International Journal of Fuzzy Logic and Intelligent Systems, vol. 1, no. 1, June 2001 pp. 56-61

Modeling, Control, and Optimization of Activated Sludge Processes

Hye-on Bae, Bong-chul Kim, Sung-shin Kim, Chang-won Kim*, Sang-hyun Kim*, and Hae-jin Woo**

School of Electrical and Computer Engineering, Pusan National University
*Department of Environmental Engineering, Pusan National University
**Institute for Environmental Technology and Industry, Pusan National University
30, Changjeon-Dong, Keumjeong-Ku, Pusan 609-735, Korea

Abstract

Activated sludge processes are broadly used in the biological wastewater treatment processes. The activated sludge processes are complex systems because of the many factors such as the variation of influent flowrate and ingredients, the complexity of biological reactions, and the various operation conditions. The main motivation of this research is to develop an intelligent control strategy for activated sludge process (ASP). ASP is a complex and nonlinear dynamic system owing to the characteristic of wastewater, the change in influent flowrate, weather conditions, and so on. The mathematical model of ASP also includes the uncertainty which is a ignored or unconsidered factor from process designers. The ASP model based on Matlab®/Simulink® is developed in this paper. And the model performance is examined by IWA (International Water Association) and COST (European Cooperation in the filed of Scientific and Technical Research) data. The model tests derive steady-state results of 14 days. In this paper, fuzzy logic control approach is applied to handle DO concentration. The fuzzy logic controller includes two inputs and one output to adjust air flowrate. The objective function for the optimization, in the implemented evolutionary strategy, is formed with focusing on improving the effluent quality and reducing the operating cost.

Key Words : Activated sludge process, modeling, fuzzy control, evolutionary strategy

Ⅰ. Introduction

Nowadays, biological processes like wastewater treatment processes are using the microbial reaction for dealing with organic matter, nitrogen, phosphorus, and so on. It is very important to provide the optimal conditions to make the microbe move actively for the effective treatment.

In the wastewater treatment process, operating management of sequential reactors for biological nutrient removal is coupled with the cause-effect relationship of the various parameters. Thus, it could lead very difficult problems to analyze the characteristics of the systems.

The sequential reactors contain large numbers of parameters which have to be adjusted. And systematic operating methods that could adapt to the altered quality and quantity of influent water, should be determined to design and to operate the reactor processes. Up to now, the operating methods are chosen subjectively based on the fixed control method with trial-and-error of the operator's empirical knowledge at the primary design stage.

In this paper, before designing a controller, a basic sequential reactor model is constructed based on the activate sludge model No.1. The variation of the volume and features of influent water is analyzed under the different rector conditions. Fuzzy controller is then applied to control the treatment system.

In the wastewater treatment system, air flowrate is the most important element to increase the effluent quality and the efficient energy management. The reaction conditions of each reactor are decided by the flowrate. The large amounts of cost in treatment plants are dissipated to blow air into the aerobic reactors. Therefore, it is necessary to handle the flowrate and the reaction time. And improved control methods must be implemented for solving the problems mentioned above.

In this paper, the fuzzy controller based upon the operator's knowledge is designed to control the system [1], [2]. The control performances with fuzzy controller are evaluated by the fitness function forced on the effluent quality and the effective energy management.

Ⅱ. Sequential Reactor Model

2.1 Activated Sludge Model No.1

Analyzing the characteristics of plants and making out the processing of wastewater treatment systems have to achieved earlier then proposing and applying the practical control methods, Thus, the modeling is completed based on the benchmark of IWA and COST

Manuscript received March 15, 2001; revised May 1, 2001.
This work was financially supported by the Fund from Korean Science Foundation through RRC-IETI with project number 00-10-01-03-A-3.

