Using fuzzy inference system to improve neural network for predicting hospital wastewater treatment plant effluent


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ABSTRACT

In this study, three types of adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) were employed to predict suspended solids (SS d) and chemical oxygen demand (COD d) in the effluent from a hospital wastewater treatment plant. The results indicated that ANFIS statistically outperforms ANN in terms of effluent prediction. The minimum mean absolute percentage errors of 11.95% and 12.75% for SS d and COD d could be achieved using ANFIS. The maximum values of correlation coefficients for SS eff and COD eff were 0.75 and 0.92, respectively. The minimum mean square errors of 0.17 and 0.19, and the minimum root mean square errors of 0.41 and 0.42 for SS eff and COD eff could also be achieved. ANFIS's architecture consists of both ANN and fuzzy logic including linguistic expression of membership functions and if-then rules, so it can overcome the limitations of traditional neural network and increase the prediction performance.

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1. Introduction

The activated sludge process (ASP) in which the pollutant degradation mainly results from microbial reaction has long been used for industrial wastewater treatment as well as for hospital wastewater treatment plant (HWWTP). Since the raw hospital wastewater contains several thousand types of medicines, chemicals, and even antibiotic agents, some problems will be yielded when adopting ASP in HWWTP. The literatures showed that many water quality indices were investigated to implement detailed study or to valid mechanistic models such as activated sludge model (ASM) or Taiwan extension activated sludge model No. 1 (TWESAM A) (Henze, Gujer, Mino, & Van Loosdrecht, 2000; Pai, 2007; Pai et al., 2009). So the more the items for wastewater characterization are, the more the reactions in ASP can be understood. In our previous work, different mechanistic models were employed to describe these reactions in ASP (Pai, OuYang, Su, & Leu, 2001a, 2001b; Pai, Tsai, et al., 2004; Pai, Chuang, Tsai, & OuYang, 2004; Pai, 2007; Pai et al., 2009).

In Taiwan, if the effluent comes from the designated sewers of communities or other residential area, only four effluent characteristics, i.e., suspended solids (SS), biochemical oxygen demand (BOD), chemical oxygen demand (COD) and true color, were regulated according to effluent quality investigation from HWWTPs were only carried out to meet regulation standard, so their investigation data were few and incomplete compared with general study cases. Under this situation, the effluent quality trend could not be predicted accordingly using some numerical models, especially mechanistic models. Some soft computation techniques, such as artificial neural network (ANN), in which the mechanism reactions can be ignored are available presently and applied in biological wastewater treatment process (Aubrun, Thelliol, Harmand, & Steyer, 2001; Baruch, Georgieva, Barrera-Cortes, & Feyo de Azevedo, 2005; Cote, Grandjean, Lessard, & Thibault, 1995; Griu, Traore, Pollet, & Colprin, 2005; Contarski, Rodrigues, Mori, & Prenem, 2000; Hack & Kohne, 1996; Holubar et al., 2002; Hong, Lee, & Park, 2007; Kim et al., 2006; Lee, Jeon, Park, & Chang, 2002; Lee, Lee, Woo, Kim, & Park, 2006; Luccarini et al., 2002; Machón, López, Rodríguez-Iglesias, Marañón, & Vázquez, 2007; Moral, Aksay, & Gokcay, 2008; Pai, Tsai, Lo, Tsai, & Lin, 2007; Pai, Ho, et al., 2008; Pai, Wan, et al., 2008; Pai, in press; Ren, Chen, Wang, Hu, & Wang, 2005; Simenov & Chorukova, 2004; Sinha, Bose, Jawed, John, & Tare, 2002; Zhua, Zurcher, Raoc, & Menga, 1998; Zeng et al., 2003). Although ANN can predict the effluent from HWWTPs successfully, traditional neural network schemes still have several limitations which are resulted from possibility of getting trapped in local minimum, and the choice of model architecture. If the predicting performance can be further promoted, better operation strategy can be formed.
overcome these limitations of traditional ANNs, and to increase their reliability, many new training algorithms have been proposed such as adaptive neuro fuzzy inference system (ANFIS) (Jang, 1993). ANFIS's architecture consists of both ANN and fuzzy logic including linguistic expression of membership functions (MFs) and if-then rules. ANFIS has been successfully applied in many fields such as automated control, water resource management, fishing catch (Abolpour, Javana, & Karamouz, 2007; Calmăceli, 2007; Chang & Chang, 2006; Chau, Wu, & Li, 2005; Civelekoglu, Perendeci, Yigit, & Kurtis, 2007; Furt & Güngör, 2007; Iglesias, Dafonte, Arcay, & Cotos, 2007; Kalyanaraman & Aklandeswar, 2005; Karthikeyan, Sabarathinam, & Arunselvi, 2005; Perendeci, Arslan, Tanyolaç, & Çelebi, 2007; Raman, Arunselvi, & Geetha, 2005; Sterry, Rolland, Bouvier, & Moletta, 1997; Tav & Zhang, 1999, 2000; Varol, Avet, Koca, & Ortop, 2007; Yordanova, Petrova, Mastorakis, & Miladov, 2006; Yu & Qiao, 2006). However, no study has been applied in prediction of effluent quality from HWWT using ANFIS.

