Modeling a Paper-Making Wastewater Treatment Process by Means of an Adaptive Network-Based Fuzzy Inference System and Principal Component Analysis

ARTICLE *in* INDUSTRIAL & ENGINEERING CHEMISTRY RESEARCH · APRIL 2012

Impact Factor: 2.59 · DOI: 10.1021/ie203049r

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Modeling a Paper-Making Wastewater Treatment Process by Means of an Adaptive Network-Based Fuzzy Inference System and Principal Component Analysis

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ABSTRACT: In this paper, a predictive control system based on an adaptive network-based fuzzy inference system (ANFIS) was employed to develop models for predicting and controlling the performance of a paper-making wastewater treatment process. The system includes an ANFIS predictive model and an ANFIS controller. In order to improve the network performance, fuzzy subtractive clustering, euclidean distance clustering, and principal component analysis (PCA) were used to identify model architecture and extract and optimize the fuzzy rule of the model. For the developed predictive model, when predicting, mean absolute percentage error (MAPE) lay 6.06% adopting ANFIS, root mean square normalized error (RMSE) was 24.4485 and R was 0.9731. The control model, taking into account the difference between the predicted value of chemical oxygen demand (COD) and the set point, can effectively change the additive dosages. In order to verify the developed predictive control model, a paper-making wastewater treatment process was picked up to support the operational performance. When the influent COD value or inflow flow rate was changed, the dosage could be accurately adjusted to make the effluent COD remain at the set point, and its MAPE was only 5.19%. The results indicated that reasonable forecasting and controlling performances had been achieved through the developed system.

1. INTRODUCTION

Due to the increased concern about environmental issues, many experts focus their attention on the proper operation and control of wastewater treatment process (WWTP).[1] Improper operation of a WWTP may give rise to serious environmental and public health problems, as its effluent to a received water body can cause or spread various diseases to human beings. However, the efficient operation of WWTP is limited and difficult because it is affected by a variety of physical, chemical, and biological factors.[2,3] Applications of control theory to WWTP mainly focus on issues of nonlinearity, uncertainty, and posterity where it is difficult to set up accurate mathematical models and design reliable controllers.[4] The most significant advantage of artificial intelligent (AI) techniques is that no precise mathematical model is needed, which can well approach any nonlinear continuous function and overcome the shortcomings of traditional control that over depend on an accurate mathematical model.

In recent years, many studies about wastewater treatment based on AI techniques were realized.[5,6] This research is related to modeling WWTP, predictions of WWTP parameters, process control of WWTP, and estimating WWTP parameter characteristics.

Some of these studies based on intelligent methods are as follows. Artificial neural network (ANN) model has been widely employed to model complex dynamic wastewater treatment system. Curteanu et al.[7] used different types of neural networks to model the electrolysis process in wastewater treatment. The simulation results can represent accurate predictions, useful for experimental practice. Yilmaz et al.[8] developed different ANN models to predict the effluent chemical oxygen demand (COD) in an upflow anaerobic filter (UAF) reactor treating cyanide containing wastewater. The models' results showed that the multilayer perceptron (MLP) neural network with Levenberg–Marquardt algorithm was found to be better than the radial basis neural network (RBNN) and generalized regression neural network (GRNN) techniques. Han and Qiao[9] developed an adaptive controller based on a dynamic structure neural network (ACDSNN) which can provide an effective solution to the control of the dissolved oxygen (DO) concentration in a WWTP.

Although ANN can model, simulate, and predict successfully in the wastewater treatment process, the ANN still has several limitations which are caused by the possibility of falling into local minimum and the choice of model architecture.[10] If the performance can be further promoted, better operation strategy can be formed. To overcome these shortcomings of traditional ANN and to increase their reliability, many new hybrid intelligent techniques have been proposed, for example, hybrid fuzzy neural network. Hybrid fuzzy neural network combines fuzzy logic control (FLC) with ANN and realizes fuzzy logic by

Received: December 27, 2011
Revised: March 7, 2012
Accepted: April 9, 2012
Published: April 9, 2012

neural network. Meanwhile, the network can get hold of fuzzy rules and optimize its subjection function online by self-learning ability of the neural network. Application of fuzzy neural network in wastewater treatment process, it can acquire better effect.[11]

Recently, active research has been carried out in fuzzy neural network model.[12−14] Chaiwat et al.[15] integrated fuzzy systems and neural networks in monitoring process response and control of anaerobic hybrid reactor (AHR) in wastewater treatment and biogas production, which showed that it had great potential to control an anaerobic hybrid reactor in high stability and performance and quick response. Dilek and Sukran[16] combined fuzzy systems with neural networks in modeling the input selection and prediction of anaerobic digestion effluent quality in a sequential upflow anaerobic sludge bed reactor (UASBR) system. They illustrated that the model-based-control system on the anaerobic digester system can have a high feasibility to produce an effluent amenable for a consecutive aerobic treatment unit.

In addition, the prediction capability of AI techniques strongly depends on the status of the training data.[17] If there is noise and uncertainty in the training data, a problem of overfitting often arises. Since AI techniques use only input and output data observed from the target system, it is necessary to extract required information from large and noisy input vectors through data preprocessing. Therefore, having a large number of input vectors can be considered as one of the main common problems for modeling processes using these techniques. The best method for solving this problem is using a multivariate statistical data analysis technique, such as clustering analysis (CA) and principal component analysis (PCA).