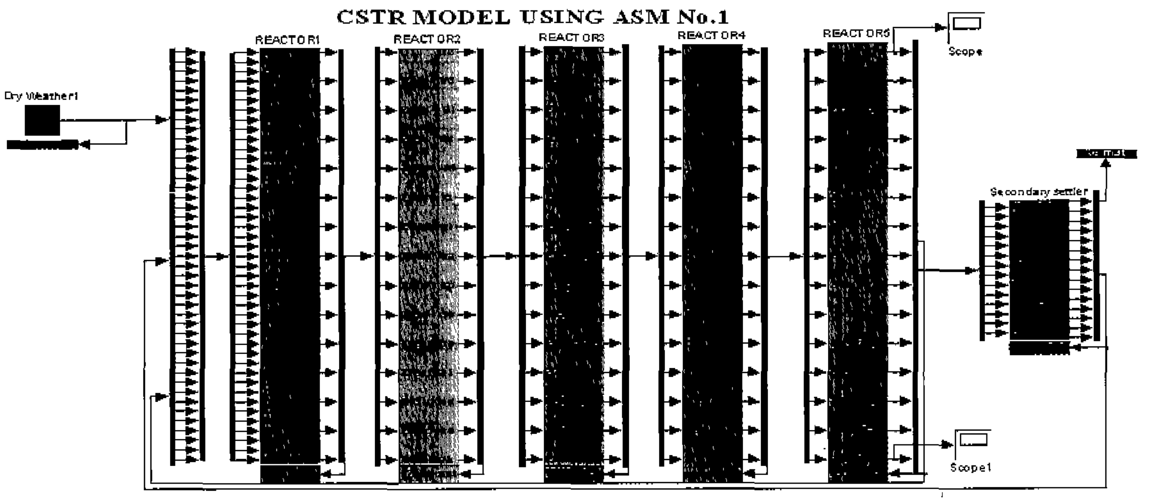


Fig. 1. Denitrification Configuration Using Matlab®/Simulink®.

shown in [3]. The benchmark plant consists of 5 reactors corresponding to ASM No.1 and 2 settling tanks using the double-exponential settling velocity function. IWA realized carbon removal configuration, nitrification configuration, and denitrification configuration, however, COST used only denitrification configuration. In this paper, the former configuration is used because it commonly applied by IWA and COST.

ASM No.1 represented in 1986, is formed by 8 processes, whose constituents include growth, decay, hydrolysis of heterotrophs, hydrolysis of autotrophs, and so on [4]. The input variables of the system consist of 13 components that are formed by 4 sorts of nitrogenous or carbonaceous matter. The components in the model are shown in the top and bottom of Table 2. The kinetics of organic matter removal is formulated with the Monod's equation corresponding to growth-limiting substrate. The second settler is classified to 10 layers using the double-exponential settling velocity function. It is assumed that there is no biological reactions inner settler. Equation (1) is the double-exponential settling velocity function.

Table 1. The parameters of double-exponential settling velocity function

	Parameter	Units	Value
Maximum settling velocity	ν'_0	$m.d^{-1}$	250.0
Maximum Mesilind settling velocity	ν_0	$m.d^{-1}$	474
Hindered zone settling parameter	r_h	$m^3.(g\ SS)^{-1}$	0.000576
Flocculant zone settling parameter	r_p	$m^3.(g\ SS)^{-1}$	0.00286
Non-settleable fraction	f_{ns}	$m^3.(g\ SS)^{-1}$	0.00228

$$J_s = \nu_s(X)X$$

$$\nu_s(X) = \max\left[0, \min\left\{\nu'_0, \nu_0\left(e^{-r_h(X-X_{min})} - e^{-r_p(X-X_{min})}\right)\right\}\right] \quad (1)$$

$$X_{min} = f_{ns}X_f$$

where, Js, X, υ 0', υ 0, rh, and rp represent the solid flux due to gravity sedimentation, the total sludge concentration, the maximum settling velocity, the maximum vesilind settling velocity, hindered zone settling parameter, and flocculant zone settling parameter, respectively.

