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Enhancing dissolved oxygen control using an on-line hybrid fuzzy-neural soft-sensing model-based control system in an anaerobic/anoxic/oxic process

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Abstract An on-line hybrid fuzzy-neural soft-sensing model-based control system was developed to optimize dissolved oxygen concentration in a bench-scale anaerobic/anoxic/oxic (A^2/O) process. In order to improve the performance of the control system, a self-adapted fuzzy c-means clustering algorithm and adaptive network-based fuzzy inference system (ANFIS) models were employed. The proposed control system permits the on-line implementation of every operating strategy of the experimental system. A set of experiments involving variable hydraulic retention time (HRT), influent pH (pH), dissolved oxygen in the aerobic reactor (DO), and mixed-liquid return ratio (r) was carried out. Using the proposed system, the amount of COD in the effluent stabilized at the set-point and below. The improvement was achieved with optimum dissolved oxygen concentration because the performance of the treatment process was optimized using operating rules implemented in real time. The system allows various expert operational approaches to be deployed with the goal of minimizing organic substances in the outlet while using the minimum amount of energy.

Keywords Anaerobic/anoxic/oxic (A^2/O) process · Intelligent control · Soft-sensing · Adaptive network-based fuzzy inference system (ANFIS)

Introduction

The Ministry of Environmental Protection of the People's Republic of China has required most existing paper mill wastewater treatment plants to meet new, stricter conditions, particularly with regards to the presence of organic substances in the effluent. Paper mill wastewater contains a variety of organic and inorganic constituents, including fiber fines, printing ink, and additives, and may therefore be high in COD. Thus, excess organic matter in wastewater must be removed prior to discharging effluent into particularly sensitive media. These new requirements entail redesigning former removal procedures and developing new ones to meet the regulations. The new goals can be reached in various ways that involve alterations of existing civil works (extensions, purchases of new equipment), changes in operating procedures (e.g., the development of new treatments) or the use of control systems to optimize processes [1]. It is well known that constructing control systems to optimize processes is practical and easy to implement. For control and automation of biological treatment processes, lack of reliable on-line sensors to measure water quality parameters is one of the most important problems to overcome [2]. Many researchers have turned their attention to software sensors or inferential models, which use other readily available on-line measurements because these soft sensors can either replace the hardware sensors or be used in parallel with them to

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provide redundancy and verify whether the hardware sensors are drifting [3].

There are two types of approaches in developing software sensors. One is a method that estimates required parameters on the basis of a deterministic model and the other is the black-box approach that depends only on the observed values. The most common deterministic model used for the modeling of A^2/O process is the activated sludge model (ASM). However, the ASM has its shortcomings in processing activated sludge, as the process is not a linear system and has many operational parameters [4–6]. Recently, different procedures based on artificial intelligence (e.g., artificial neural networks and fuzzy logic) have been used to develop software sensors [7–11]. Fuzzy neural networks (FNN) combine fuzzy logic control (FLC) with artificial neural networks (ANN) and realizes fuzzy logic by fuzzy neural network, and it can use the advantages of both. Meanwhile, the FNN can get hold of fuzzy rules and optimize its subjection function on-line by a self-learning ability of the neural network [12, 13]. Several studies have been done to prove that the online monitoring parameters could be applied to the prediction of effluent quality using adaptive network-based fuzzy inference system (ANFIS). A neural fuzzy model based on ANFIS was proposed in terms of on-line input variables to estimate the effluent chemical oxygen demand of a real scale unsteady anaerobic wastewater treatment plant of a sugar factory [14]. Pai et al. [15] designed three types of ANFIS, which adopted four on-line parameters as input variables to predict effluent SS, COD, and pH from a WWTP of an industrial park in Taiwan. During the last decade, more attention has been paid to the study and development of models to predict the effluent quality of wastewater treatment systems using ANFIS [16–19]. However, no study has been applied in the soft-sensing of effluent quality from paper mill wastewater treatment plant using ANFIS.

The present work was aimed at improving the efficiency of dissolved oxygen control consequently to meet discharge standards (GB3544-2008) for the treatment of paper mill wastewater. By using a control system suited to the specific operating conditions of an anaerobic/anoxic/oxic (A^2/O) process, organic substances can be removed with substantially higher efficiency simply by adapting the process conditions to the requirements in real time. The study was conducted by performing a series of experiments at a bench-scale plant. The response of the system to changes in hydraulic retention time (HRT), influent pH (pH), dissolved oxygen in the aerobic reactor (DO), and mixed-liquid return ratio (*r*)was examined, and various operational and control approaches were used with the goal of maximizing COD removal while reducing energy costs.