In previous studies, these two approaches are used to explore significant information from the origin data.[18,19] Lu et al.[20] used PCA and CA to analyze the performance assessment of air quality monitoring networks in Hong Kong. Shah and Shaheen[21] applied CA and PCA to identify the major source of airborne trace metals in area of Islamabad. Meanwhile Gokhan et al.[22] developed an advanced neuro-fuzzy model with PCA for modeling carbon and nitrogen removal in an industrial wastewater treatment plant. They all demonstrated that these two statistical data analysis methods could complement each other, and the combination of AI and statistical data analysis technique could provide a practical alternative approach for analyzing and solving an environmental problem.

Therefore, in this context, by means of adaptive network-based fuzzy inference system (ANFIS) which is the combination of neural network and fuzzy logic, CA and PCA have been used to increase performance and decrease complexity and dimension of the modeling system. In addition, the main objective of this study was to develop an ANFIS model for addressing the operational problem of a paper-making wastewater treatment plant. According to the relationship between the dosages of chemical addition and COD of the influent and effluent in a paper-making wastewater treatment process, ANFIS model is developed to predict and control a paper-making wastewater treatment plant based on the available historical data. Using the developed models, the dosages of chemical addition could be accurately controlled in the paper-making wastewater treatment plant.

2. MATERIALS AND METHODS

2.1. Reactor System. The data used in this work were collected from a bench-scale paper-making wastewater treatment as shown in Figure 1. The raw water was the papermaking wastewater from a paper-making mill in City Dongguan,

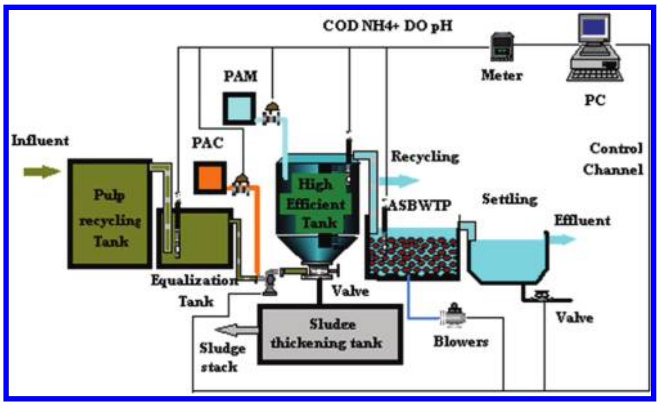

Figure 1. Paper-making wastewater treatment process.

Guangdong province of China. The COD, BOD5, suspended solid (SS), pH, and chromaticity of raw water were 620−2200 mg/L, 250−510 mg/L, 500−1100 mg/L, 6.5−8.5, and 50−80, respectively. Paper-making wastewater was pumped into the high efficient reactor of 140 L after entering into the adjustment tank by direct current (DC) pump. The high efficient reactor was invented by South China University of Technology. Chemical addition (poly aluminum chloride, PAC) was added in front of DC pump, where it had a certain stirring action. A mixer was employed to keep the liquor completely mixed in the adjustment pool. Wastewater had sufficient reaction of coagulation−flocculation and sedimentation in the integrative reactor, and the effluent of the integrative reactor was poured into the clean water tank and was recycled. There was an electromagnetic valve at the bottom of the reactor which was used for discharging the sludge. With the sludge accumulating, when the mud height of the reactor was higher than the given high level, the electromagnetic valve would be open, and vice versa; therefore, the sludge height of the reactor could be kept at a proper position.

COD was measured by COD online monitoring instrument of HACH (USA) according to the standard methods issued by the Environmental Protection Agency of China.[23] The dosages of chemical addition were accurately controlled by BT00-100 M peristaltic pump (Baoding, China). The inflow flow rate was acquired by the relationship between flow and speed of peristaltic pump.

2.2. Adaptive Network-Based Fuzzy Inference System (ANFIS). The ANFIS represents a useful neural network approach for solving the function approximation problems, which develop various learning techniques for training of NN to fuzzy modeling or a fuzzy inference system (FIS).[24] Data driven procedures for the synthesis of ANFIS are typically based on clustering a training set of numerical samples of the unknown function to be approximated. In the ANFIS, each input parameter might be clustered into several class values to build up fuzzy rules, and each fuzzy rule would be constructed using two or more MFs. Several methods have been proposed to classify the input data and making the rules, the most conventional of them are grid partition[24] and subtractive fuzzy clustering.[25] When there are a few input vectors, grid partition is a suitable method for data classification, but in this research because of many input vectors (8 inputs) and need for considerable MFs for each of them, we cannot use this method. In this paper, the developed predictive model was based on the way of subtractive fuzzy clustering, and the control model was based on the method of grid partition.

ANFIS creates an FIS for which membership function parameters are adjusted using either a backpropagation algorithm alone or a combination of a backpropagation algorithm and a least-squares method.[26] In other words, this allows the fuzzy system to learn from the data being modeled. Selection of the FIS is the major concern when designing an ANFIS to model a specific target system. Several types of fuzzy reasoning have been proposed in the literature. Depending on the type of fuzzy reasoning and fuzzy if−then rules employed. The current study uses the Sugeno fuzzy model since the consequent part of this FIS is a linear equation and the parameters can be estimated by a simple least-squares error method. A simple example of ANFIS shown in Figure 2 has five layers with node and link