The basic construction of the plants formed by IWA, consists of 3 configurations, which are carbon removal configuration, nitrification configuration, and denitrification configuration. And IWA is offering these models that are implemented by using GPS-XTM (Hydomantis Inc.), SimbaTM (ifak system GmbH), WESTTM (Hemmis n.v.), STOATTM (WRc), and Fortran code (Alex et al., 1999; Pons et al., 1999). In this paper, Matlab®/Simulink® is used to design the denitrification configuration, which is a sort of the three basic configurations. The full constructed model is shown in Fig. 1.

The validity and the performances of the model are simulated using ODE45 (Fourth-order Runge-Kutta Method) of Matlab and the relative tolerance is set to 1exp-6. The dry weather data for 14 days considering the volume and the concentration of influent water, are used to evaluate the performances of the designed model. These data are proposed by IWA. There is no airflow using external sources in the first and second reactors. These tanks are called as the anoxic reactors. KLa (Oxygen mass transfer coefficient rate) is initially set to 240 day-1 for the third and forth reactors. In the fifth reactor, KLa is chosen to 84 day-1. Three of these reactors are known as aerobic reactors. The simulations for 100 days are achieved to compute the steady state results of the treatment plant.

Table 2. Activated Sludge Model No.1

		1	2	3	4	5	6	7	8	9	10	11	12	13	Process Rate, ρ_j[ML^{-3}T^{-1}]
j	Process	S_I	S_S	X_I	X_S	X_{BH}	X_{BA}	X_P	S_O	S_{NO}	S_{NH}	S_{ND}	X_{ND}	S_{ALK}	
1	Aerobic growth of heterotrophs		$-\frac{1}{Y_H}$			1			$-\frac{1-Y_H}{Y_H}$		$-i_{XB}$			$-\frac{i_{XB}}{14}$	$\hat{\mu}_H\left(\frac{S_S}{K_S+S_S}\right)\left(\frac{S_O}{K_{O,H}+S_O}\right)X_{B,H}$
2	Anoxic growth of autotrophs		$-\frac{1}{Y_H}$			1				$-\frac{1-Y_H}{2.86Y_H}$	$-i_{XB}$			$-\frac{1-Y_H}{14\times 2.86Y_H}-\frac{i_{XB}}{14}$	$\hat{\mu}_H\left(\frac{S_S}{K_S+S_S}\right)\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\eta_g X_{B,H}$
3	Aerobic growth of autotrophs						1		$-\frac{4.57-Y_A}{Y_A}$	$\frac{1}{Y_A}$	$-i_{XB}-\frac{1}{Y_H}$			$-\frac{i_{XB}}{14}-\frac{1}{7Y_A}$	$\hat{\mu}_A\left(\frac{S_{NH}}{K_{NH}+S_{NH}}\right)\left(\frac{S_O}{K_{O,A}+S_O}\right)X_{B,A}$
4	Decay of heterotrophs				$1-f_P$	-1		f_P					$i_{XB}-f_Pi_{XP}$		$b_HX_{B,H}$
5	Decay of autotrophs				$1-f_P$		-1	f_P					$i_{XB}-f_Pi_{XP}$		$b_AX_{B,A}$
6	Ammonification of soluble organic nitrogen										1	-1		$\frac{1}{14}$	$k_aS_{ND}X_{B,H}$
7	Hydrolysis of entrapped organics		1		-1										$k_h\frac{X_S/X_{B,H}}{K_X+(X_S/X_{B,H})}\left[\left(\frac{S_O}{K_{O,H}+S_O}\right)+\eta_h\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\right]X_{B,H}$
8	Hydrolysis of entrapped organic nitrogen											1	-1		$\rho_7(X_{ND}/X_S)$
Observed conversion rate[ML^{-3}T^{-1}]		$r_i=\sum_j\nu_{ij}\rho_j$													

The stoichiometric parameters, kinetic parameters, and double-exponential velocity function's parameters used in ASM No.1, are shown in Table 1 and Table 3, respectively. The double-exponential velocity function applied for modeling of the second settler, is shown in Table 1 (Tacks et al., 1991).

