# Control of the Coagulation Process in a Paper-mill Wastewater Treatment Process Using a Fuzzy Neural Network

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Original scientific paper
Received: June 30, 2009
Accepted: October 4, 2010

In this paper, an integrated neural-fuzzy process controller was developed to study the coagulation of wastewater treatment in a paper mill. In order to improve the fuzzy neural network performance, the self-learning ability embedded in the fuzzy neural network model was emphasized for improving the rule extraction performance. It proves the fuzzy neural network more effective in modeling the coagulation performance than artificial neural networks (ANN).

For comparing between the fuzzy neural controller and PID controller, a coagulation unit in a paper mill wastewater treatment process (PMWTP) was chosen to support the derivation of a fuzzy control rule base. It is shown that, using the fuzzy neural controller, in terms of cost effectiveness, enables us to save almost 25 % of the operating costs during the time when the controller can be applied.

*Key words:*
Fuzzy neural network, wastewater treatment, predictive control, coagulation process, fuzzy hybrid algorithm

## Introduction

Operation of a wastewater treatment plant (WWTP) is often affected by a wide range of physical, chemical, and biological factors.[1] Applications of control theory to wastewater treatment have mainly focused on issues of nonlinearity, uncertainty and posterity[2] where there existed difficulties in establishing accurate mathematical models and designing reliable controllers. The most significant advantage of intelligent control, which can well approximate any nonlinear continuous function and overcome the shortcomings of traditional control that over-depend on an accurate mathematical model, is that no precise mathematical model is needed.

In recent years, many studies were realized in wastewater treatment based on intelligent methods. These researches are related to modeling WWTP. These researches are about 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 ANN model that was designed to provide better predictions of nitrogen contents in treated effluents was reported.[3] Total suspended solid (TSS) is an indication of plant performance. A simple prediction models based on neural network for TSS was demonstrated in Belanche *et al.*[4] Serodes *et al.*[5] developed a decision support tool, Chlorocast, based on neural networks for modeling the chlorination process in the final disinfection phase of a water treatment system. They illustrated the power of the developed tool by applying it to forecast the residual chlorine in the drinking water tank and distribution system of the city of Sainte-Foy. Holubar *et al.*[6] applied neural networks based on the feed-forward back-propagation algorithm to model and control methane production in anaerobic digesters. The model was trained using data generated from four anaerobic continuous stirred tank reactors operating at steady state.

Fuzzy control algorithms have been widely applied to pursue better effluent quality and higher economic efficiency on aerobic biological treatment processes.[7–14] To increase the settling process effi-

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ciency, Traore *et al.*[15] successfully used the fuzzy algorithm to control DO (dissolved oxygen) in a sequencing batch reactor pilot plant, and showed that fuzzy logic was a robust and effective DO control tool, and easy to integrate in a global monitoring system for cost managing. In regulating aeration, Fiter *et al.*[16] tried to save energy by fuzzy logic control. They used 42 different rules defined in accordance with expert knowledge to shape a fuzzy control rule base. In spite of some successful practical applications, there still is no all-inclusive procedure or method to design such intelligent controllers by far because of its semi-empirical nature.

In addition, neural network and fuzzy control both have some disadvantages. The neural network has limitations in performing heuristic reasoning of the domain problem; On the other hand, fuzzy control is very difficult to design and adjust automatically. Therefore, it is necessary to design a fuzzy neural network model that can make use of the advantages of both techniques.[17,18] Fuzzy neural network (FNN) combines fuzzy logic control (FLC) with artificial neural network (ANN) and realizes fuzzy logic by fuzzy neural network. Meanwhile, the controller can get hold of fuzzy rules and optimize its subjection function online by the self-learning ability of the neural network. It can acquire a better effect on using fuzzy neural network in wastewater treatment.

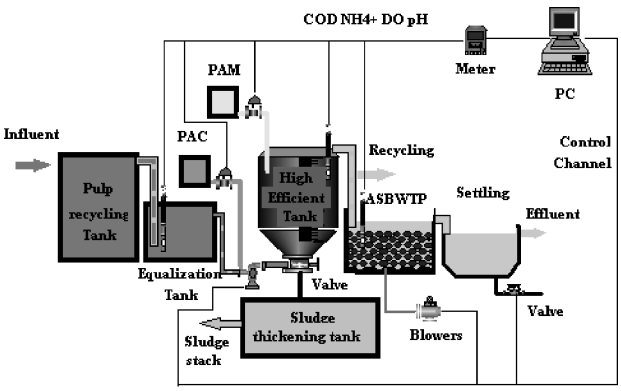
Recently, active research has been carried out in fuzzy-neural control. Tay and Zhang[19] integrated fuzzy systems and neural networks in modeling the complex process of anaerobic biological treatment of wastewater. They illustrated the power of the technique in two case studies of up flow anaerobic sludge blanket and anaerobic fluidized bed reactor. The fuzzy-neural model simulated the system performance well and provided satisfactory prediction results based on observed past information, although a disadvantage of the model was its high dependence on the quality of the training data. Philippe *et al.*[20] used the fuzzy logic and the artificial neural networks to examine on-line and analyze the question that appeared during the processing of 120 L of grape wine wastewater in an anaerobic digestion fluidized bed reactor. According to the fuzzy logic that can distinguish, the characteristic vector was divided into the appointed category. Then the process condition was classified by the artificial neural networks. Chen and Chang[21] integrated fuzzy systems and neural networks in modeling the complex process of aeration in a submerged biofilm wastewater treatment process. They illustrated that using bounded difference fuzzy operator in connection with back propagation neural networks (BPN) algorithm 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 operating problem of a paper mill wastewater treatment plant. According to the relationships between the dosages of chemical and COD of the influent and effluent in a paper-mill wastewater treatment process, an FNN model was developed to predict and control a paper-mill wastewater treatment plant based on available historical data. Using the developed model, the chemical dosages could be accurately controlled in the paper mill wastewater treatment plant.

