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Multi-objective optimization of cascade controller in combined biological nitrogen and phosphorus removal wastewater treatment plant

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ABSTRACT

The multi-objective genetic algorithm (MOGA), aiming at determining the optimal set points for controllers existed in the supervisory control layer, is developed to enhance the treatment performance of a combined biological nitrogen and phosphorus removal wastewater treatment process (i.e. an anaerobic-anoxic-oxic process). Firstly, a cascade ammonia controller that consists of a primary proportional-integral (PI) controller and a secondary PI controller is set up and tuned using the internal model control tuning rule. The primary controller is used to control the ammonia concentration in the effluent and the secondary controller is used to control the dissolved oxygen concentration in the last reactor. This cascade controller could lead to better set point tracking and disturbance rejection control performance. Then, the multi-objective optimization (MOO) of the effluent ammonia controller set point and the nitrate controller set point in the fourth reactor is performed using the MOGA. The two conflicting optimization objectives are (1) effluent quality index which is a function of various main effluent loads and (2) energy consumption which is the sum of aeration energy consumption and pumping energy consumption. The MOO results indicate that the optimal set points for the effluent ammonia concentration and the nitrate concentration in the fourth reactor are both about 1.1 g N/m^3. The cascade controller with the optimal set points has the capability of enhancing the effluent quality and the energy-saving performance simultaneously.

Keywords: Multi-objective optimization; Genetic algorithm; Cascade control; Anaerobic-anoxic-oxic process

1. Introduction

Due to the more stringent effluent quality standards in biological wastewater treatment processes (WWTP), modeling, control, monitoring, and optimization issues have gained an increasing public awareness during the last two decades [1,2]. The main control objectives for the biological WWTP are: (1) to meet the effluent quality requirement, (2) to maintain the controlled variables at their set points for counteracting the effects of the changing loads and disturbances, and (3) to minimize the energy consumption [3]. As one of the advanced control strategies, cascade control has the advantages as follows. On the one hand, this control structure is more effective to

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eliminate the strong disturbances that existed in the influent in WWTP. On the other hand, identification task could become easier because the unstable or excessively slow process dynamics are stabilized or made faster by the regulatory loop [4]. As a consequence, cascade controllers have excited great interest for improving the control performance of WWTP. Cho et al. [5] developed a cascade controller to control the nitrate concentrations in the predenitrifying process using the external carbon dosage as a manipulated variable. Furthermore, Liu and Yoo [6] proposed a cascade model predictive control (MPC) strategy to improve the effluent quality in a biological wastewater treatment plant. It should be noted that the advanced cascade control strategy which contains two control loops is structurally a little more complicated compared to the simple proportional-integral-derivative (PID) control strategy.

In recent years, the benchmark simulation models including BSM1 and BSM2 have become standard simulation platforms for testing new control strategies in the field of WWTP. These models can be used for modeling the biological nitrogen (N) removal process successfully [7,8]. However, they have the structural limitation of not considering the phosphorus (P) removal process, which should be taken into account for achieving a more realistic simulation model in the anaerobic-anoxic-oxic (AAO) process. To evaluate the influence of control strategies on the AAO process, Gernaey and Jorgensen [9] have developed a new simulation benchmark model that defines a default plant layout, a biological process model with detailed model parameters, realistic influent disturbances, and plant performance indices. Since then, this AAO benchmark model has aroused wide interest. For example, implemented in the modified AAO benchmark platform, the effluent quality controllers [10] were designed to reduce the operating costs for the AAO process.

Controller set points could have significant impacts on the performance of highly complex and nonlinear WWTP. One straightforward approach to determining the optimal set points is to construct the operational maps that could find optimal set point values by evenly changing the controller set points within their normal bounds [11]. Although this method is simple and easy to implement, it may fail to find the best solutions for controller set points because of the highly complex and nonlinear feature of WWTP. Therefore, the optimization of controller set points is necessary. A model-based set point optimization method for the improvement of an AAO control system was proposed [12]. This approach could obtain better results compared with the operational map approach, but it could not be applied to the control system where multiple controllers' set points need to be optimized.

Alternatively, multi-objective optimization (MOO) technique having the advantage that it can simultaneously optimize more than one conflicting objective functions has been successfully applied to a good deal of engineering applications [13–15]. Although the MOO technique [16] has been applied to the BSM1, to our knowledge, there is no literature about the MOO of the AAO wastewater treatment process. Therefore, the main contribution of this study is to improve the control performance and reduce the energy consumption simultaneously for the AAO process using the MOO technique. To achieve this purpose, an extra cascade controller was designed firstly, followed by the MOO of the set points of two tuned PI controllers.