The upper values of Table 4 are the steady state results of denitrification configuration proposed by COST, and the second values of the table are the results of this research model designed by using Matlab®/Simulink®. In the lower values of Table 4, more reasonable comparison of the models is demonstrated using the percentage of the difference between two models. For instance, SO concentration proposed by COST in the first reactor and the fifth reactor are 0.0042984 and 0.4909435, respectively. The values of the same variables in the our model are 0.00429853 and 0.49094176, respectively. The difference of the two models is 0.0002%. This error is

Table 3. Typical parameter values at neutral pH

(a) Stoichiometric parameters

Y_A	g cell COD formed (g N oxidized)$^{-1}$	0.24
Y_H	g cell COD formed (g COD oxidized)$^{-1}$	0.67
f_P	dimensionless	0.08
i_{XB}	g N (g COD)$^{-1}$ in biomass	0.08
i_{XP}	g N (g COD)$^{-1}$ in endogenous mass	0.06

(b) Kinetic parameters

μH	day^{-1}	4.0
K_S	g COD m^{-3}	10.0
$K_{O,H}$	g COD m^{-3}	0.2
K_{NO}	g NO_3-N m^{-3}	0.5
b_H	day^{-1}	0.3
η_g	dimensionless	0.8
η_h	dimensionless	0.8
k_h	g slowly biodegradable COD (g cell COD . day)$^{-1}$	3.0
K_X	g slowly biodegradable COD (g cell COD)$^{-1}$	0.1
μA	day^{-1}	0.5
K_{NH}	g NH_3-N m^{-3}	1.0
b_A	day^{-1}	0.05
$K_{O,A}$	g O_2 m^{-3}	0.4
k_a	m^3 . COD(g.day)$^{-1}$	0.05

Table 4. Steady-state results proposed by COST and using Matlab$^{®}$/Simulink$^{®}$ Model

(a) Dry Weather Steady State Simulation Result

	TANK1	TANK2	TANK3	TANK4	TANK5
SI_in	30.00	30.00	30.00	30.00	30.00
Ss_in	2.8082131	1.458794	1.1495418	0.9953239	0.8894928
XI_in	1149.1252	1149.1252	1149.1252	1149.1252	1149.1252
Xs_in	82.134908	76.386187	64.854922	55.693982	49.305586
Xbh_in	2551.7658	2553.3851	2557.1314	2559.1826	2559.3436
Xba_in	148.38943	148.30914	148.94126	149.52712	149.79714
Xp_in	448.85186	449.52273	450.41834	451.31469	452.21112
So_in	0.0042984	0.0000631	1.7183778	2.4288838	0.4909435
Sno_in	5.36994	3.6619672	6.5408820	9.2989988	10.41522
Snh_in	7.9178845	8.3444148	5.5479452	2.9673854	1.7333316
Snd_in	1.2166405	0.8820648	0.8288868	0.7667866	0.6882900
Xnd_in	5.2848894	5.0290873	4.3924277	3.8790101	3.5271755
Salk_in	4.9277103	5.0801748	4.6747902	4.2934562	4.1255794
Q_in	92230.00	92230.00	92230.00	92230.00	92230.00

(b) Our Model's Steady-State Result

	TANK1	TANK2	TANK3	TANK4	TANK5
SI_in	30.00	30.00	30.00	30.00	30.00
Ss_in	2.8081634	1.458772	1.1495288	0.995314	0.889485
XI_in	1149.1686	1149.1686	1149.1686	1149.1686	1149.1686
Xs_in	82.135498	76.386787	64.855512	55.69456	49.306164
Xbh_in	2551.8199	2553.4392	2557.1854	2559.2365	2559.3975
Xba_in	148.39509	148.3148	148.94693	149.5328	149.80281
Xp_in	448.87847	449.54936	450.44499	451.34136	452.2378
So_in	0.0042985	6.31E-05	1.7183006	2.4288224	0.4909418
Sno_in	5.3699727	3.6619852	6.5409593	9.2991026	10.415292
Snh_in	7.9176956	8.3442304	5.5476945	2.9671081	1.733085
Snd_in	1.216629	0.8820543	0.8288784	0.7667790	0.6882746
Xnd_in	5.2849396	5.0291387	4.392478	3.8790592	3.5272242
Salk_in	4.9276945	5.0801604	4.6747668	4.293429	4.1255567
Q_in	92230.00	92230.00	92230.00	92230.00	92230.00

