Desalination and Water Treatment
www.deswater.com
doi: 10.1080/19443994.2014.940646

55 (2015) 3241–3246
September

Taylor & Francis
Taylor & Francis Group

Analysis of a transmembrane pressure (TMP) jump prediction model for preventing TMP jumps

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Received 22 March 2014; Accepted 16 June 2014

ABSTRACT

In water treatment process such as membrane bioreactors (MBRs), transmembrane pressure (TMP) must be monitored for process control when the process is operated under a condition of constant-rate filtration. One of the reasons making it difficult to monitor, predict, and control TMP is TMP jumps, which means that TMP rise-up rapidly even under the critical flux. We previously constructed a statistical model that predicts the time of a TMP jump by inputting elapsed time, flux, TMP, and other MBR parameters such as operating conditions and water quality. This model is called a TMP jump prediction model. The predictive ability of the TMP jump prediction model was demonstrated through many data sets obtained from real MBRs. In this study, we analyzed the TMP jump prediction model to search optimal operating conditions that can prevent TMP jumps. By changing the values of operating conditions and predicting the time of TMP jumps for each candidate of operating conditions, we could control the time of a TMP jump in a full-scale MBR.

Keywords: Membrane bioreactor; Fouling; Transmembrane pressure jump; Prediction; Control

1. Introduction

Membrane bioreactors (MBRs) have been widely used in water treatment fields such as sewage treatment and industrial wastewater treatment to purify wastewater for reuse [1]. MBRs combine biological treatment with membrane filtration. First, bacteria within activated sludge metabolize the organic pollutants and produce environmentally-acceptable metabolites, then a microfiltration or ultrafiltration membrane separates liquids from solids. MBR can be distributed at various locations such as residential sections and industrial plants. Thus, we can create an environment in which treated water is effectively reused in society.

However, MBRs have some practical problems. One of the critical problems is membrane fouling [2]. Membrane fouling is a phenomenon wherein foulants, such as activated sludge, sparingly soluble compounds, and high-molecular-weight solutes and colloids, absorb or deposit on the membrane surface and absorb into and block the membrane pores. To clean membrane with chemicals at an appropriate time, membrane fouling must be predicted in the long term

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Presented at the Conference on Desalination for the Environment: Clean Water and Energy May 11–15, 2014, Limassol, Cyprus

[3–8]. When an MBR plant is operated under a condition of constant-rate filtration, this corresponds to prediction of the transmembrane pressure (TMP) [9–17].

One of the reasons to make TMP difficult to predict is a TMP jump [18]. After the long-term operation of MBR under the condition of constant-rate filtration, TMP increases rapidly [19]. This is called a TMP jump. Yu et al. proposed a mechanism for the TMP jump whereby the membrane is partially blocked by foulants, after which the local flux exceeds the critical flux [20], below which only reversible fouling happens and irreversible fouling can be neglected [21]. It can be said that a TMP jump is a rapid increase in TMP after a period of processing even though the measured flux is less than the critical flux.

We previously proposed the construction of a model that predicts the elapsed time of a TMP jump [22]. The model where input variables $\boldsymbol{X}$ are time, flux, TMP and other MBR parameters such as operating conditions (aeration rate, hydraulic retention time, sludge retention time, and so on) and water quality (water temperature, total organic carbon, concentrations of extracellular polymeric substances and soluble microbial products, and so on), and output variable $\boldsymbol{y}$ is a label variable representing whether TMP jumps happen or not is constructed by using physical and statistical approaches. The model used to detect a TMP jump is called a TMP jump prediction model. This model f is represented as follows:

$$\boldsymbol{y} = f(\boldsymbol{X}) + \boldsymbol{e}, \tag{1}$$

where $\boldsymbol{e}$ means the errors of $\boldsymbol{y}$. A support vector machine (SVM) [23], which is a nonlinear classification method, was applied for the construction of f. By inputting new data of $\boldsymbol{X}$ into f, we can estimate whether a TMP jump happens or not at the time when the new data are measured. Additionally, the presence of a TMP jump can be predicted at the target time by inputting setting values into f. The predictive ability of the TMP jump prediction model was demonstrated through many data sets obtained from real MBRs [24]. In addition, the domains where a TMP jump prediction model estimates TMP jumps will happen can be visualized to discuss the possibility of TMP jumps and the ways to prevent TMP jumps in the future [25].