Since the predicting performance of ANFIS is good, so the objectives of this study are listed as follows. (1) Implement ANFIS to establish the relationship between effluent and influent quality of a HWWT in which the continuous sequence batch reactor (CSBR) process was applied, then to predict the effluent quality. (2) For comparison, ANN was also employed to predict the effluent in this study.

2. Materials and methods

2.1. Treatment process

The CSBR ASP was adopted in this HWWT. The flow rate was 200 cubic meters per day (CMD) and the effective volume of reactor was 190 m³. The process scheme and the performance of this HWWT are shown in Fig. 1 and Table 1, respectively. The influent and effluent quality from 3rd of June 2002 to 27th of June 2003 were investigated. They were sampled and investigated every 2-3 days and their total numbers were 146. Among the total numbers of data, the numbers for training and testing (predicting) were 100 and 46, respectively. The influent wastewater quality indices included influent pH (pH_{infl}), influent temperature (T_{infl}), influent SS (SS_{infl}), and influent COD (COD_{infl}). The effluent wastewater quality indices included effluent SS (SS_{eff}), effluent COD (COD_{eff}), and effluent pH (pH_{eff}). All analytical methods used in this study were according to Standard Method (APHA, 1995).

![](image)

**Fig. 1. Process scheme of HWWT.**

<table>
<thead>
<tr>
<th>Table 1</th>
<th>The performance of the HWWT.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SS (mg L⁻¹)</td>
</tr>
<tr>
<td>Influent maximum value</td>
<td>338.0</td>
</tr>
<tr>
<td>Influent median value</td>
<td>91.0</td>
</tr>
<tr>
<td>Influent minimum value</td>
<td>6.0</td>
</tr>
<tr>
<td>Effluent average value</td>
<td>278.0</td>
</tr>
<tr>
<td>Effluent average value</td>
<td>36.9</td>
</tr>
<tr>
<td>Effluent standard deviation</td>
<td>0.7</td>
</tr>
</tbody>
</table>

2.2. Brief description on ANFIS

Both artificial neural network and fuzzy logic are adopted in ANFIS's architecture in which if-then rules with appropriate MFs and the specified input-output pairs are used. The learning algorithms of neural network are used for ANFIS training. Two methods are employed for updating MF parameters in ANFIS learning; (1) backpropagation for all parameters (steepest descent method), and (2) backpropagation for the parameters associated with the input MFs and least squares estimation for the parameters associated with the output MFs. Subsequently, the training errors decrease, at least locally, during the learning procedure. The more the initial MFs resemble the optimal ones, the more quickly the training parameters converge (Jang, 1992, 1993, 1996; Jang & Sun, 1993, 1995; Jang & Gulley, 1995; Jang, Sun, & Mizutani, 1997).

When adopting ANFIS, 2 parameters with higher correlation coefficients (ANFIS2-1), 3 parameters with higher correlation coefficients (ANFIS3-1) and all 4 parameters (ANFIS4-1) were taken as the input layer variables, respectively. Meanwhile each effluent quality, i.e. SS_{eff} and COD_{eff} was the single output layer variable.

To compare with ANFIS, 2 parameters with higher R (ANN2-1), 3 parameters with higher R (ANN3-1) and all 4 parameters (ANN4-1) were taken as the input layer variables, respectively. Meanwhile each effluent quality, i.e. SS_{eff} and COD_{eff}, was the single output layer variable. The calculation of both ANFIS and ANN were carried out using MATLAB.

