Development of a real-time control strategy with artificial neural network for automatic control of a continuous-flow sequencing batch reactor

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Abstract The purpose of this study is to develop a reliable and effective real-time control strategy by integrating artificial neural network (ANN) process models to perform automatic operation of a dynamic continuous-flow SBR system. The ANN process models, including ORP/pH simulation models and water quality ([NH_4^+-N] and [NO_x^--N]) prediction models, can assist in real-time searching the ORP and pH control points and evaluating the operation performances of aerobic nitrification and anoxic denitrification operation phases. Since the major biological nitrogen removal mechanisms were controlled at nitritification (NH_4^+-N$\rightarrow$$NO_2^-$-N) and denitritification (NO_2^--N$\rightarrow$$N_2$) stages, as well as the phosphorus uptake and release could be completely controlled during aerobic and anoxic operation phases, the system operation performances under this ANN real-time control system revealed that both the aeration time and overall hydraulic retention time could be shortened to about 1.9–2.5 and 4.8–6.2 hrs/cycle respectively. The removal efficiencies of COD, ammonia nitrogen, total nitrogen, and phosphate were 98%, 98%, 97%, and 84% respectively, which were more effective and efficient than under conventional fixed-time control approach.
Keywords Artificial neural network (ANN); automatic control; biological nitrogen removal (BNR); continuous-flow SBR; denitrification; nitrification; on-line monitoring; ORP; pH; real-time control

Introduction

As a simple and compact wastewater treatment system, the continuous-flow sequencing batch reactor (continuous-flow SBR) is capable of removing the oxygen-demanding carbonaceous materials, nitrogen and phosphorus biological nutrients by cycling anaerobic, aerobic, anoxic, settling and discharge operation phases. Therefore, it is suitable for water pollution control in remote areas and communities without sewer services, especially in developing countries. However, continuous-flow SBR is usually controlled with a steady-state sequential approach, in which it is difficult to adjust the operational and control conditions to dynamic influent loading and system state variations, and always led to tremendous energy and resources consumption for meeting the effluent standards and increasing the system operation performances.

Since a continuous-flow SBR system consists of a sequence of complex biochemical reactions, it is difficult to simulate the overall system behaviors with mathematical models and there has seldom been success in process control (Avoyama and Venkatasubramanian, 1995). Recently, oxidation-reduction potential (ORP) and pH have been recognized as relatively flexible and efficient on-line monitoring and control parameters for biological and chemical treatment processes (Chang *et al*., 1997), particularly applied to the biological nitrogen removal (BNR) processes (Chang and Hao, 1996; Hao and Huang, 1996). The ORP and pH monitoring profiles can locate the end-points of nitrification and denitrification by identifying the feature points (e.g. NH_4^+-N breakpoint and NO_3^--N knee-point) in

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aerobic and anoxic operation phases of SBR system (Plisson-Saune *et al.*, 1995; Yu *et al.*, 1997). Therefore, many researchers have tried to fit nonlinear mathematical formulas based on ORP and pH feature points for real-time control of the BNR processes. However, these process control approaches still involve limitations applied to dynamic influent and complex wastewater treatment systems, and highly subject to risks caused by monitoring noise.

A process control system built with artificial neural network (ANN) models has been revealed as a reliable tool to optimize the operation performance in a dynamic complex water and wastewater treatment system (Zhang and Stephen, 1999; Hamoda *et al.*, 1999; Cohen *et al.*, 1997). Generally, the ANN approaches, especially back-propagation neural networks (BPNs), focus on finding repeated, recognizable and predictable patterns between the causes and the effects from the past operational records, and bypass the modeling of actual chemical and biological reactions. This situation makes the ANN modeling approach a rational choice for process modeling and control in water and wastewater treatment system (Cote *et al.*, 1995).

Based on these concepts, the purpose of this study is to develop a real-time control strategy integrated with ANN process models to evaluate the operation performances and perform the automatic control of a dynamic continuous-flow SBR system by acquiring on-line ORP, pH, and DO monitoring information.

