Application of artificial neural network to control the coagulant dosing in water treatment plant


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Abstract: Coagulant dosing is one of the major operation costs in water treatment plant, and conventional control of this process for most plants is generally determined by the jar test. However, this method can only provide periodic information and is difficult to apply to automatic control. This paper presents the feasibility of applying artificial neural network (ANN) to automatically control the coagulant dosing in water treatment plant. Five on-line monitoring variables including turbidity (NTU_{in}), pH (pH_{in}) and conductivity (C_{on}) in raw water, effluent turbidity (NTU_{out}) of settling tank, and alum dosage (Dos) were used to build the coagulant dosing prediction model. Three methods including regression model, time series model and ANN models were used to predict alum dosage. According to the result of this study, the regression model performed a poor prediction on coagulant dosage. Both time-series and ANN models performed precise prediction results of dosage. The ANN model with ahead coagulant dosage performed the best prediction of alum dosage with a R^2 of 0.97 (RMS =0.016), very low average predicted error of 0.75 mg/L of alum were also found in the ANN model. Consequently, the application of ANN model to control the coagulant dosing is feasible in water treatment.

Keywords: Artificial neural network; coagulant dosing; real-time control; on-line monitoring; water treatment plant

Introduction

Coagulation, flocculation, sedimentation and filtration processes are the most typical units of a water treatment plant in Taiwan. Coagulant dosing is not only one of the major control parameter in coagulation process, but also the major operation cost in water treatment plant. Most coagulant dosing is determined by the way of jar test. However, the jar test can only provide periodic operation information, which can not be applied to real-time control of the coagulation process, especially with a time-varying raw water quality. Since the coagulation and flocculation process involve complex chemical and physical phenomena, therefore, conventional process control used in chemical engineering is difficult to apply (Mirsepassi, et al. 1995). However, the ANN has been viewed as being very effective in representing the relationships between the input and output variables in complex systems (Capodaglio et al., 1991, Cote et al., 1995). The Artificial Neural Networks (ANNs), especially Back-propagation Neural Network (BPN), has been widely used to address the problems of system forecasting and diagnosing in the fields of industry, business and engineering (Zadeh, 1994; Widrow et al., 1994).

Some ANN models were developed to predict the coagulant dosing of water treatment process. Baba et al. (1990) had proposed an ANN model to analysis the correlation between water treatment parameters and chemical dosages from a plant with effective water treatment. A fuzzy neural system, coupling of ANN with fuzzy theory, has been applied to extract the control rules by learning history operational data of water treatment process (Enbutsu et al., 1993). Kim and Oh (1995) had proposed a multi-layered perceptron neural network to predict the ratio of chemicals dosing for coagulation. The ANN and Box–Jenkins (ARIMA) models have been applied to forecast the alum and polymer
dosages, and the ANN showed better results than Box–Jenkins model in predicting alum as well as polymer dosages (Mirsepassi, et al. 1997).

Most above studies constructed the coagulant dosing prediction model using the daily data. However, the turbidity of raw water may vary from 10 NTU to over 100 NTU in few minutes during rainy season in Taiwan (Kan and Huang, 1998). Therefore, a coagulation prediction model with daily data may not be adequate. In this study, five on-line monitoring variables including turbidity (T_in), pH (pH_in) and conductivity (C_in) in raw water; effluent turbidity (T_e) of settling tank; and alum dosage (Al) were collected every 15 minutes during the period of one year from a full-scale water treatment plant in Taipei city. In this water treatment plant, the chemical dosing was optimized by a multi-parameter model, which contains feed-back and feed-forward control approaches (Shin and Chiang, 1997).

Methodology
Three types of model including regression model, time-series model and ANN model were used to build the coagulant dosing prediction model.

Regression model
Two regression models including linear regression and nonlinear regression models were used in this study, and shown as follows:

**Linear regression:**
\[ \text{Dosage} = \alpha + a(\text{NTU}_\text{in}) + b(\text{Con.}) + c(pH) + d(\text{NTU}_\text{out}) \]  

**Nonlinear regression:**
\[ \text{Dosage} = \alpha + a(\text{NTU}_\text{in})^K_1 \times (\text{Con.})^{K_2} \times (pH)^{K_3} \times (\text{NTU}_\text{out})^{K_4} \]  

Time series model
An ARIMA (auto-regressive integrated moving average) time series model with Box–Jenkins approach was used in this study. The general Box–Jenkins model is described as equation 3, and software of Time Series Processor (TSP) was used.

\[ \phi_p(B) \phi_p(B^L)(1-B^L)^D(1-B)^d y_t = \delta + \theta_q(B)\theta_q(B^L)a_t \]  

