval of membrane using traditional mechanistic fouling model; and 2) to propose the new fouling index based on the usually obtained traditional technique. As the traditional fouling technique use an exponential fouling model, however, this method has some shortcomings, such as inadequate comprehension of the fouling mechanism and steady state assumption. Therefore, in this study, the coefficient (κ) of the exponential fouling model is proposed as a new fouling index to overcome the inadequate understanding of the fouling mechanism and steady state assumption in traditional technique. To propose the coefficient (κ) as the new fouling index, least-square (LS) method and recursive least-square (RLS) methods are applied in the exponential fouling model. The coefficient (κ) shows the similar tendency with the permeability which is another kind of fouling index. It is verified that the coefficient has been validated as the new index for diagnosis of the fouling progress as well as the prediction of membrane fouling.

Keywords: Membrane bioreactor; Membrane fouling; Membrane cleaning interval; Fouling mechanistic model; New fouling index; Recursive least square method

1. Introduction

A membrane bioreactor (MBR) system is a combination of biological degradation process (by activated sludge) and direct solid-liquid separation (by membrane filtration). Use of an MBR system in membrane technology offers several prominent advantages over conventional activated sludge (CAS) system in terms of a smaller footprint, less sludge production and better effluent quality, etc. Hence, MBR has become state-of-the-art process in wastewater treatment and it is becoming a more popular process is water treatment nowadays [1,2].

However, widespread application of MBRs has been impeded by a phenomenon of membrane fouling. Membrane fouling refers to a deposition or adsorption of material on the surface of the membrane or within the pores. The fouling causes a decline in permeate flux or increase in trans-membrane pressure (TMP), loss of

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product quality and deterioration of the membrane etc. [3,4]. Main drawback of membrane fouling is high cost of operation. Hence, fouling has become the main contribution to overall MBR operating costs, since high energy is required for backflush, aeration and frequent cleaning of membrane to remove the foulants [5,6]. Therefore, for an economical operation of MBR process, the high energy requirement caused by the fouling should be reduced. And for a minimization of the energy requirement, a precise diagnosis and prediction of the membrane fouling is necessary.

The main drawbacks of use of traditional techniques for diagnosis and prediction of the membrane fouling are: 1) most protocols to diagnosis and prediction of membrane fouling are confidential and provided by manufacturers; 2) the membrane fouling mechanisms remain poorly understood, for example, steady state operation of MBR; and 3) different parameters, required to evaluate flux and resistance of the membrane, which are used for calculation of membrane fouling need to be evaluated [7]. This could generate questionable conclusions regarding the real membrane fouling. Therefore, new techniques to overcome the drawbacks of the traditional technique are necessary for the precise diagnosis and prediction of the fouling.

The first objective of this study is to predict the membrane fouling using the traditional techniques, which use the trans-membrane pressure (TMP) as a fouling index. An exponential fouling model is a traditional technique, which is a prevailing mechanistic model in an MBR system is used. For an economical and optimal operation of MBRs, it needs to determine an appropriate membrane chemical cleaning time, since it is important for operators to start the membrane cleaning. Therefore, a determination of the membrane chemical cleaning time based on the traditional technique is carried out, too.

As the second objective, a new index for the fouling diagnosis is suggested based on the fouling mechanistic model to overcome the second drawback of the traditional technique. For a verification of the new fouling index, value of a new index is compared with permeability, which is another index of the membrane fouling.

An outline of this paper is as follows. The first section introduces the basic mechanistic equation for membrane fouling by an exponential model. In the material and method section, motivation of this study is introduced and the proposed method is explained. Then two case studies of an MBR pilot-plant are illustrated and discussed. Finally, the conclusions of this article are addressed.

2. Membrane fouling mechanism

In a constant flux operation of MBR process, the trans-membrane pressure (TMP) curve shows the typical exponential characteristic with a slow increase during the first 1–2 months, followed by a rapid steep increase in TMP near the end of the filtration run. The sudden rise in TMP near the end of the filtration process is called TMP jump [8].