Experimental materials and methods

Apparatus of continuous-flow SBR

The continuous-flow SBR wastewater treatment system used in this study was modified from the ICEAS by developing a new vertical up-downward decanter and rearranging appropriate sequencing operation processes to remove the C, N, and P constituents of domestic wastewater in a single tank. A laboratory-scale continuous-flow SBR, as shown in Figure 1, was set up as a rectangular tank with an effective volume of approximately 150 litres. The monitoring and control system applied in this continuous-flow SBR system consisted of sensors, computer, monitoring and control interfaces. The on-line monitoring/control meters of ORP, pH, DO, and MLSS were installed on control panel, with sensor analog signals transferred to digital forms by an AD/DA converter, and received by an IBM compatible PC. Three solid-state relays were devised for on/off control of mixers, blower, and decanter to perform the changes of different operational phases cyclically.

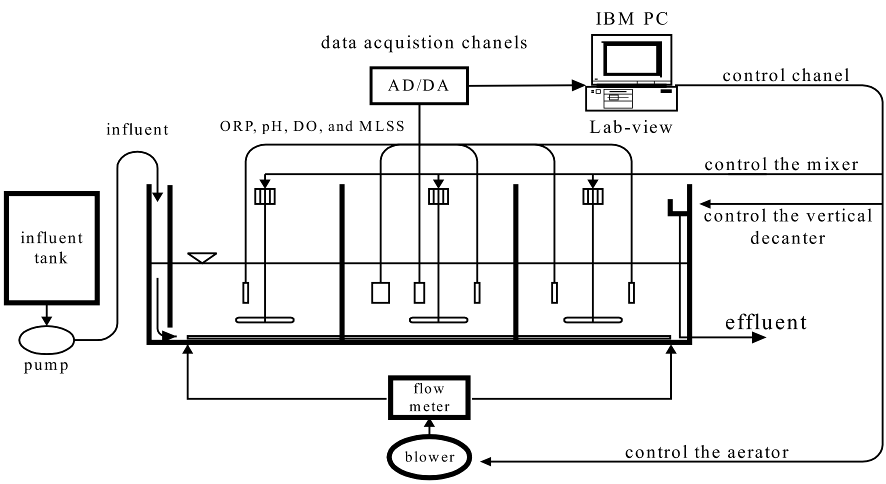


Figure 1 Schematic diagram of continuous-flow SBR with monitoring and control system

Experimental process

In this study, synthetic sewage (Table 1) was prepared to simulate the constituents and water qualities of domestic wastewater, and fed continuously with a dynamic influent pattern (Figure 2) simulated from Taipei Min-Sheng community wastewater treatment plant. In addition to on-line monitoring of ORP, pH, DO, and MLSS, the variations of COD, MLSS, NH_4^+-N, NO_2^--N, NO_3^--N, and PO_4^{3-}-P were analyzed following the *Standard Methods* (APHA, 1995). The MLSS variations of continuous-flow SBR under experimental proceeding were maintained at 1,500~2,500 mg/L and with different dynamic influent loadings (F/M = 0.06~0.58 kg COD/kg MLSS/day). A fixed-time control study was initialized to examine the treatment capacity of continuous-flow SBR system under dynamic influent conditions, and operational results could be as training and testing samples of ANN process models. The system operation under fixed-time control study was fixed with time intervals of different sequencing operation phases with cyclical overall hydraulic retention time (HRT) of 8 and 12 hours. In the period of real-time control study, the major difference to fixed-time control was to determine the HRTs of aerobic and anoxic phases by an ANN real-time control system.

Architecture and algorithm of ANN process models

In this study, the architecture of ANN process models consists of input, hidden, and output layers connected in feed-forward topology. The calculations between input vector (X_i), hidden vector (Z_j), and output vector (Y_k) were defined as equations (1) and (2). Generalized delta-learning rule was used as a training algorithm for network learning, and

Table 1 Compositions and simulated influent water quality of synthetic sewage

Compositions of stock synthetic sewage				Influent water quality			
Contents and Concentration (g/L)				Parameters and Concentration (mg/L)			
Lactose	50	Mineral	7.75	TCOD	120–430	NH_4^+-N	11.8–40.2
Glucose	30	Urea	60	SCOD	75–275	NO_2^--N	<0.1
Fat	38	$FeCl_3$ (10%)	0.2	PO_4^{-3}-P	2.4–7.9	NO_3^--N	<0.1
NH_4Cl	75	KH_2PO_4	20	TP	3.1–10.4	Organic-N	2.7–7.5
CH_3COOH	27	$NaHCO_3$	32	Alkalinity (as $CaCO_3$)	14.6–49.2	TKN	14.5–47.7
Protein	36					TN	14.6–47.9