(c) Error

	TANK1	TANK2	TANK3	TANK4	TANK5
SI_in	0.00%	0.00%	0.00%	0.00%	0.00%
Ss_in	0.00%	0.00%	0.00%	0.00%	0.00%
XI_in	-0.04%	-0.04%	-0.04%	-0.04%	-0.04%
Xs_in	0.00%	0.00%	0.00%	0.00%	0.00%
Xbh_in	-0.05%	-0.05%	-0.05%	-0.05%	-0.05%
Xba_in	-0.01%	-0.01%	-0.01%	-0.01%	-0.01%
Xp_in	-0.03%	-0.03%	-0.03%	-0.03%	-0.03%
So_in	0.00%	0.00%	0.00%	0.00%	0.00%
Sno_in	0.00%	0.00%	0.00%	0.00%	0.00%
Snh_in	0.00%	0.00%	0.00%	0.00%	0.00%
Snd_in	0.00%	0.00%	0.00%	0.00%	0.00%
Xnd_in	0.00%	0.00%	0.00%	0.00%	0.00%
Salk_in	0.00%	0.00%	0.00%	0.00%	0.00%
Q_in	0.00%	0.00%	0.00%	0.00%	0.00%

acceptable value because it could be influenced by round-off error of used numerical method to solve the differential equations.

2.2 External Carbon and DO Control

In the most of biological nitrification and denitrification processes, sufficient organic carbon energy is required to convert bacteria contained in wastewater into nitrate or gaseous nitrogen. The consumed amounts of carbon must be supplied by internal sources contained in wastewater or microbial cells, or external sources as methanol. In this paper, insufficient amounts of carbon sources of the influent water are taken by external methanol effectively for the harmonious reaction condition in the total processes.

In wastewater treatment system under aerobic reaction conditions, the DO concentration is the most important factor for the microbe in substrates of the influent water. If the DO is not sufficient, the activity of microbe could be slowed down. And substrates could be also removed insufficiently. Thus, the quality of effluent water should be worse because of the insufficient DO concentration. On the other hand, if the airflow is exceeded, oxygen is supplied into anoxic reactors by the internal recycle. This phenomenon could disturb the denitrification. Therefore, the DO concentration must be properly retained. In most of wastewater treatment plants, operators who have empirical knowledge observe influent water, state of reactors, and effluent water. Thereafter, they control the plant manually based upon the collected information.

In this paper, a fuzzy logic controller is implemented to maintain the quality of effluent water and to enhance the efficiency of total processes.

III. Simulation Results

3.1. Fuzzy Controller

It is necessary to analyze the characteristics of the wastewater treatment systems to be controlled before applying an intelligent control strategy. The sequential reactor system is modeled, evaluated, and simulated using Matlab®/Simulink®. This mathematical model is constructed referred to activated sludge model No. 1 (ASM No.1) which is based on the Ulf Jeppsson's paper and the benchmark suggested by IWA [3-5]. Fig. 2 illustrates the total schematic diagram to control external carbon sources and the DO concentration.

There are two methods to make the decision of the external carbon sources dosage. The first method is to take the insufficient external carbon sources in anoxic reactors based upon SNO concentration of the second reactor without constraint. The other way is to supply the external carbon sources, when SNO concentration become over 2mg/l. In this paper, both of methods are applied as shown in Fig. 2.