In this work, a control system for intelligent optimal dissolved oxygen concentration in aerobic reactor of an A^2/O treating paper mill wastewater is presented. Some improvements have been made on the control system and have allowed for real-time control. In order to evaluate the efficiency and reliability of the dissolved oxygen intelligent optimal control system, several groups of controlled experiments were carried out.

Materials and methods

Experimental apparatus and operation

A schematic representation of the A^2/O system is shown in Fig. 1. The reactor had a working volume of approximately 240 l (40 l for anaerobic reactor, 40 l for anoxic reactor, and 160 l for aerobic reactor), and included a settling reactor and a regulating tank. Motor-driven mixers were applied in the regulating tank, and anaerobic and anoxic reactors. An air compressor and a set of diffusion aerators were employed to supply air to the aerobic reactor. A peristaltic pump was used to automatically furnish the system from the regulating tank. The mixed liquor was recycled from the aerobic reactor to the anoxic reactor. Simultaneously, the sludge was returned from the bottom of the settling reactor to the anaerobic reactor, and the circulation ratio was 1. The controls of peristaltic pumps, mixers, and air supply were automatically achieved by an in-house-developed data acquisition and control (DAC) system. The DAC system consisted of a computer, interface cards, individual meters, transmitters, and a programmable logic controller (Siemens, Berlin, Germany). Electrodes of pH and Dissolved Oxygen (Hach Company, Loveland, Colorado) were installed and connected to an individual meter. Seed sludge for starting up the A^2/O was obtained from the wastewater treatment facilities (secondary settling tank) of a paper mill in Guangzhou, China. The raw wastewater was initially stored in a regulating tank

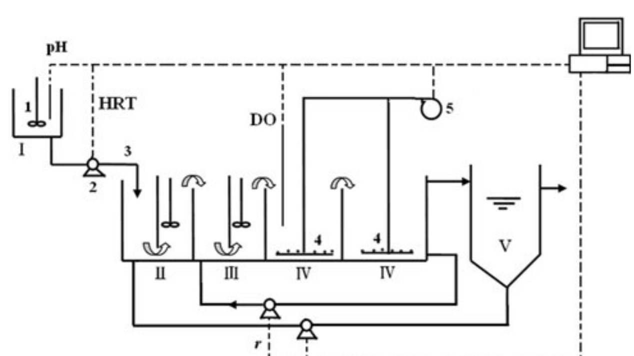

Fig. 1 Schematic diagram of the experimental apparatus. *I* Regulating tank, *II* anaerobic reactor, *III* anoxic reactor, *IV* aerobic reactor, *V* settlingreactor. *1* Stirrer, *2* peristaltic pump, *3* influent, *4* diffuser, *5* air compressor

Table 1 Composition of feed concentrates

COD (mg/l)	BOD (mg/l)	pH	SS (mg/l)	TN (mg/l)	TP (mg/l)	NH_3^+ -*N* (mg/l)
570–1,300	220–390	6.5–7.0	500–1,000	40–60	3–8	10–30

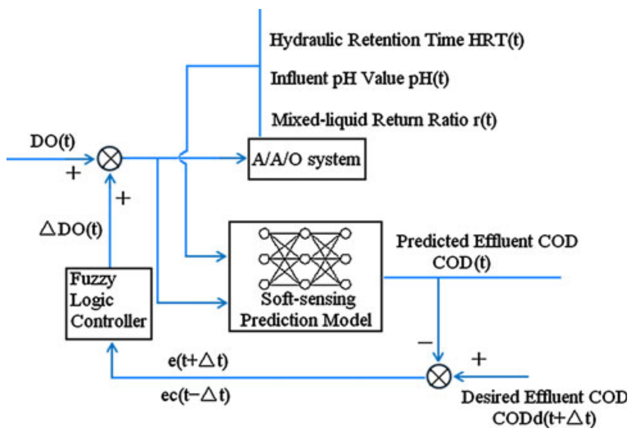

Fig. 2 Architecture of the control system

and then pumped at a fixed-flow rate of 12.0, 11.0, 10.0, 9.0, and 8.0 l/h through the A^2/O, resulting in an HRT of 20.0, 21.8, 24, 26.7, and 30.0 h, respectively. Similarly, a mixed-liquid return ratio (*r*) of 1, 2, and 3 was controlled. The A^2/O reactor was operated at a temperature of 25 ± 3 °C, and a dissolved oxygen (DO) content of 1.0–3.0 mg/l. All chemical analyses were performed according to Chinese Standard Methods [20].