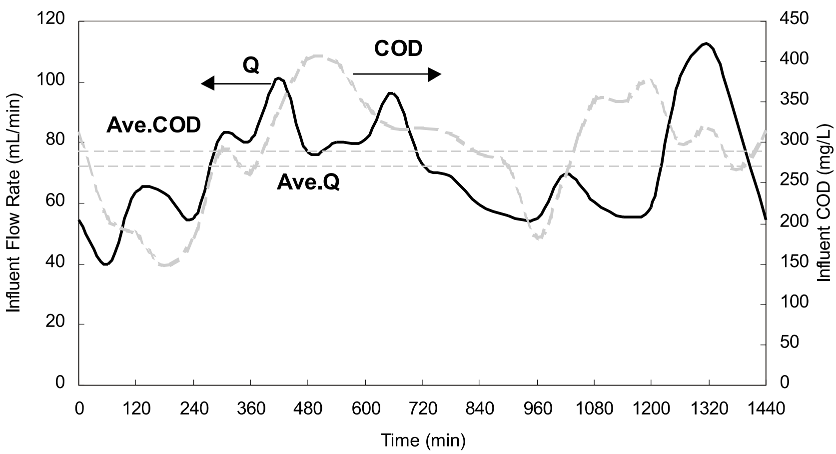


Figure 2 Simulated dynamic influent conditions of continuous-flow SBR with varied F/M loadings

the gradient descent method was used to minimize the errors. Sigmoid function, as equation (3), was used as activation function. Evaluating the scatter between the measured and predicted results via correlation coefficients (R^2), Root Mean Squares (RMSs) and the Mean Absolute Errors (MAEs) assessed the performances of ANN process models. The correlation coefficient was calculated based on linear regression; RMSs and MAEs were calculated according to equations (4) and (5) respectively. The training and testing proceeding of ANN process models were performed on LabView DataEngine 2.0.

Hidden Layer: $$Z_j = f\left(\sum_{i=1}^{I} W_{ij} \times X_i\right) \tag{1}$$

Output Layer: $$Y_k = f\left(\sum_{j=1}^{J} W_{jk} \times Z_j\right) \tag{2}$$

Activation function: $$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

RMSs = $$\sqrt{\sum_j (T_k - Y_k)^2 / N_{\text{out}}} \tag{4}$$

MAEs = $$\frac{1}{n}\sum \left|T_k - Y_k\right| \tag{5}$$

where X_{i}, Z_{j}, and Y_k are the input, hidden, and output vectors respectively, W_{ij}, W_{jk} are weights connecting X_i to Z_j and Z_j to Y_k. T_k and Y_k are the target and output vectors in BPN. N_{out} is the number of output elements and n is the number of testing samples.