TMP exhibits a simple exponential relationship with the filtration time, is described by the following mathematical expression [9]:

$$\mathrm{TMP} = \mathrm{TMP}_0 \cdot e^{\kappa_t \cdot t} \tag{1}$$

where TMP_0 is the initial TMP at filtration time $t = 0$ day, prior to the initiation of fouling (kPa). The exponent κ_t is the time-based fouling coefficient (1/d), and is determined by the characteristics of the MBR system. Once κ_t is known, the membrane cleaning timing can be found for the maximum allowable TMP (40–50 kPa). Recovery of the membrane should be done at that chemical cleaning time at which TMP reaches maximum allowable TMP.

For the MBR system operated in a constant-flux mode, the cumulative volume (V) of permeate filtered is the product of the applied permeate flux (J), the membrane surface area (A) and the filtration time (t) [see Eq. (2)]. Therefore, Eq. (1) can be converted into a function of the cumulative volume of permeate filtered instead of the filtration time, as shown in Eq. (3) [9]:

$$V = JAt \tag{2}$$

$$\mathrm{TMP} = \mathrm{TMP}_0 \cdot e^{\kappa_t \cdot t} = \mathrm{TMP}_0 \cdot e^{[\kappa_t/(JA)]V} = \mathrm{TMP}_0 \cdot e^{\kappa_V \cdot V} \tag{3}$$

where κ_V is defined as the volume-based irreversible fouling coefficient, 1/m^3.

3. Material and methods

3.1. Motivation of this study

The contribution points of this study are 1) to capture the dynamics of membrane fouling by recursive least-square (RLS) method with updated data set, and 2) to monitor and predict the MBR fouling simultaneously with new fouling index by updating RLS model.

The traditional techniques for diagnosis and prediction of the membrane fouling cannot capture the dynamics of membrane filtration and fouling, since the traditional techniques are developed based on steady state assumption of MBRs. The steady state assumption has not been justified for the wastewater treatment plant in the manner employed such as continuous-flow reactor, which operates in dynamic condition [10]. Therefore, a dynamic model is necessary and RLS method is used to suggest the dynamic model of membrane fouling. The basic idea of RLS is to compute the updated parameter at certain time by adding a correction term to the previously estimated parameter once the new information becomes available [11]. By applying the RLS method, the dynamic prediction model of membrane fouling and the recursively updated fouling index are proposed. This proposed method is able to overcome the drawback of traditional static membrane fouling technique, since RLS can capture dynamic characteristics of the membrane fouling mechanism.

3.2. Proposed method

Generally, TMP in the MBR system has an exponential relationship with filtration time, that is, lognormal distributed, which is a kind of non-Gaussian distribution. Non-Gaussian process is used to represent the variation in time and/or space of many relevant parameters encountered in applied science and engineering [12]. However, because of this non-Gaussian characteristic of exponential trend, small changes in MBR operation may affect on the progress of membrane fouling. Moreover, this nonlinear distribution has shortcoming that the necessity to predict the future MBR fouling cause false detection, because the predicted values may distort the data information [13].

A framework for the 1) diagnosis and prediction of membrane fouling using traditional technique; and 2) suggestion of mew fouling index is shown in Fig. 1.

First, a variable transformation using natural logarithm is carried out to make the TMP as a Gaussian distribution (from non_Gaussian distribution). The exponential fouling model is transformed into a first-order linear model as shown in Eq. (4). This linearized fouling model is used to diagnosis and predict the membrane fouling.

$$\mathrm{TMP} = A \cdot \mathrm{e}^{\kappa_t \cdot t} \rightarrow \ln(\mathrm{TMP}) = \ln(A) + \kappa_t \cdot t = b + \kappa_t \cdot t \qquad (4)$$

Second, least-square method is applied to find coefficient (κ_t) and intercept (b) of the linearized fouling model using original MBR data, in order to predict the TMP as the traditional fouling index. To compare the predictive accuracy of lineazied fouling model, a root mean squared error (RMSE) is used. RMSE is defined by Eq. (5), where Y_i is the actually observed value, $\hat{Y}_i$ is the predicted value, and n is the number of data points [14].