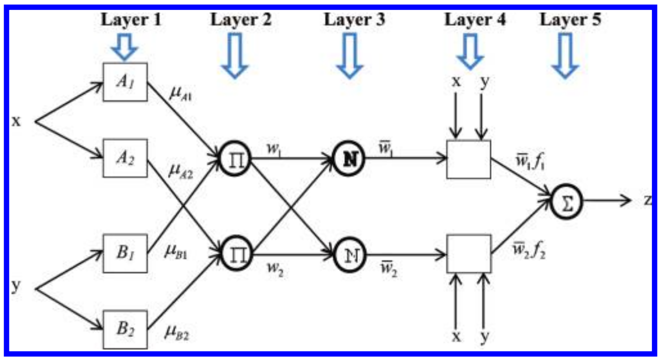

Figure 2. ANFIS structure for a two-input Sugeno model with four rules.

numbering defined in the brackets. Nodes at layer 1 are input nodes (linguistic nodes) that represent input linguistic variables. Layer 5 is the output layer. Nodes at layer 2 are term nodes that act as membership functions to represent the terms of the respective linguistic variable. Each node at layer 3 is a rule node, which represents one fuzzy logic rule. Thus, all third layer nodes form a fuzzy rule base.

The more recent learning algorithm for ANFIS is a hybrid algorithm, which is based on the gradient descent and least-squares estimate method (LSM). According to this method, the total number of parameters of an ANFIS model is separated into two sets, premise parameters and consequent parameters. In the forward pass of the hybrid learning algorithm, the node output goes forward until the consequent parameters are identified by the LSM. In the backward pass, the error signals, which are the derivatives of the squared error with respect to each node output, propagate backward from the output layer to the input layer. In this backward pass, the premise parameters are updated by the gradient descent algorithm.

3. EUCLIDEAN DISTANCE CLUSTERING

Euclidean distance clustering is one of the tree clustering methods, which uses the similarities (dissimilarities) or distances between objects when forming the clusters. Similarities are a set of rules that serve as criteria for grouping or separating items.[27] These distances (similarities) can be based on a single dimension or multiple dimensions, with each dimension representing a rule or condition for grouping objects. The most straightforward way of computing distances between objects in a multidimensional space is to compute Euclidean distances.

Euclidean distance is probably the most commonly chosen type of distance. It simply is the geometric distance in the multidimensional space. It is computed as:

$$\text{distance}\ (x, y) = \left\{\sum \sum i(xi - yi)^2\right\}^{1/2} \tag{1}$$

This method has certain advantages (e.g., the distance between any two objects is not affected by the addition of new objects to the analysis, which may be outliers).

4. PRINCIPAL COMPONENT ANALYSIS

PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system.[28] PCA is a way of identifying patterns in data and expressing the data in such a way so as to emphasize their similarities and differences. It describes the data set in terms of its variance. The main results of PCA are factor loadings, which reflect how much the variable contributes to that particular PC and how well one variable is similar with others. The higher the loading of a variable, the more that the variable contributed to the variation accounted for by the particular PC.

In this paper, the use of PCA for characterization and interpretation of water quality signals was explained. Principal components were calculated using eigenvectors and seigenvalues of covariance matrixes or correlation matrix.

$$E(X_{\mathrm{ij}}) = \frac{1}{n-1}\sum_{l=1}^{n}(X_{\mathrm{il}} - \overline{X}_{\mathrm{i}})(X_{\mathrm{jl}} - \overline{X}_{\mathrm{j}}) \tag{2}$$

where n is the total number of samples, $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, m$ (m sample dimension) and $\overline{X}\, i$ is the average value of the samples.

The eigenvectors e_{i} and the corresponding eigenvalues λ_{i} are the solutions of the equation.

$$C_{\mathrm{x}}e_{\mathrm{i}} = \lambda_{\mathrm{i}}e_{\mathrm{i}}, \quad i = 1, 2, 3, \ldots, n \tag{3}$$

The coefficients of the principal components of q^{th} signal are then given by

$$a_{\mathrm{qp}} = \sum_{i=1}^{m} x_{\mathrm{qi}}e_{\mathrm{ip}}, \quad p = 1, 2, 3, \ldots, m, \quad q = 1, 2, 3\ldots, n \tag{4}$$

The data sets were analyzed by PCA in Matlab 6.5.

5. RESULTS AND DISCUSSION

5.1. ANFIS Predictive Model. *5.1.1. Data Collection and Preprocessing.* Training sample data is the main factor which could affect learning ability and generalization ability of network, so it should possess three factors: compactness, ergodicity, and compatibility. In this paper, the orthogonal method was used in the process. During the operation of the wastewater process for the development, the influent COD, the inflow flow rate, and the dosage of chemical addition are three main factors, so four levels for each factor were chosen to design the experiment and the relationship between them and the effluent COD was studied. Thus, 64 data points were obtained from the coagulation process and used to develop the ANFIS predictive model, and then a standard procedure was used for preparing the network data. The main objective here is to ensure that the statistical distribution of the values for the net input and output is roughly uniform. The data sets are usually scaled so that they always fall within a specified range or they are normalized so that they have zero mean and unitary variance. These data were normalized by

$$S(i) = \frac{s(i) - \min(s)}{\max(s) - \min(s)} \tag{5}$$

5.1.2. Analysis of Historical Process Data. The quality of the training database is critical for the model to produce correct information about the system. In order for the model to describe the system accurately, the database should contain adequate and correct information on the system. On the other hand, it is common for a raw database to contain some redundant and conflicting data. Thus, sometimes it is necessary for the raw training database to be pretreated to remove redundancies and resolve conflicts in the data. The samples analyzed by Euclidean distance clustering were shown in Figure 3. From