Wastewater characteristics

Paper mill wastewater was obtained from Guangzhou Paper Group Nansha Environmental Protection Paper Base that uses waste paper to manufacture newspaper. The paper mill wastewater was mainly generated from waste paper deinking process and product manufacturing, and it had been treated in an anaerobic digester before it entered the experimental setup. The characteristics of the paper mill wastewater are shown in Table 1.

Dissolved oxygen intelligent optimal control system

The control system architecture is shown in Fig. 2. The software for the bench-scale plant control computer, developed in MCGS (Beijing Kunluntongtai Automation Software Technology Co., Ltd. China) which is the most commonly used control configuration software in China, includes graphic monitoring, data backup, PLC supervision, and control of key process parameters (HRT, DO, and *r*). The dissolved oxygen intelligent optimal control system was developed using MATLAB (R2009b) as a tool to develop the real-time control system, although implementation is also possible using the OPC (OLE for Process Control) communication tool. All functions and features of the control system were developed using the built-in tools. Due to its auto-control and further development in industrial environments, a programmable logic controller (Siemens S7-200) was used for data acquisition and for the final control. The PLC collects and sends the data to the MCGS database through RS-232, which makes the exchange possible, and the control system is fed with monitored on-line data (HRT, pH, DO, and *r*) using the MCGS database. Using rules based on available data, the control system continuously determines the optimum dissolved oxygen concentration required to achieve the required organic matter removal efficiency. Finally, control actions are transmitted to the process computers that actuate on each element of the plant. In the control system, a soft-sensing model and a fuzzy logic controller intended to assist in dissolved oxygen intelligent optimal control. A brief description of these is summarized below.

The soft-sensing model is used for effluent COD soft-sensing while monitored on-line data (HRT, pH, DO, and *r*) is available. In fuzzy logic controller, some rules for the intelligent optimal control of dissolved oxygen concentration of the aerobic reactor are established.

Soft-sensing prediction model

In our previous work, online monitoring data from simple and cheap online meters such as DO or pH meters were used to train the ANFIS soft-sensing model for effluent prediction. The results indicated that reasonable monitoring A^2/O process performance, just using on-line monitoring parameters, has been achieved through the ANFIS soft-sensing model that has potential application for control of wastewater treatment processes [21]. Consequently, an ANFIS was employed as a soft-sensing prediction model in this study.

Adaptive network-based fuzzy inference system

The fuzzy inference system with two inputs (I_1 and I_2), three fuzzy if–then rules, and one output was taken for example to explain the ANFIS architecture in this study. Considering a first-order three-rule Sugeno fuzzy inference system [19, 22], the if–then rule base can be expressed as:

Rule 1: If I_1 is A_1 and I_2 is B_1, then $f_1 = \alpha_1 I_1 + \beta_1 I_2 + \sigma_1$

Rule 2: If I_1 is A_2 and I_2 is B_2, then $f_2 = \alpha_2 I_1 + \beta_2 I_2 + \sigma_2$

Rule 3: If I_1 is A_3 and I_2 is B_3, then $f_3 = \alpha_3 I_1 + \beta_3 I_2 + \sigma_3$

where A_i and B_j ($i, j = 1$–3) are the MFs for the inputs I_1 and I_2, respectively. α_i, β_j and σ_k ($i, j, k = 1$–3) denote the

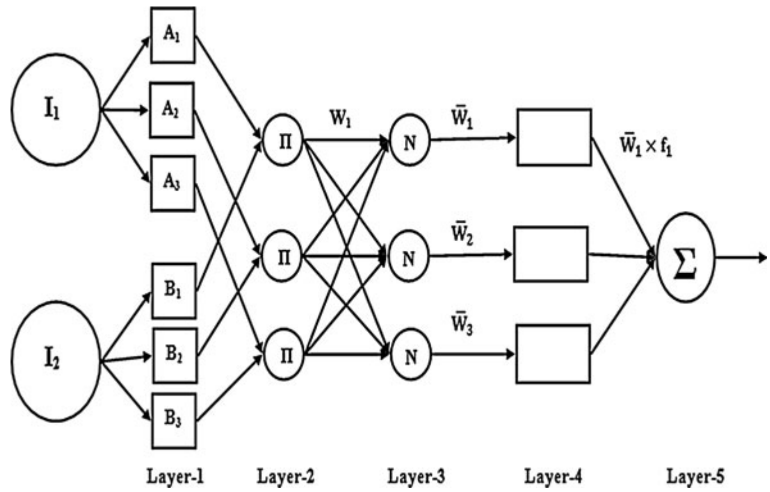

Fig. 3 ANFIS's architecture with two input variables and three MFs

consequent parameters [23]. As shown in Fig. 3, the ANFIS's architecture is formed by using five layers and three if–then rules as follows:

