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# Modeling of a paper-making wastewater treatment process using a fuzzy neural network

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**Abstract**−An intelligent system that includes a predictive model and a control was developed to predict and control the performance of a wastewater treatment plant. The predictive model was based on fuzzy C-means clustering, fuzzy inference and neural networks. Fuzzy C-means clustering was used to identify model's architecture, extract and optimize fuzzy rule. When predicting, MAPE was 4.7582% and R was 0.8535. The simulative results indicate that the learning ability and generalization of the model was good, and it can achieve a good predication of effluent COD. The control model was based on a fuzzy neural network model, taking into account the difference between the predicted value of COD and the setpoint. When simulating, R was 0.9164, MAPE was 5.273%, and RMSE was 0.0808, which showed that the FNN control model can effectively change the additive dosages. The control of a paper-making wastewater treatment process in the laboratory using the developed predictive control model and MCGS (monitor and control generated system) software shows the dosage was computed accurately to make the effluent COD remained at the setpoint, when the influent COD value or inflow flowrate was changed. The results indicate that reasonable forecasting and control performances were achieved through the developed system; the maximum error was only 3.67%, and the average relative error was 2%.

Key words: Fuzzy Neural Network, Industrial Wastewater Treatment, Predictive Control, Fuzzy C-means Clustering, Hybrid Algorithm

## INTRODUCTION

The efficient operation of a wastewater treatment process (WWTP) is limited because it is affected by a variety of physical, chemical, and biological factors [1,2]. Applications of control theory to wastewater treatment have mainly focused on issues of nonlinearity, uncertainty and posterity where existed difficulties in establishing accurate mathematical models and designing reliable controllers [3]. The most significant advantage of intelligence control 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 intelligent methods have been realized. These researches are related to modeling WWTP, predictions of WWTP parameters, process control of WWTP, and estimating WWTP output parameters characteristics.

Some of these studies based on intelligent methods are as follows. A novel approach on the basis of artificial neural network (ANN) model has been widely employed to model complex dynamic wastewater treatment system. Mjalli et al. [5] developed an ANN model as a valuable performance assessment tool for plant operators and decision makers, which can provide accurate predictions of the effluent stream in terms of biochemical oxygen demand (BOD), chemical oxygen demand (COD) and total suspended solids (TSS). Hakan et al. [6] developed an ANN model to model the activated sludge process (ASP) in an industrial WWTP with the aim of predicting the effluent COD. The ANN model can continuously predict a cardinal effluent parameter that is cumbersome to quantify, and the correlation coefficient (R) between the observed and predicted output variables reached up to 0.980. Elmolla et al. [7] applied neural networks based on the feed-forward back-propagation algorithm to model and predict antibiotic degradation in terms of COD removal by the Fenton process. ANN predicted results are very close to the experimental results with correlation coefficient of 0.997 and mean square error (MSE) of 0.000376.

Fuzzy logic algorithms have been widely applied to pursue better effluent quality and higher economic efficiency in wastewater treatment processes [8-10]. Turkdogan-Aydınol and Yetilmezso [11] developed a MIMO (multiple inputs and multiple outputs) fuzzy-logic-based model to predict biogas and methane production rates in a pilot-scale mesophilic up-flow anaerobic sludge blanket (UASB) reactor treating molasses wastewater. Compared to non-linear re-

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gression models, the proposed MIMO fuzzy-logic-based model produced smaller deviations and exhibited a superior predictive performance in forecasting of both biogas and methane production rates with satisfactory determination coefficients over 0.98. To increase the settling process efficiency, Traore et al. [12] successfully used fuzzy algorithm to control sludge height in a secondary settler.

In addition, neural network and fuzzy logic both have some limitations. Neural network has limitations in performing heuristic reasoning of the domain problem. On the other hand, fuzzy logic is very difficult to design and adjust automatically. So it is necessary to design the fuzzy neural network model: it can use the both of their advantages [13,14]. Fuzzy neural network (FNN) combines fuzzy logic control (FLC) with ANN and realizes fuzzy logic by 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 the wastewater treatment process can result in a better effect.

Recently, active research has been carried out on the fuzzy-neural network model. Chaiwat et al. [16] integrated fuzzy systems and neural networks in monitoring process response and control of anaerobic hybrid reactor in wastewater treatment and biogas production, which showed that it had great potential to control an anaerobic hybrid reactor (AHR) in high stability and performance and quick response. Chen and Chang [17] combined fuzzy systems with neural networks in modeling the complex process of aeration in a submerged biofilm wastewater treatment process. They illustrated that using a bounded difference fuzzy operator in connection with back propagation neural networks would be the best choice to build up this feed forward fuzzy controller design.