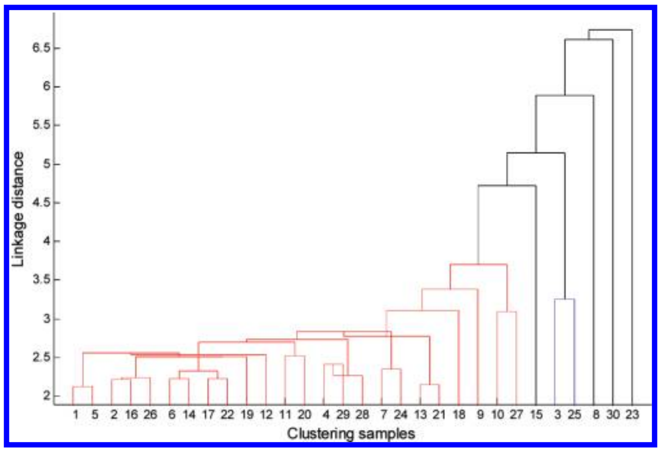

Figure 3. The dendrogram of data set based on Euclidean distances clustering.

Figure 3, it can be seen that the samples were divided into 30 clusters, and the 30th cluster (46th data point) and the 23rd cluster (33rd and 64th data points) were offset from the stagnation point at a certain distance, which indicate that they are different from other clusters. Thus, according to the clustering analysis results, the points of 33, 46, and 64 were outliers.

PCA was performed to clarify and evaluate the relationships among model variables. The percentage of process variance explained as a function of the number of principal components is shown in Table 1. As it can be noted from this table, eight PCs were extracted from the PCA, and over 90% of the variation within the data could be explained by four PCs for predictive model. The projections of the process vectors into the space of the first four loading vectors are shown in Figure 4, respectively. From Figure 4, some samples (e.g., 64, 46, and 29) were outliers that have longer distance from the center of the cluster.

Thus, according to the analysis results of Euclidean distance clustering and PCA, the 46th and 64th data were outliers and need to be abandoned. Overall, the samples were reduced from 64 to 62 for ANFIS predictive models, by considering PCA and Euclidean distance clustering results, and the numbers for training and testing (predicting) were 32 and 30, respectively.

5.1.3. Predictive Model and Modeling Results. According to COD of the influent and effluent, the dosages of the chemical addition, the inflow flow rate at time t, and the historical COD of the effluent, the model can provide accurate predictions of the effluent COD at time $(t + \Delta t)$. With respect to the inputs of the ANFIS predictive model, the formula can be written as follows:

$$y(t + \Delta t) = F\begin{Bmatrix} x(t),\, v(t),\, u(t),\, y(t),\, y(t - \Delta t) \\ y(t - 2\Delta t),\, y_1(t - \Delta t),\, y_2(t - \Delta t) \end{Bmatrix} \tag{6}$$

where $y(t + \Delta t)$ represents the model prediction as the effluent COD at time $(t + \Delta t)$, where the influent COD and the effluent COD at time t is defined as $x(t)$ and $y(t)$, respectively; $u(t)$ is the dosage of chemical addition at time t; $v(t)$ is the inflow flow rate at time t; the effluent COD at time $(t - \Delta t)$ and the effluent COD at time $(t - 2\Delta t)$ are defined as $y(t - \Delta t)$ and $y(t - 2\Delta t)$, respectively; the first-order derivative and second-order derivative of the effluent COD at time $(t - \Delta t)$ are represented as $y_1(t - \Delta t)$ and $y_2(t - \Delta t)$, respectively, where the sample time Δt is set as 30 min.

In this research, a subtractive fuzzy clustering is used in order to establish the rule based on the relationship between the input and output vectors. This method is based on a measure of the density of data points in the feature space, which calculates according to the given search radius (r_a). The optimal values for r_a are identified through a trial and error procedure by varying the r_a from 0.1 to 0.9 (in increments of 0.05). In this paper, a Gaussian-type MF is used. The optimum value for r_a and the optimum number of rules for model achieved are 0.9 and 12, respectively. Thus, each cluster represented a rule, and the rules may be stated as:

Ri: if x is Ai and v is Bi and ... and y is Fi and $y2$ is Hi,

then $z = f(x, v, ...y), \quad i = 1, 2, ..., 12$

where A, B,..., G, and H are the fuzzy sets in the antecedents and $z = f(x, v,..., y)$ is a crisp function in the consequent. The cluster centers represent the initial value of premise parameter.

Thus, the structure of the network shown in Figure 5 was identified. The model has five layers with six nodes in the input layer and one node in the output layer. The second layer calculates the membership corresponding each input variable (nodes: 8 × 12); the third layer is the rules layer with 12 nodes; the forth layer is the normalization processing layer, which has 12 nodes too. Root mean square normalized error (RMSE), mean absolute percentage error (MAPE), and correlation coefficient (R) are used as a performance index to evaluate the prediction capability of ANFIS.