Layer 1: Each "i" node in this layer is a square node with a node function as,

$$O^1_{1,i} = \varphi_{A_i}(I_1) \tag{1}$$

$$O^1_{2,j} = \varphi_{B_j}(I_2) \tag{2}$$

where I_1 and I_2 are inputs to node i, and A_i and B_j ($i, j = 1, 2, 3$) are the linguistic variables associated with these nodes functions. φ_{A_i} and $\varphi_{B_j}$are the membership functions of A_i and B_j, respectively. The fuzzy MFs of $\varphi_{A_i}(I_1)$ and $\varphi_{B_j}(I_2)$can be described in many types. Four types of common MFs including Gaussian, generalized bell shaped, triangular and trapezoidal shaped functions with maximum value of 1 and minimum value of 0 described as follows: Gaussian

$$\varphi(I) = \mathrm{e}^{-\frac{(I-c)^2}{2\sigma^2}} \tag{3}$$

Bell shape

$$\varphi(I) = -\frac{1}{1+\left(\frac{I-c}{a}\right)^{2b}} \tag{4}$$

Triangular shape

$$\varphi(I) = \max\left(\min\left(\frac{I-a}{b-a}, \frac{c-I}{c-b}\right), 0\right) \tag{5}$$

Trapezoidal shape

$$\varphi(I) = \max\left(\min\left(\frac{I-a}{b-a}, 1, \frac{c-I}{c-b}\right), 0\right) \tag{6}$$

where a, b, c, and σ are the parameters set, which are referred to as premise parameters.

Layer 2: Each circle node labeled Π multiplies the incoming signals and sends the product out, which is given by:

$$O^2_i = w_i = \varphi_{A_i}(I_1) \times \varphi_{B_i}(I_2),\ i = 1, 2, 3 \tag{7}$$

Layer 3: Each circle node is labeled by N, which is a fixed node. The i*th* node calculates the ratio of the i*th* rule's firing strength to the sum of all rules' firing strengths, i.e., the normalized firing strength.

$$O^3_i = \overline{w_i} = \frac{w_i}{w_1 + w_2 + w_3},\ \mathrm{i}\ = 1, 2, 3 \tag{8}$$

Layer 4: Each square node in this layer is a linear node function whose output is simply the product of the normalized firing strength, and a first-order polynomial (for a first-order Sugeno model) is described as,

$$O^4_i = \overline{w_i} \times f_i = \overline{w}_i \times (\alpha_i I_1 + \beta_i I_2 + \sigma_i),\quad \mathrm{i} = 1, 2, 3 \tag{9}$$

Layer 5: The single circle node in this layer is depicted by Σ and calculates the overall output as the summation of all incoming signals, i.e.,:

$$O^5_i = \sum_{i=1}^{3} \overline{w_i} \times f_i = \frac{\sum_{i=1}^{3} w_i \times f_i}{\sum_{i=1}^{3} w_i} \tag{10}$$

Self-adapted fuzzy c-means clustering

In order to optimize the ANFIS's fuzzy rules automatically. In this study, a new validity function was introduced to the FCM clustering algorithm, B (c), which is the value of the ratio of the compactness and the divergence. The numerator of B (c) denotes the sum of the distances between classes, and the denominator represents the sum of the intra-distances of all the clusters. So the bigger B (c) is, the more reliable the result of clustering is. The cluster number c is the best one when B (c) reaches its maximum value, as defined by:

$$B(c) = \frac{\sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} \|v_i - \bar{x}\|^2 \Big/ (c-1)}{\sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} \|x_j - v_i\|^2 \Big/ (n-c)} \tag{11}$$

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} x_j \tag{12}$$

in which, ||·|| stands for Euclidean distance measure.

