An intelligent detecting system for permeability prediction of MBR
Honggui Han, Shuo Zhang, Junfei Qiao and Xiaoshuang Wang

ABSTRACT
The membrane bioreactor (MBR) has been widely used to purify wastewater in wastewater treatment plants. However, a critical difficulty of the MBR is membrane fouling. To reduce membrane fouling, in this work, an intelligent detecting system is developed to evaluate the performance of MBR by predicting the membrane permeability. This intelligent detecting system consists of two main parts. First, a soft computing method, based on the partial least squares method and the recurrent fuzzy neural network, is designed to find the nonlinear relations between the membrane permeability and the other variables. Second, a complete new platform connecting the sensors and the software is built, in order to enable the intelligent detecting system to handle complex algorithms. Finally, the simulation and experimental results demonstrate the reliability and effectiveness of the proposed intelligent detecting system, underlying the potential of this system for the online membrane permeability for detecting membrane fouling of MBR.

Key words: intelligent detecting system, membrane bioreactor, partial least squares, permeability, soft computing method

INTRODUCTION
The membrane bioreactor (MBR), which integrates membrane technology and conventional activated sludge (CAS) treatment, is a promising technology for wastewater treatment and reuse (Trad et al. 2015; Neoh et al. 2016). In comparison to the conventional CAS technique, MBR has many advantages, such as smaller footprint, less sludge production, higher separation efficiency and highly improved effluent quality and so on (Bell et al. 2016; Chen et al. 2016). However, the MBR has some practical difficulties. One of the critical difficulties is membrane fouling. The problems of membrane fouling, which result in additional capital and maintenance costs to the wastewater treatment plants (WWTPs), have limited the excessive advantages of MBR (Chen et al. 2017; Meng et al. 2017). Generally, to reduce membrane fouling, it is important to understand the membrane properties and membrane fouling mechanisms. In fact, previous studies have demonstrated that the values of membrane permeability are important for the healthy functioning of an MBR and its running state (Ruiz et al. 2016; Gurung et al. 2017). It is of great significance to measure membrane permeability during MBR operation (Alibardi et al. 2014; Barreto et al. 2016).

For evaluating the performance of an MBR, several chemical principles and mechanism models have been introduced (Luna et al. 2014; Ding et al. 2016; Teychene et al. 2016). These results indicate that the membrane permeability is influenced by the membrane (membrane configuration, material, hydrophobicity, pore size, etc.), the sludge conditions (mixed liquor suspended solids, viscosity, dissolved matter, etc.), the operating conditions (solids retention time, hydraulic retention time, MBR configuration, etc.) and other factors (floc size and density, filamentous bacteria abundance, extracellular polymeric substances, etc.). However, membrane fouling is a dynamic and complex process, the chemical principles and mechanism models could not be successfully applied, due to their basic assumption under stationary ideal operating conditions (Bounceur et al. 2017). Moreover, many parameters should be adjusted to characterize the extent of membrane permeability, so the accuracy of these methods is questionable (Lee & Park 2016; Kasemset et al. 2017).

To improve the mechanistic understanding of the MBR, soft computing methods are becoming more common for predicting the water qualities in the MBR. For instance, in
the process industry, soft computing methods are extensively exploited (Ferrero et al. 2012; Dalmau et al. 2015; Mirbagheri et al. 2015). In soft computing methods, input information and the internal model are used to return output information associated with the hard-to-measure primary variables (Mehrizad & Gharbani 2016). For soft computing methods, models based on the artificial neural network and fuzzy system are the most popular ones (Han et al. 2016; Picos-Benítez et al. 2017). For example, Barello et al. (2014) used a multi-layer perceptron (MLP) to estimate the performance of an MBR. The results indicate that this MLP can predict the values of membrane permeability in practical application with salinity, operating pressure and membrane type as the inputs. Geissler et al. (2005) introduced a feedforward neural network with 29 collected process variables as the inputs to predict the values of membrane permeability. The results demonstrate that this feedforward neural network can obtain a prediction accuracy of around 81.6%. Moreover, a radial basis function neural network (RBFNN) was used to obtain the predictions of membrane permeability in Chellam 2005. The results show that the RBFNN could improve the prediction accuracy with low testing root mean square error (RMSE). Recently, the fuzzy neural network (FNN) method has attracted a lot of attention for nonlinear system modeling (Lin et al. 2013). The soft computing methods, based on FNNS, have provided the advantages of both neural networks and fuzzy systems, i.e., adaptability, high accuracy, and quick convergence (Yadav & Chandel 2014; Huang et al. 2015). However, one drawback of these methods is that they are essentially static input-to-output maps and their capability for representing nonlinear systems is limited (Ruan et al. 2017).