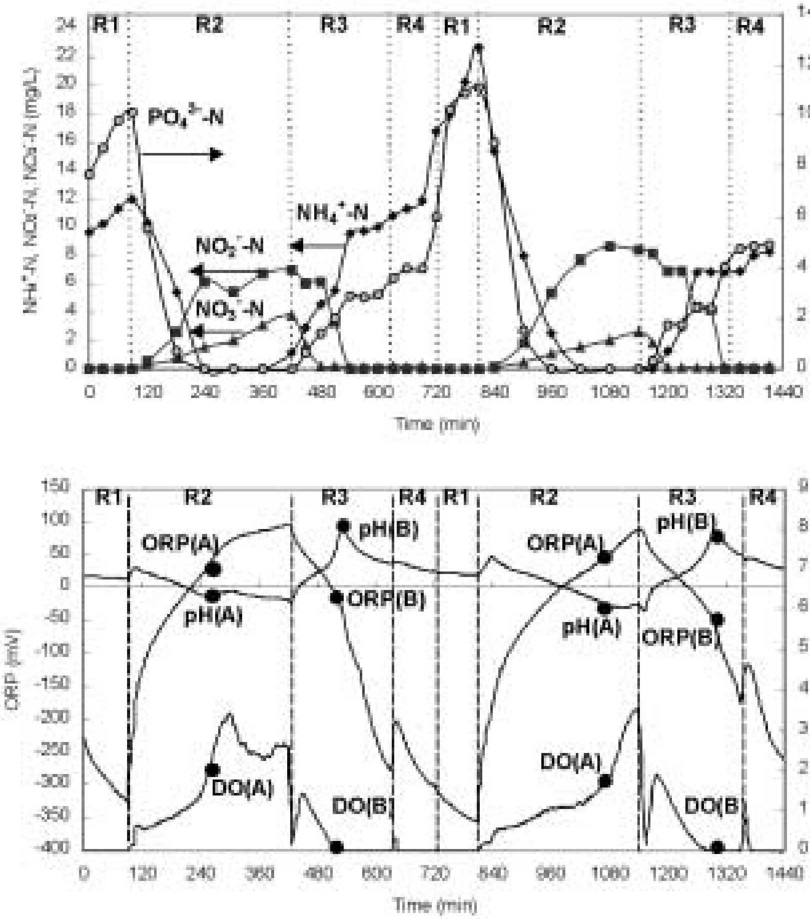
Results and discussions

Adequate knowledge of process mechanisms and identification of major control variables are necessary for developing the ANN process models, which can assist in determining the proper input and output parameters of ANN models, and help to qualify the direct relationships between the causes and effects.

Relationships between BNR mechanisms and monitoring/control parameters

The major BNR mechanisms during the sequencing operation phases of continuous-flow SBR system include the anaerobic organic nitrogen ammonification, aerobic ammonia nitrogen nitrification, and anoxic NO_x^--N (NO_2^--N and NO_3^--N) denitrification. In the fixed-time control study, the variations of water quality and monitoring parameters under dynamic influent continuous-flow SBR system were shown in Figure 3. Prior knowledge has been demonstrated that many feature points of ORP, pH, and DO monitoring profiles appeared while the nitrification and denitrification completions under steady-state influent conditions. These feature points include DO and ORP bending-points, pH break-point period of nitrification, ORP knee-points and pH break-point period of denitrification, which were expressed as DO(A), ORP(A), pH(A), ORP(B), and pH(B) respectively in this study (Cho *et al.*, 2001).

The study results revealed that the feature points of ORP(A), pH(A), and DO(A) appeared while the NH_4^+-N was radically removed in the aerobic operation phase, which could indicate the end-point of nitrification and be the monitoring and control variables of aerobic phase under dynamic influent operated system. The feature points of ORP(B) and pH(B) could also indicate the end-point of denitrification with no external electronic accep-



*R1: Anaerobic phase; R2: Aerobic phase; R3: Anoxic phase; R4: Reareation, Settling, and Discharge phases

Figure 3 The variations of water quality and monitoring parameters under dynamic influent and fixed-time controlled continuous-flow SBR system

tors (e.g. DO) and the lowest NO_x^--N electronic activity (Plisson-Saune *et al.*, 1995), and which could be the monitoring and control variables of anoxic phase. Theoretically, observing and detecting the slope variations of ORP, pH, and DO profiles could identify these feature points locations and producing times. However, this practice is inefficient, and highly risks directly caused by the instrument noises and system disturbances. Therefore, this study attempts to apply the ANN approach to predict the oncoming ORP and pH values in aerobic and anoxic operation phases for real-time precisely searching the ORP and pH control points of nitrification and denitrification completions.

ANN ORP and pH simulation models

The basic operational parameters and the measured and predicted results for ANN ORP and pH simulation models were listed in Table 2. While these models accomplished the training and testing procedures, the final correlation coefficients R^2, RMSs, and MAEs were {0.9985, 0.0009, 1.44 mV} and {0.9988, 0.0008, 0.067} for ORP and pH models of nitrification, as well as {0.9981, 0.0011, 2.23 mV} and {0.9978, 0.0012, 0.014} for ORP and pH

Table 2 The operational parameters and performance evaluations of ANN ORP and pH simulation models