The FCM clustering algorithm, in which an object can be a member of different classes at the same time, is an unsupervised classification algorithm which uses a certain objective function to iteratively determine the local minima. The objective function minimized iteratively is a weighted within-groups sum of distances $d_{i,j}$. The weighting is done by multiplying the squared distances by membership values $u_{i,j}$ [24, 25]:

$$J_m(U, V) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2} \tag{13}$$

$$\sum_{i=1}^{c} u_{ij} = 1, \ 1 \le j \le n \tag{14}$$

where c is the total number of clusters, n is the total number of objects in the calibration data, d_{ij} is the distance between an object j and a cluster i, u_{ij} is the membership function. m is the fuzzy weighting exponent that represents the fuzziness of the classification. Roughly estimating, a good value for m lies in the range of 1.5–2.5. For simplicity, we assume $m = 2$ in this study. d_{ij} stands for the Euclidean distance between an object j (x_j) and a cluster i (v_i), which is defined by:

$$d_{ij} = \|x_j - v_i\| \tag{15}$$

where x_j is the observed value, v_i is the cluster centroid, ||·|| stands for Euclidean distance measure. Membership values for the individual objects are calculated using Eq. (4). Membership u_{ij} to a certain cluster i of an instance at the time k can be represented as:

$$u_{ij}^{(k)} = \frac{1}{\sum_{r=1}^{c} \left(\frac{d_{ij}^{(k)}}{d_{rj}^{(k)}} \right)^{\frac{2}{m-1}}} \tag{16}$$

After computing the membership values for all calibration objects, the cluster centers v_i are given by Eq. (7).

$$v_i^{(k+1)} = \sum_{j=1}^{n} \left(u_{ij}^{(k)} \right)^m x_j \Big/ \sum_{j=1}^{n} \left(u_{ij}^{(k)} \right)^m \tag{17}$$

The minimization of Eq. (3) commences after giving initial values for the cluster centers. Then Eqs. (4, 5, 6, 7) are repeated successively in each iteration step.

Fuzzy logic controller

In general, the fuzzy logic controller consists of four principal components: fuzzification interface, fuzzy rule base, fuzzy inference engine, and defuzzification interface. The fuzzification interface converts real-world data into an acceptable form for the fuzzy controller, using fuzzy membership as a tool. The fuzzy rule base contains a set of "if–then" rules relating measured variables to control variables. The antecedent part of each rule classifies the behavior of measured variables by fuzzy membership functions, whereas the consequence part expresses the essential action in terms of a set of control variables. Available domain experts must be invited to build the rule base in most cases. The purpose of the inference engine is to derive a reasonable action with respect to a specific situation based on the given rule base. It can be viewed as a procedure by which a possibly imprecise conclusion is deduced from a collection of imprecise premises. Finally, the defuzzification interface converts the fuzzy control action to the non-fuzzy action that can be accepted by the real-world system [26].

The most important part of the fuzzy logic controller is the knowledge base. The knowledge base of the fuzzy logic controller comes from two sources: mathematical models and the operator's experience. The nonlinear mathematical model of the fuzzy logic controller in this study can be expressed as:

$$\Delta\mathrm{DO}(t) = \mathrm{F}(\mathrm{e}(t+\Delta t), \ \mathrm{ec}(t+\Delta t)) \tag{18}$$

$$\mathrm{e}(t+\Delta t) = \ \mathrm{COD}_d(t+\Delta t) - \mathrm{COD}(t) \tag{19}$$

$$\mathrm{ec}(t+\Delta t) = [\mathrm{COD_d}(t+\Delta t) - \ \mathrm{COD}(t)]/\Delta t \tag{20}$$

in which, the index t in the context stands for time, $\Delta\mathrm{DO}(t)$ is the correction of dissolved oxygen, $\mathrm{COD}_d(t+\Delta t)$ the desired effluent COD, COD(t) the predicted COD, e($t + \Delta t$) the COD variation, ec($t + \Delta t$) the rate of COD change.

Knowledge that comes from the operator's experience is called heuristic knowledge. According to heuristic knowledge in this study, e($t + \Delta t$) and ec($t + \Delta t$) were set at [−40, +40] and [−8, +8], respectively. They were all mapped to [−6, +6] by multiplying the index $k_e = n/x_e = 6/40 = 0.15$ and $k_{ec} = n/x_{ec} = 6/8 = 0.75$, respectively. The following rules are some examples of heuristic knowledge:

Rule 1: if $e = -6$ and ec $= -6$ then ΔDO = 6
Rule 2: if $e = -6$ and ec $= -4$ then ΔDO = 6
Rule 3: if $e = -6$ and ec $= -2$ then ΔDO = 6
Rule 4: if $e = -6$ and ec $= 0$ then ΔDO = 6
Rule 5: if $e = -6$ and ec $= 2$ then ΔDO = 4
Rule 5: if $e = -6$ and ec $= 4$ then ΔDO = 2
Rule 7: if $e = -6$ and ec $= 6$ then ΔDO = 0

Heuristic knowledge can provide qualitative diagnoses, but it has minimal quantitative information. Process simulation is based on mathematical models of activated sludge processes, so it can provide quantitative predictions. An ANFIS model was developed for the fuzzy logic controller, and the fuzzy logic controller based on ANFIS can accurately simulate the major process dynamics of dissolved oxygen. The topological architecture of the fuzzy logic controller illustrated in Fig. 4 shows a five-layer network comprising two nodes representing the input variables, which had Gaussian MFs in input layer, 14 nodes in the second layer, 49 nodes in the third layer represent the fuzzy rules, 49 nodes in the fourth layer, and one node in the output layer.