In this paper, we focus on how to evaluate the membrane fouling of the MBR by predicting the values of membrane permeability. To support the existing hard sensors by providing a reliable back-up system in case of malfunction, an intelligent detecting system is developed. First, with simplicity being one of the main requirements for a full-scale implementation, the partial least squares (PLS) method is used to select the most relevant process variables of membrane permeability. Second, a soft computing method, using the recurrent fuzzy neural network (RFNN), is designed to find the nonlinear relations between the membrane permeability and the relevant process variables. The RFNN is capable of providing long range predictions even in the presence of measurement noise and has some other advantages due to the recurrent structures. Third, a complete new platform connecting the sensors and the software is built to provide the intelligent detecting system to handle complex algorithms. The simulation and experimental results demonstrate the reliability and effectiveness of the intelligent detecting system, underlying the potential of this system for the online detecting of membrane fouling of an MBR.

The rest of this paper is organized as follows: after a detailed description of the intelligent detecting system, the main stages of the soft computing model design are discussed in detail, starting from the introduction of PLS, which is used to determine input variables. Finally, the performance results are discussed and the conclusion is given.

**METHODS**

**The intelligent detecting system setup**

The intelligent detecting system, located in the real WWTPs with MBR technology for the online monitoring of the membrane permeability, is shown in Figure 1. The MBR system contains a pre-treatment system with grit chambers and regulating tank, the biological reaction tank with UCT configuration, the MBR tank with the membrane unit, and the backwashing tank. The grit chamber and regulating tank in the pre-treatment system are used for pre-screening and sedimentation, respectively. The biological reaction tank contains an anaerobic tank, anoxic tank and aerobic tank, which are used for clarification purposes. Each reactor is equipped with a sensor for process variable acquisition and a mixer to ensure adequate mixing of the mixed liquor. In the aerobic tank and in the MBR tank, the blowers are set to supply oxygen for microorganism for biochemical reaction. The MBR tank is used for secondary treatment of wastewater. The backwashing tank transports the clean water from the top of the MBR unit through the membrane fibers by pump 2. Furthermore, the external recycle (MBR tank → aeration tank) is carried out by the circulation pump (pump 1).

Membrane fouling is mainly caused by adsorption or deposition on the membrane surface. In real WWTPs, three modes – air scouring, chemically enhanced backwash (CEB) and cleaning in place (CIP) – are used to relieve the membrane fouling. In the first mode, the air is continuously supplied to the MBR system to flush the membrane surface. In the second mode, the membrane is chemically cleaned using sodium hypochlorite once or twice a week to maintain the operational state of membrane. In the third mode, the membrane is washed by sodium hypochlorite, and then pickled using citric acid. During the CEB and
CIP, the intake pump may stop to miss the data from the process. Therefore, in order to ensure the integrity of data acquisition, the data are collected when the intake pumps are running.

This intelligent detecting system consists of four parts: the data acquisition module, the real-time data transmission module, the online prediction module and the real-time display module. As shown in Figure 1, the data acquisition module is used to obtain the values of the process variables from the sensors. There are 21 accessible process variables: six influent variables, six effluent variables and nine reaction process variables. The details of the process variables used in this intelligent detecting system are listed in Table 1.

Meanwhile, the real-time data transmission module is applied to transmit the data from the sensors to the local programmable logic controllers (PLCs). Because of the small volume and easy installation, the protocol converter is used as the communication channel for the data transmission module. Furthermore, the communication between the industry network and the office network is transmitted through the data receiving gateway. Moreover, the online prediction module is designed to predict the values of membrane permeability based on the soft computing method. In order to provide the usual system to handle complex intelligent algorithms, a platform has been designed by MATLAB software as the online prediction module. Finally, the real-time display module is developed for the database server and application server. The real-time display module has an extremely effective role, allowing the system manager to monitor the membrane permeability online and to take appropriate actions.