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n-1}} \qquad (5)$$

Third, recursive least-square (RLS) method is used to update the model used parameters of the linearized fouling mechanism by using a daily updated MBR data. RLS method can be possible to predict continuously updated dynamic model parameters. Covariance matrices are updated using data and weights at time t and covariance matrix at time $t-1$, as shown below in Eqs. (6) and (7):

$$(X^T X)_t = \lambda_t (X^T X)_{t-1} + x_t^T x_t \qquad (6)$$

$$(X^T Y)_t = \lambda_t (X^T Y)_{t-1} + x_t^T y_t \qquad (7)$$

$(X^T X)_t$ and $(X^T Y)_t$ used in the above equations are updated covariance matrices, as covariance vectors sets updated x_t and y_t are the predictor and response vectors at time t, and $\lambda_t (0 < \lambda_t \le 1)$ is a forgetting factor. Model parameters are computed recursively using the following Eqs. (8) and (9):

$$b_t = (X^T X)_t^{-1} (X^T Y)_t \qquad (8)$$

$$b_t = b_{t-1} + (X^T X)_t^{-1} x_t^T (y_t - x_t b_{t-1}) \qquad (9)$$

The coefficient (κ_t) and intercept (b) of the fouling mechanism are recursively updated in the dynamic op-

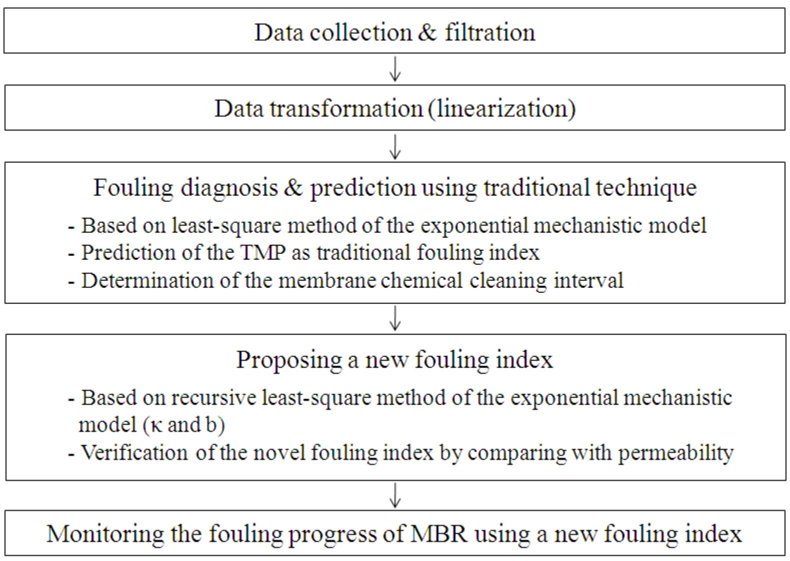


Fig. 1. Scheme for prediction of membrane fouling and the proposed new fouling index.

eration of MBR. Therefore, the coefficient (κ_t) obtained in RLS method is used as a new fouling index since the coefficients vary as the filtration of MBR progress. To verify a validity of the new fouling index, the coefficients obtained RLS method is compared with permeability. The permeability is defined by Eq. (10):

$$\text{Permeability} = \frac{\text{Flux}}{\text{TMP}} \tag{10}$$

Permeability is an ability of particle matter to get through the membrane, and is regarded as another index for the membrane fouling [15]. From the variations of the coefficient (κ_t) and permeability on the same figure a similar trend and direct/inverse proportion of new fouling index and permeability is suggested.

3.3. A pilot-scale MBR process

A pilot-scale MBR plant located in Y-city, Korea is a source of this study. The MBR plant consists of four basins: anoxic 1, aerobic, anoxic 2 and a membrane bioreactor as shown in Fig. 2, with capacities of 38 m^3, 63.8 m^3, 38 m^3, and 24.3 m^3 respectively. Average flowrate of influent is 25 m^3/d, and the average components of the influent, namely biochemical oxygen demand (BOD), chemical oxygen demand (COD), total nitrate (TN) and total phosphorus (TP) are provided in Table 1.

This MBR plant has been operated under a constant-flux (or constant flowrate) mode. Sludge retention time (SRT) for the efficient nitrate treatment is set to more than 9 d, and internal recycle rate is maintained at 200% of the influent flow. MLSS concentration is kept at 7000–9000 mg/L, depends on the characteristics of membrane type. To minimize the membrane fouling, the periodic coarse bubble is supplied to membrane.