2.3. Evaluation of predicting performance

In order to evaluate the predicting performance of ANFIS and ANN, the mean absolute percentage error (MAPE), correlation coefficient (R), mean square error (MSE), and root mean square error (RMSE) were employed and described as

\[
\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{|\text{obs}_i - \text{pre}_i|}{\text{obs}_i} \times 100\%
\]

\[
R = \frac{\left(\sum_{i=1}^{n} \left(\text{obs}_i - \text{obs} \times \text{pre}_i - \text{pre}_i\right)\right)^2}{\left(\sum_{i=1}^{n} \left(\text{obs}_i - \text{obs} \times \text{pre}_i - \text{pre}_i\right)\right)^2}
\]

In Table 1, the performance of the HWWT is shown.
MSE = \frac{1}{n} \sum_{i=1}^{n} (obs_i - pre_i)^2 \tag{3}

RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (obs_i - pre_i)^2} \tag{4}

where obs_i is the observed value, pre_i is the prediction value, obs and pre are the average values of observed values and prediction values, respectively.

3. Results and discussion

3.1. Variation trend of water quality

The numbers of data investigated from June 2002 to June 2003 were totally 146, as shown in Fig. 2. Among the total numbers of data, the numbers for training and testing (predicting) were 100 and 46, respectively. In Taiwan, the effluent regulation limits of SS_{ef} and COD_{ef} were 30 mg L^{-1} and 100 mg L^{-1}, respectively. The effluent quality from this HWWTP met the Effluent Standard of Taiwan.

3.2. Correlation coefficients between influent and effluent quality

To observe which influent wastewater quality index affected the effluent quality significantly, the correlation coefficients (R) between the effluent quality (SS_{ef} and COD_{ef}) and four different influent wastewater quality indices (pH_{in}, Temp_{in}, SS_{in}, and COD_{in}) were calculated as shown in Table 2. The R values of SS_{ef} were in the order: SS_{ef} (-0.01743) > Temp_{in} (-0.06446) > pH_{in} (-0.11065) > COD_{ef} (-0.17106). Those of COD_{ef} were in the order: Temp_{in} (-0.01301) > pH_{in} (-0.01919) > SS_{in} (-0.06474) > COD_{ef} (-0.12941). Based on the results of R values, the selected input variables in three types of ANFIS (ANFIS4-1, ANFIS3-1 and ANFIS2-1) and ANN (ANN4-1, ANN3-1 and ANN2-1) were shown in Table 3.

<table>
<thead>
<tr>
<th>Table 2</th>
<th>The correlation coefficients between the effluent quality and influent quality.</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS_{ef}</td>
<td>pH_{in}</td>
</tr>
<tr>
<td>SS_{ef}</td>
<td>0.01743</td>
</tr>
<tr>
<td>COD_{ef}</td>
<td>-0.06474</td>
</tr>
</tbody>
</table>

3.3. Determination of an appropriate ANFIS and ANN model

The types and numbers of MFs in ANFIS including Gaussian, generalized bell-shaped, triangular and trapezoidal shaped functions, and the parameters were tested to determine an appropriate ANFIS model. The choosing criteria for selecting best final architecture were based on the values of MAPE and R between the model output values and observed values. After many trials in which backpropagation for the parameters were implemented, the final architectures of the ANFIS models are given in Table 4. With different input variables, all ANFIS models had generalized bell-shaped MFs gave the best result. The numbers of MFs for each input variables in ANFIS4-1, ANFIS3-1 and ANFIS2-1 were 4, 4, and 6, respectively. Their numbers of training were 120 which were determined according to the values of MAPE and R between the model output values and observed values. The numbers of fuzzy rules in ANFIS models which showed the highest accuracy are also provided in Table 4. The rule base reflected the physical property of the system meanwhile each rule represented a certain type of reaction or operating region (Calma, 2007). Obviously, there were too many fuzzy rules to show them completely. In the mechanically based modeling technique, the influent wastewater quality indices and operation parameters were adopted as the input variables. Then the mechanic models which consisted of lots of differential equations and first order kinetic reactions outputted the results which were calculated according to mass balance concept (Pai et al., 2001a, 2001b; Pai, Tsai, et al., 2004; Pai, Chuang, et al., 2004; Pai, et al., 2009; Pai, 2007). In the ANFIS-based modeling technique, the influent wastewater quality indices or operation parameters could be chosen as the input variables. Although the mechanisms were unclear, the whitening part of the ANFIS-based model (which is the set of

<table>
<thead>
<tr>
<th>Table 3</th>
<th>The selected input variables in ANFIS and ANN.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANFIS</td>
<td>Structure</td>
</tr>
<tr>
<td>SS_{ef}</td>
<td>ANFIS2-1</td>
</tr>
<tr>
<td>ANFIS3-1</td>
<td>ANN3-1</td>
</tr>
<tr>
<td>ANFIS4-1</td>
<td>ANN4-1</td>
</tr>
<tr>
<td>COD_{ef}</td>
<td>ANFIS2-1</td>
</tr>
<tr>
<td>ANFIS3-1</td>
<td>ANN3-1</td>
</tr>
<tr>
<td>ANFIS4-1</td>
<td>ANN4-1</td>
</tr>
</tbody>
</table>
fuzzy rules could serve as useful references to help operators realize more operation conditions.