The main objective of this study was to develop a fuzzy neural network model for addressing the operational problem of a paper-making wastewater treatment plant. According to the relationships between the dosages of chemical addition and COD of the influent and effluent in a paper-making wastewater treatment process, the FNN model is developed to predict and control a paper-making wastewater treatment plant based on the available historical data. Using the developed model, the dosages of chemical addition could be accurately controlled in the paper-making wastewater treatment plant.

## MATERIALS AND METHODS

### 1. Reactor System

The data used in this work were collected from a bench-scale paper-making wastewater treatment as shown in Fig. 1. The raw water was papermaking wastewater from a paper-making in Dongguan city of Guangdong province, China. The COD, $BOD_5$, suspended solid (SS), pH and chromaticity of raw water were 620-2,200 mg/L, 250-510 mg/L, 500-1,100 mg/L, 6.5-8.5 and 50-80, respectively. Paper wastewater was pumped into the high efficiency reactor of 140 L after entering into the adjustment tank by direct current (DC) pump. The high efficiency reactor was researched and developed 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

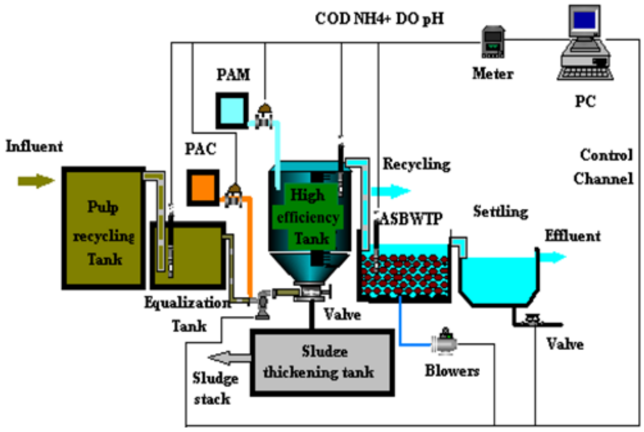


**Fig. 1. The paper-making wastewater treatment process.**

integrative reactor was poured into the clean water tank and was recycled. An electromagnetic valve at the bottom of the reactor 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 on-line monitoring instrument of HACH (USA) according to the standard methods issued by the Environmental Protection Agency of China [18]. The dosages of chemical addition were accurately controlled by BT00-100M peristaltic pump (Baoding, China). The inflow flowrate was acquired by the relationship between flow and speed of peristaltic pump.

### 2. Fuzzy Neural Network

2-1. Adaptive Network Based Fuzzy Inference System (ANFIS)

The adaptive network based fuzzy inference system (ANFIS) represents a useful neural network approach for the solution of function approximation problems. Data driven procedures for the synthesis of ANFIS networks are typically based on clustering a training set of numerical samples of the unknown function to be approximated. Since their introduction, ANFIS networks have been successfully applied to classification tasks, rule-based process controls, pattern recognition problems and the like. Here a fuzzy inference system is comprised of the fuzzy model proposed by Takagi, Sugeno and Kang to formalize a systematic approach to generate fuzzy rules from an input output data set [19,20].

2-2. ANFIS Structure

For simplicity, it is assumed that the fuzzy inference system under consideration has two inputs and one output. The rule base contains two fuzzy if-then rules of Takagi and Sugeno type [21] as follows:

If x is A and y is B then z is f(x, y)

where A and B are the fuzzy sets in the antecedents and (z=f(x, y)) is a crisp function in the consequent. f(x, y) is usually a polynomial for the input variables x and y. But it can also be any other function that can approximately describe the output of the system within the fuzzy region as specified by the antecedent. When f(x, y) is a constant, a zero-order Sugeno fuzzy model is formed, which may be considered to be a special case of Mamdani fuzzy inference system where each rule consequent is specified by a fuzzy singleton. If f(x, y) is taken to be a first-order polynomial, a first-order Sugeno