ORP models: Input variables	ORP models: Output variables	pH models: Input variables	pH models: Output variables	Operational parameters	Aerobic nitrification	Anoxic denitrification
				Hidden Layer and Units	1 (12)	1 (12)
ORP(*t*–8)	ORP(*t*+2)	pH (*t*–8)	pH(*t*+2)	Training Samples	2093	1212
ORP(*t*–6)		pH (*t*–6)		Testing Samples	154	102
ORP(*t*–4)		pH (*t*–4)		Training Cycles	3000	3000
ORP(*t*–2)		pH (t–2)		Testing Period	10	10
ORP(*t*)		pH (*t*)		Learning Rate	1.0	1.0

Performance evaluations of ANN ORP and pH models

Performance parameters	Aerobic nitrification: ORP model	Aerobic nitrification: pH model	Anoxic denitrification: ORP model	Anoxic denitrification: pH model
R^2	0.9985	0.9988	0.9981	0.9978
RMSs	0.0009	0.0008	0.0011	0.0012
MAEs	1.44 mV	0.067	2.23 mV	0.014

models of denitrification respectively. These results revealed that these ANN ORP and pH simulation model could precisely predict the oncoming ORP and pH values during aerobic and anoxic phases by acquiring the prior time-series ORP and pH monitoring data.

Identification of ORP and pH control points

As prior descriptions, observing the slope variations of ORP and pH profiles can estimate the ORP and pH control points of nitrification and denitrification completions. Theoretically, these ORP and pH control points will locate the calculated slopes of ORP and pH profiles (dORP/d*t* and dpH/d*t*) equal to zero with no external electronic accepters disturbance (Yu *et al.*, 1997; Plisson-Saune *et al.*, 1995). However, these identification approaches are unreliable and highly uncertain, since the ORP and pH monitoring information are influenced by the DO and SO_4^{2-} appearing in aerobic nitrification and anoxic denitrification stages and by monitoring noise. Therefore, many researchers always set a series of experiential and conservative upper and lower location bounds of dORP/d*t* and dpH/d*t* values to searching the ORP and pH control points. In this study, the ORP and pH simulation models can precisely and less interferingly predict the oncoming ORP and pH values, as shown in Figure 4, and the slopes of ORP and pH have significant changes while the control points appeared. These observational results supply the practical advantages of time-saving and narrow searching regions to identify the ORP and pH control point locations during aerobic and anoxic operation phases. In the searching regions, the ORP and pH control points well located on the points with abruptly adverse slopes, and the slope of after these control points were less than before ones, i.e. $dORP(t+2)/dt < dORP(t)/dt$ and $dpH(t+2)/dt < dpH(t)/dt$. These characteristics could be programmed as real-time searching rules to assist in effectively identifying the ORP and pH control points of aerobic and anoxic operation phases.

ANN water quality prediction models

ANN water quality prediction models, like as the performance evaluation tools, were developed to supply the searching starts of ORP and pH control points for increasing the reliability and efficiency of real-time control system. Essentially, the major mechanisms of BNR processes, nitrification and denitrification, belong to oxidation-reduction reactions.