In this study, we search appropriate MBR operating conditions where a TMP jump never happens by analyzing the constructed TMP jump prediction model. This type of analysis is called as inverse analysis. For example, set values of flux for each time or set values of aeration for each time are changed, and then, these values are input into the TMP jump prediction model. Afterwards, the predicted time of a TMP jump can be obtained. By repeating the changes of set values and the check of the prediction results, the appropriate operating condition with which a TMP jump does not happen can be found. The effectiveness of the proposed method is demonstrated through a case study using a full-scale MBR plant.

2. Method

The basic concept of the TMP jump discriminant model is shown in Fig. 1 [24]. $\boldsymbol{X}$-variables are elapsed time, flux, TMP and other MBR parameters, and a $\boldsymbol{y}$-variable is a label variable representing whether there are TMP jumps. The data before TMP jumps are labeled −1, the data after TMP jumps are labeled 1, and an SVM model determining values of −1 and 1 is then constructed for $\boldsymbol{X}$ and $\boldsymbol{y}$. The details of SVM are shown in Appendix A.

In the prediction of a TMP jump in the long term, the target time is input, a set flux relating to the constant-rate filtration is input, and the predicted TMP should be inputted into the SVM model. Fortunately, the increase in TMP is represented as a linear function of time because the initial increase in the fouling resistance can be assumed to be due to cake fouling [22]. Predicted TMP values are then input into the TMP jump prediction model. For other parameters, predicted values or set values are input into the model. Accordingly, we can predict whether a TMP jump will happen at the target time.

By using the constructed TMP jump prediction model and inputting future set values of flux and water quality with changing them, i.e. repeating trial and error, we can search the conditions where a TMP jump will hardly happen. MBR can be accordingly controlled for a TMP jump not to happen in the future. In addition, by projecting the results of a discriminant

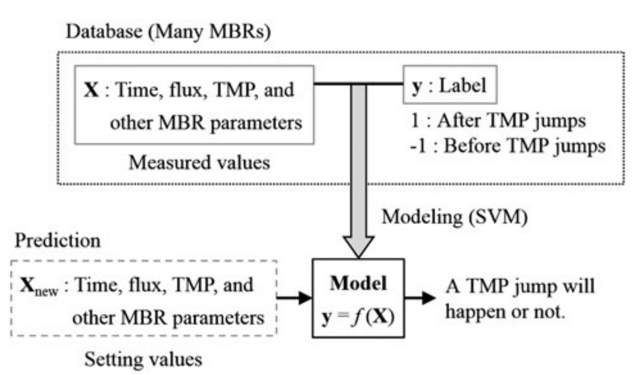

Fig. 1. TMP jump prediction model [24].

model to a two-dimensional map with visualization methods such as principal component analysis [26], kernel PCA [27], self-organizing map [28], and generative topographic mapping [29], we can discuss optimal MBR conditions where TMP jumps hardly happen [25].

Basically, y-values can be predicted by inputting X-values into f (see Fig. 1), which is direct analysis. Reversely, X-values can be also obtained to meet desired y-values, which is inverse analysis. It is difficult to solve inverse problem compared to direct problem because X-values are underspecified for a y-value. Then, a trial and error method, an exhaustive search method, and an optimization method such as genetic algorithm are used in inverse analysis. Of course, there exist the cases that there are no X-values to meet a required y-value.

3. Results and discussion

Data were obtained from a full-scale MBR plant operating in Japan. A brief summary of the target MBR plant is given in Table 1. The MBR system comprises anaerobic, anoxic, aerobic, and membrane tanks. A membrane module is immersed in a membrane tank. In this case study, we used data for the first six batches as a training data set and data for the last three batches as a test data set to verify the predictive ability of the proposed method for external data. A batch of data means the operation from the start or membrane fouling to next membrane cleaning or the end of the operation. An MBR operator defined the data before TMP jumps (−1) and the data after the TMP jumps (1).

X-variables of the discriminant models are three variables, i.e. elapsed time [h], flux [m/d], and TMP [kPa], or seven variables, i.e. elapsed time [h], flux [m/d], TMP [kPa], water temperature [℃], dissolved oxygen [mg/l], pH [−], and aeration [l/min]. Table 2 presents the results for the construction and prediction of discriminant models with three and seven X-variables using the SVM. The accuracy rate (AR), precision (PR), and the detection rate (DR) are defined as:

$$\mathrm{AR} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{TN}+\mathrm{FN}}, \tag{2}$$

$$\mathrm{PR} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}, \tag{3}$$

$$\mathrm{DR} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}. \tag{4}$$

Here, TP denotes the number of true positives, or the number of test data for which the state after TMP jumps is correctly detected; TN represents the number of true negatives, or the number of test data for which the state after TMP jumps is not detected and the transition is indeed incomplete; FP denotes the number of false positives, or the number of test data for which the state after TMP jumps is incorrectly detected; and FN represents the number of false negatives, or the number of test data for which there are actually TMP jumps but they are not detected.