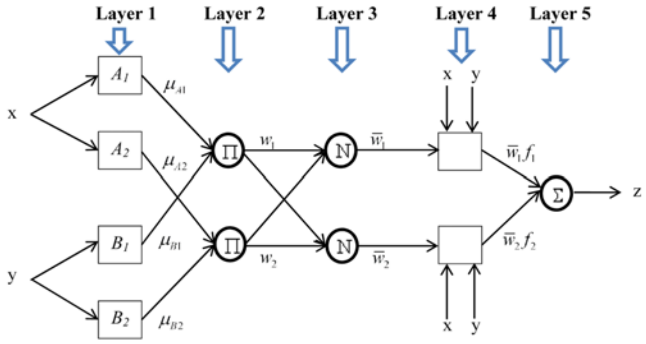


**Fig. 2. ANFIS structure for a two-input Sugeno model with four rules.**

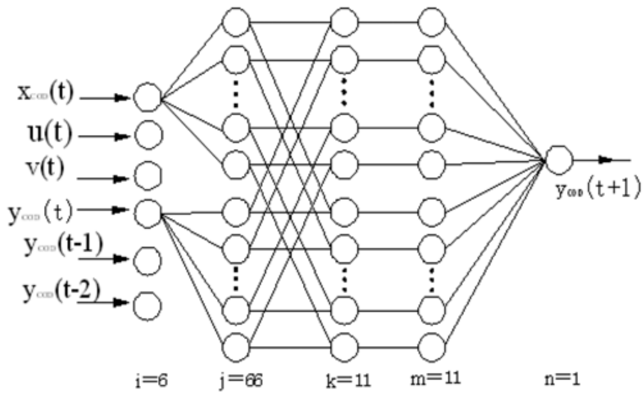


**Fig. 3. The structure of the FNN predictive model.**

fuzzy model is formed. For a first-order two-rule Sugeno fuzzy inference system, the two rules may be stated as:

Rule 1: If x is $A_1$ and y is $B_1$ then $f_1=p_1x+q_1y+r_1$
Rule 2: If x is $A_2$ and y is $B_2$ then $f_2=p_2x+q_2y+r_2$

Here a type-3 fuzzy inference system proposed by Takagi and Sugeno is used [22]. In this inference system the output of each rule is a linear combination of input variables added by a constant term. The final output is the weighted average of each rule's output. The corresponding equivalent ANFIS structure is shown in Fig. 2.

The individual layers of this ANFIS structure are described below:

Layer 1: Every node i in this layer is adaptive with a node function

$$o_i^1=u_{A_i}(x) \tag{1}$$

where x is the input to node i, $A_1$ the linguistic variable associated with this node function and $u_{A_i}$ is the membership function of $A_1$. Usually $u_{A_i}(x)$ is chosen as:

$$u_{A_i}(x)=\frac{1}{1+[(x-c_i/a_i)^2]^{b_i}} \text{ or } u_{A_i}(x)=\exp\left\{-\left(\frac{x-c_i}{a_i}\right)^2\right\} \tag{2}$$

where x is the input and $\{a_i, b_i, c_i\}$ is the premise parameter set.

Layer 2: Each node in this layer is a fixed node which calculates the firing strength $w_i$ of a rule. The output of each node is the product of all the incoming signals to it and is given by,

$$o_i^2=w_i=u_{A_i}(x)\times u_{B_i}(x),\ i=1, 2 \tag{3}$$

Layer 3: Every node in this layer is a fixed node. Each *i*th node calculates the ratio of the *i*th rule's firing strength to the sum of firing strengths of all the rules. The output from the *i*th node is the normalized firing strength given by,

$$o_i^3=\overline{w}_i=\frac{w_i}{w_1+w_2},\quad i=1, 2 \tag{4}$$

Layer 4: Every node in this layer is an adaptive node with anode function given by,

$$o_i^4=\overline{w}_i f_i=\overline{w}_i(p_i+q_i y+r)_i,\quad i=1, 2 \tag{5}$$

where $\overline{w}_i$ is the output of Layer 3 and $\{p_i, q_i, r_i\}$ is the consequent parameter set.

Layer 5: This layer consists of only one fixed node that calculates the overall output as the summation of all incoming signals:

$$o_i^5=\text{overalloutput}=\sum_i \overline{w}_i f_i=\frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6}$$

2-3. Learning Algorithm

From the proposed ANFIS structure, it is observed that given the values of premise parameters, the final output can be expressed as a linear combination of the consequent parameters. The output f in Fig. 3 can be written as

$$f=\frac{w_1}{w_1+w_2}f_1+\frac{w_2}{w_1+w_3}f_2=\overline{w}_1 f_1+\overline{w}_2 f_2=(\overline{w}_1 x)p_1 +(\overline{w}_2 y)q_1+(\overline{w}_1)r_1+(\overline{w}_2 x)p_2+(\overline{w}_2 y)q_2+(\overline{w}_2)r_2 \tag{7}$$

f is linear in the consequent parameters ( $p_1$, $q_1$, $r_1$, $p_2$, $q_2$, $r_2$).

In the forward pass of the learning algorithm, consequent parameters are identified by the least squares estimate. 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.

## RESULTS AND DISCUSSION

### 1. Data Collection and Pre-processing

Training sample data is the main factor which could affect the 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 wastewater process for the development, the influent COD, the inflow flowrate 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 sets were obtained in the whole process, 32 sets of training samples were used to train network, the numbers for validating were 16, and 16 sets of testing samples were used to test the generalization capability of the trained network.