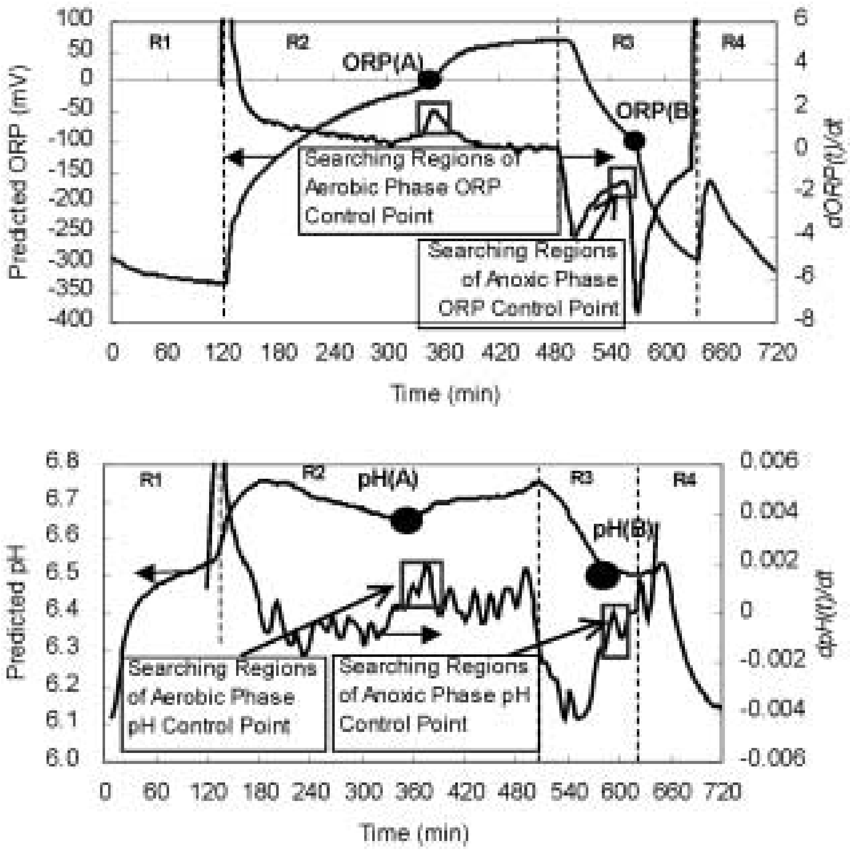


Figure 4 Comparisons of predicted ORP and pH variations and the calculated dORP/d*t* and dpH/d*t* profiles

Table 3 The operational parameters and performance evaluations of ANN water quality prediction models

Input variables	Output variables	Operational parameters			
ORP(*t*)	$[NH_4^+\text{-N}(t)]$	Hidden Layer (Units)	1 (7)	Training Cycles	3000
PH(*t*)	$[NO_x^-\text{-N}(t)]$	Training Samples	1049	Testing Period	10
DO(*t*)		Testing Samples	262	Learning Rate	1.0

Performance evaluations of ANN water quality simulation models

Performance Parameters	$[NH_4^+\text{-N}]$ Model	$[NO_x^-\text{-N}]$ Model
R^2	0.9514	0.9698
RMSs	0.0365/0.0320	0.0390/0.0480
MAEs	0.61 mg/L	0.44 mg/L

According to the Nernst type equations of nitrification and denitrification (Schön *et al.*, 1993), the influential factors of NH_4^+-N and NO_x^--N (NO_2^--N, NO_3^--N) concentration distributions include oxidation/reduction states, pH, and external electronic activity, which can be represented as ORP, pH, and DO respectively. Therefore, this study attempted to develop ANN water quality simulation models to predict the NH_4^+-N and NO_x^--N (NO_2^--N+NO_3^--N) concentrations in treatment processes by on-line acquiring the ORP, pH, and DO monitoring data. The basic operational parameters and the performance evaluation results of ANN water quality simulation models were listed in Table 3.

During training and testing processes, these models were still converging and generalized well enough to obtain the final RMSs of training and testing samples were less than 0.0365 and 0.0320 for NH_4^+-N, and 0.039 and 0.048 for NO_x^--N respectively. High correlation between predicted and measured data and the MASs of predicted NH_4^+-N and NO_x^--N concentrations of 0.61 mg/L and 0.44 mg/L were obtained. These results also revealed that ANN water quality simulation models could well predict the variations of NH_4^+-N and NO_x^--N (NO_2^--N+NO_3^--N) during aerobic and anoxic operation phases by real-time acquiring the on-line ORP, pH, and DO monitoring data.

Performance evaluations of ANN real-time control strategy

Once the highly reliable ORP/pH control point searching rules and performance evaluation tools were developed by ANN process models, which could be integrated into a real-time control strategy to perform the sequencing operation phase changes of a continuous-flow SBR by setting the operation and control constraints. These constraints included setting rational searching regions, effluent limitations, and the maximum HRTs of operation phases for meeting the operation performance requirements. The operational results, as shown in Figure 5, revealed that the ANN real-time control strategy could properly control the end-points of nitrification and denitrification stages by real-time detecting the ORP and pH control points. It is obviously indicated the major BNR mechanisms in aerobic and anoxic operational phases were *Nitrosomonas* nitritification (NH_4^+-N→NO_2^--N) and denitritifi-