From Table 2, although the DR-value decreased a little, the AR-value increased and the PR value significantly increased by adding X-variables, compared to three X-variables. Fig. 2 shows the plots of actual and predicted time of TMP jump. The data became closer to the diagonal with the addition of water quality and operating conditions to X-variables. It was confirmed that the predictive ability of the discriminant model increased by using water quality and operating conditions as X-variables. We used the TMP jump prediction model constructed with seven X-variables in the next analysis.

Table 1
Brief Summary of an MBR in Japan

Operation	Constant-rate filtration
Treatment object	Urban wastewater
Anaerobic tank volume	1,000 l
Anoxic tank volume	4,000 l
Aerobic tank volume	2,000 l
Membrane tank volume	4,000 l
Membrane	Flat sheet
Material	Polyvinylidene difluoride
Pore diameter	0.1 μm
Total membrane area	65 m^2

Table 2
Modeling and prediction results. AR, PR and DR values with test data for the discriminant model. The indices are expressed by Eqs. (2)–(4) and explained in the text

#var[a]	3[b]	7[c]
AR [%]	88.1	93.5
PR [%]	56.1	93.5
DR [%]	62.7	56.9

[a]Number of X-variables.
[b]Elapsed time [h], flux [m/d] and TMP [kPa].
[c]Elapsed time [h], flux [m/d],TMP [kPa], water temperature [℃], dissolved oxygen [mg/l], pH [−] and aeration [l/min].

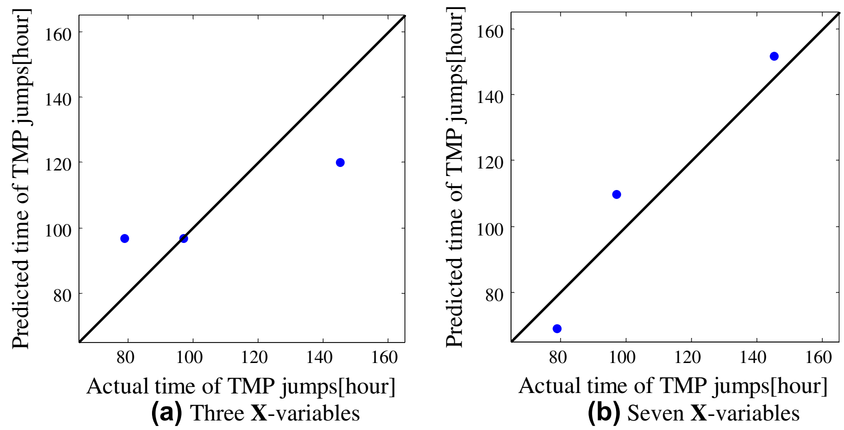

Fig. 2. The plots of actual and predicted time of TMP jump. Three ***X***-variables and seven ***X***-variables are explained in Table 2.

Operating conditions with which TMP jumps never happen were searched by using the constructed TMP jump prediction model. The target batch is the last batch of the test batches. Fig. 3 shows the time plot of TMP in the target batch. The time of the TMP jump that the MBR operator decided beforehand was 79th h.

Four scenarios shown in Table 3 were handled in this case study. Fig. 4 shows the time plot of aeration for each scenario. The times of the TMP jump predicted by the TMP jump prediction model for the scenarios are shown in Table 3. In scenario B, by decreasing aeration compared to that of scenario A, it is predicted that the TMP jump will happen earlier than the TMP jump in scenario A. Low aeration could not clean membrane well, which would cause the early TMP jump. This early TMP jump with small aeration is a reasonable result. Reversely, the TMP jump would not happen by increasing aeration to 250 [l/min]. High aeration could remove foulants on the membrane, which would be appropriate. However, high aeration increases the operating cost.