The best value which FNN presents is that it can approximate the nonlinear function of the controlled object. The trained network can get similar response immediately when the inputs are similar with the controlled object. Meanwhile, the data were analyzed by Fuzzy C-Means clustering function, and were divided into 11 classes.

The last step in data procedure is the data scaling. This is a standard procedure for the networks data preparation. 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 scale 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

$$S(i)=\frac{s(i)-\min(s)}{\max(s)-\min(s)} \tag{8}$$

## 2. Fuzzy Neural Network Predictive Control Model

### 2-1. Predictive Model and Modeling Results

According to COD of the influent and effluent, the dosages of the chemical addition, the inflow flowrate at time t and the historical COD of the effluent, the model can provide accurate predictions of the fluent COD at time (t+Δt). With respect to the inputs of the FNN predictive model, the formula can be written as follows:

$$y(t+\Delta t)=F\begin{Bmatrix} x(t), v(t), u(t), y(t), \\ y(t-\Delta t), y(t-2\Delta t), \end{Bmatrix} \tag{9}$$

Where y(t+Δt) represents the model prediction as the effluent COD at time (t+Δt), where the influent COD and the effluent COD at time t is defined as x(t) and y(t) repectively; u(t) is the dosage of chemical addition at time t; v(t) is the inflow flowrate at time t; the effluent COD at time (t+Δt) and the effluent COD at time (t−2Δt) are defined as y(t−Δt) and y(t−2Δt) repectively; where the sample time Δt is set as 30 min.

The architecture of the network model was based on Takagi-Sugeno inference. The grade function of membership is the Gauss function shown as follows:

$$y=e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{10}$$

where x is the input and {c, $\sigma$} is the premise parameter set. The form of the Gauss function would be changed when these parameters is changed.

In this study the training data were analyzed by fuzzy C-means clustering function in Matlab software, and were divided into 11 clusters. Thus each cluster represents a rule, which corresponds to Eq. (3) as stated:

Ri: If x is Ai and v is Bi and … and y1 is Gi and y2 is Hi, then z=f (x, v, …, y2 ), i=1, 2, …, 11.

Where A, B, …, G and H are the fuzzy sets in the antecedents and z=f(x, v, …, y2 ) is a crisp function in the consequent.

The cluster centers represent the initial value of premise parameter in function (10). Thus the structure of the network shown in Fig. 3 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: 6×11); the third layer is the rules layer with 11 nodes; the fourth layer is the normalization processing layer, which also has 11 nodes. 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 FNN.

After the initial value of premise parameter and the architecture of the predictive model were determined, the network was trained by the hybrid algorithm. FNN training performance is shown in