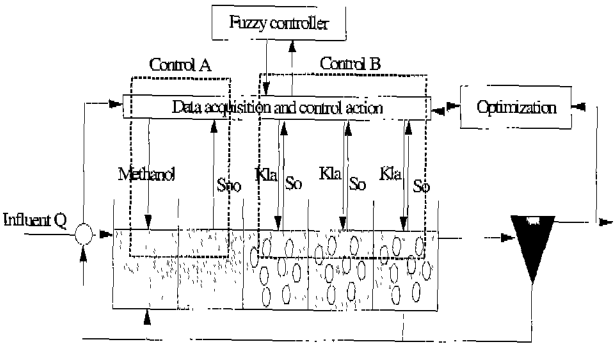


Fig. 2. Schematic diagram of external carbon source and DO concentration control strategy.

In aerobic reactors, the fuzzy logic controllers are designed to control the DO concentration by adjusting KLa value. It is necessary to measure oxygen concentration of reactors using DO probes for this purpose. The error is defined by the difference between the setpoint value and the present value. Also the derivative error is defined by dividing error by sampling time for the fuzzy logic.

The uncontrolled values shown in Fig. 3 are compared with the controlled values using the control performances. With considering the KLa and SNO concentrations variation in the reactor, the performance of fuzzy controllers could offer reasonable results. KLa and SNO are input variables of the fuzzy controllers. The setpoint of DO concentration is fixed to 2mg/l and the results of the concentration of each aerobic reactor are shown in Fig. 4.

Gaussian functions are used for fuzzy membership functions and the max-min operation is employed for the inference system. And then center of area method is applied to defuzzify the previous inferred values. In the simulation, dry weather data of IWA for 14 days are utilized for the condition of influent water, and the sampling time is set up with the interval of 15 minutes. The SO concentration in the second reactor and the SO

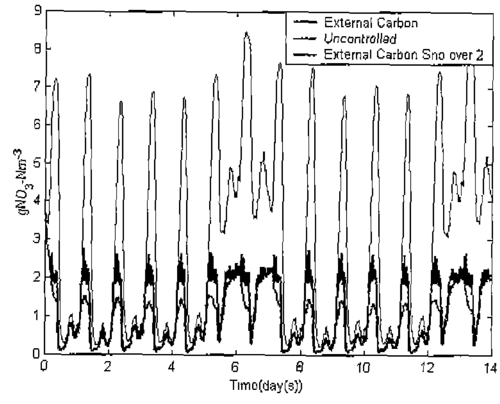


Fig. 3. SNO concentrations using external carbon dosage control in the 2nd reactor.

concentration of effluent water flowed out from the second settling tank are reduced by the external carbon sources dosage, and the DO concentration in all aerobic reactors is maintained to around 2mg/l simultaneously. The SO concentration can be kept to around the setpoint of 2 by dosage control.. With referring to the results, we can trust that the SO concentration in reactors could be admirably controled by the designed fuzzy controller.

Fuzzy membership functions are classified with 4 error and 2 derivative error variables. In this control strategy, the consequent outputs are decided by the antecedent inputs. Fuzzy singleton is used in this paper because of its simplicity. The fuzzy rules are designed by operator's knowledge as follows.

If *Error* is *NB* and *E* is *N* then K_La is *N*
If *Error* is *N* and *E* is *N* then K_La is *NS*
If *Error* is *NS* and *E* is *N* then K_La is *Z*
⋮
If *Error* is *PS* and *E* is *P* then K_La is *ZR*
If *Error* is *P* and *E* is *P* then K_La is *PS*
If *Error* is *PB* and *E* is *P* then K_La is *P*

3.2. Objective Function

The characteristics of the given systems, the final goal of the operation and the possibility of implementation are very important information for objective functions. For the combination of these factors, the relationship and the interaction among the factors must be defined. In addition to, effluent quality, operating cost, and amount of producted waste sludge should be considered for operating CSTR (Continuous Stirred Tank Reactor).