Table 1
Compositions of influent stream in the pilot-scale MBR plant in Y-city

Components	Mean concentration (mg/L)	Standard deviation
BOD	166	50.37
COD	301	74.63
TN	38	10.18
TP	6.4	2.20

4. Results and discussion

The proposed method is tested on two kinds of data obtained in operational periods of a pilot-plant: 1) training data set, and 2) test data set. The training data set is a part of the data set used to fit a model for a system, in which it is used to predict regression relation. The test data set which is not a part of training set is also used to evaluate accuracy of the established model. That is, the training data set is used for model development, while the test set is used for evaluating the predictive ability of the model [16]. The first training data set is collected from 2nd March 2009 to 24th April 2009 and the second one is obtained from 18th May 2009 to 8th July 2009. Two training data sets used here are obtained under same operational conditions. Test data set is generated randomly and is used to validate the newly proposed fouling index, κ_t. Time gap between two measured data points corresponds with time gap for updated parameters of RLS methods, which is one day.

4.1. Fouling diagnosis and prediction by the traditional technique

We predict the membrane fouling by least-square method of the exponential mechanistic model and then determine the proper membrane chemical cleaning interval based on the fouling model. Fig. 3a shows the exponential distribution of TMP of a pilot-scale MBR. Because these non-linear data have the shortcoming that the predictive capability is more inadequate than Gaussian distribution, the data linearization by taking the natural logarithm is carried out (see Fig. 3b).

Fig. 4 shows the TMP prediction result by the linearized fouling mechanistic model, which shows to

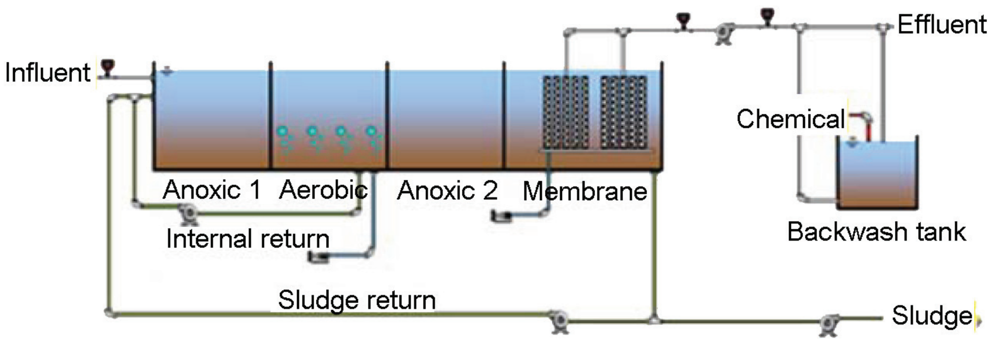
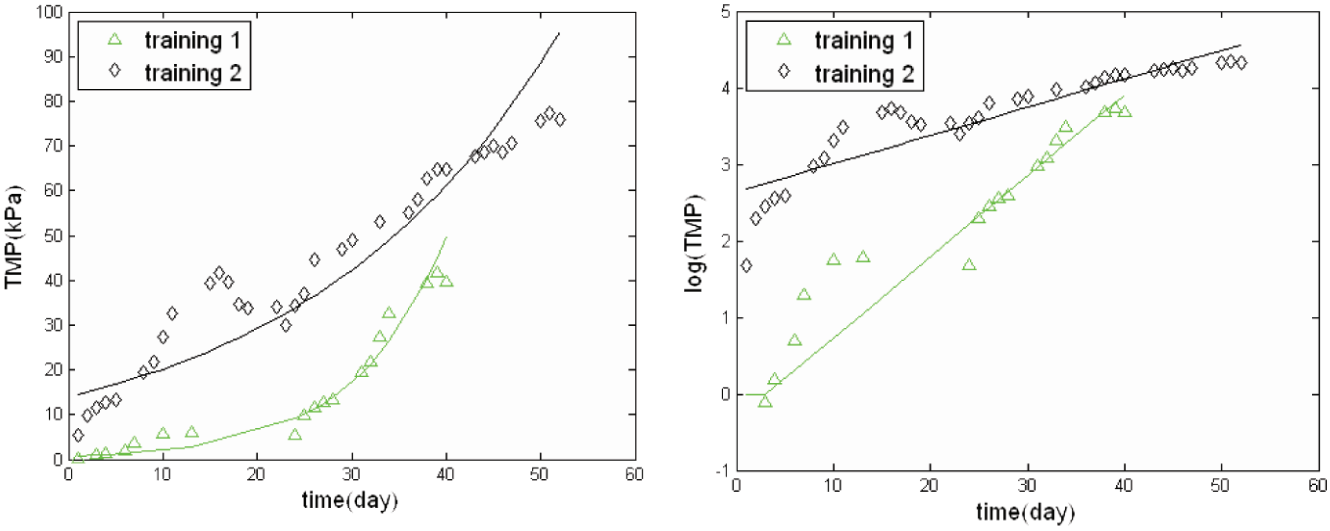


Fig. 2. Layout of a pilot-scale MBR plant located in Y-city, Korea.