## Materials and methods

### Paper-mill wastewater treatment process (PMWTP)

A paper-mill wastewater treatment plant (Fig. 1), located at the Dongguan city Guangdong province, was used as a demonstration site for assessing the application of this hybrid fuzzy controller. The annual wastewater discharge amount from the mill was $4.532 \cdot 10^6$ tons: 5674.14 tons of COD, 937.02 tons of BOD, and 4.73 tons of volatile phenol. Chemical coagulation and sedimentation methods were used to handle the wastewater, and the highly efficient reactor researched and developed by South China University of Technology. Most of the effluent of the highly efficient reactor was recycled, but some was sent to an aerated submerged biofilm wastewater treatment process. The design waste-treatment capacity was $5.83 \cdot 10^5$ L h$^{-1}$.




F i g . 1 – *Wastewater treatment process in the Dabu Paper Mill*

The coagulant used in this plant is PAC (polyaluminium chloride, whose concentration is 10 g L$^{-1}$ in this paper). Several key parameters could influence the treatment efficiency. In the case of PAC coagulant, the optimum pH for coagulation tends to lie between 6 and 7. The average pH level of the influent is 7.5. Thus, pH adjustment is essential before the coagulation process begins. The addition of additive chemicals (e.g., polyacrylamides at 2–8 mg $L^{-1}$) will enhance the coagulation through promoting the growth of flocs. The optimum pH and temperature are controlled at 6.5 and 25 °C, respectively. Control of PAC dosages and coagulant additions is critical for optimizing the treatment process.

The monitoring and control system is based on probes from HACH® and SIEMENS®, cards and interfaces from Advantech®. The plant is equipped with SUPERSONIC MUD METER (Inter Ranger DPS300), DO-temperature (D53) and pH (DRD1P5) probes, and COD ($COD_{max}$) and $NH_4^+$ (Amtax) on-line monitoring instrument. The signals, filtered in a transmitter, are captured by a data acquisition card (ADAM4017, Advantech, China). The control is conducted using a power relay output board (ADAM4024, Advantech, China) which allowed an optimal equipment functioning. The software consisted of user-friendly interfaces and was able to repeat over time a previously defined operation cycle by controlling pumps, mixing device and coagulant supply. The dataset used for developing an ANFIS was achieved by operating the PMWTP. During operation of the PMWTP, $COD_{in}$, $U$ (addition dosage) and $Q_{in}$ are the three main factors, so the interrelationship between them and the effluent COD ($COD_{out}$) was studied.

## Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is a multilayer feed-forward network that uses neural network learning algorithms and fuzzy reasoning to map inputs into an output. It is a fuzzy inference system (FIS) implemented in the framework of adaptive neural networks. Fig. 2 shows the architecture of a typical ANFIS with two inputs, four rules and one output for the first-order Sugeno fuzzy model, where each input is assumed to have two associated membership functions (MFs).

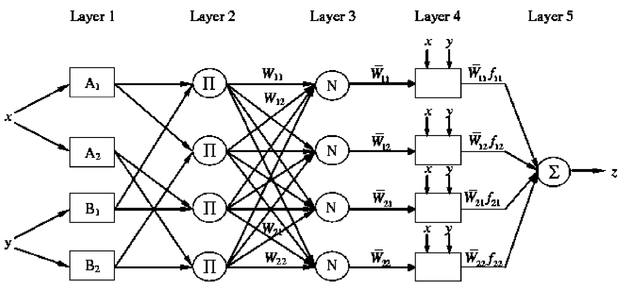



Fig. 2 – *ANFIS structure for a two-input Sugeno model with four rules*

For a first-order Sugeno fuzzy model,[22] a typical rule set with four fuzzy if–then rules can be expressed as

Rule 1:

if $x$ is $A_1$ and $y$ is $B_1$, then $\boldsymbol{f_{11} = p_{11}x + q_{11}y + r_{11}}$,

Rule 2:

if $x$ is $A_1$ and $y$ is $B_2$, then $\boldsymbol{f_{12} = p_{12}x + q_{12}y + r_{12}}$,

Rule 3: (1)

if $x$ is $A_2$ and $y$ is $B_1$, then $\boldsymbol{f_{21} = p_{21}x + q_{21}y + r_{21}}$,

Rule 4:

if $x$ is $A_2$ and $y$ is $B_2$, then $\boldsymbol{f_{22} = p_{22}x + q_{22}y + r_{22}}$,

where $A_1$, $A_2$, $B_1$ and $B_2$ are the MFs for inputs $x$ and $y$, respectively, $p_{ij}$, $q_{ij}$ and $r_{ij}$ ($i, j$ = 1, 2) are consequent parameters.[23,24]

As can be seen from Fig. 2, the architecture of a typical ANFIS consists of five layers, which perform different actions in the ANFIS and are detailed below.

Layer 1: All the nodes in this layer are adaptive nodes. They generate membership grades of the inputs. The outputs of this layer are given by

$$o_{Ai}^1 = u_{A_i}(x) \quad i = 1, 2$$
$$o_{Bj}^1 = u_{B_j}(x) \quad j = 1, 2 \tag{2}$$

where $x$ and $y$ are crisp inputs, and $A_i$ and $B_j$ are fuzzy sets such as low, medium, high characterized by appropriate MFs, which could be triangular, trapezoidal, Gaussian functions or other shapes. In this study, the generalized bell-shaped MFs defined below were utilized

$$u_{A_i}(x) = \frac{1}{1+\left(\dfrac{x-c_i}{a_i}\right)^{2b_i}} \quad i = 1, 2$$
$$u_{B_j}(x) = \frac{1}{1+\left(\dfrac{x-c_j}{a_j}\right)^{2b_j}} \quad j = 1, 2 \tag{3}$$

where $\{a_i, b_i, c_i\}$ and $\{a_j, b_j, c_j\}$ are the parameters of the MFs, governing the bell-shaped functions. Parameters in this layer are referred to as premise parameters or antecedent parameters.