The control performances are evaluated by the objective function. In this paper, the quality of effluent water and the operating cost are considered as objective functions.

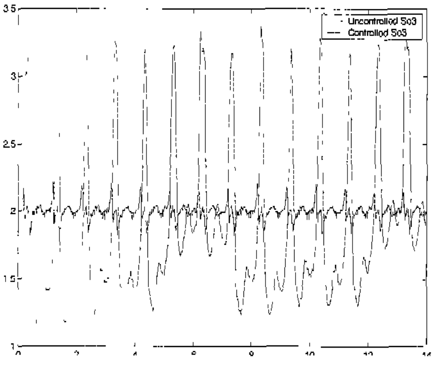
The air flowrate and the power consumption are considered as the operating cost in aerobic reactors. Effluent quality (EQ) is defined as equation (2).

$$EQ=\frac{1}{T\cdot 1000}\int_{t_0}^{t_1}[\ PU_{TSS}(t)+PU_{COD}(t)+PU_{BOD}(t)+PU_{TKN}(t)+PU_{NO}(t)]Q_e(t)\,dt \tag{2}$$

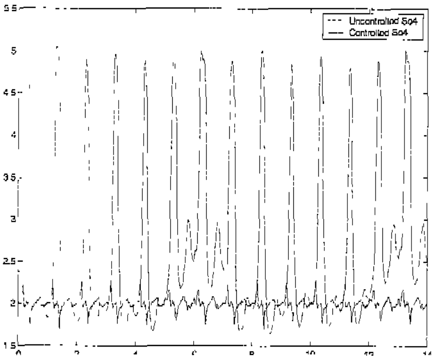
Operating cost for aeration energy (AE, in units of kWhd-1) is formulated as equation (3).

$$AE=\frac{24}{T}\int_{t_0}^{t_1}\sum_{i=0}^{i=1}[\ 0.4032K_La_i(t)^2+7.8408K_La_i(t)]dt \tag{3}$$

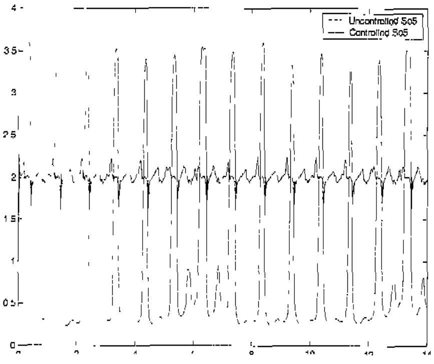
where, KLai(t) is the mass transfer coefficient in the ith aerobic reactor at time t (in units of hr-1). The practical objective function is formed by the combination of EQ and AE. Thus, the effluent quality and the aeration energy are treated by the objective function at the same time.



(a) The S_O concentration in the 3rd reactor.



(b) The S_O concentration in the 4th reactor.



(c) The S_O concentration in the 5th reactor.

Fig. 4. SO in each aerobic reactor.

$$f(t)=EQ+AE \tag{4}$$

3.3. Evolutionary Strategy

In this paper, ES is employed and implemented with 11 parameters and 30 initial populations are constructed by Gaussian random functions. The populations are fixed to 30. During the optimization processing, 10 superior populations are re-selected by evaluating the results using influent water data for 14 days. After selecting new population sets, the new populations are regenerated by the mutation operations based on the current generation.

Each chromosome consists of variance of PB, P, PS, ZR and center values of P, PS for error, variance of P, ZR for derivative error, and 3 consequent parameters.

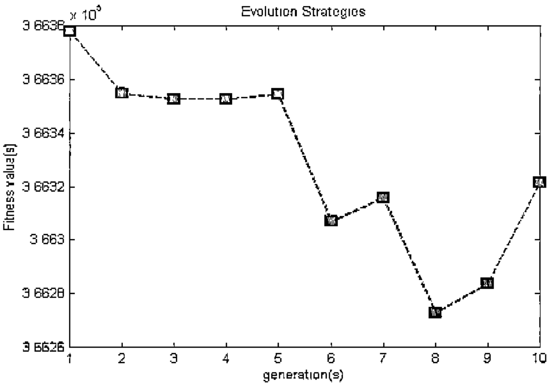


Fig. 5. Optimized results using ES.