After determining the initial value of premise parameter and the architecture of the predictive model, the network was trained by the hybrid algorithm. ANFIS training performance is shown in Figure 6. After about 937 times of training, the error is then lower than the given level. The ANFIS predictions for

Table 1. Percentage of Principle Component Variances

PCs	1	2	3	4	5	6	7	8
variance explained percent (%)	42.43	23.08	13.71	12.25	4.53	1.98	1.65	0.37
variance cumulative percent (%)	42.43	65.51	79.22	91.47	96.00	97.98	99.63	100

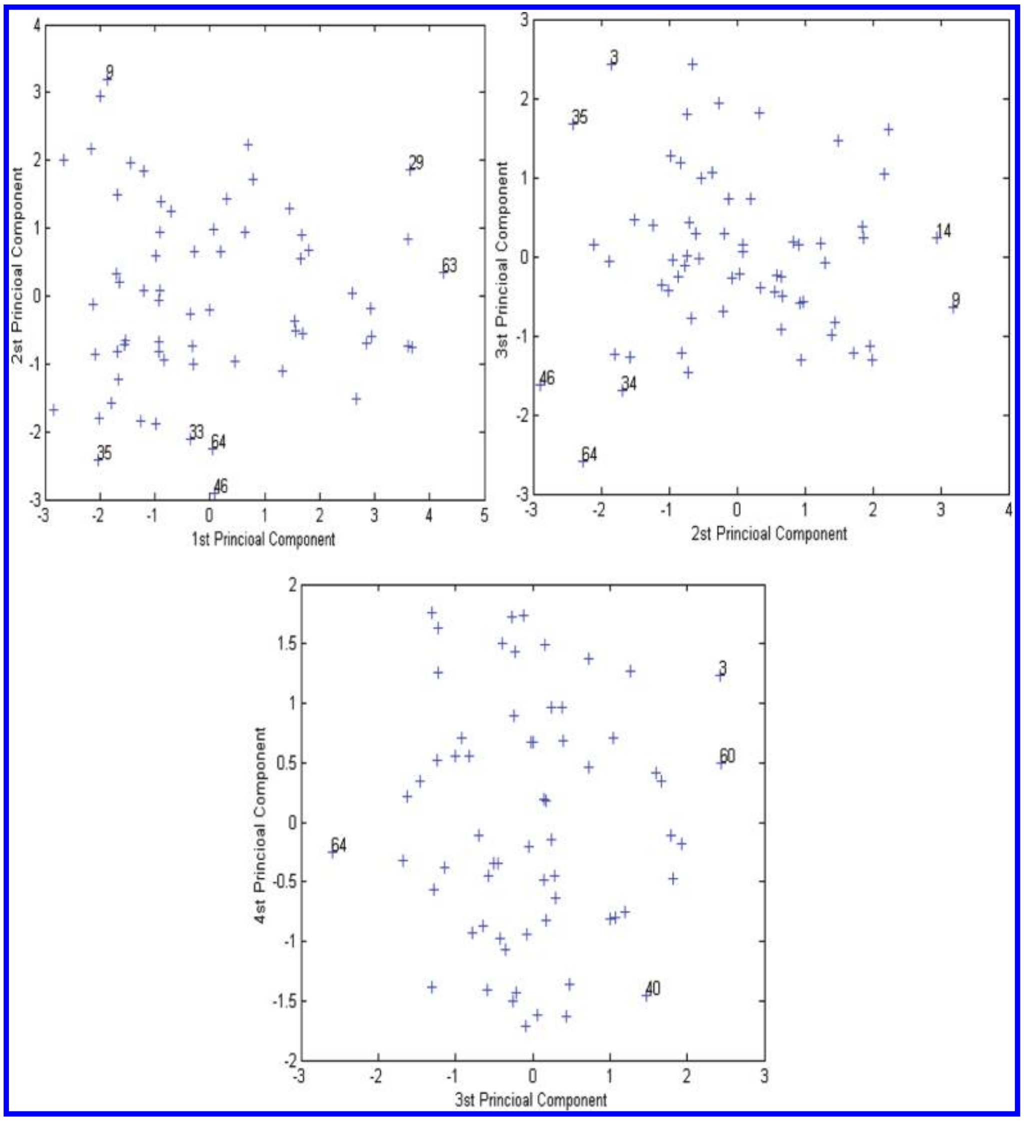

Figure 4. The distribution of data under two PCs.

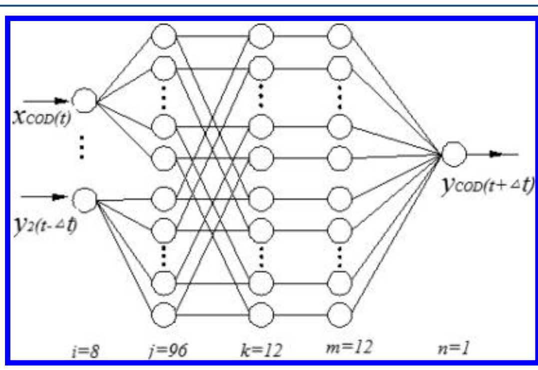

Figure 5. Structure of the ANFIS predictive model.

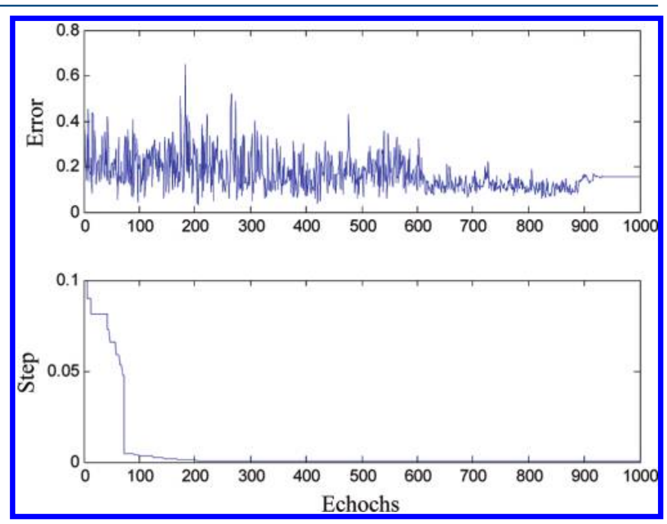

Figure 6. Training process of the ANFIS predictive model.

the training data are shown in Figure 7. When training, MAPE between the predicted and observed values was 0.0032% using ANFIS, RMSE was 0.0246, and R was 0.9999. From Figure 7, a good agreement is achieved that the predicted values of the network were able to follow the desired values well, which indicates that the network has a strong learning capability.