(a) Exponential TMP distribution

(b) Linearized TMP distribution

Fig. 3. Data transformation from (a) exponential TMP distribution, to (b) linearized TMP distribution.

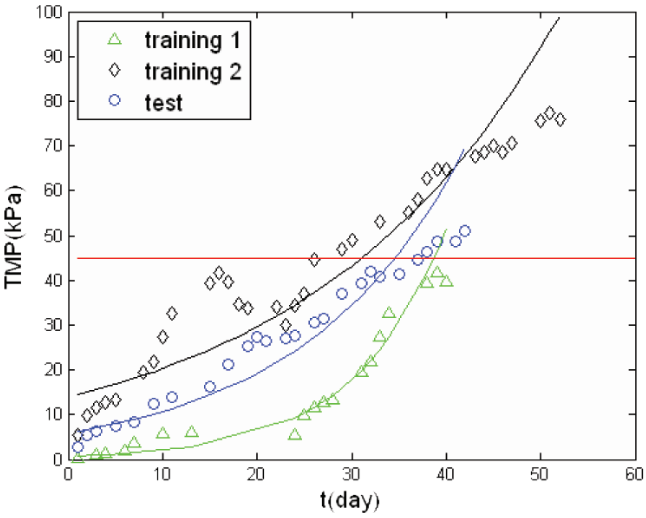


Fig. 4. TMP prediction by linearized the fouling mechanistic model.

an original exponential trend. The fouling mechanistic model demonstrates an excellent fitting results with all data sets, and it means that this fouling model explains and predicts the membrane fouling well in actual MBR plants. In this figure, it is noted that the TMP reaches its critical TMP limit much rapidly as operational time of MBR is passed from training set 1 to 2. It means that the progressive rate of fouling is increased proportionally to operational time. It results from the hindrance of membrane operational stability caused by the progress in membrane fouling.

Table 2 presents the results of prediction, which includes the fouling mechanistic model, RMSE value, and determined membrane chemical cleaning interval for each data set. To determine the interval of membrane chemical cleaning, at which is the operator starts to a chemical cleaning, the critical TMP limit is set as 45 kPa traditionally. When the TMP arrives to the critical limit, the chemical cleaning is carried out to remove the foulants on membrane.

The determined intervals for membrane chemical cleaning are almost similar with the timings that the actual TMP in pilot-scale MBR arrives to the critical limit. It means that the exponential fouling model is a prevailing mechanistic model in a MBR system. The membrane cleaning interval becomes shorter as operational time passes from training set 1 to 2. Although membrane is

Table 2
The results of the fouling prediction and membrane cleaning interval determination

	Mechanistic model	RMSE	Critical cleaning interval in plant (d)	Predicted cleaning interval (d)
Training 1	TMP = 2.634 ·$\exp^{0.037t}$	3.70	42	40
Training 2	TMP = 0.718 ·$\exp^{0.106t}$	5.58	28	32
Test	TMP = 1.787 ·$\exp^{0.0584t}$	4.43	37	35

cleaned chemically, it doesn't seem that cleaned membrane is better than new one. As mentioned previously, it corresponds to the rate at which membrane fouling progress accelerated, due to the continuous accumulation of foulants.