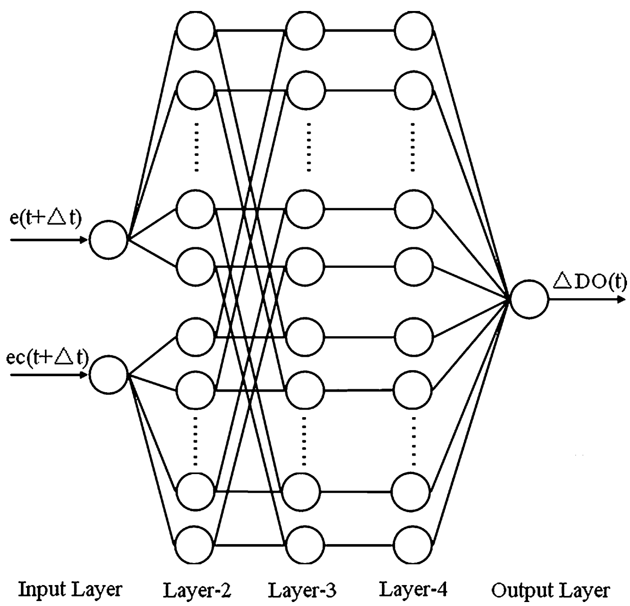

Fig. 4 Topological architecture of fuzzy logic controller

Results and discussion

To study the efficiency of COD removal in different operational modes, two groups of experiments were carried out. In the first group of experiments, the plant operation was maintained in a fixed way and different operational conditions were tested using an open-loop scheme. Data (Fig. 5) obtained in this group of experiments resulted in determination of appropriate soft-sensing prediction model implemented in the control system. Among the total numbers of data, the numbers for training and testing were 60 and 30, respectively. In the second group of experiments, different strategies were implemented and checked using the previously developed control system, and Table 2 summarizes the operational parameters studied in each experiment.

Determination of appropriate soft-sensing prediction model

In order to find an optimal cluster number automatically, a validity function, $B\ (c)$, was defined, as shown in Eq. (1). The data set used here was a four-dimension feature space. For visualization, we showed the data in terms of two coordinates, as shown in Fig. 6. The values of validity function $B\ (c)$ were: $B\ (2) = 642.5$, $B\ (3) = 1{,}070.5$, $B\ (4) = 1{,}421.5$, $B\ (5) = 1{,}751.5$, $B\ (6) = 1{,}869.8$,