Artificial neural network model
The back-propagation neural network was used in this study and demonstrated in Fig. 1, which consists of three layers; viz. one input, hidden and output layers. Calculations between input vector (X_i), hidden vector (Z_j) and output vector (Y_k) were defined by the following equations:

**Hidden layer:**
\[ Z_j = f \left( \sum_{i=1}^{I} W_{ij} \times X_i \right) \]  

**Output layer:**
\[ Y_k = f \left( \sum_{j=1}^{J} W_{jk} \times Z_j \right) \]  

where: X_i, Z_j and Y_k are input, hidden and output vectors, respectively.

\[ W_{ij} \text{ and } W_{jk} \] are weights from X_i to Z_j and, Z_j to Y_k.

\[ f(\cdot) \], the activation/transfer function: \[ f(x) = \frac{1}{1 + e^{-x}} \]  

In this BPN model, the generalized delta learning rule was used as training algorithm for
network learning, and the gradient descent method was used to minimize the errors. Sigmoid function was used as activation function. Root Mean Square (RMS) was used to evaluate the performance of training and testing procedures. The software used in this study was the program developed by Yeh (1993) for a personal computer.

\[ RMS = \sqrt{\frac{\sum (T_k - Y_k)^2}{N_{out}}} \]  

(6)

where: \( T_k \) and \( Y_k \) are the target and output vectors in BPN
\( N_{out} \): the number of output elements.

**Results and discussion**

**Regression model**

From the results of correlation analysis on selected parameters, the key factors for coagulant dosing are NTU\(_{in}\) (\( R^2 = 0.62 \)) and NTU\(_{out}\) (\( R^2 = 0.45 \)). Therefore, NTU\(_{in}\) and NTU\(_{out}\) are contained in all regression models.

The predicted results of linear and nonlinear regression models are listed in Table 1. All the regression models present poor results in predicting coagulant dosing. The prediction results of nonlinear regression are more precise than linear regression models. The nonlinear regression models of R8 and R10 performed the highest correlation coefficient (\( R^2 \)) of 0.79 between predicted and observed coagulant dosing.

**Time series model**

Since the quality of raw water is regarded with time-series attributes, and the coagulant dosing is highly correlating to the raw water as time-series events, therefore, time-series model is practical to be used to forecast the coagulant dosing. In this study, a series of time-series models including single input parameter and multi-parameter were used to predict the coagulant dosing, and the details of input parameters and correlation coefficients (\( R^2 \)) are shown in Table 2. All of the time-series models performed high correlation coefficients (over 0.9) between predicted and observed coagulant dosing, which are higher than those predicted by regression models. The time-series model of T1 with single input parameter shows the best prediction result.

**Artificial neural network model**

The prediction results by ANN model without ahead coagulant dosing are listed in Table 3, and poor performance was found. However, both models of A1 and A2 performed better at forecasting results than those of linear regression models. They also showed higher \( R^2 \) of 0.77 and 0.49 than those of correlation analysis on NTU\(_{in}\) (\( R^2 = 0.62 \)) and NTU\(_{out}\) (\( R^2 = 0.45 \)). This finding indicates that ANN is more effective in representing the relationships between the input and output variables of coagulant dosing prediction in water treatment plant.
Since the coagulant dosing is highly correlating to the raw water as time-series events, the ANN model with ahead coagulant dosing was used. Table 4 lists the prediction results of ANN model with ahead coagulant dosing. It was found that all ANN models performed precise results. High correlation coefficients (over 0.9) between predicted and observed coagulant dosages were found, which are little higher than those predicted by time-series models. The ANN model with four-step-ahead coagulant dosages (A7) showed the most precise prediction with a $R^2$ of 0.93.

Some multi-parameter ANN models were also developed to improve the accuracy of prediction of coagulant dosing. The ANN model A13 with multi-parameter of four-step-ahead coagulant dosage, turbidity of raw water and turbidity of effluent performed the highest $R^2$ of 0.97 (Table 4). Comparison of observed and predicted coagulant dosing by ANN model A13 is shown in Fig. 2.

The predicted errors of ANN model A13 were also investigated and are shown in Table 5. Very low average predicted error of 0.75 mg/L of coagulant dosing was found. Higher predicted errors were found with higher coagulant dosage conditions. However, the probability of high dosages is relatively low. Normally, most of the coagulant dosages, approximately 97%, are less than 30 mg/L of alum. In this dosing range, the predicted errors are always less than 1.2 mg/L of alum. Moreover, approximately 70% of alum dosages are less than 15 mg/L. The predicted errors are even less than 0.5 mg/L in this dosing period.