The remainder of this paper is organized as follows. In the Material and methods section, we briefly describe the AAO plant layout and the proposed cascade control structure. Then, we explain the Pareto front and list the key optimization parameters. Two optimization objectives are also explained in this part. A procedure showing the main steps to achieve a global MOO is highlighted at the end of this section. In the Results and discussion section, we evaluate the control performance of the tuned cascade controller based on an identified process model. The optimal set points are obtained using the MOO technique. Finally, we draw the conclusions.

2. Material and methods

2.1. AAO process

The basic AAO plant layout used for simulation is similar to the one suggested by Gernaey and Jorgensen [9]. The proposed cascade control structure for the control and optimization of a biological nitrogen and phosphorus removal process is shown in Fig. 1. This process mainly consists of seven biological reactors with a total volume of 6,749 m^3 and one settler with a volume of 6,000 m^3. The first two reactors used for phosphorus removal are anaerobic reactors, the following two reactors are anoxic reactors where the denitrification is performed, and the last three reactors are oxic reactors where the nitrification of ammonia to nitrate is happening. The activated sludge model No. 2d (ASM2d) [17], which has the capability of modeling the biological phosphorus removal process, was implemented. The settler model was developed using the Takacs's double exponential settling velocity model [18].

In the simulated AAO process, the main measured variables are the liquid flow rates in the pipes of

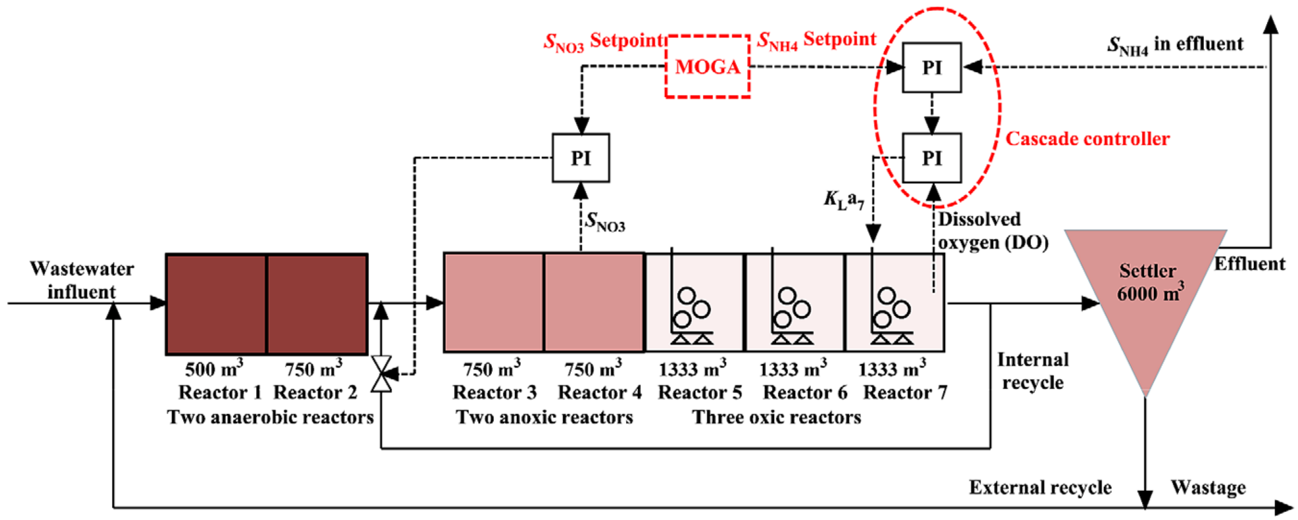

Fig. 1. Schematic of the AAO process with a cascade controller and MOGA.

influent, effluent, wastage, internal and external recycles; air flow rates to the last three oxic reactors; dissolved oxygen (DO) concentrations in the last three oxic reactors; nitrate (S_{NO_3}), ammonia (S_{NH_4}), phosphate (S_{PO_4}), and total suspended solids (TSS) concentrations in Reactors 2, 4, and effluent. The influent disturbance has important effects on optimization and control performance in AAO process. Fig. 2 shows the diurnal variations of the dry weather influent data [9] for influent flow rate (Q_{in}), S_{NH_4} concentration, and S_{PO_4} concentration. To improve the control performance of the effluent ammonia concentration, a cascade controller was designed and applied in the AAO process. This controller consists of a primary PI controller to control the ammonia concentration in effluent and a secondary PI controller to control DO concentration in the last reactor (Fig. 1).