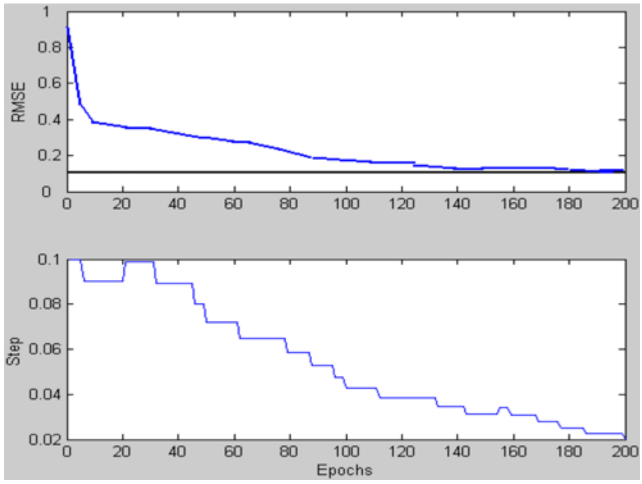


**Fig. 4. Training process of The FNN predictive model.**

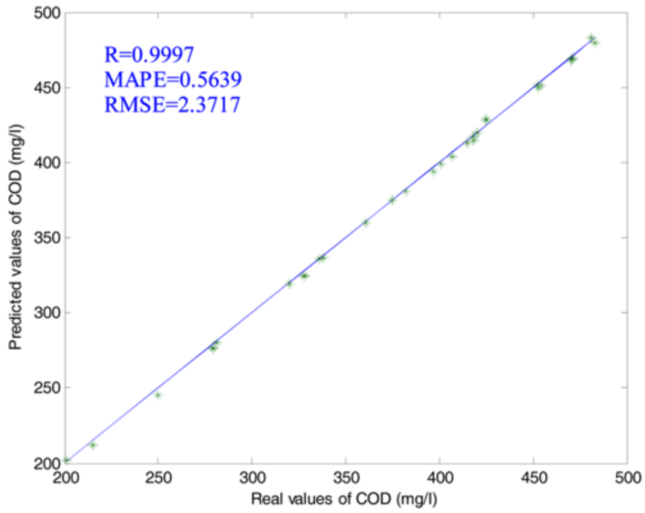


**Fig. 5. Train performance of training data by FNN predictive model.**

Fig. 4. After about 200 times of training, the root mean square errors (RMSE) are then lower than the given level. The FNN predictions for the training data are shown in Fig. 5. When training, MAPE between the predicted and observed values of COD was 0.5639% using FNN, RMSE was 2.3717 and R was 0.9997. Meanwhile 16 data sets were used for validating the model. When validating, the MAPE was 5.6964% adopting FNN, RMSE was 27.9933 and R was 0.9288. From Figs. 5 and 6, a good agreement is achieved in 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. At this stage, the testing data was employed to measure the generalization of the network. The testing results of the developed FNN are shown in Fig. 7. When predicting, the MAPE was 4.7582% adopting FNN, RMSE was 27.4112 and R was 0.8535, which shows that the hybrid fuzzy neural network model can achieve a good predication of effluent COD in wastewater treatment process.

### 2-2. Fuzzy Neural Network Control Model

The principle of FNN control is shown in Fig. 8. The approach

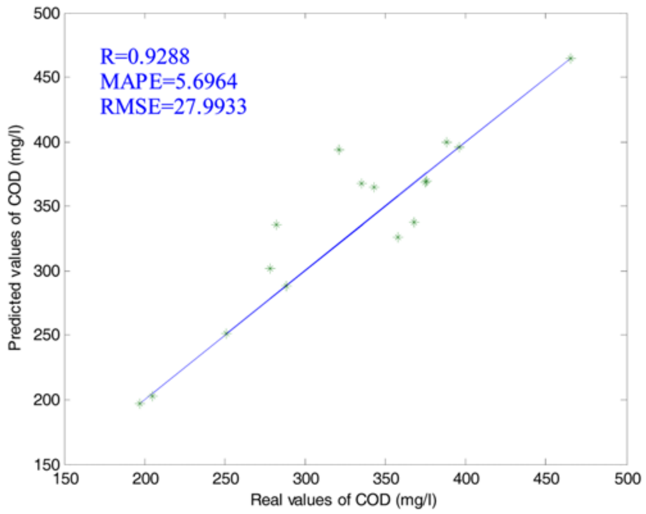


**Fig. 6. Validation performance of testing data by FNN predictive model.**

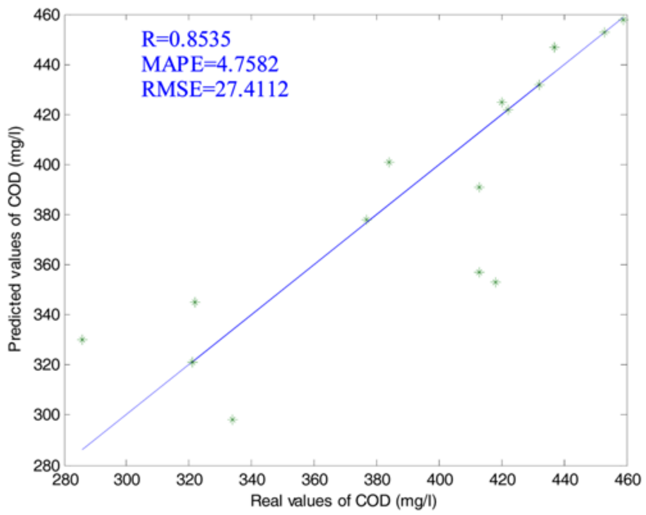


**Fig. 7. Test performance of testing data by FNN predictive model.**

to achieve stable control was based on a fuzzy neural network model, taking into account the difference between the predicted value of COD and the setpoint at time t. The model could be expressed well