After the training, the premise and consequent parameters of the network were pruned (Table 2). At this stage, the testing data was employed to measure the generalization of the network. The testing results of the developed ANFIS are shown in Figure 8. When predicting, the MAPE lay 6.06% adopting

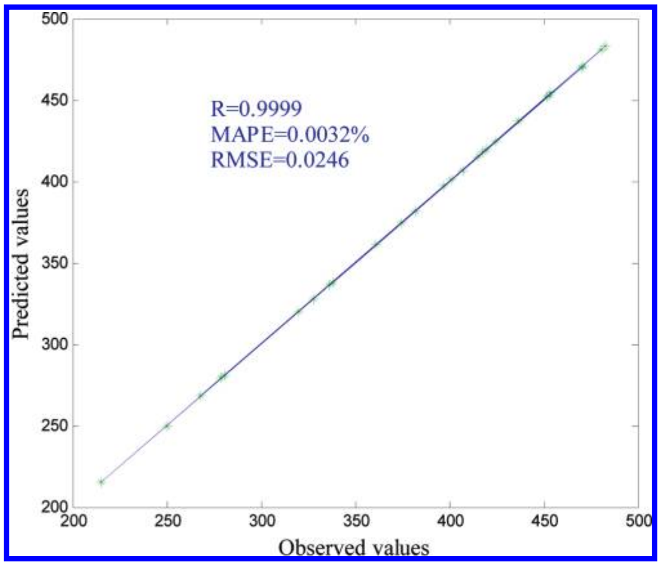

Figure 7. Training performance of training data by ANFIS predictive model.

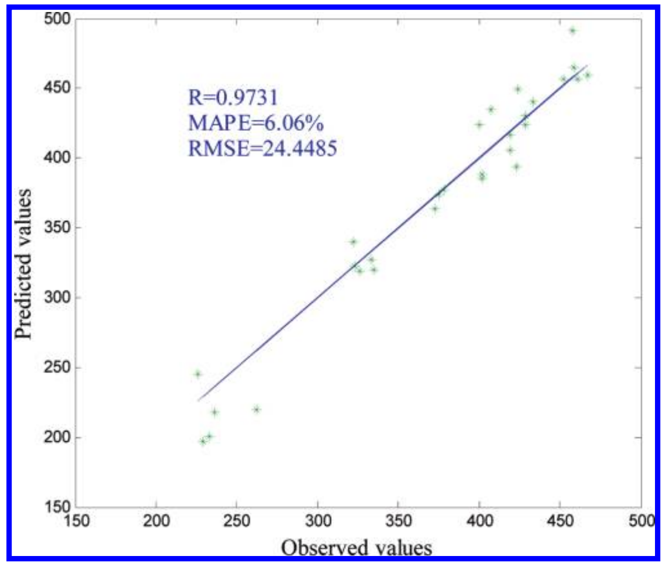

Figure 8. Test performance of testing data by ANFIS predictive model.

ANFIS, RMSE was 24.4485, and R was 0.9731, which shows that the hybrid fuzzy neural network model can achieve a good predication of effluent COD in the wastewater treatment process.

5.2. ANFIS Control Model. The approach to achieve stable control was based on an ANFIS model, taking into account the difference between the predicted value of COD and the set point at time t, and the developed control model was based on the grid partition, which could be expressed well by the following equation:

$$\Delta u(t) = F(E, \mathrm{Ec}) \tag{7}$$

where $\Delta u(t)$ represents the correction value of the dosage at time t; E is the error between the predicted value and the set point at time t; Ec is the change rate of the predicted COD at time t.

Membership functions of the variables are drawn (Figure 9). E, Ec, and Δu included seven fuzzy subsets, respectively, that is, {NB, NM, NS, ZE, PS, PM, PB}. Thereby, it got 49 fuzzy rules. The rules may be stated as:

$$\mathrm{R_m}\text{: if } E \text{ is } A_i \text{ and Ec is } B_j,$$

$$\text{then } u \text{ is } \mathrm{C_m},\; i = j = 1, 2, ..., 7;\; m = i^*j$$

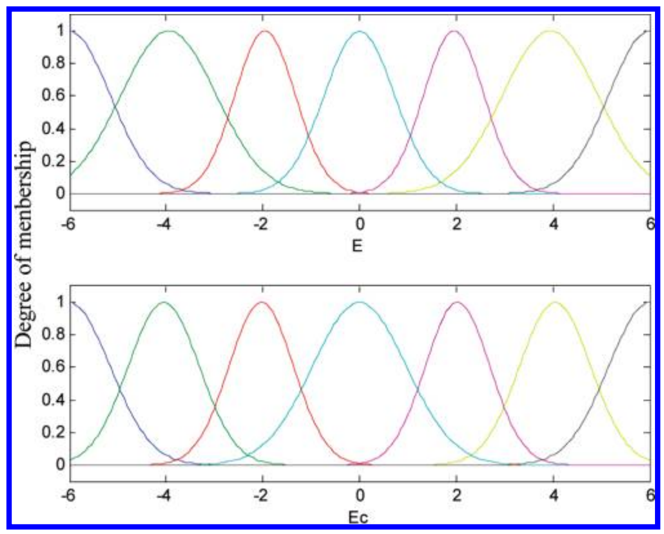

Figure 9. Membership functions of the variables.

where A, B, and C represent seven fuzzy sets of E, Ec, and Δu, respectively.