4.2. Proposing of a new fouling index

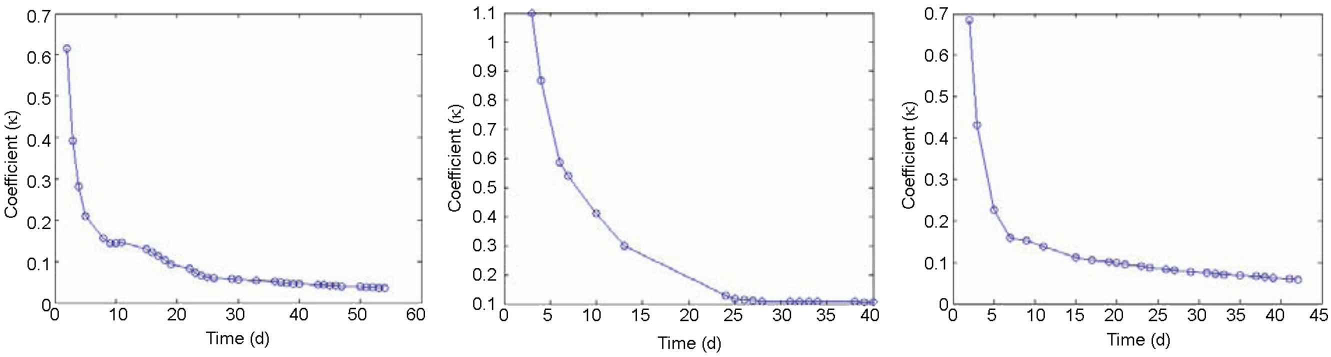
To suggest the novel index for monitoring membrane fouling, recursive least-square method is applied to the linearized fouling model and the coefficients (κt) obtained in RLS method is proposed as the new fouling index. Fig. 5 shows the variation of recursively updated coefficients for three different operational times which are different from one another. Plots of new fouling index in Fig. 5 have a common characteristic that the value of coefficient is decreased continuously as the membrane fouling is progressed.

Fig. 6 compares the variations of fouling coefficient (κt) and permeability with time, to check the validation of the coefficient as the new index. In the pilot-scale MBR plants, the MBR is operated under constant-flux mode, with a flux of 20 L/m^2·h, this value is used to calculate the permeability. To compare the values of coefficients with permeability more easily, cumulative percentage curves of coefficient and permeability are shown in Fig. 6.

In the two training data sets, the coefficient of RLS shows the similar trend with the permeability. And the result of the test set presents the same trend, which matches with the two training set results. It means that the coefficient of RLS can be substituted in place of permeability (which is another kind of the traditional fouling index) for diagnosis of membrane fouling. It is known that the speed at which membrane fouling takes place increases as the value of the coefficient increases, the coefficient has not been suggested as the fouling index. However, this sub-study verified that the coefficient of the exponential mechanistic fouling model has been validated as the new membrane fouling index.

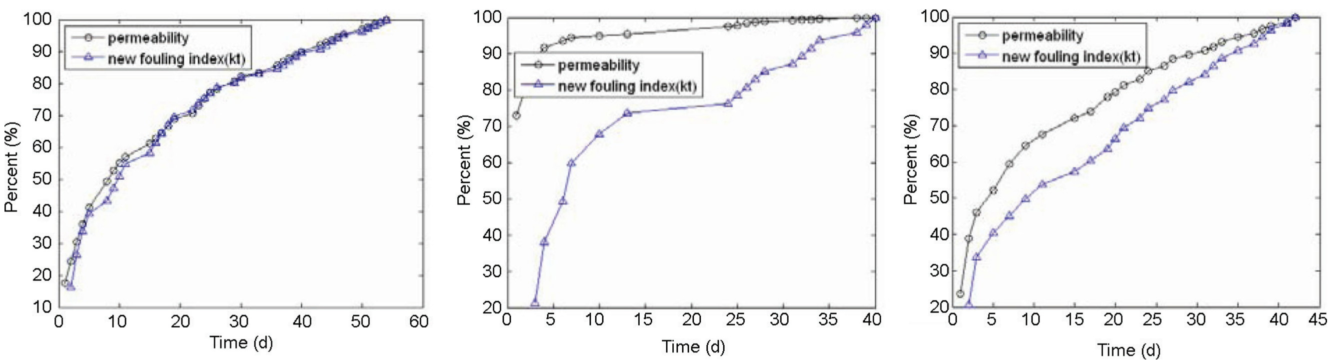
4.3. Monitoring and prediction of MBR fouling using new fouling index