Layer 2: The nodes in this layer are fixed nodes labelled Π, indicating that they perform as a simple multiplier. The outputs of this layer are represented as

$$o_{ij}^2 = w_{ij} = u_{A_i}(x)u_{B_j}(y), \qquad i,j = 1,2 \quad (4)$$

which represents the firing strength of each rule. Firing strength means the degree to which the antecedent part of the rule is satisfied.

Layer 3: The nodes in this layer are also fixed nodes labeled Σ, indicating that they play a normalization role in the network. The outputs of this layer can be represented as

$$o_{ij}^3 = \overline{w_{ij}} = \frac{w_{ij}}{w_{11} + w_{12} + w_{21} + w_{22}}, \quad i,j = 1,2 \qquad (5)$$

which are called normalized firing strengths.

Layer 4: Each node in this layer is an adaptive node, whose output is simply the product of the normalized firing strength and a first-order polynomial (for a first-order Sugeno model). Thus, the outputs of this layer are given by

$$o_{ij}^4 = \overline{w_{ij}}\, f_{ij} = \overline{w_{ij}}\,(p_{ij}x + q_{ij}y + r_{ij}), \quad i,j = 1,2 \quad (6)$$

Parameters in this layer are referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labelled Σ, which computes the overall output as the summation of all incoming signals, i.e.

$$z = O_1^5 = \sum_{i=1}^{2}\sum_{j=1}^{2}\overline{W_{ij}}\, f_{ij} =$$
$$= \sum_{i=1}^{2}\sum_{j=1}^{2}\overline{W_{ij}}\,(p_{ij}x + q_{ij}y + r_{ij}) = \qquad (7)$$
$$= \sum\sum[(\overline{W_{ij}}x)p_{ij} + (\overline{W_{ij}}y)q_{ij} + (\overline{W_{ij}})r_{ij}],$$

which is a linear combination of the consequent parameters when the values of the premise parameters are fixed. It can be observed that the ANFIS architecture has two adaptive layers: Layers 1 and 4. Layer 1 has modifiable parameters $\{a_i, b_i, c_i\}$ and $\{a_j, b_j, c_j\}$ related to the input MFs. Layer 4 has modifiable parameters $\{p_{ij}, q_{ij}, r_{ij}\}$ pertaining to the first-order polynomial. The task of the learning algorithm for this ANFIS architecture is to tune all the modifiable parameters to make the ANFIS output match the training data. Learning or adjusting these modifiable parameters is a two-step process, which is known as the hybrid learning algorithm. In the forward pass of the hybrid learning algorithm, the premise parameters are hold fixed, node outputs go forward until Layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the consequent parameters are held fixed, the error signals propagate backward and the premise parameters are updated by the gradient descent method. The detailed algorithm and mathematical background of the hybrid learning algorithm can be found in Jang.[23]

## Results and discussions

### Data collection and pre-processing

The dataset used for developing an ANFIS was achieved by operating the PMWTP. During operation of the PMWTP, $COD_{in}$, $U$ (addition dosage) and $Q_{in}$ are the three main factors, so the interrelationship between them and the effluent COD ($COD_{out}$) was studied. Thus, 100 sets of data were obtained in the entire process, 80 sets of training samples were used to train the network, and 20 sets of testing samples were used to test the generalization capability of the trained network. Some of these data are shown in Table 1.

Table 1 – *A group of data is used for training*

| $COD_{in}$ mg L$^{-1}$ | $COD_{out}$ mg L$^{-1}$ | $Q_{in}$ m$^3$ h$^{-1}$ | $U$ m$^3$ h$^{-1}$ | $COD_{in}$ mg L$^{-1}$ | $COD_{out}$ mg L$^{-1}$ | $Q_{in}$ m$^3$ h$^{-1}$ | $U$ m$^3$ h$^{-1}$ |
|---|---|---|---|---|---|---|---|
| 2120 | 453 | 500 | 5.51 | 1875 | 408 | 540 | 5.00 |
| 2082 | 432 | 480 | 5.32 | 1763 | 500 | 434 | 4.81 |
| 1971 | 447 | 420 | 4.63 | 1687 | 442 | 480 | 4.61 |
| 1849 | 439 | 580 | 5.27 | 1674 | 429 | 550 | 4.94 |
| 1595 | 424 | 450 | 4.45 | 2090 | 448 | 580 | 5.82 |
| 1762 | 438 | 580 | 5.23 | 1245 | 427 | 425 | 2.45 |
| 1687 | 442 | 480 | 4.61 | 1375 | 418 | 400 | 3.12 |
| 1350 | 426 | 450 | 3.35 | 1638 | 429 | 450 | 4.33 |
| 1465 | 445 | 600 | 4.38 | 1815 | 438 | 380 | 4.00 |
| 1233 | 413 | 350 | 2.3 | 1520 | 427 | 480 | 3.90 |

The last step in the data procedure is 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 scaled so that they always fall within a specified range or are normalized so that they have zero mean and unitary variance. These data were normalized by

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

## Development of the ANFIS

The key concept of T–S fuzzy control model is to use an aggregation of a set of linear functions to capture and mimic the global nonlinear features of a complex system within the designated control domain. To implement this idea, a set of control rules has to be derived from experience based on the history of the plant's performance. This rule base may consist of a series of implications that are defined in the following format (9), in which the antecedent part is characterized by a logic connective "AND" and the consequence part is represented by a linear equation in each control rule:

$$S_k\text{: if } COD_{in} \text{ is } C_i \text{ AND } COD_{out} \text{ is } C_o \text{ AND } Q_{in} \text{ is } Q \text{ then } Y = f_k(COD_{in}, COD_{out}, Q_{in})\, f_k(COD_{in}, COD_{out}, Q_{in})$$

$$f_k(COD_{in}, COD_{out}, Q_{in}) = W_{ck} + Wc_{idk}\, COD_{in} + Wc_{ok}\, COD_{out} + W_{qk} Q_{in} \quad (9)$$

where $S_k$ is the k$^{th}$ fuzzy control rule (i.e., $k$ is from 1 to 27 in this case). $Y$ is the overall dosages output inferred by fuzzy logic controller. $f_k(\,)$ is the consequence of the rule $S_k$ in the form of linear functions of antecedent input variables with coefficients ($W_{ck}$; $W_{bodk}$; $W_{nh}$; and $W_{qk}$).