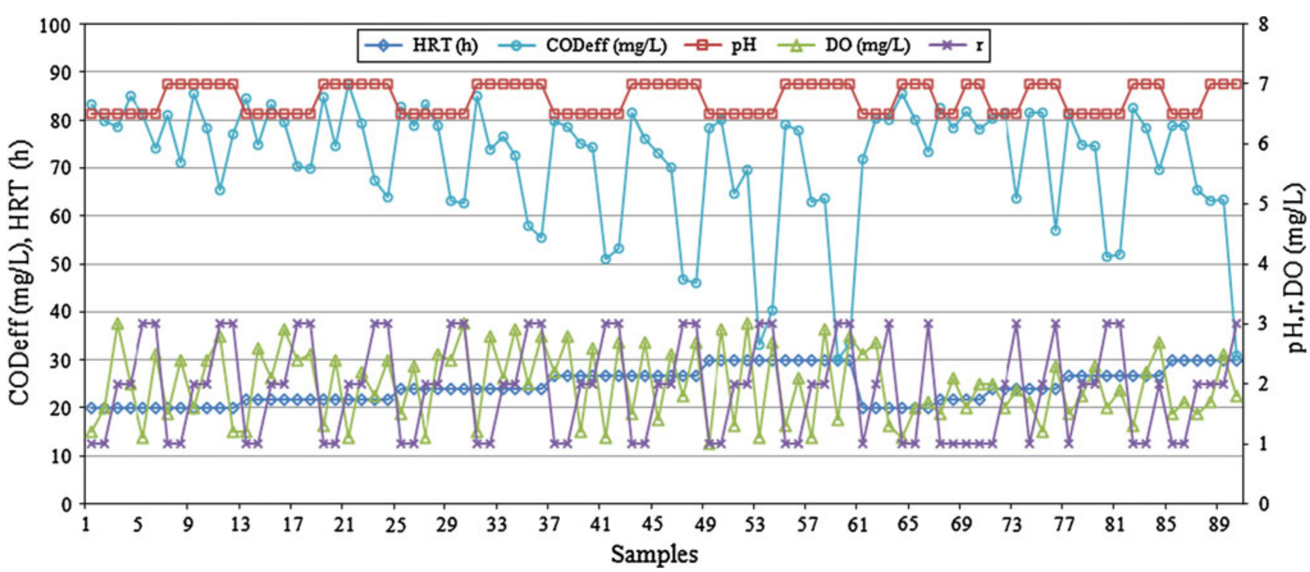

Fig. 5 Sample data of experiment

Table 2 Operational conditions used in every experiment

Experiment	Desired COD_{eff} (mg/l)	HRT (h)	pH	DO (mg/l)	*r*	Observed COD_{eff} (mg/l)
1		20	6.5	2.2	1	74.62
2		20	6.5	2.3	3	74.98
3		20	7	2.5	2	77.27
4		20	7	2.9	2	72.34
5		20	7	2.6	3	66.74
6		21.8	6.5	3.6	2	69.76
7		21.8	7	2.6	2	76.45
8	70	21.8	7	2.8	2	74.60
9		21.8	7	2.1	3	65.74
10		24	6.5	2.4	1	78.10
11		24	6.5	2.6	2	78.46
12		24	7	2.7	1	74.44
13		24	7	2.3	2	75.64
14		24	7	1.5	3	60.86
15		26.7	6.5	2.7	1	78.77
16		26.7	7	1.7	2	72.63
17		30	7	2.4	1	77.69

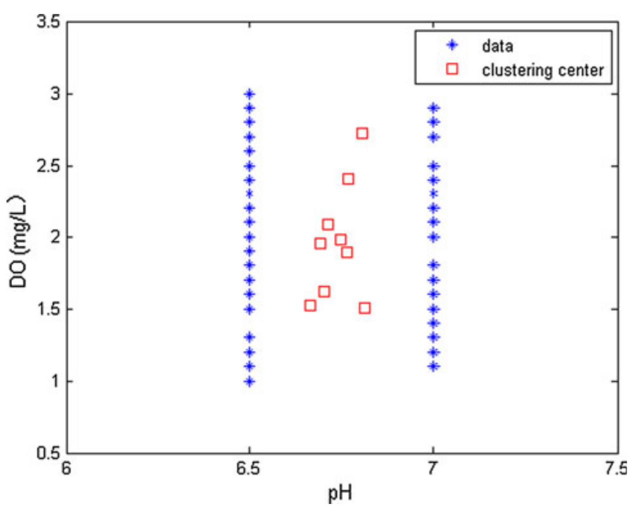

Fig. 6 Visualization of pH and DO

B (7) = 1,895.7, B (8) = 1,922.1, B (9) = 1,996.3, B (10) = 1,951.5, from which we could see that 9 was the best cluster number.

The types and numbers of MFs in ANFIS included Gaussian, generalized bell-shaped, triangular, and trapezoidal-shaped functions, and the parameters were tested to determine an appropriate ANFIS model. After many trials, the ANFIS soft-sensing model that had Gaussian MFs for each input variable gave the best results, so they were used for predicting the effluent COD(COD_{eff}) of the A^2/O process.

Figure 7 shows the training and predicting results of COD_{eff} using ANFIS, and the relative errors of training and testing is shown in Fig. 8. As can be seen from Figs. 7 and 8, the maximum relative error between the observed and predicted values of COD_{eff} was 0.7878 % when training. When predicting, the maximum relative error value, root mean square error, mean absolute percentage error, and correlation coefficient value were 4.8641 %, 1.7365, 2.0402 % and 0.99033, respectively. As a result, the ANFIS soft-sensing model which was optimized by trial and error during the training process was satisfactory to monitor the COD_{eff} in the A^2/O process.