Conclusions

| Table 1 Predictions of coagulant dosing by regression models |
|----------------|----------------|
| Model | Equation | $R^2$ |
| R1 | $\text{Dos.} = 7.03 + 0.218(\text{NTU}_{in}) + 0.788(\text{NTU}_{out})$ | 0.69 |
| R2 | $\text{Dos.} = 15.52 + 0.282(\text{NTU}_{in}) - 0.014(\text{Con.}) - 0.701(\text{pH})$ | 0.62 |
| R3 | $\text{Dos.} = 7.184 + 0.218(\text{NTU}_{in}) - 0.0018(\text{Con.}) + 0.786(\text{NTU}_{out})$ | 0.69 |
| R4 | $\text{Dos.} = 6.96 + 0.218(\text{NTU}_{in}) + 0.10(\text{pH}) + 0.788(\text{NTU}_{out})$ | 0.69 |
| R5 | $\text{Dos.} = 7.746 + 0.035(\text{Con.}) + 0.187(\text{pH}) + 1.546(\text{NTU}_{out})$ | 0.46 |
| R6 | $\text{Dos.} = 7.03 + 0.22(\text{NTU}_{in}) - 0.002(\text{Con.}) + 0.02(\text{pH}) + 0.79(\text{NTU}_{out})$ | 0.69 |
| R7 | $\text{Dos.} = 11.07(\text{NTU}_{in})^{0.374}(\text{Con.})^{0.241}(\text{pH})^{0.927}(\text{NTU}_{out})^{0.056}$ | 0.78 |
| R8 | $\text{Dos.} = 23.39(\text{NTU}_{in})^{0.36}(\text{pH}) - 0.75(\text{NTU}_{out})^{0.054}$ | 0.79 |
| R9 | $\text{Dos.} = 2.27(\text{NTU}_{in})^{0.36}(\text{Con.})^{0.19}(\text{pH})^{0.074}$ | 0.71 |
| R10 | $\text{Dos.} = 5.346(\text{NTU}_{in})^{0.353}(\text{NTU}_{out})^{0.071}$ | 0.79 |

Table 2 Predictions of coagulant dosing by time series models

<table>
<thead>
<tr>
<th>Model</th>
<th>Equation</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>$\text{Dos.} = f(\text{Dos}<em>{t}, \text{Dos}</em>{t-1}, \text{Dos}_{t-2})$</td>
<td>0.92</td>
</tr>
<tr>
<td>T2</td>
<td>$\text{Dos.} = f(\text{Con.}, \text{Dos}<em>{t-1}, \text{Dos}</em>{t-2})$</td>
<td>0.91</td>
</tr>
<tr>
<td>T3</td>
<td>$\text{Dos.} = f(\text{Con.}, \text{pH}, \text{Dos}<em>{t-1}, \text{Dos}</em>{t-2})$</td>
<td>0.90</td>
</tr>
<tr>
<td>T4</td>
<td>$\text{Dos.} = f(\text{NTU}<em>{in}, \text{NTU}</em>{out}, \text{Dos}<em>{t-1}, \text{Dos}</em>{t-2})$</td>
<td>0.91</td>
</tr>
<tr>
<td>T5</td>
<td>$\text{Dos.} = f(\text{NTU}<em>{in}, \text{Con.}, \text{NTU}</em>{out}, \text{Dos}<em>{t-1}, \text{Dos}</em>{t-2})$</td>
<td>0.91</td>
</tr>
<tr>
<td>T6</td>
<td>$\text{Dos.} = f(\text{NTU}<em>{in}, \text{pH}, \text{NTU}</em>{out}, \text{Dos}<em>{t-1}, \text{Dos}</em>{t-2})$</td>
<td>0.90</td>
</tr>
<tr>
<td>T7</td>
<td>$\text{Dos.} = f(\text{NTU}<em>{in}, \text{Con.}, \text{pH}, \text{NTU}</em>{out}, \text{Dos}<em>{t-1}, \text{Dos}</em>{t-2})$</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Table 3 Predictions of coagulant dosing by ANN without ahead coagulant dosages