Fuzzy membership functions are formed symmetrically.

The system performance is gradually enhanced as the number of iteration is increased as shown in Fig. 5. But in the 7th, 9th, and 10th generation, control performance goes to worse because the elitism is not applied in this ES. If the elitism is used for the optimization, the performances could be better than these results. This simulation is performed for 10 days and the 8th generation among 10 generations is selected for the optimal controller.

IV. Conclusion

Sequential reactors have lots of adjustable variables and systematic operating methods that can be adapted to the variation of amounts and quality of influent water. In this paper, the effective energy management and optimal operating conditions are deduced from dosage of external carbon sources in anoxic reactors. The fuzzy controllers are designed by fuzzy rules that are extracted by the empirical knowledge for the aerobic reactors. Antecedent parameters in fuzzy membership functions and consequent parameters are optimized by the evolutionary strategy.

The simulation results show that the effective energy management and the stable control could be achieved. Also, the results indicate that the non-linearity of system and the variation of influent water could be managed.

References

[1] S. Kim, A. Kumar, J. L. Dorrity, and G. Vachtsevanos, "Fuzzy Modeling, Control, and Optimization of Textile Process," Proc. of the 1994 Int. Joint Conf. of NAFIPS/IFIS/NASA, pp. 32-38, Dec. 1994.

[2] J. Yen and R. Langari, Fuzzy Logic: Intelligence, Control, and Information, Prentice Hall, 1999.

[3] Jeppson U., Modelling Aspects of Wastewater Treatment Processes, Ph. D Thesis, Dept. of Industrial Electrical Engineering and Automation, Lund Institute of Technology, Sweden, 1996.

[4] Henze M. Grady, C. P. L. Jr., Gujer W. Marais, G. V. R., and Matsuo T., IAWQ Task Group on Mathematical Modelling for Design and Operation of Biological Wastewater Treatment Activated sludge model No. 1, Scientific and Technical Reports No. 1, IAWQ, 1986.

[5] IAWQ Scientific and Technical Report Task Group: Respirometry in Control of the Activated Sludge Process Interim Report #1, 2, 1999.

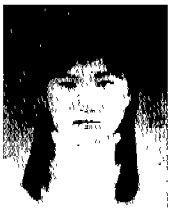
Hye-on Bae
received the M.S. degree in electrical engineering from Pusan National University, Pusan, Korea, in 2001. He is currently pursuing the Ph.D. degree. His research interests include intelligent control, fuzzy logic control, and manufacturing systems.

Bong-chul Kim
received the B.S. degree in electrical engineering from Kyungsung University, Pusan, Korea, in 2000. He is currently pursuing the M.S. degree at Pusan National University, Pusan, Korea. His research interests include fuzzy logic control.

Sung-shin Kim
received the Ph.D. degree in electrical engineering from Georgia Institute of Technology, Atlanta, 1996. He is currently an Assistant Professor in the School of Electrical & Computer Engineering, Pusan National University, Pusan, Korea.

Chang-won Kim
received the Ph.D. degree in environmental engineering from University of Florida, Gainesville, 1985. He is currently a Professor in the Department of Environmental Engineering, Pusan National University, Pusan, Korea.

Sang-hyun Kim
received the Ph.D. degree in environmental engineering from Purdue University, West Lafayette, IN. He is currently an Assistant Professor in the Department of Environmental Engineering, Pusan National University, Pusan, Korea.



Hae-jin Woo
received the Ph.D. degree in civil engineering from University of Tennessee, Knoxville, 1999. She is currently an Assistant professor in Institute of Environmental Technology and Industry (IETI), Pusan. Korea.