In this study, the input $COD_{in}$, $COD_{out}$ and $Q_{in}$ are subdivided into three reference fuzzy sets: big (b), mean (me), and small (s). With the 80 training datasets, we choose three generalized bell-shaped MFs for each of the three inputs to build the ANFIS, which leads to 27 if–then rules containing 162 parameters to be learned. Fig. 3 shows the model structure of the ANFIS that is to be built for dosage control in this study. The model structure is implemented using the fuzzy logic toolbox of the MATLAB software package.

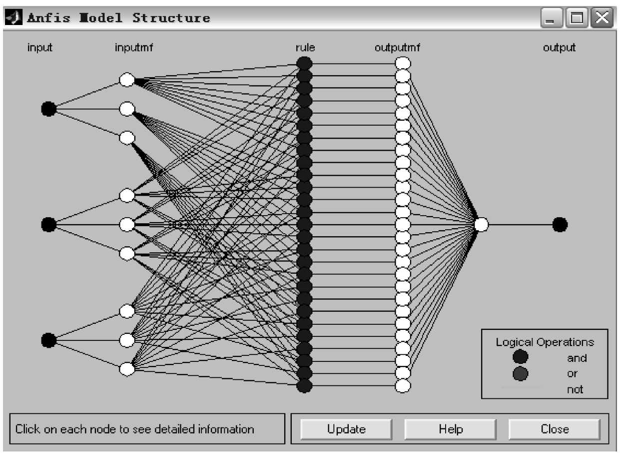



Fig. 3 – *Model structure of the ANFIS for modeling coagulation process in PMWTP*

## Performance analysis

Figs. 4 and 5 show the initial and final MFs before and after 500 epochs of training (Epoch is set as 500 in this study), from which it can be seen that significant modifications have been done to the shapes of initial MFs through the learning process. After determining the initial value of the premise parameter and the architecture of the predictive model, the network was trained by the hybrid algorithm. FNN training performance is shown in Fig. 6. Then the premise and consequent parameters of the network were pruned (Table 2).