Therefore, we changed aeration by trial and error so that the total amount of aeration is the same as that of scenario A, which produced scenario D. By increasing

Table 3
Scenarios of aeration and the predicted time of the TMP jump for the scenarios

	Operation of aeration	Predicted timeof the TMP jump
Scenario A	Actual operation	69
Scenario B	100 l/min	55
Scenario C	250 l/min	None
Scenario D	Changing so that the total amount of aeration is the same as that of scenario A	None

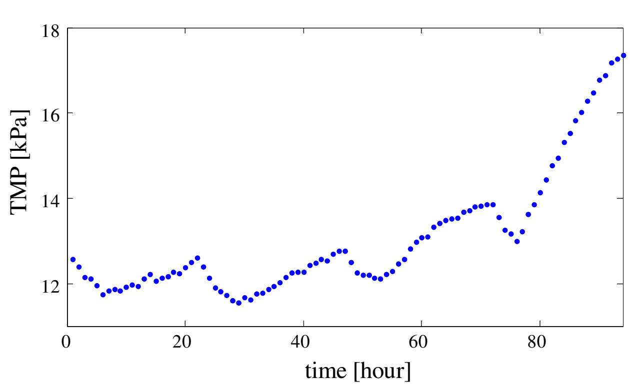

Fig. 3. The time plot of TMP in the target batch.

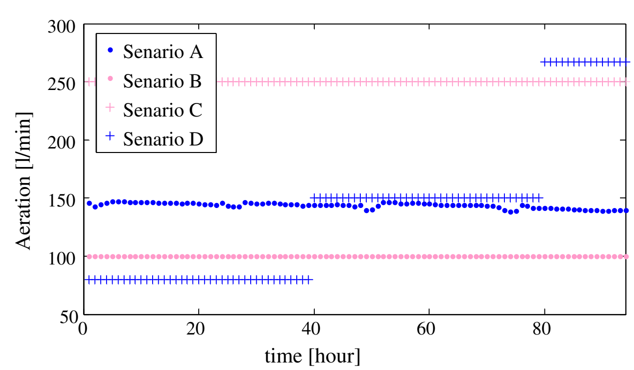

Fig. 4. The time plot of aeration for each scenario in Table 3.

aeration step by step as shown in Fig. 4, the TMP jump could be prevented. It is important that the total amount of aeration does not change and the operating cost is also the same as that of the actual operation, i.e. scenario A. We confirmed that the adequate operating conditions could be searched by using the proposed method. Actually, the water quality would change when aeration changed, the effect of which is important and must be considered in the future.

4. Conclusion

In this paper, we constructed a TMP jump prediction model for predicting TMP jumps with MBR parameters first, and then, analyzed the TMP jump prediction model to investigate MBR operating conditions with which a TMP jump never happened. It was confirmed that the appropriate aeration scenario could be found by changing the values of aeration, inputting them into the TMP jump prediction model and checking the prediction results. It is important to consider the correlation between operating conditions and water quality to search reliable operating conditions in the future. Using the proposed method, we will achieve the effective control of an MBR.

Acknowledgment

The authors acknowledge the support of the Core Research for Evolutional Science and Technology (CREST) project "Application of Integrated Intelligent Satellite System (IISS) to construct regional water resources utilization system" of the Japan Science and Technology Agency (JST).

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Appendix A: SVM [23]

For constructing the above discriminant model, an SVM method is used in this paper. An SVM is one of the classification methods used to generate nonlinear classifiers by applying the kernel approach. In a linear SVM, the discriminant function $f(\boldsymbol{x})$ is defined as follows (Eq. A.1):

$$f(x) = \boldsymbol{x} \cdot \boldsymbol{w} + b \tag{A.1}$$

where $\boldsymbol{x}$ is a query sample, $\boldsymbol{w}$ is a weight vector; and b is a bias. The primal form of the SVM can be expressed as an optimization problem:

Minimize (Eq. A.2)

$$\frac{1}{2}\|\mathbf{w}\|^2 + C\sum_i \xi_i \tag{A.2}$$

subject to (Eq. A.3)

$$\begin{aligned} y_i(\boldsymbol{x}_i \cdot \boldsymbol{w} + b) &\geq 1 - \xi_i \\ y_i &\in \{-1, 1\} \end{aligned} \tag{A.3}$$

where y_i and $\boldsymbol{x}_i$ represent training data; ξ_i is slack variables; and C is the penalizing factor that controls the trade-off between a training error and a margin. By minimizing (A.2), we can construct a discriminant model that shows a good balance between the ability to adapt to the training data and the ability to generalize. In our application, a kernel function is a radial basis function as follows (Eq. A.4):

$$K(\boldsymbol{x}, \boldsymbol{x}') = \exp\left(-\gamma\|\boldsymbol{x} - \boldsymbol{x}'\|^2\right) \tag{A.4}$$

where γ is a tuning parameter that controls the width of the kernel function. By using (A.4), a nonlinear model can be constructed because the inner product of $\boldsymbol{x}$ and $\boldsymbol{w}$ in (A.1) is represented as the kernel function of $\boldsymbol{x}$. In this study, LIBSVM [30] is used as the machine learning software.