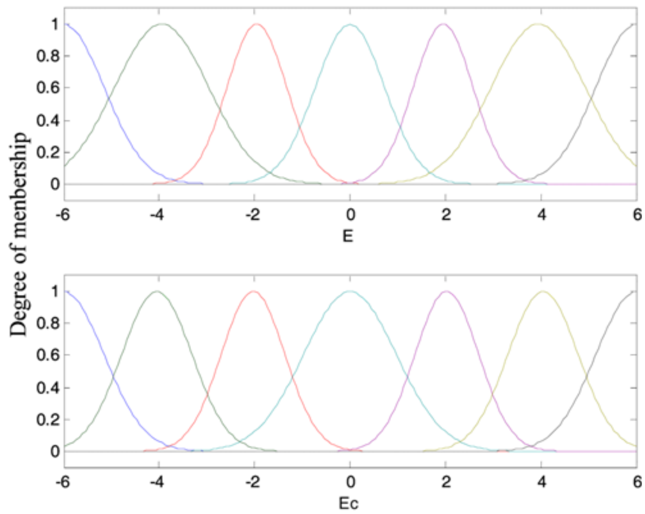


**Fig. 9. Membership functions of the variables.**

by the following equation:

$$\Delta u(t)=F(E, Ec) \tag{11}$$

Where Δu(t) represents the correction value of the dosage at time t; E is the error between the predicted value and the setpoint at time t; Ec is the change rate of COD at time t.

Membership functions of the variables are drawn (Fig. 9). E, Ec and Δu inclueded seven fuzzy subsets respectively, that is, {NB, NM, NS, ZE, PS, PM, PB}.Thereby, 49 fuzzy rules were obtained, as shown in Table 2. The rules may be stated as:

$R_m$: if E is $A_i$ and Ec is $B_j$ then Δu is $C_m$, i=j=1, 2, ⋯, 7; m=i*j

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

After the model structure was identified, 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 was already completed; correspondingly, the premise and consequent parameters of the network were pruned. After the rules are given to the system, defuzzified results and graphical outputs can be derived. Fig. 10 illustrates an example of the Surface Viewer screen obtained from Fuzzy Logic Toolbox. Two- or three-dimensional graphic results of variables can be plotted and

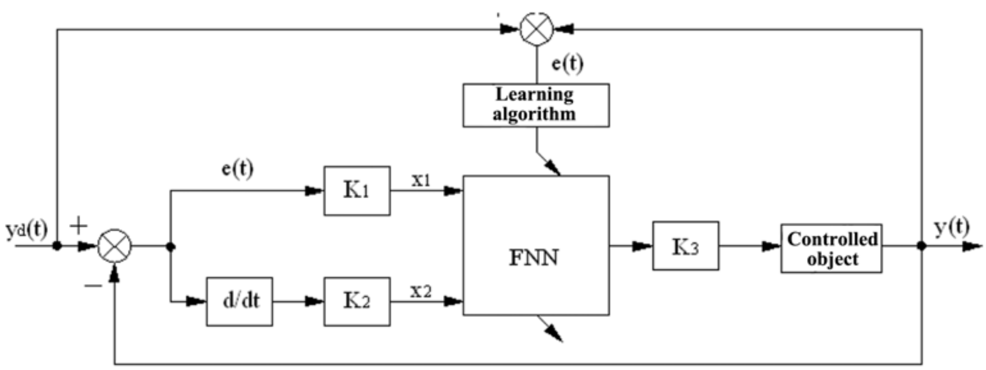


**Fig. 8. Schematic diagram of control theory of FNN.**

**Table 1. Cluster centers of the input and output variable values**

| Cluster number | x(t) | u(t) | v(t) | y(t) | y(t−Δt) | y(t−2Δt) | y(t+Δt) |
|---|---|---|---|---|---|---|---|
| 1 | 978.94 | 0.40698 | 17.898 | 281.94 | 298.81 | 285 | 280.14 |
| 2 | 978.93 | 0.40429 | 17.933 | 298.31 | 284.7 | 279.69 | 268.86 |
| 3 | 648.03 | 0.65378 | 12.463 | 215.44 | 221.22 | 214.82 | 208.16 |
| 4 | 1400 | 0.39978 | 14.415 | 495.61 | 483.97 | 470.41 | 474.94 |
| 5 | 979.06 | 0.3989 | 15.205 | 339.06 | 342.39 | 336.77 | 332.63 |
| 6 | 648.03 | 0.31672 | 16.764 | 293.19 | 294.98 | 283.27 | 277.44 |
| 7 | 1246.7 | 0.40491 | 12.104 | 372.14 | 384.83 | 391.16 | 380.47 |
| 8 | 978.89 | 0.50007 | 12.003 | 233.39 | 229.71 | 225.91 | 211.55 |
| 9 | 1244.4 | 0.69833 | 16.018 | 302.7 | 310.58 | 317.46 | 321.91 |
| 10 | 1244.8 | 0.50094 | 17.989 | 338.96 | 332.5 | 328.93 | 332.25 |
| 11 | 1249.9 | 0.21797 | 14.135 | 435.14 | 439.45 | 427.71 | 421.63 |