To compare with ANFIS, the appropriate ANN models were also shown in Table 4. All ANN consisted of three independent layers: input, hidden, and output layers. The hidden layer was comprised of 6 operating neurons. The numbers of training were between 12,000 and 18,000.

3.4. Simulation of $SS_{off}$

All MAPE, R, MSE, and RMSE values for $SS_{off}$ are shown in Table 4. When training, the MAPE values of 14.72–17.42% using ANFIS were lower than those of 22.10–25.43% using ANN. The MAPE values of 11.98–13.65% using ANFIS were also lower than those of 15.08–19.81% using ANN when predicting. When training, the R values of 0.86–0.88 using ANFIS were higher than those of 0.59–0.87 using ANN. The R values of 0.67–0.75 using ANFIS were also higher than those of 0.16–0.71 using ANN when predicting. When training, the MSEs of $SS_{off}$ were between 0.12 and 0.16 using ANFIS, but they were 0.25–0.34 using ANN. When predicting, the MSEs lay between 0.17 and 0.20 adopting ANFIS, but they were between 0.28 and 0.67 when using ANN. The RMSE values of 0.33–0.39 using ANFIS were lower than those of 0.50–0.59 using ANN when model training. When predicting, the RMSE values of 0.41–0.45 using ANFIS were also lower than those of 0.53–0.92 using ANN. After comparison, the best structures for ANFIS and ANN were ANFIS2-1 and ANN2-1, respectively. Fig. 3(a) and (b) depicts the training and predicting results using ANFIS2-1 and ANN2-1, respectively (Table 5).
Table 5
Predicting performance using different ANFIS and ANN.

<table>
<thead>
<tr>
<th></th>
<th>ANFIS</th>
<th>ANFIS3-1</th>
<th>ANFIS2-1</th>
<th>ANFIS4-1</th>
<th>AN4-1</th>
<th>AN3-1</th>
<th>AN2-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS_0</td>
<td>Train</td>
<td>17.42</td>
<td>15.56</td>
<td>14.72</td>
<td>25.43</td>
<td>23.38</td>
<td>22.10</td>
</tr>
<tr>
<td></td>
<td>Predict</td>
<td>13.65</td>
<td>12.87</td>
<td>11.90</td>
<td>15.81</td>
<td>16.27</td>
<td>15.06</td>
</tr>
<tr>
<td>MAPE(%)</td>
<td>Train</td>
<td>0.86</td>
<td>0.87</td>
<td>0.88</td>
<td>0.59</td>
<td>0.65</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>Predict</td>
<td>0.67</td>
<td>0.71</td>
<td>0.75</td>
<td>0.66</td>
<td>0.68</td>
<td>0.71</td>
</tr>
<tr>
<td>K</td>
<td>Train</td>
<td>0.16</td>
<td>0.13</td>
<td>0.12</td>
<td>0.34</td>
<td>0.29</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>Predict</td>
<td>0.20</td>
<td>0.19</td>
<td>0.17</td>
<td>0.67</td>
<td>0.31</td>
<td>0.28</td>
</tr>
<tr>
<td>MSE</td>
<td>Train</td>
<td>0.39</td>
<td>0.36</td>
<td>0.32</td>
<td>0.50</td>
<td>0.54</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>Predict</td>
<td>0.45</td>
<td>0.43</td>
<td>0.41</td>
<td>0.82</td>
<td>0.56</td>
<td>0.53</td>
</tr>
<tr>
<td>RMSE</td>
<td>Train</td>
<td>5.88</td>
<td>5.81</td>
<td>5.56</td>
<td>11.14</td>
<td>7.20</td>
<td>5.70</td>
</tr>
<tr>
<td></td>
<td>Predict</td>
<td>6.51</td>
<td>4.80</td>
<td>4.42</td>
<td>11.25</td>
<td>8.37</td>
<td>6.70</td>
</tr>
</tbody>
</table>