**Soft computing method**

The soft computing method can be described as an input-output process model, in which the inputs consist of the easy-to-measure parameters and the output is the target parameters (Liu & Wang 2015). The schematic diagram of the soft computing method is shown in Figure 2.

In this soft computing method, as shown in Figure 2, the online instruments will consistently collect and transmit new data to the soft computing method. Then the soft computing method will update its parameters to follow the change in the data online. In this study, the proposed WWTP is instrumented and many on-line easy-to-measure...
process variables are routinely acquired. In fact, the state of membrane permeability is closely geared to the real-time information of process variables. However, the remarkable characteristics of the data acquired are redundancy and possibly insignificance. The amount and quality of the data together with their high-dimensionality can be a limiting

![Table 1](image1)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Explanation</th>
<th>Unit</th>
<th>Collecting sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Influent chemical oxygen demand (COD)</td>
<td>mg/l</td>
<td>DH310C1</td>
</tr>
<tr>
<td>2</td>
<td>Influent ammonia nitrogen (NH₃-N)</td>
<td>mg/l</td>
<td>AmmoLy700IQ</td>
</tr>
<tr>
<td>3</td>
<td>Influent pH</td>
<td>–</td>
<td>SensoLy700IQ</td>
</tr>
<tr>
<td>4</td>
<td>Influent biochemical oxygen demand (BOD)</td>
<td>mg/l</td>
<td>HACH29524-00</td>
</tr>
<tr>
<td>5</td>
<td>Influent suspended solids (SS)</td>
<td>mg/l</td>
<td>ViSolid700IQ</td>
</tr>
<tr>
<td>6</td>
<td>Influent total phosphorus (TP)</td>
<td>mg/l</td>
<td>DH312P1</td>
</tr>
<tr>
<td>7</td>
<td>Effluent BOD</td>
<td>mg/l</td>
<td>HACH29524-00</td>
</tr>
<tr>
<td>8</td>
<td>Effluent COD</td>
<td>mg/l</td>
<td>DH310C1</td>
</tr>
<tr>
<td>9</td>
<td>Effluent total nitrogen (TN)</td>
<td>mg/l</td>
<td>HC304</td>
</tr>
<tr>
<td>10</td>
<td>Effluent ammonia nitrogen (NH₃-N)</td>
<td>mg/l</td>
<td>AmmoLy700IQ</td>
</tr>
<tr>
<td>11</td>
<td>Effluent TP</td>
<td>mg/l</td>
<td>DH312P1</td>
</tr>
<tr>
<td>12</td>
<td>Turbidity</td>
<td>NTU</td>
<td>TC-730H</td>
</tr>
<tr>
<td>13</td>
<td>Effluent pH</td>
<td>–</td>
<td>SensoLy700IQ</td>
</tr>
<tr>
<td>14</td>
<td>Anaerobic zone oxidation-reduction potential (ORP)</td>
<td>mV</td>
<td>SensoLy700IQ</td>
</tr>
<tr>
<td>15</td>
<td>Anoxic zone ORP</td>
<td>mV</td>
<td>SensoLy700IQ</td>
</tr>
<tr>
<td>16</td>
<td>Aerobic zone dissolved oxygen (DO)</td>
<td>mg/l</td>
<td>TriOxmatic700IQ</td>
</tr>
<tr>
<td>17</td>
<td>Aerobic zone nitrate (NO₃-N)</td>
<td>mg/l</td>
<td>NitraLy700IQ</td>
</tr>
<tr>
<td>18</td>
<td>Water flow</td>
<td>m³/h</td>
<td>DN1200</td>
</tr>
<tr>
<td>19</td>
<td>Water pressure</td>
<td>kPa</td>
<td>WH131</td>
</tr>
<tr>
<td>20</td>
<td>Aeration rate</td>
<td>m³/h</td>
<td>–</td>
</tr>
<tr>
<td>21</td>
<td>MBR DO</td>
<td>mg/l</td>
<td>TriOxmatic700IQ</td>
</tr>
</tbody>
</table>

![Figure 2](image2)

**Figure 2** | The schematic diagram of the soft computing model.
factor for the development of soft computing method (Liu et al. 2014). A soft computing method works satisfactorily if only those secondary variables that are most relevant to the primary variable are employed. Therefore, it is necessary to prepare the data before they are processed by the soft computing method (Maere et al. 2012).