**Table 2. Fuzzy control rule**

| Ec / ΔU / E | NB | NM | NS | ZE | PS | PM | PB |
|---|---|---|---|---|---|---|---|
| NB | PB | PB | PB | PB | PM | ZE | ZE |
| NM | PB | PB | PB | PB | PM | ZE | ZE |
| NS | PM | PM | PM | PM | ZE | NS | NS |
| ZE | PM | PM | PS | ZE | NS | NM | NM |
| PS | PS | PS | ZE | NM | NM | NM | NM |
| PM | ZE | ZE | NM | NB | NB | NB | NB |
| PB | ZE | ZE | NM | NB | NB | NB | NB |

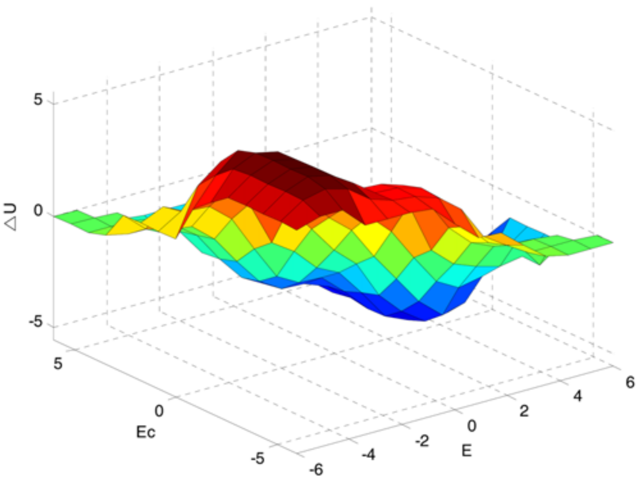


**Fig. 10. Characteristic curves of FNN control model.**

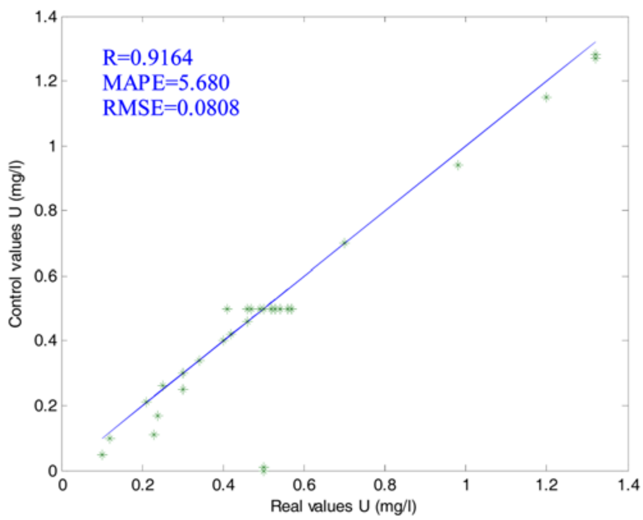


**Fig. 11. Comparative chart of real values and predicted valuse by FNN control model.**

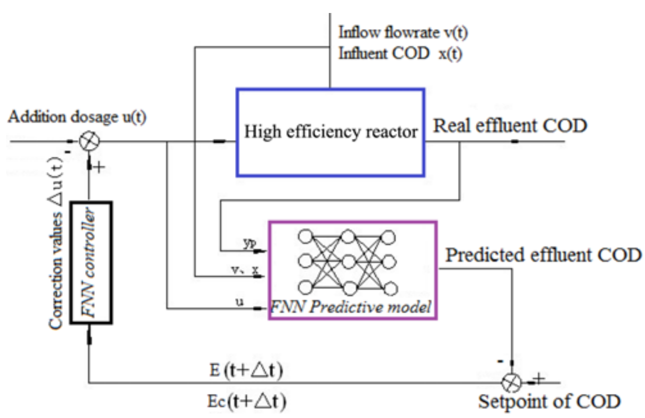


**Fig. 12. Schematic diagram of FNN predictive control in wastewater treatment.**

compared.

Fig. 11 shows the results of applied rules and their corresponding outputs according to the mass center of variables. R was 0.9164, MAPE was 5.273%, and RMSE was 0.0808. From Fig. 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.