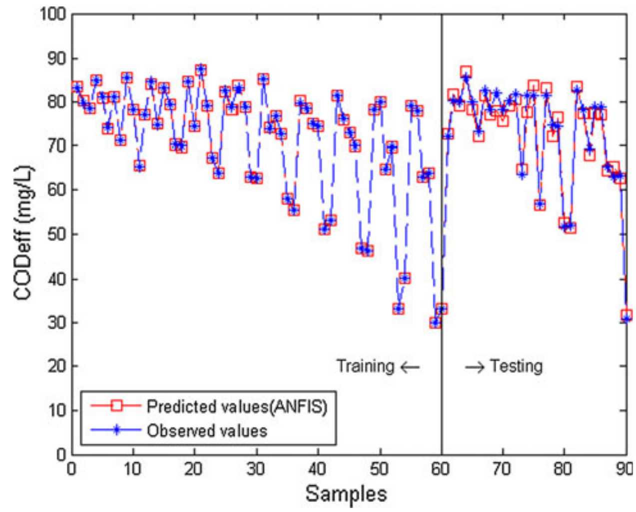

Fig. 7 Prediction results of COD_{eff} by ANFIS soft-sensing model

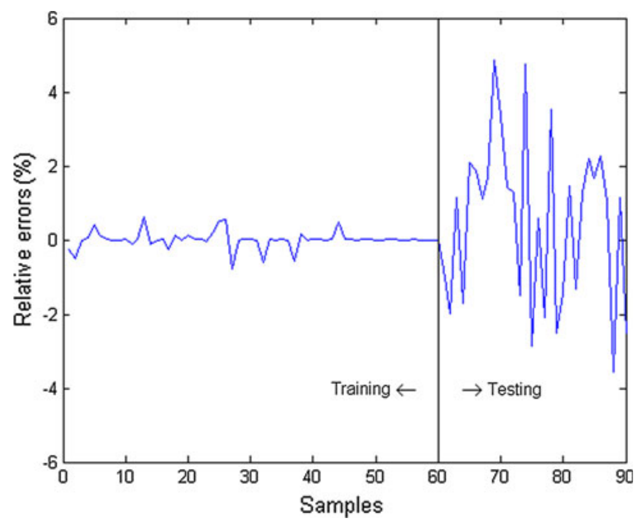

Fig. 8 Relative errors of training and testing by ANFIS soft-sensing model

Control performance

Several experiments with different strategies were implemented to check the previously developed control system. The results (Table 2) demonstrated that when the desired

COD_{eff} was set to 70 mg/l, the observed COD_{eff} was between 60.86 and 78.77 mg/l. It indicated that the intelligent control system can dynamically optimize dissolved oxygen consequently to meet discharge standards and steady effluent quality.

As shown in Table 2, experiments 1, 10, and 15 were used to examine the response of the control system to an influent of flow rate by comparing the removal efficiency obtained with a constant pH and *r*. Experiment 15 using the highest HRT set-point provided a high COD removal efficiency of 88.75 %. In experiment 1, HRT was decreased to 20 h; the removal efficiency was 89.34 % next to that of experiment 1. Experiments 3 and 4, and 7 and 8 were used to examine the response of the control system to A^2/O process with a constant HRT, pH and *r* by comparing the optimum DO obtained from the control system. The DO was changed by the control system automatically. The result of experiment 7 was compared with that of experiment 8, where a control strategy that altered the DO as a function of the concentration of COD in the effluent was implemented. The optimum DO obtained from the control system was almost the same, 2.6 mg/l for experiment 7 and 2.8 mg/l for experiment 8.

Conclusions

The implementation of the dissolved oxygen intelligent optimal control system in A^2/O has resulted in the transformation of a classical control system with a fixed behavior into a system adaptable to different situation that could appear in a WWTP to automatically optimize dissolved oxygen concentration. The capacity is useful for controlling abnormal situations and maintaining the effluent within legal restrictions. Furthermore, changes in the control strategies do not require a deep knowledge of the physical implementation of the control system. Overall, the COD removal efficiency of the A^2/O process was substantially increased with available resources while meeting the discharge standards and avoiding wasting energy on aeration. Based on the results of this work, the following conclusions can be drawn:

(a) Such very good prediction performances of ANFIS models just adopting on-line monitoring parameters for predicting the effluent COD are particularly important considering the high level of complexity in A^2/O process. The ANFIS soft-sensing modeling approach may provide an alternative generic framework for the monitoring of wastewater treatment processes.

(b) The proposed control system architecture permits the implementation of dissolved oxygen intelligent optimal control system on MCGS (Monitor and Control Generated System)—the type of system most frequently used by control systems at full-scale treatment plants. The system also allows for the easy implementation of different operational strategies in order to adapt the system to the actuation variables involved.

(c) The intelligent control system can dynamically optimize dissolved oxygen consequently to meet discharge standards and steady effluent quality.

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