Besides the input variable selection, the model design is another critical step in the soft computing method. Moreover, the adjustment of the model parameters determines the generalization abilities of the soft computing method. In this soft computing method, to overcome the limitations of feedforward neural networks (Qin et al. 2012), a RFNN is designed to find the nonlinear relations between the membrane permeability and the relevant process variables. This proposed RFNN can map a set of input patterns onto a corresponding set of output patterns after learning a series of past processing data from a given system (Lee & Teng 2000; Wai 2001).

Variable selection

The variable selection, to eliminate useless process parameters and choose important variables, is a difficult task, since a model has too many inputs and hence too many parameters may lead to overfitting and time-consuming. Selecting appropriate input variables is crucial to enhance the estimation accuracy and maintain the reliability of soft computing method. In this paper, the PLS method, which can construct new variables that are maximally uncorrelated among themselves and also maximally linearly related with the output variables, is used to select the input variables of soft computing method (Liu 2014).

In MBR, suppose that there is a data set \( \{X, y\} \), where \( X \) is an \( m \times a \) data matrix with \( a \) being the number of independent variables and \( m \) the number of samples. \( y \) is the corresponding dependent variable vector with size \( m \times 1 \). The underlying assumption of PLS is that the observed data are generated by a system or process with a small number of latent variables. In the following, PLS adopts a two-step strategy to generate a functional relationship between \( X \) and \( y \) blocks. Firstly, PLS builds the inner relations between the two blocks,

\[
X = TP^T + E = \sum_{i=1}^{a} t_i p_i^T + E, \quad (1)
\]

\[
y = UQ^T + F = \sum_{i=1}^{a} u_i q_i^T + F, \quad (2)
\]

where \( T, P \) and \( E \) are the score matrix, loading matrix and residual matrix of \( X \) block, respectively. \( U, Q \) and \( F \) are the score matrix, loading matrix and residual matrix of \( y \) block. \( t_i, p_i, u_i \) and \( q_i \) \((i = 1, 2, \ldots, a)\) are the corresponding vectors of \( T, P, U \) and \( Q \); \( a \) is the total number of available secondary variables.

Then, a linear regression between \( u_i \) and \( t_i \) is given as below

\[
u_i = b_i t_i, \quad (3)
\]

\[
b_i = \frac{u_i^T t_i}{t_i^T t_i}, \quad (4)
\]

where \( b_i \) is the regression coefficient between \( t_i \) and \( u_i \).

The prediction/fitted values of new sample \( j(i = 1, 2, \ldots, m) \) based on all samples is

\[
y_j^p = x_j b^* + c^*, \quad (5)
\]

where \( y_j^p \) is the prediction/fitted values of the \( j \)th new sample, \( x_j \) is the process variable vector \((1 \times p)\) of sample \( j \), \( b^* \) is the regression coefficient vector \((p \times 1)\), and \( c^* \) is the offset.

Based on the above analysis, the number of final extracted components is determined by the cross validation criterion \( Q_h^2 \)

\[
Q_h^2 = 1 - \frac{\sum_{j=1}^{b} (y_j - y_j^p)^2}{\sum_{j=1}^{b} (y_j - \bar{y})^2}, \quad (6)
\]

when \( Q_h^2 < 0.075 \), the model achieves the accuracy requirements, then the algorithm is stopped; \( h \) is the number of extracted components.