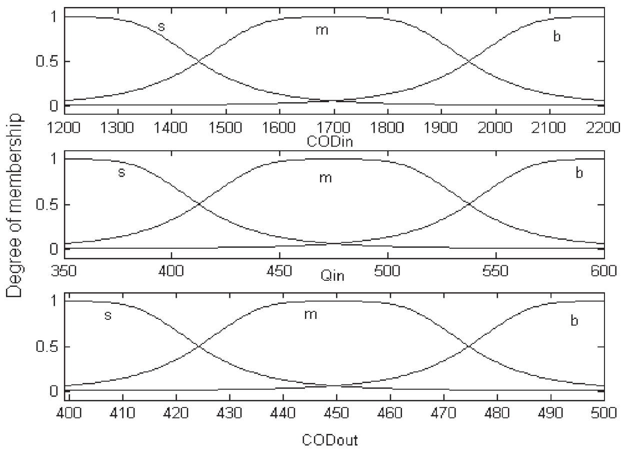



Fig. 4 – *Membership functions before training*

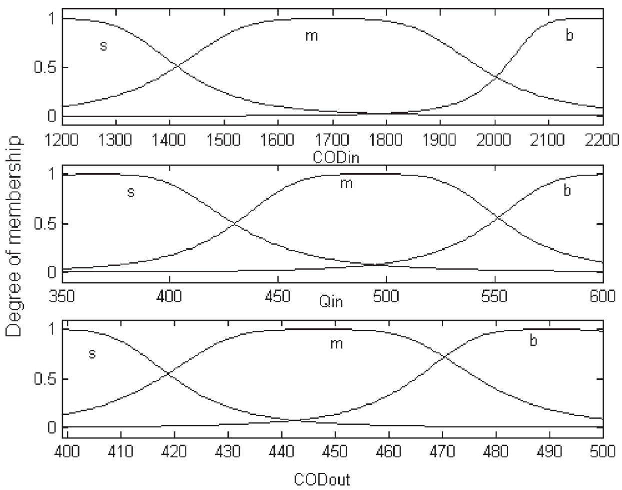



Fig. 5 – *Membership functions after training*

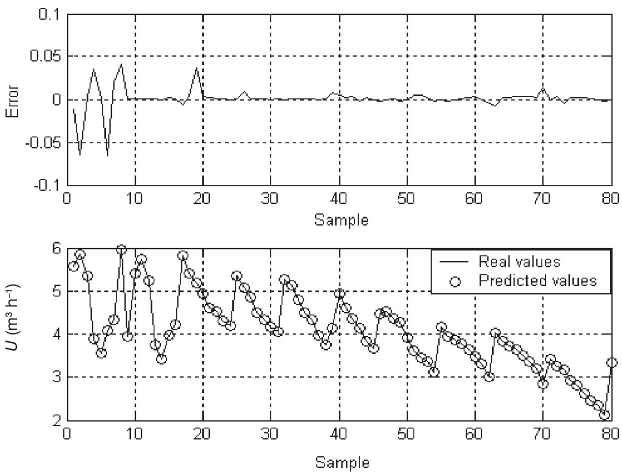



Fig. 6 – *Intelligent model training*

Table 2 – *Parameters of the network*

| Rules | Coefficients | | | | Rules | Coefficients | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W_{Cik}$ | $W_{qk}$ | $W_{Cok}$ | $W_{ck}$ | | $W_{bodk}$ | $W_{nh}$ | $W_{qk}$ | $W_{ck}$ |
| 1 | 0.1278 | 0.2463 | 0.6073 | 4.957 | 15 | –1.045 | –1.396 | 5.636 | 1.895 |
| 2 | –0.185 | 0.6583 | 1.144 | 3.182 | 16 | 0.1049 | 2.839 | 3.169 | 1.781 |
| 3 | 2.579 | 16.31 | –21.93 | 0.1574 | 17 | –0.09058 | 0.4428 | 0.1842 | –7.909 |
| 4 | 0.005657 | 0.02324 | –0.04988 | –0.1513 | 18 | 0.9092 | 2.834 | –7.229 | 0.2835 |
| 5 | 0.06959 | –0.5864 | 0.4933 | 4.536 | 19 | –0.9511 | 2.003 | 2.587 | 4.595 |
| 6 | –1.787 | 18.65 | –16.06 | 0.07738 | 20 | 0.502 | –0.5847 | –1.671 | –0.7839 |
| 7 | 0.04205 | –0.9057 | 1.09 | 0.01984 | 21 | –9.124 | 27.12 | 18.95 | –0.09323 |
| 8 | 0.04271 | 0.4103 | –0.306 | 0.1387 | 22 | 2.16 | –1.072 | 8.787 | 5.369 |
| 9 | 4.598 | 7.149 | –26.64 | –0.0471 | 23 | 0.1228 | 5.693 | –6.501 | –1.81 |
| 10 | 0.02548 | 0.01963 | –0.05466 | 6.23 | 24 | 0.8176 | 2.055 | –1.715 | 0.3915 |
| 11 | 0.03521 | 0.07188 | 0.3737 | –3.52 | 25 | –28.06 | 46.92 | 68.34 | 0.3839 |
| 12 | 0.6868 | 1.744 | –4.637 | 3.796 | 26 | 3.512 | 7.477 | –26.96 | –0.3477 |
| 13 | 0.001711 | 0.002811 | 0.03924 | 5.99 | 27 | –22.57 | 52.04 | 42.46 | 0.03467 |
| 14 | 0.0488 | 0.005396 | 0.1833 | 1.173 | | | | | |

In addition, defuzzified results and graphical outputs can be derived. The trained if–then rules are presented in Fig. 7, which can be used for prediction. Using the interface, defuzzified values for output variables can be derived changing input values manually. Different output values can be obtained through the Rule Viewer according to the given input values. For example, if the values of the three inputs vary from 1700 to 1905 mg $L^{-1}$, from 475 to 478 $m^3$ $h^{-1}$, from 460 to 447 mg $L^{-1}$, respectively, then we immediately get the new output value of the ANFIS as 4.88 $m^3$ $h^{-1}$. This is illustrated in Fig. 8. Fig. 9 (a, b, c) illustrates an example of the Surface Viewer screen obtained from the fuzzy logic toolbox. Two- or three-dimensional graphic results of variables can be plotted and compared.

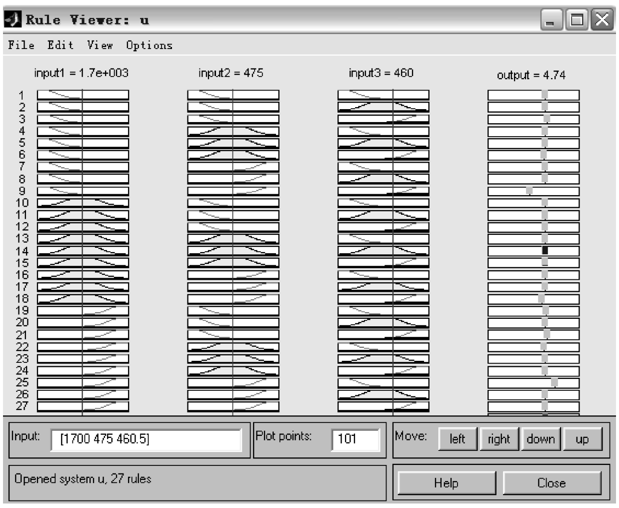



Fig. 7 – *If-then rules after training*

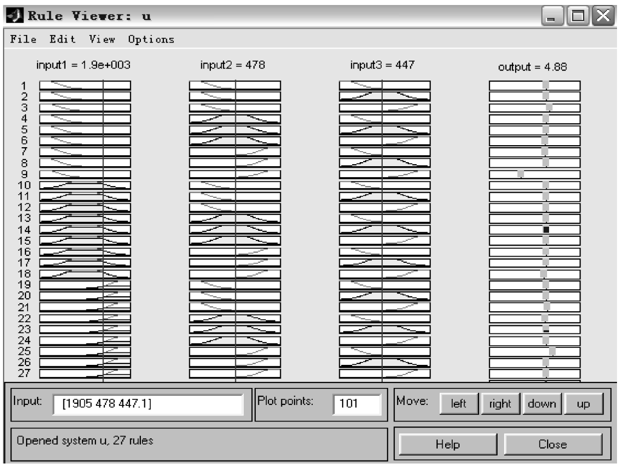
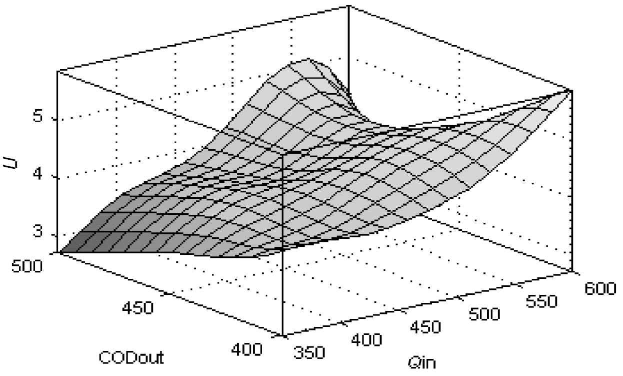
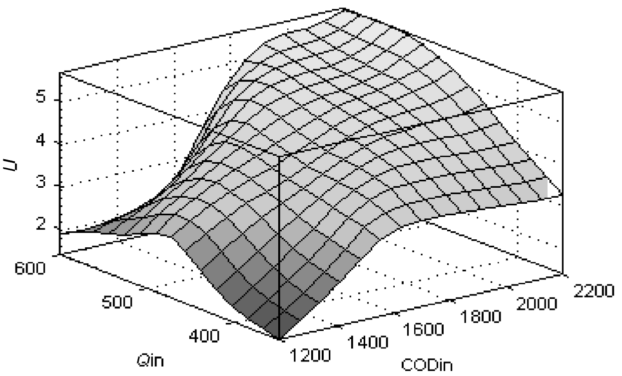