2.2. Multi-objective optimization

Several well-known multi-objective genetic algorithms, such as the vector evaluated genetic algorithm

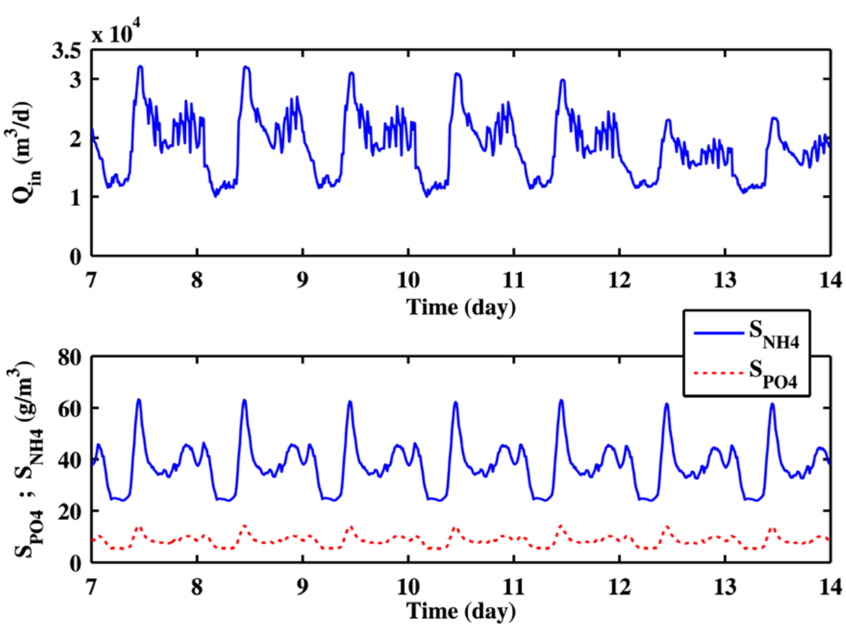

Fig. 2. Diurnal variations of the three influent disturbance variables under dry weather condition.

(VEGA), the strength Pareto evolutionary algorithm (SPEA), and the Pareto envelope-based selection algorithm (PESA), have been developed to search for the Pareto front [19]. The concept of Pareto front is shown in Fig. 3 where points A and B correspond to non-dominated solutions and point C corresponds to a solution that is dominated by at least one of the solutions corresponding to the Pareto front. As a mature MOO technique, the non-dominated sorting genetic algorithm II (NSGA-II) [20] was used in the current work. Specifically, the population size and the number of running generations were 30 individuals and 60, respectively. The choice of these two parameters is based on authors' knowledge due to the shortage of theoretical approach to determine them. The values for the crossover and mutation probability related to NSGA-II were set to 0.95 and 0.05, respectively.

To evaluate the control performance of the AAO benchmark simulation model, two performance criteria [9] including the effluent quality index (EQI) which is the function of the effluent loads and the energy consumption index (ECI) which is the sum of the aeration energy consumption and the pumping energy consumption are defined as follows:

$$\mathrm{EQI} = \frac{1}{1000(t_f - t_0)} \int_{t_0}^{t_f} \left[\begin{array}{l} \beta_{\mathrm{TSS}} \cdot \mathrm{TSS}(t) + \beta_{\mathrm{COD}} \cdot \mathrm{COD}(t) + \beta_{\mathrm{BOD}} \cdot \mathrm{BOD}(t) \\ + \beta_{\mathrm{TKN}} \cdot \mathrm{TKN}(t) + \beta_{\mathrm{NO_3}} \cdot \mathrm{NO_3}(t) + \beta_{\mathrm{P_{tot}}} \cdot \mathrm{P_{tot}}(t) \end{array} \right] Q_e(t)dt \quad (1)$$

$$\mathrm{ECI} = \alpha_{\mathrm{AE}}\mathrm{AE} + \alpha_{\mathrm{PE}}\mathrm{PE} \quad (2)$$

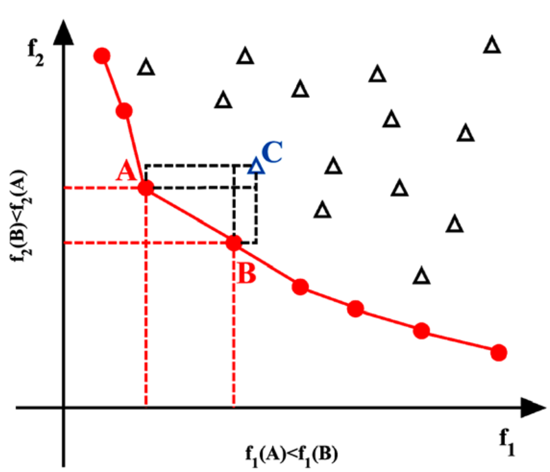

Fig. 3. Schematic of the Pareto front for a two objective function optimization problem.

where t_0 and t_f stand for the starting and ending times; Q_e is the effluent flow rate; COD, BOD, TKN, NO_3, and P_{tot} stand for chemical oxygen demand, biochemical oxygen demand, total organic nitrogen, nitrate, and total phosphorus concentrations in the effluent, respectively, and these concentrations can be calculated using the mathematical expressions explained in more detail in [9]; AE and PE represent the aeration energy and pumping energy, respectively; β in Eq. (1) is the weighing factor, and α in Eq. (2) is the cost factor.