Table 2. Parameters of the Predictive ANFIS Model[a]

rules	a	b	c	d	e	f	g	h	i
1	0.0381	0.1335	0.7011	−0.2504	0.4787	0.5674	0.134	−0.5961	−0.0585
2	0.1022	−0.0576	−0.1834	−1.629	0.5868	1.636	1.051	−1.164	−0.0073
3	−0.1196	−0.0061	0.1664	1.117	0.1733	0.1759	0.002588	0.9459	0.0017
4	0.1108	−0.0661	0.2988	0.5106	−0.0533	0.15	0.2041	0.7681	0.0470
5	0.0751	−0.0793	−0.4774	0.4437	0.1466	0.1452	−0.00123	0.2958	−0.0213
6	−0.007	−0.0249	0.3868	0.902	0.1793	−0.03632	−0.2039	0.5186	0.0137
7	−0.2193	−0.0026	0.0627	0.4808	0.5947	0.6468	0.05214	−0.06175	0.0027
8	5.71×10^{-5}	8.42×10^{-9}	5.17×10^{-7}	2.12×10^{-5}	2.03×10^{-5}	1.93×10^{-5}	−1.05e06	−1.60e-7	4.21×10^{-8}
9	0.2424	0.0002	0.0308	−0.2247	0.1379	0.08007	−0.05783	−0.4204	−0.0012
10	−0.0853	−0.0007	0.0108	0.4018	0.3873	0.4229	0.03562	0.05007	0.0007
11	−0.3877	−0.0110	−0.1032	1.108	1.305	−0.701	−0.191	−0.4263	−0.0053
12	−0.1019	−0.0014	0.1137	0.47	0.8502	0.2029	−0.6473	−1.028	0.0026

[a] $f = a\,x(t) + b\,v(t) + c\,u(t) + d\,y(t - 2\Delta t) + e\,y(t - \Delta t) + f\,y(t) + g\,y_1(t - \Delta t) + h\,y_2(t - \Delta t) + i$.

Table 3. Parameters of the ANFIS Control Model

numbers	weight						
w_1−w_7	5.999	5.999	5.996	6.02	3.833	−0.05263	0.00031
W_8−w_{14}	6.011	6.011	6.008	6.031	3.859	−0.04094	0.01219
W_{15}−w_{21}	3.714	3.713	3.751	3.858	−1.029	−2.255	−2.237
W_{22}−w_{28}	4.015	4.041	2.202	5.33×10^{-7}	−2.202	−4.041	−4.015
W_{29}−w_{35}	2.237	2.255	1.029	−3.858	−3.751	−3.713	−3.714
W_{36}−w_{42}	−0.01219	0.04094	−3.859	−6.031	−6.008	−6.011	−6.011
W_{43}−w_{49}	−0.00031	0.05263	−3.833	−6.02	−5.996	−5.999	−5.999

After identifying the model structure, the hybrid algorithm was used for training the network in MATLAB. When the output error of the network was lower than the given level, the task of "remembering" fuzzy rules has been already completed; correspondingly, the premise and consequent parameters of the network were pruned (Table 3). After giving the rules to the system, defuzzified results and graphical outputs can be derived. Figure 10 illustrates an example of Surface Viewer screen obtained from Fuzzy Logic Toolbox. Two- or three-dimensional graphic results of variables can be plotted and compared. Using the interface, defuzzified values for output variables can be derived by changing input values manually. Different output values can be obtained from the Rule Viewer according to the given input values. Getting defuzzified output values for all the real input values is not flexible using the interface. For that reason, a program is written using Matlab codes to drive defuzzified output results in accordance with real input values.

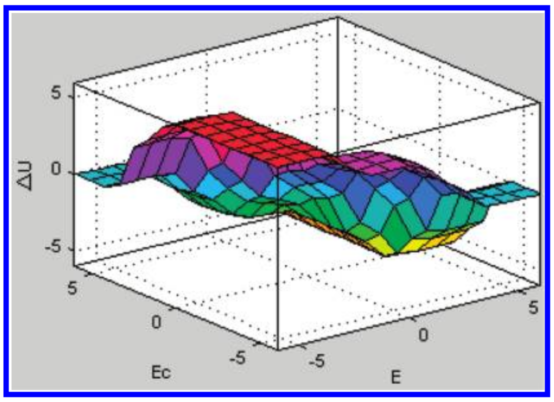

Figure 10. Characteristic curves of ANFIS control model.

Figure 11 shows the results of applied rules and their corresponding outputs according to the mass center of variables. From Figure 11, we can see that the FNN control model can effectively change the additive dosages, and the relative error was very low. The results of simulation showed that the effect of the control is good.

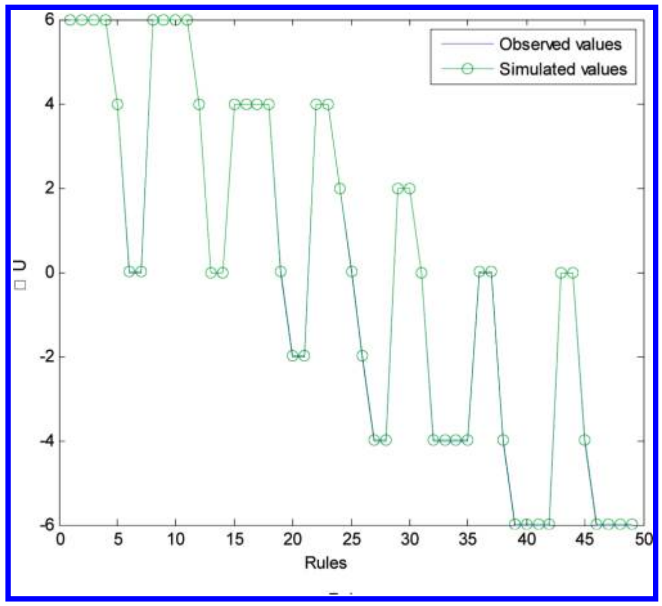

Figure 11. Comparative chart of real values and predicted value by ANFIS control model.