Fig. 8 – *If-then rules for prediction by changing the values of inputs*

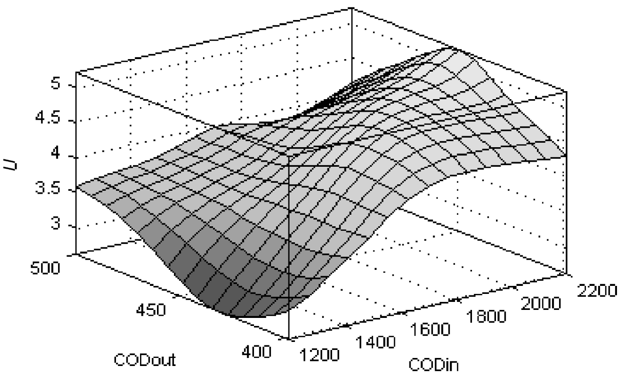
The trained ANFIS is validated by the testing dataset. Fig. 10 represents the validation results of the proposed fuzzy neural network model. For convenience, the testing errors for the testing dataset are also shown in Fig. 10, from which it can be observed that the fitting and testing errors for all the testing dataset are all nearly zero. This clearly indicates the effectiveness and the reliability of the proposed approach for extracting features from input data.




(a) ***U(t)*** according to ***COD$_{out}$(t)*** and ***Q$_{in}$(t)*** interaction




(b) ***U(t)*** according to ***Q$_{in}$(t)*** and ***COD$_{in}$(t)*** interaction




(c) ***U(t)*** according to ***COD$_{out}$(t)*** and ***COD$_{in}$(t)*** interaction

Fig. 9 – *3D Response surface graph for the FNN model*

## Comparisons with ANN

To compare the performances of the ANFIS and ANN, the following evaluation criteria were adopted. Root mean squared error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(A_t - F_t)^2}, \qquad (10)$$

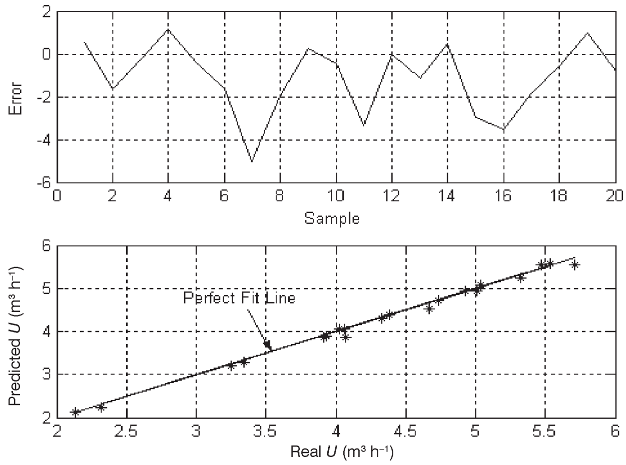



Fig. 10 – *Test performance and testing errors of the 20 testing datasets by ANFIS*

where $A_t$ and $F_t$ are actual (desired) and fitted (or predicted) values, respectively, and $N$ is the number of training or testing samples.

Mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - F_t}{A_t}\right| \cdot 100 \qquad (11)$$

Correlation coefficient ($R$):

$$R = \frac{\sum_{t=1}^{N}(A_t - \overline{A})(F_t - \overline{F})}{\sqrt{\sum_{t=1}^{N}(A_t - \overline{A})^2 \cdot (F_t - \overline{F})^2}}, \qquad (12)$$

where $\overline{A} = \frac{1}{N}\sum_{t=1}^{N} A_t$ and $\overline{F} = \frac{1}{N}\sum_{t=1}^{N} F_t$ are the average values of $A_t$ and $F_t$ over the training or testing dataset. The smaller RMSE and MAPE and larger R mean better performance.

According to comparative analysis, the best ANN structure for dosage performance in PMWTP is a three-layer back propagation network with 10 hidden neurons, as shown in Fig. 11. The perfor-

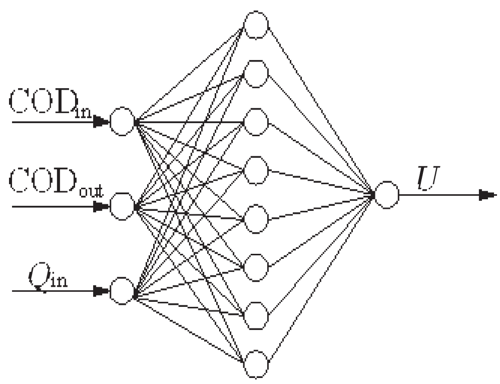



Fig. 11 – *ANN architecture for modeling coagulation performance in PMWTP*

mances of the ANFIS and ANN in modeling dosage performance in PMWTP are presented in Table 3, where the two models are trained using the same training dataset and validated by the same testing dataset. Fig. 12 shows the fitting and testing errors for the 100 data obtained by the ANN. It is very clear from Table 1 and Figs. 10 and 12 that the ANFIS has smaller RMSE and MAPE as well as bigger $R$ for both the training and testing datasets than the ANN model. In other words, the ANFIS achieves better properties than the ANN model in this wastewater treatment process. Therefore, ANFIS is a good choice for modeling dosage performance in PMWTP. Moreover, ANN is a black box in nature and its relationship between inputs and outputs are not easy to be interpreted, while ANFIS is transparent and its if–then rules are very easy to understand and interpret.