3.5. Simulation of COD_{eff}

All MAPE, K, MSE, and RMSE values for COD_{eff} are also shown in Table 4. When training, MAPEs between the predicted and observed values of COD_{eff} were between 15.15% and 17.95% using ANFIS, but they were 23.06–38.88% using ANN. When predicting, the MAPEs lay between 12.75% and 14.30% adopting ANFIS, but they were between 20.22% and 48.82% when using ANN. When training, K values increased from 0.36–0.85 to 0.84–0.88 using ANFIS. When predicting, K values also increased from 0.34–0.82 to 0.85–0.92. MSE and RMSE values also showed that the predicting performance of ANFIS prevailed. The MSE values of 30.94–43.28 using ANFIS were lower than those of 32.45–124.00 using ANN when model training. When predicting, the MSE values of 19.58–42.34 using ANFIS were also lower than those of 37.25–126.82 using ANN. When training, the RMSE values of 5.56–6.58 using ANFIS were lower than those of 5.70–11.14 using ANN. The RMSE values of 4.42–6.51 using ANFIS were also lower than those of 6.10–11.26 using ANN when predicting. After comparison, the best structures for ANFIS and ANN were ANFIS2-1 and ANN2-1, respectively. Fig. 4(a) and (b) shows the training and predicting results using ANFIS2-1 and ANN2-1, respectively.

Fig. 4. Prediction results of COD_{eff}. (a) ANFIS2-1 and (b) ANN2-1.
Comparable observations were similarly made by Cote et al. (1995). Cote et al. (1995) compared different types of model by which the effluent from an industrial WWTP was predicted. They found that the MAPEs lay between 37.1–206% using mechanistic model and 31.69% even using mechanistic model with optimized parameters. When they adopted hybrid model, the MAPEs decreased to 16.3–46.8% significantly. In the study proposed by Gontarski et al. (2000), ANN was used to predict the effluent total organic carbon (TOC) from an IWWTP. Since TOC was the single output layer variable, high fitness was achieved. The results showed that the RMSE values were between 0.0229 and 0.0463 for testing. R values fell in the range of 0.9615 and 0.9812. In our previous work in which the hospital effluent was predicted, the minimum MAPEs of prediction were 19.81% and 48.22%, respectively using ANN (Pai et al., 2007). Cakmakci (2007) used ANFIS to predict the effluent volatile solids (VS) and methane yield from the anaerobic digestion system of primary sludge in municipal WWTP. The results indicated that the R² value of effluent VS concentration was 0.80 for testing, the value of methane yield was 0.90. R² values showed good results.

In this study, the minimum MAPEs of 11.99% and 12.75% for SSₜₐ₇ and CODₜₑₓ₇ could be achieved using ANFIS. The maximum R values for SSₜₐ₇ and CODₜₑₓ₇ were 0.74 and 0.92, respectively. The maximum MSEs of 0.17 and 19.58, and the minimum RMSEs of 0.41 and 4.42 for SSₜₐ₇ and CODₜₑₓ₇ could also be achieved. ANFIS's architecture consists of both ANN and fuzzy logic including linguistic express of MFs and if-then rules, so it can overcome the limitations of traditional neural network including possibility of getting trapped in local minimum and the choice of model architecture, and to increase the predicting performance. With different structure, ANFIS-2 models gave the best result. The significant influent wastewater quality indices were selected as the input variables in accordance with the R evaluation. The input variables of ANFIS-2 belonged to the two most significant influent wastewater quality indices. It was the reason why ANFIS-2 outperformed other structures. Since the influent indices were adopted in the input layer and good predicting results were gained, it indicated that the influent indices could be applied on the prediction of effluent quality.

4. Conclusions

Three types of ANFIS were used to predict SSₜₐ₇ and CODₜₑₓ₇ from a IWWTP in Taiwan. The ANN was also adopted for comparison. The simulation results can be drawn as follows.

- According to the results, ANFIS could predict the effluent variation. The maximum MAPEs of 11.99% and 12.75% for SSₜₐ₇ and CODₜₑₓ₇ could be achieved using ANFIS. The maximum R values for SSₜₐ₇ and CODₜₑₓ₇ were 0.74 and 0.92, respectively. The maximum MSEs of 0.17 and 19.58, and the minimum RMSEs of 0.41 and 4.42 for SSₜₐ₇ and CODₜₑₓ₇ could also be achieved.
- It also revealed that the influent indices could be applied on the prediction of effluent quality.

Since good predicting results were gained using ANFIS, after prediction, it is suggested that the ANFIS can be used as the objective function or constrain in optimization for best design or operation in the future study.

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