3-3. Predictive Control System for Wastewater Treatment

The control system in a paper-making wastewater treatment, combined with the predictive control model, is shown in Fig. 12. The specific process is as follows: according to x(t), u(t), v(t), yp(t), the prediction model can predict the influent COD at time (t+Δt). Then comparing the predicted value of COD with the setpoint at time (t+Δt), E and Ec at time (t+Δt) are obtained; thus the control model can complete adjusting the dosage automatically. Repeat the same

**Table 3. Effluent COD value under condition of fixing influent COD and changing inflow flowrate**

| Influent COD (mg/L) | Inflow flowrate (ml/s) | Addition dosages (ml/s) | | Desired influent COD (mg/L) | Effluent COD (mg/L) | |
|---|---|---|---|---|---|---|
| | | Control dosage | Manual dosage | | Control dosage | Manual dosage |
| 844 | 14 | 0.96 | 1.2 | 300 | 289 | 315 |
| | 15 | 1.04 | 1.2 | | 303 | 280 |
| | 16 | 1.13 | 1.2 | | 291 | 285 |
| | 17 | 1.21 | 1.2 | | 304 | 306 |
| | 18 | 1.32 | 1.2 | | 295 | 327 |
| | 19 | 1.41 | 1.2 | | 292 | 341 |
| | 20 | 1.49 | 1.2 | | 302 | 363 |

**Table 4. Effluent COD under condition of fixing inflow flowrate and changing influent COD**

| Effluent COD (mg/L) | Inflow flowrate (ml/s) | Addition dosage (ml/s) | | Desired influent COD (mg/L) | Influent COD (mg/L) | |
|---|---|---|---|---|---|---|
| | | Control dosage | Manual dosage | | Control dosage | Manual dosage |
| 1166 | 17 | 1.49 | 1.2 | 300 | 310 | 372 |
| 1048 | | 1.41 | 1.2 | | 288 | 353 |
| 923 | | 1.34 | 1.2 | | 293 | 330 |
| 865 | | 1.25 | 1.2 | | 294 | 303 |
| 789 | | 1.20 | 1.2 | | 209 | 296 |
| 703 | | 1.06 | 1.2 | | 289 | 282 |
| 632 | | 0.98 | 1.2 | | 296 | 271 |

step into the next cycle.

3-4. Control Results

According to changing the inflow flowrate and the influent COD, an intelligent control system was investigated to calculate the change of dosages and the effluent COD. Meanwhile, compared with manual dosing, the advantage of intelligent control can be embodied. In this paper, the validation experiment was finally implemented in laboratory - taking the influent COD remaining at 844 mg/*l* and the inflow flowrate remaining at 14 ml/s for instance, and the setpoint of effluent COD was 300 mg/*l*. When the influent COD or the inflow flowrate was changed, the dosage was computed by the intelligent control system, which ensured the effluent COD remained at 300 mg/*l*. The operating data were saved in the MCGS database, as shown in Table 3-4. From these tables we can see that the dosage was computed by fuzzy neural network control system to control the effluent COD around the recommended value (300 mg/L): the fluctuation range of effluent COD was small, the maximum error was only 3.67%, and the average relative error was 2%. Whereas, compared with automatic dosing, for manual dosing the fluctuation range of effluent COD was large, the maximum error was 18%, and the average relative error was 8.9%.

In addition, intelligent control can save the cost of processing. The results show that the intelligent control system based on fuzzy neural network is effective.

## CONCLUSION

A FNN predictive control model was developed to control the dosages of chemical addition. The FNN predictive control model integrates the advantages of ANN and FLC. With the supervised learning capabilities of neural networks and the heuristic reasoning capability of fuzzy rules, the FNN model is able to learn complex functional relations and at the same time generate logic rules for heuristic reasoning. Combined with fuzzy c-means clustering, it can reduce the bulkiness of the division space of the FNN model, and the network can approximate the wastewater process system with a good degree of accuracy. With this method, new information can be accessed with an approach different from the traditional analysis methods.

The FNN model can provide accurate prediction of the effluent COD and control the dosages of chemical addition effectively. Compared with manual dosing, the FNN model can make the effluent COD remain at the setpoint; meanwhile the dosages of chemical addition would be minimized, and the average relative error of this model is much smaller. The results indicate that network has stronger ability in learning and is suitable to predict and control the wastewater treatment process.

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## ABBREVIATION AND NOMENCLATURE

WWTP : wastewater treatment process
ANN : artificial neural network
BOD : biochemical oxygen demand
COD : chemical oxygen demand
TSS : total suspended solids
SS : suspended solids
ASP : activated sludge process
R : correlation coefficient
MSE : mean square error
MIMO : multiple inputs and multiple outputs
UASB : anaerobic sludge blanket
FNN : fuzzy neural network
FLC : fuzzy logic control
AHR : anaerobic hybrid reactor
ANFIS : adaptive network based fuzzy inference system
RMSE : root mean square error
MAPE : mean absolute percentage error
MF : membership function
DO : dissolved oxygen
Eq : equation
x : the influent COD
y : the effluent COD
v : the inflow flowrate
u : the dosage of chemical addition
$\Delta$u : the correction value of the dosage
E : the error between the predicted value and the setpoint
Ec : the change rate of COD

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