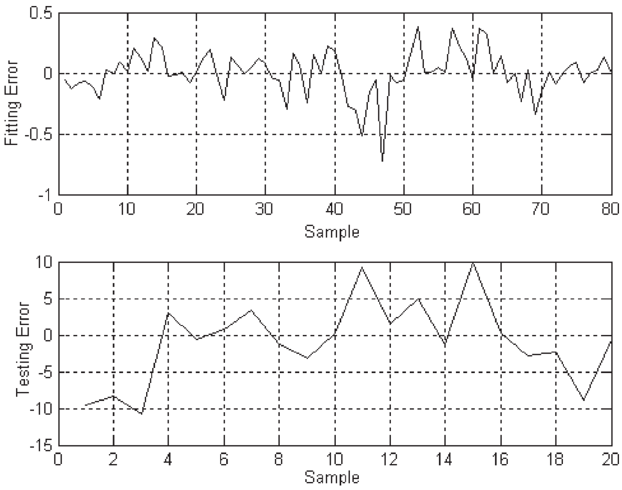



Fig. 12 – *Fitting and testing errors of the 100 data by ANN*

Table 3 – *Performances of ANFIS and ANN in modeling coagulation performance in PMWTP*

| Model | Training dataset | | | Testing dataset | | |
|---|---|---|---|---|---|---|
| | RMSE | MAPE (%) | $R$ | RMSE | MAPE (%) | $R$ |
| ANFIS | 0.0067 | 0.0054 | 0.9999 | 0.083 | 1.4972 | 0.9975 |
| ANN | 0.012 | 0.1745 | 0.9985 | 0.1406 | 9.941 | 0.8875 |

## Choice of MFs

So far, ANFIS had been built using the generalized bell-shaped MFs which performed well, but what about using other-shaped MFs? In this section, we test three more MFs, which are triangular, trapezoidal and Gauss MFs. They are respectively defined as follows:

$$\mu_A(x) = \begin{cases} (x-a)/(b-a) & a \le x \le b \\ (c-x)/(c-b) & b \le x \le c \\ 0 & otherwise \end{cases}$$

$$\mu_A(x) = \begin{cases} (x-a)/(b-a) & a \le x \le b \\ 1 & b \le x \le c \\ (d-x)/(d-c) & c \le x \le d \\ 0 & otherwise \end{cases} \tag{13}$$

$$\mu_A(x) = \frac{1}{1+((x-c)/a)^2}\,.$$

For these three different MFs, Figs. 13–15 show the fitting and testing errors of the coagulation performance in PMWTP by the ANFIS trained with the same dataset but different MFs. It is easy to find that the generalized bell-shaped MFs are the best choice for modeling the coagulation process because they lead to minimum fitting and testing errors when compared with Figs. 13–15.

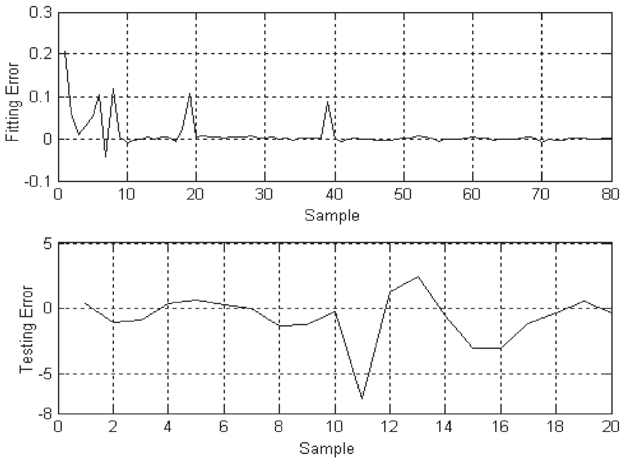



Fig. 13 – *Fitting and testing errors by the ANFIS with Gauss membership functions*

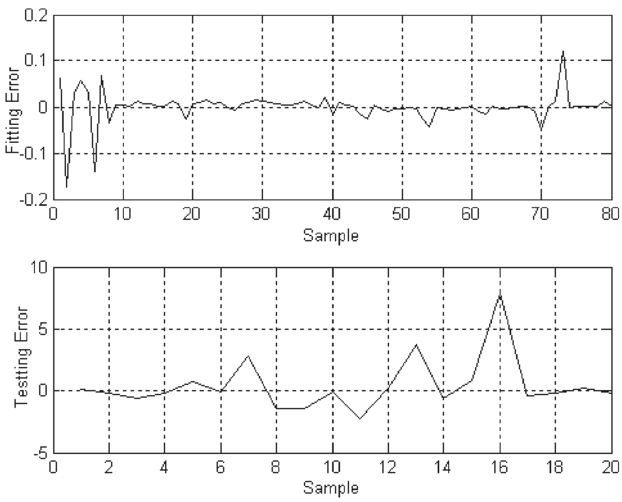
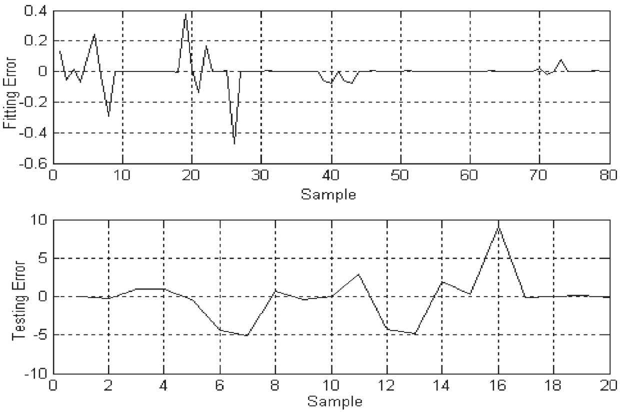



Fig. 14 – *Fitting and testing errors by the ANFIS with triangular membership functions*

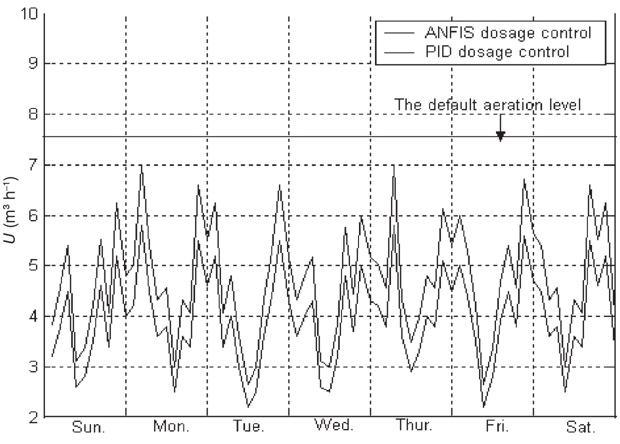



F i g . 1 5 – *Fitting and testing errors by the ANFIS with trapezoidal membership functions*

## Neural fuzzy control application

The NNs-based T–S fuzzy controller devised based on the generalized bell-shaped MFs should be examined for its application potential in dealing with the coagulation control under dynamic inflow in PMWTP. The control system in PMWTP, which combined with the ANFIS control model, is show in Fig. 1.