Neural network model design

As shown in Figure 2, the RFNN, which can provide long-range predictions in the presence of measurement noise due to its structure, is developed in this study. The structure of the RFNN comprises four layers: the input layer, the membership layer, the rule layer, and the output layer. The input layer receives the values of input variables. The membership layer is used to calculate the Gaussian membership values of the input variables. Every node in this layer performs a membership function and acts as a unit of memory. The rule layer forms the fuzzy rule base. Each node in the rule layer represents a fuzzy rule. The output

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layer performs the defuzzification operation. Then, the output of RFNN can be described as

\[ y(t) = \sum_{j=1}^{m} w_j(t) \prod_{i=1}^{n} \exp\left[ -\frac{\left[ x_i(t) + O(t-1) \times \theta(t) - m_{ij}(t)\right]^2}{(\sigma_{ij}(t))^2} \right], \]

where \( y(t) \) is the output of RFNN at time \( t \), \( n \) is the number of input nodes, \( m \) denotes the rule number, \( w_j(t) \) is the weight between the \( j \)th rule layer node and the output layer, \( x_i(t) \) is the input value of the \( i \)th node in the input layer, \( m_{ij}(t) \) and \( \sigma_{ij}(t) \) are the center and the width of the \( j \)th node in the membership layer, respectively; \( \theta(t) \) is the weight of the feedback unit of the membership layer. \( O(t) \) is the feedback unit of the membership layer, and \( O(t-1) = \exp[ -[x_i(t-1) + O(t-2) \times \theta(t-1) \times m_{ij}(t-1)]^2/(\sigma_{ij}(t-1))^2] \).

In this study, the gradient descent algorithm is used to train the tuning parameters \( (m_{ij}(t), \sigma_{ij}(t), \theta(t) \text{ and } \omega_k(t)) \) of RFNN, for the detail of the operation process refer to Soudry et al. (2015).

Performance indices

To evaluate the performance of the proposed soft computing method and intelligent detecting system, the following indices are used: root-mean-square error (RMSE) and percentage prediction accuracy (P):

\[ \text{RMSE}(t) = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (y(t) - y_d(t))^2}, \]

\[ P(t) = \frac{1}{N} \sum_{t=1}^{N} \left( 1 - \frac{e(t)}{y(t)} \right) \times 100\%, \]

where \( y(t) \) is the measured values, \( y_d(t) \) is the predicted values, \( e(t) \) is the error of the method and \( e(t) = y_d(t) - y(t) \).

RESULTS AND DISCUSSION

Variable selection results

In this study, the total 21 process variables, measured online for the intelligent detecting system, are presented in Table 1. The sampling frequency of all variables is 8 minutes. And a dataset, corresponding to the real process operation (from 15th February 2015 to 1st December 2015), is set up.

Based on the above analysis, the results of the PLS method are shown in Figure 3, with \( h = 5, Q_B^2 < 0.075 \). Then, for the intelligent detecting system, the number of extracted components is 5. The main components are: water flow, water pressure, aeration rate, anoxic zone ORP and aerobic zone nitrate. The main components have significant impact on the permeability rate. In the MBR, water flow and water pressure have a direct effect on the membrane permeability. Anoxic zone ORP and aerobic zone nitrate are about the chemical reaction and nitrogen content, which are the main nitrogen source for microorganisms (Wu et al. 2013; Phan et al. 2014). In addition, the aeration rate is considered as one of the major parameters for the process performance. The bubbles generated by the aeration air pumps can suppress the accumulation of pollutants on the membrane surface. Therefore, the main components are reasonable in theory and practice.

Simulation results

In order to show the effectiveness of the proposed intelligent detecting system with the soft computing method, its performance is demonstrated using simulation and experimental studies under various operating conditions. All the simulations were programmed with Matlab version 2014, and were run on a PC with a clock speed of 2.6 GHz and 4 GB RAM, under a Microsoft Windows 8.0 environment. The data used for the simulations were collected from 15 February 2015 to 1 December 2015 in a real WWTP. The dataset was then separated into a training set with 1,500 samples and a test set with 1,000 samples. The process variables that were used as the inputs of the proposed intelligent detecting system were two cases: 21 input variables for the process and five input variables selected according to the PLS technique.