5.3. Predictive Control System for Wastewater Treatment. The control system in paper-making wastewater treatment, which is combined with the predictive control model, is show in Figure 12. The specific process is as follows: according to $x(t)$, $u(t)$, $v(t)$, and $y_p(t)$, the prediction model can predict the influent COD at time $(t+\Delta t)$. Then, comparing the predicted value of COD with the set point at time $(t+\Delta t)$, E and Ec at time $(t+\Delta t)$ are obtained; thus, the control model can complete adjusting the dosage automatically and repeat the same step into the next cycle.

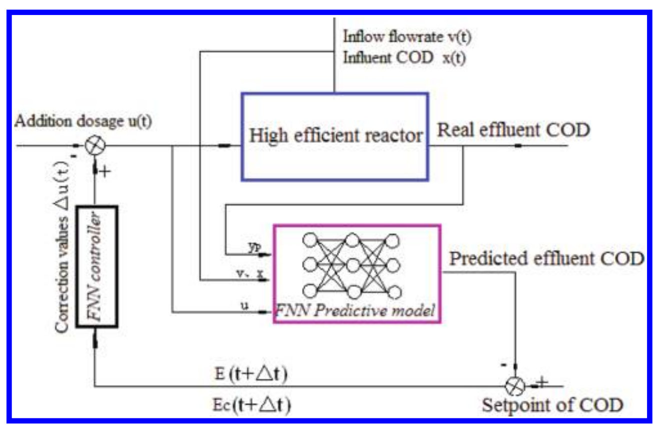

Figure 12. Schematic diagram of ANFIS predictive control in wastewater treatment process.

5.4. Control Results. According to changing the inflow flow rate and the influent COD, the developed control system was investigated to calculate the change of dosages. Meanwhile compared with manual dosing, the advantage of intelligent control can be embodied. In this paper, the validation experiment was finally implemented in the laboratory, taking the influent COD remaining at 1044 mg/L or the inflow flow rate remaining at 18 mL/s for instance, and the set points of effluent COD were 374 mg/L and 365 mg/L, respectively. When the influent COD or the inflow flow rate was changed, the dosage was computed by the control system, which ensured the effluent COD remained at 374 and 365 mg/L, respectively. The operating data were saved in the MCGS database, as shown in

Tables 4 and 5. From these tables, we can see that the developed control system can save the cost of processing, the dosage was computed by ANFIS control system to control the effluent COD around the recommended value (374 mg/L and 365 mg/L), and comparing manual dosing, the fluctuation range of effluent COD was small, MAPE of which was only 5.19%. Therefore, the results proved that the intelligent control system based on ANFIS is a robust and effective control tool, which is easy to integrate in a global monitoring system for cost managing.

Table 4. Effluent COD Value under Condition of Fixing Influent COD and Changing Inflow Flow Rate

influent COD (mg/L)	inflow flow rate (mL/s)	addition dosage (mL/s)	desired effluent COD (mg/L)	effluent COD (mg/L)
	12	0.44		359
	13	0.56		395
	14	0.66		348
	15	0.74		350
1044	16	0.83	374	355
	17	0.91		376
	18	1.02		387
	19	1.11		411
	20	1.19		413

Table 5. Effluent COD under Condition of Fixing Inflow Flow Rate and Changing Influent COD

influent COD (mg/L)	inflow flow rate (mL/s)	addition dosage (mL/s)	desired effluent COD(mg/L)	effluent COD (mg/L)
1250		1.17		371
1166		1.14		337
1048		1.06		378
923		0.99		395
865	18	0.9	365	368
789		0.85		361
703		0.71		347
632		0.63		336

6. CONCLUSIONS

A predictive control system based on the ANFIS was developed to control the dosages of chemical addition. The predictive control system integrates the advantages of ANN and FLC. With the supervised learning capabilities of neural networks and the heuristic reasoning capability of fuzzy rules, the ANFIS model is able to learn a complex functional relation and at the same time generate logic rules for heuristic reasoning. Combined with fuzzy subtractive clustering, Euclidean distance clustering, and principal component analysis, the network can approach the wastewater process system with a good degree of accuracy. The developed ANFIS models can provide accurate prediction of the effluent COD and control the dosages of chemical addition effectively. ANFIS models could make the effluent COD remain at the set point; the dosages of chemical addition were minimized, and MAPE of this model was much smaller. The results indicate that the network has a stronger ability in learning and is suitable to predict and control the wastewater treatment process.

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Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

This research has been supported by Guangdong Provincial Department of Science (No.2008A080800003), Guangdong Natural Science Foundation (No. S2011040000389), State Key Laboratory of Pulp and Paper Engineering in China (201003), the Fundamental Research Funds for the Central Universities (2011ZM0049), Guangdong High-level Talents Foundation and Shanghai Tongji Gao Tingyao Environmental Science & Technology Development Foundation (STGEF). The authors are thankful to the anonymous reviewers for their insightful comments and suggestions.

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