Regulation tools like PID were also tested. The default level was set up at a constant rate of 7.5 $m^3$ $h^{-1}$ by a timer connected with a pump in the PMWTP. During the test, it shows that the setting of the timer actually follows through the logic of ANFIS control output. Fig. 16 presents the comparisons of the default level, PID, and the optimal control strategy according to the ANFIS controller developed here. In regards to coagulation, it shows that the dosage supply based on the ANFIS control scheme has a consistent trend with the dynamic variation of dosage required theoretically in the traditional coagulation process. Yet, the dosage via ANFIS control exhibits a relatively cheaper and steady way. In terms of the cost effectiveness, it enables us to save almost 25 % of the operating cost during the time period when ANFIS control can be applied.




F i g . 1 6 – *Comparison of the theoretical dosage required and ANFIS aeration control*

A comparison between operation with and without the ANFIS controller can be made as well. When implementing the system on the process, the ANFIS control that was run by a PC was operated in a discrete-time manner. $COD_{in}$, $COD_{out}$ and the real-time flow rate are the three parameters that were used to infer the optimal dosage supply in the beginning test. This leads to finding out the dosage flow that needs to be supplied based on the ANFIS's judgment.

A long-term sampling and analysis program was carried out between 2006 and 2007 to ensure the reliability of such a hybrid fuzzy control scheme (see Table 4). With the ANFIS controller, it eventually leads to a satisfactory situation from a long-term point of view. Table 4 actually illustrates a cost-effective long-term performance of the neuro-fuzzy approach with respect to the control before implementing fuzzy control rules. All of the measurements were still within the regulatory limit, one part of the effluent was recycled, and the other was sent to an aerated submerged biofilm wastewater treatment process. Cost effective operation by injecting a lower dose would be the major contribution. Not only the stability but also the compliance with the effluent quality standards can be fully confirmed.

Although PID feedback dosage control has been applied in some wastewater treatment processes, the inevitable time delay in response to the actual needs might deter the improvement in terms

T a b l e 4 – *Tendency of effluent quality in a long-term investigation*

| Date | pH | COD | BOD | SS |
|---|---|---|---|---|
| The effluent quality before performing control rules | | | | |
| 15/2/2006 | 7.5 | 426 | 270 | 45 |
| 20/4/2006 | 6.8 | 529 | 257 | 52 |
| 3/6/2006 | 7.4 | 443 | 189 | 63 |
| 10/8/2006 | 7.3 | 512 | 285 | 58 |
| 2/11/2006 | 6.9 | 497 | 190 | |
| The effluent quality after performing control rules | | | | |
| 18/2/2007 | 7.1 | 391 | 260 | 32 |
| 22/4/2007 | 7.2 | 448 | 225 | 30 |
| 7/6/2007 | 7.4 | 492 | 205 | 26 |
| 13/8/2007 | 7.2 | 475 | 237 | 19 |
| 4/11/2007 | 6.9 | 426 | 214 | 22 |

of both effluent quality and treatment efficiency. An open-loop control based on the proposed ANFIS control strategy here can easily judge the dosage supply rate by historical experience. Therefore, it is more suitable to fit in the actual need.

## Conclusions

This paper presents a process control scheme for a waste coagulation process based on fuzzy neural control. An adaptive fuzzy neural network was developed to model the nonlinear relationships between the pollutant removal rates and the chemical additive dosages. The method can adapt the system to a large variety of operating conditions with an enhanced learning ability. In order to cope with this problem and perform a cost effective operation, the hybrid neural-fuzzy control scheme has been extensively tested in managing the wastewater treatment in this paper.

It addresses the problem of controlling PAC dosage to a paper-mill wastewater treatment plant to meet the demands of a variable inflow rate and variable organic load measured as chemical oxygen demand (COD). This is accomplished using a fuzzy logic controller coupled with a NNs model to derive the necessary control rule base of Takagi–Sugeno (T–S) type. The ANFIS controller designed in this analysis brings the spirit of human thinking and reasoning into a neural network structure that help derive the representative state function for use in simulating system behavior. Such an advanced hybrid fuzzy control approach effectively achieves the required real-time control objectives and may become an efficient and cost-effective tool to deal with the unexpected uncertainties in the wastewater treatment process. Regulation tools like PID were also tested but had much more difficulty in carrying out an effective control.

Based on a series of computer simulation runs, results are provided demonstrating the control performance of the ANFIS controller in terms of environmental and economic objectives simultaneously. Such an advanced hybrid fuzzy control system may provide immediate guidance and control with respect to multi-objective requirements for distributed control system using on-line process data. It is believed that the control architecture developed in this paper may even function well within limited time for various types of physical, chemical, and biological waste treatment systems when coping with on-line upset conditions. It is believed that this approach can also be used to handle many other types of waste treatment systems to meet the cost effectiveness criteria.

*ACKNOWLEDGEMENTS*

*This research has been supported by Guangdong Provincial Department of Science (2008A080800003) and Technology Research Project (2003A30406) and the Science and Technology Foundation of Guangzhou city (2004Z3-D027). The authors are thankful to the anonymous reviewers for their insightful comments and suggestions.*

### Nomenclature

SS – Suspended Solids

COD – Chemical Oxygen Demand

BOD – Biochemical Oxygen Demand

DO – Dissolved Oxygen

$Q_{in}$ – Input flow rate

$R$ – Correlation coefficient

RMSE – Root Mean Square Error

MAPE – Mean Absolute Percentage Error

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