The results in Figure 4 show the prediction values and errors of membrane permeability with different inputs. It can be seen that the performance of five input variables is better than that of 21 input variables. Meanwhile, the details of the comparisons of the two cases are given in Table 2, and it can be seen that the mean testing RMSE and the maximum prediction accuracy of the intelligent detecting system with five input variables are 0.3142 and 94.32%, respectively, illustrating that the intelligent detecting system with five input variables has better prediction accuracy than the 21 input variables.
Figure 3 | The regression coefficient of each parameter.

Figure 4 | The prediction performance of different input variables.
In addition, in order to evaluate the prediction efficiency of the proposed intelligent detecting system with RFNN, it was compared with some other methods, including the multi-layer perceptron neural network (MLPNN) (Barello et al. 2014), RBFNN (Chellam 2005) and recurrent radial basis function neural network (RRBFNN) (Mirbagheri et al. 2015). The structures of these neural networks were selected by trial and error. The input and output variables were the values of the five selected variables and the membrane permeability, respectively. The prediction values and errors of membrane permeability are displayed in Figure 5. The results in Figure 5 show that the proposed intelligent detecting system with RFNN can possess the values of membrane permeability with suitable accuracy.

Table 3 provides a performance comparison; it is clearly shown that the proposed intelligent detecting system with RFNN presents better results in the membrane permeability prediction than the other methods. The results demonstrate that the proposed intelligent detecting system with RFNN can predict the values of membrane permeability efficiently compared with the other methods.

Based on the above simulation results, the proposed intelligent detecting system has been demonstrated to be a suitable and efficient method for predicting the membrane permeability in an MBR. Meanwhile, the proposed method obtains the best RMSE and best prediction accuracy. It
can be stated that the proposed intelligent detecting system is more suitable for predicting membrane permeability.

Experimental results

In this section, the proposed intelligent detecting system is applied to three different real WWTPs. The MBRs of the different WWTPs are operated under different process conditions and operating parameters, as shown in Table 4. It is well known that the different process conditions and operating parameters can lead to different microbial communities, which relates to different reactor performance. Therefore, in order to ensure the applicability and generality of the system, this proposed intelligent detecting system was used in three different real WWTPs.

The experimental results are presented and discussed to illustrate the effectiveness of the proposed intelligent detecting system. Figures 6–8 show the prediction performance of the proposed intelligent detecting system in different WWTPs. The prediction results of membrane permeability are shown in the prediction interface of the intelligent detecting system. There are two lines in the permeability prediction interface, where the green line represents the measured values of permeability, and the red line represents the predicted values of membrane permeability. It is clear to see that the green line is obscured by the red line, which means that the proposed intelligent detecting system has high prediction accuracy in the three WWTPs. Moreover, from the prediction interface, the current and trend values of permeability are displayed. In addition, the pollution trend of the membrane is shown in the prediction interface.

Table 3 | Comparison of the performance with different soft computing methods

<table>
<thead>
<tr>
<th>Methods</th>
<th>Testing RMSE</th>
<th>Prediction accuracy (P)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Deviation</td>
</tr>
<tr>
<td>RFNN</td>
<td>0.3142</td>
<td>0.000442</td>
</tr>
<tr>
<td>MLPNN <em>(Barello et al. 2014)</em></td>
<td>0.7231</td>
<td>0.002107</td>
</tr>
<tr>
<td>RBFNN <em>(Chellam 2005)</em></td>
<td>0.5927</td>
<td>0.001576</td>
</tr>
<tr>
<td>RRBFNN <em>(Mirbagheri et al. 2015)</em></td>
<td>0.4664</td>
<td>0.001321</td>
</tr>
</tbody>
</table>

Table 4 | Specification of MBR in different WWTPs

<table>
<thead>
<tr>
<th>WWTPs</th>
<th>Scale /m³/d</th>
<th>HRT/h</th>
<th>Anaerobic</th>
<th>Anoxic</th>
<th>Aerobic</th>
<th>SRT/d</th>
<th>Membrane module type</th>
<th>Pore size of membrane/μm</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>40,000</td>
<td>1.45</td>
<td>3.15</td>
<td>6.28</td>
<td>18.8</td>
<td>Ultrafiltration</td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>60,000</td>
<td>2.08</td>
<td>9.5</td>
<td>6.18</td>
<td>16.6</td>
<td>Microfiltration</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>23,000</td>
<td>1.60</td>
<td>4.1</td>
<td>6.02</td>
<td>21.7</td>
<td>Microfiltration</td>
<td>0.1</td>
<td></td>
</tr>
</tbody>
</table>