To diagnose the abnormal conditions of membrane



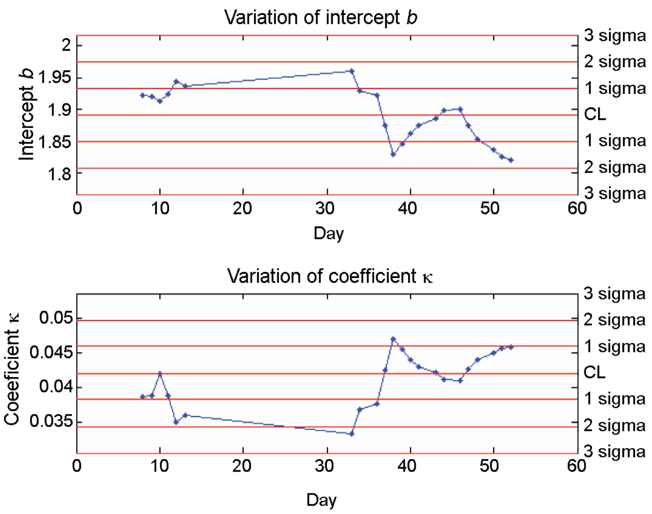
(a) Training set 1 (b) Training set 2 (c) Test set

Fig. 5. Variations of the recursive coefficient (κ_t) of the fouling mechanistic model.

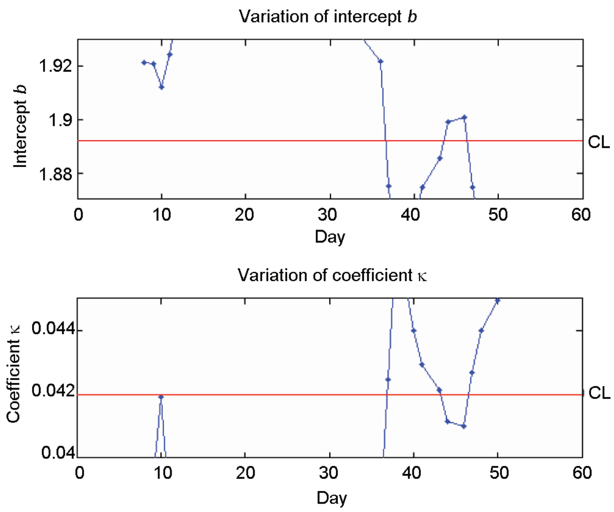


(a) Training set 1 (b) Training set 2 (c) Test set

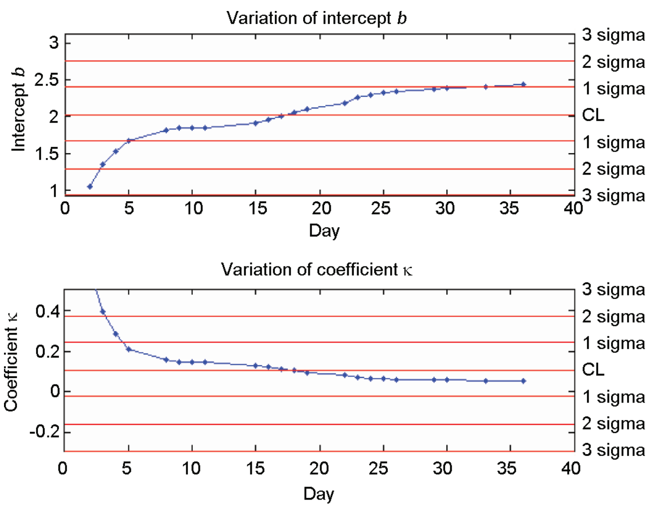
Fig. 6. Comparison of fouling coefficient (κ_t) and permeability.



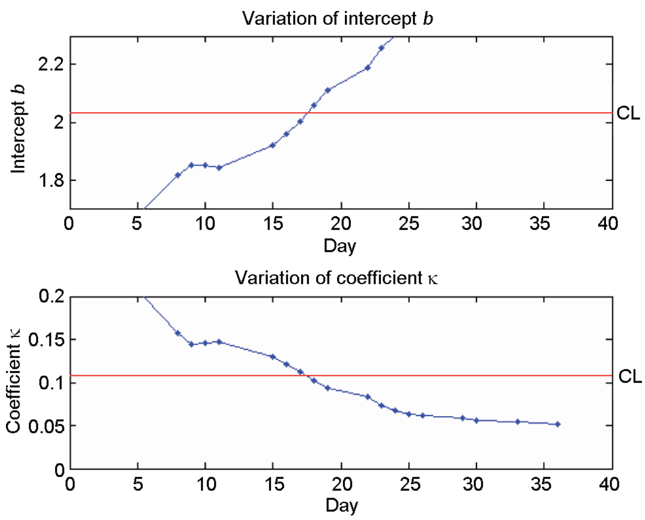
(a) The variations of κ_t and b for training set 1