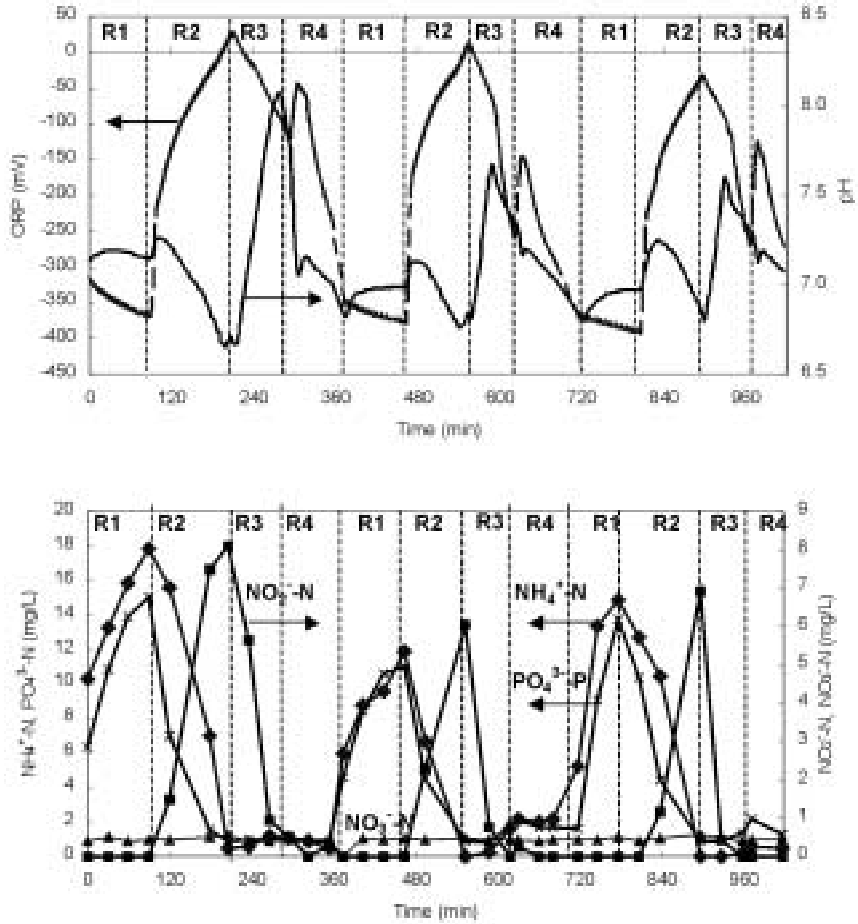


Figure 5 Variations of water quality and monitoring parameters under ANN real-time controlled system.

Table 4 Comparisons of performance between fixed-time control and real-time ANN control system

Water Quality Parameter	Fixed-Time Control				Real-Time Control	
	HRT = 8 hrs/cycle		HRT = 12 hrs/cycle			
	Concentration (mg/L)	Removal Percentage (%)	Concentration (mg/L)	Removal Percentage (%)	Concentration (mg/L)	Removal Percentage (%)
TCOD	7.6±0.6	98	18.7±5.1	95	7.2±1.1	98
TKN	5.0±2.5	95	9.1±4.2	92	1.0±1.3	97
NH_4^+-N	3.8±2.1	93	6.9±3.2	85	1.0±0.9	98
Total N	5.5±2.4	95	9.1±4.2	92	3.1±2.2	97
PO_4^{3-}-P	2.3±1.2	62	3.8±0.6	56	1.3±0.4	84

cation (NO_2^--N$\rightarrow N_2$), which could shorten the overall hydraulic retention time and aeration time to 4.8–6.2 hrs/cycle and 1.9–2.5 hrs/cycle compared with conventional fixed-time control approach.

Comparing the operation performances with fixed-time control study, the removal efficiencies of COD, ammonia nitrogen, total nitrogen, and phosphate were more than 98%, 98%, 97%, and 84% respectively. The proposed system is more effective and efficient than that under fixed-time controlled system as shown in Table 4. Since the phosphorus uptake and release can be completely controlled during the aerobic and anoxic phases, hence higher removal efficiency can be obtained in this new control approach.

Conclusions

This study demonstrated that developing a real-time control strategy integrated with the artificial neural network process models could effectively increase the operation performances of a dynamic influent continuous-flow SBR system.

Acknowledgements

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