Figure 6 | The actual prediction performance in WWTP1. The full color version of this figure is available in the online version of this paper, at http://dx.doi.org/10.2166/wst.2017.562.
From Figures 6–8, one can see that the proposed intelligent detecting system can effectively predict the values of permeability online. Moreover, to test the detecting performance of the proposed method, the prediction results of the proposed intelligent detecting system (from 1 January 2016 to 31 December 2016) are provided in Tables 4–7 with the mean testing RMSE and prediction accuracy. It can be seen that the proposed intelligent detecting system can predict the values of permeability with an accuracy of around 80%, which is better than some existing methods. Moreover, the intelligent detecting system can work effectively and successfully regardless of application environment and time.

Based on the above analysis, it is observed that the obtained simulation and experimental results are similar, confirming the validation of the proposed intelligent detecting system for permeability detection.

<table>
<thead>
<tr>
<th>Time</th>
<th>RMSE</th>
<th>Prediction accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Jan–31 Mar</td>
<td>0.921</td>
<td>82.5%</td>
</tr>
<tr>
<td>1 Apr–30 Jun</td>
<td>0.883</td>
<td>83.4%</td>
</tr>
<tr>
<td>1 Jul–30 Sept</td>
<td>0.912</td>
<td>81.4%</td>
</tr>
<tr>
<td>1 Oct–31 Dec</td>
<td>1.012</td>
<td>79.8%</td>
</tr>
</tbody>
</table>

Figure 7 | The actual prediction performance in WWTP2. The full color version of this figure is available in the online version of this paper, at http://dx.doi.org/10.2166/wst.2017.562.

Figure 8 | The actual prediction performance in WWTP3. The full color version of this figure is available in the online version of this paper, at http://dx.doi.org/10.2166/wst.2017.562.


Table 6 | Summary of actual prediction performance in WWTP2

<table>
<thead>
<tr>
<th>Time</th>
<th>RMSE</th>
<th>Prediction accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Jan–31 Mar</td>
<td>0.864</td>
<td>85.7%</td>
</tr>
<tr>
<td>1 Apr–30 Jun</td>
<td>0.902</td>
<td>82.9%</td>
</tr>
<tr>
<td>1 Jul–30 Sept</td>
<td>0.873</td>
<td>85.5%</td>
</tr>
<tr>
<td>1 Oct–31 Dec</td>
<td>1.109</td>
<td>78.1%</td>
</tr>
</tbody>
</table>

Table 7 | Summary of actual prediction performance in WWTP3

<table>
<thead>
<tr>
<th>Time</th>
<th>RMSE</th>
<th>Prediction accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Jan–31 Mar</td>
<td>0.922</td>
<td>82.5%</td>
</tr>
<tr>
<td>1 Apr–30 Jun</td>
<td>0.895</td>
<td>85.2%</td>
</tr>
<tr>
<td>1 Jul–30 Sept</td>
<td>0.847</td>
<td>84.1%</td>
</tr>
<tr>
<td>1 Oct–31 Dec</td>
<td>0.893</td>
<td>83.2%</td>
</tr>
</tbody>
</table>

**CONCLUSIONS**

In this paper, an intelligent detecting system is proposed for predicting the values of permeability. The main contributions of the intelligent detecting system are illustrated and discussed in detail, starting from the hardware with the MBR and other equipment for the measurement of process variables, to the software for transmitting the data and embedding the PLS-RFNN soft computing method. The simulation and experimental results both confirm the effectiveness of the proposed intelligent detecting system for predicting permeability.

From a practical point of view, the proposed intelligent detecting system is inexpensive and has a light computational burden. There are some potential benefits to the prediction and supervision of the other variables in WWTPs. The accuracy of the permeability prediction is able to support the potential of the early warning system to detect membrane fouling. Moreover, the expert knowledge will be added to the system to improve the accuracy in our further study.

**ACKNOWLEDGEMENTS**

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