(b) The enlargement of Fig. 7a with Center Line



(c) The variations of κ_t and b for training set 2



(d) The enlargement of Fig. 7c with Center Line

Fig. 7. (a) and (c): The linearized fouling model coefficients and intercepts; (b) and (d): their enlargements.

fouling and determine cleaning interval, data obtained by RLS is used. Figs. 7b and 7d are the magnified results of 7a and 7c. These are used to check abnormality of MBR fouling. For training set 1, coefficient, κt has shown a plain trend before sharp increase is appeared while the intercept, b has shown the opposite trend. In Figs. 7a and 7b, the time at which the variation lines of coefficient and intercept gather a certain point after they are passed Center Line can be considered as exhausted occurrence of MBR fouling. It is necessary to clean the membrane at that time. In accordance with this, first observation which has convergent value, 38th day, is decided as the cleaning time. Likewise, for training set 2, abnormality of process and prediction of MBR fouling can be recognized by finding the values at which κt and b gather into one point after passing center line. Cleaning time for the training set 2 is determined as 26th days, i.e., 5th observation stabilized after passing center line.

Variations of RMSE values in Fig. 8 are obtained using updated values of κ_t and b in dynamic state operation. Figs. 7 and 8 help accurate prediction and monitoring of MBRs. 38 days and 26 days in Fig. 7 correspond to the points of steep increase in Fig. 8. For the training set 1, RMSE trend at 38th day shows a sudden change which followed by a flat trend after increase. Similarly, for the training set 2, sharp increase found at 26th.

Integrating the variations of κ_t, b and RMSE values, some inferences in Table 3 are drawn. RMSE values ob-

Table 3
The results of the fouling prediction and membrane cleaning interval determination using traditional technique and new fouling index

	Predicted cleaning interval by traditional technique (d)	RMSE	Predicted cleaning interval by new fouling index (d)	RMSE
Training 1	40	3.70	38	11.31
Training 2	32	5.58	26	19.39

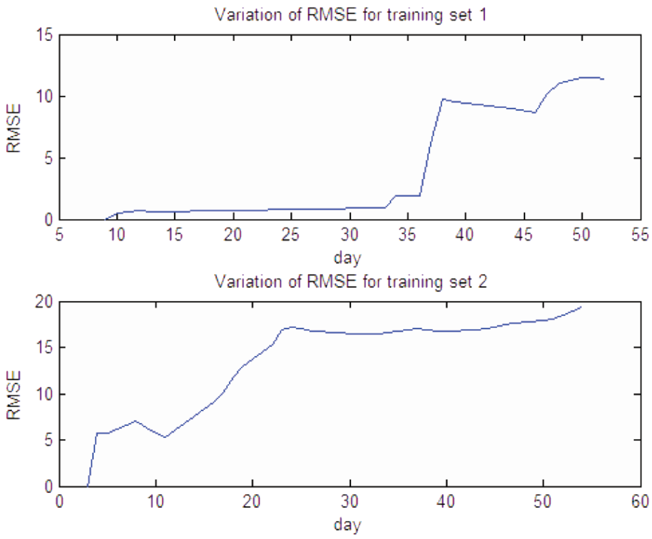


Fig. 8. The variations of RMSE values for training set 1 and training set 2.

tained using new fouling index are higher than one by traditional technique. However, RMSE values obtained using by new fouling index for training set 1, has arisen to 1.93 till MBR cleaning time.

5. Conclusion

In this study, a new fouling diagnosis index has been proposed for a pilot-scale MBR. Considering the nonlinear characteristic of MBR data with exponential trend, the variable transformation of original data was applied, and RLS method was used to model the mechanistic fouling phenomena. To overcome the drawback of the traditional fouling technique, which poorly represents the fouling mechanism and steady state assumption of MBR, the recursively updated coefficient (κ_t) of the fouling mechanistic model is suggested as the new fouling index which has the dynamic process information. The coefficient (κ_t) in a pilot-scale MBR plant shows the similar trend with the permeability of traditional fouling index. The coefficient (κ_t) of the fouling mechanistic model can also be used to monitor and predict membrane fouling in the dynamic conditions, which can overcome the steady state assumption.

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