<table>
<thead>
<tr>
<th>Model</th>
<th>Input layer</th>
<th>Training RMS</th>
<th>Testing RMS</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>$\text{NTU}_{in}$</td>
<td>0.046</td>
<td>0.045</td>
<td>0.77</td>
</tr>
<tr>
<td>A2</td>
<td>$\text{NTU}_{out}$</td>
<td>0.086</td>
<td>0.097</td>
<td>0.49</td>
</tr>
<tr>
<td>A3</td>
<td>$\text{NTU}<em>{in}, \text{NTU}</em>{out}$</td>
<td>0.047</td>
<td>0.044</td>
<td>0.80</td>
</tr>
<tr>
<td>A4</td>
<td>$\text{NTU}<em>{in}, \text{Con.}, \text{pH}, \text{NTU}</em>{out}$</td>
<td>0.045</td>
<td>0.044</td>
<td>0.80</td>
</tr>
</tbody>
</table>
This paper presents the application of ANN model to predict the coagulant dosing. On-line data collected every 15 minutes over the period of one year from a full-scale water treatment plant of was used to build the model. All the regression models present poor results in predicting coagulant dosing. All the time-series models performed high correlation coefficients (over 0.9) between predicted and observed coagulant dosing, and single input time series model (T1) shows the best result. The ANN with input parameter of ahead coagulant dosing performed precise forecasting results, which are little higher than those of time series models. The ANN model with four-step-ahead of coagulant dosage, turbidity of raw water and turbidity of effluent performed the highest R² of 0.97. Most of the coagulant dosages in this plant, approximate 97%, are less than 30 mg/L of alum, and the predicted errors by A13 are less 1.2 mg/L of alum in this dosing range. Approximately 70% of alum dosages are less than 15 mg/L. The predicted errors are even less than 0.5 mg/L in this

![Figure 2 C ontrolled of observed and predicted coagulant dosing by ANN model A13](image_url)

Table 4 Predictions of coagulant dosing by ANN with ahead coagulant dosages

<table>
<thead>
<tr>
<th>Model</th>
<th>Input layer</th>
<th>Training RMS</th>
<th>Testing RMS</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>A5</td>
<td>Dos(t-1)</td>
<td>0.030</td>
<td>0.028</td>
<td>0.90</td>
</tr>
<tr>
<td>A6</td>
<td>Dos(t-1, t-2)</td>
<td>0.027</td>
<td>0.027</td>
<td>0.91</td>
</tr>
<tr>
<td>A7</td>
<td>Dos(t-1 to t-4)</td>
<td>0.027</td>
<td>0.026</td>
<td>0.92</td>
</tr>
<tr>
<td>A8</td>
<td>Dos(t-1 to t-8)</td>
<td>0.028</td>
<td>0.027</td>
<td>0.91</td>
</tr>
<tr>
<td>A9</td>
<td>Dos(t-1 to t-16)</td>
<td>0.030</td>
<td>0.029</td>
<td>0.90</td>
</tr>
<tr>
<td>A10</td>
<td>NTU_in, Dos(t-1 to t-4)</td>
<td>0.027</td>
<td>0.026</td>
<td>0.93</td>
</tr>
<tr>
<td>A11</td>
<td>NTU_in, NTU_out, Dos(t-1, t-2)</td>
<td>0.025</td>
<td>0.024</td>
<td>0.94</td>
</tr>
<tr>
<td>A12</td>
<td>NTU_in, NTU_out, Dos(t-1 to t-4)</td>
<td>0.026</td>
<td>0.022</td>
<td>0.95</td>
</tr>
<tr>
<td>A13</td>
<td>NTU_in(t-1 to t-4), NTU_out(t-1 to t-4), Dos(t-1 to t-4)</td>
<td>0.020</td>
<td>0.016</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Table 5 Analysis of predicted errors by ANN model A13

<table>
<thead>
<tr>
<th>Range of coagulant dosage (mg/L)</th>
<th>Probability of dosage (%)</th>
<th>Predicted error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Average (mg/L)</td>
</tr>
<tr>
<td>60-90</td>
<td>0.4</td>
<td>4.2</td>
</tr>
<tr>
<td>50-60</td>
<td>0.4</td>
<td>3.4</td>
</tr>
<tr>
<td>40-50</td>
<td>0.8</td>
<td>1.8</td>
</tr>
<tr>
<td>30-40</td>
<td>1.7</td>
<td>1.9</td>
</tr>
<tr>
<td>20-30</td>
<td>14.9</td>
<td>1.2</td>
</tr>
<tr>
<td>15-20</td>
<td>11.3</td>
<td>0.9</td>
</tr>
<tr>
<td>10-15</td>
<td>42.7</td>
<td>0.4</td>
</tr>
<tr>
<td>5-10</td>
<td>27.8</td>
<td>0.5</td>
</tr>
<tr>
<td>Overall</td>
<td>100</td>
<td>0.75</td>
</tr>
</tbody>
</table>
dosing range. Moreover, the ANN model is easy to develop and operate by comparison with time-series models. Consequently, the ANN model is a practical method to control the coagulant dosing in water treatment plants.

Acknowledgements
The financial support from Water Works Association of the R. O. C. is gratefully acknowledged.

References