The weighting factors together with some other sources of uncertainties such as influent disturbances, kinetics, and stoichiometry parameters have significant impacts on the performance of the AAO process. These uncertainties could be dealt with using sensitivity analysis and Monte-Carlo simulations [21]. Because this work aimed at pursuing the optimal set points of the involved controllers using the MOO technique, the typical values of the weighting factors ($\beta_{\mathrm{TSS}} = 2$, $\beta_{\mathrm{COD}} = 1$, $\beta_{\mathrm{BOD}} = 2$, $\beta_{\mathrm{TKN}} = 20$, $\beta_{\mathrm{NO_3}} = 20$, $\beta_{P_{\mathrm{tot}}} = 20$, $\alpha_{\mathrm{AE}} = 25$, and $\alpha_{\mathrm{PE}} = 25$) were used in this study, which are in accordance with the ones proposed by Gernaey and Jorgensen [9]. These two conflicting indices were used as objective functions for the MOO.

2.3. Procedure for a global MOO

The whole procedure for fulfilling the MOO of the proposed cascade control structure in the AAO process is shown in Fig. 4. The AAO process model was implemented using Matlab/Simulink S-functions. Besides the two basic PI controllers (nitrate controller and DO controller), the cascade control structure was suggested and implemented to further improve the effluent ammonia control performance. There are two basic control loops in the cascade control: an inner DO control loop and an outer effluent ammonia control loop. The process model for effluent ammonia concentration was obtained through the system identification step. In this step, the pseudo-random binary sequence (PRBS) test signal which is widely used for the identification process in industry [22] was chosen as the exciting input signal. After getting the excited process measurements, the identification approach of prediction error method (PEM) [23] was adopted to identify a linear process model. Then, the internal model control (IMC) tuning rule that is one of the most widely used PI controller tuning methods [24] was used to get the controller parameters. Finally, the MOO was used to determine the optimal set points of the nitrate controller and the effluent ammonia controller.

3. Results and discussion

3.1. Identification and cascade controller tuning

There are three PI controllers needed to be tuned in Fig. 1. Because the IWA BSM1 suggests a set of controller parameters for the nitrate PI controller and the secondary DO controller, these parameters were determined and modified just by trial and error. The primary ammonia PI controller was tuned using the model-based IMC tuning rule. The process identifica-

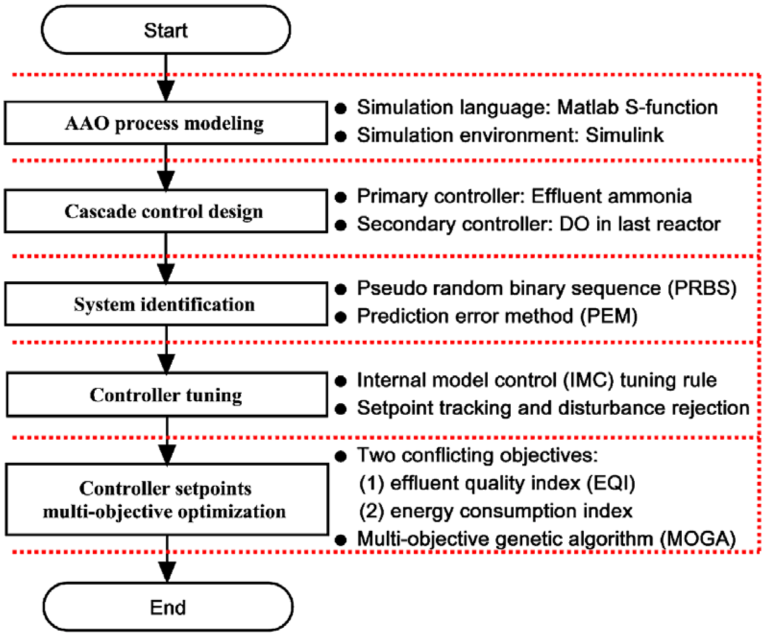

Fig. 4. Flowchart of the control system design in the AAO process.

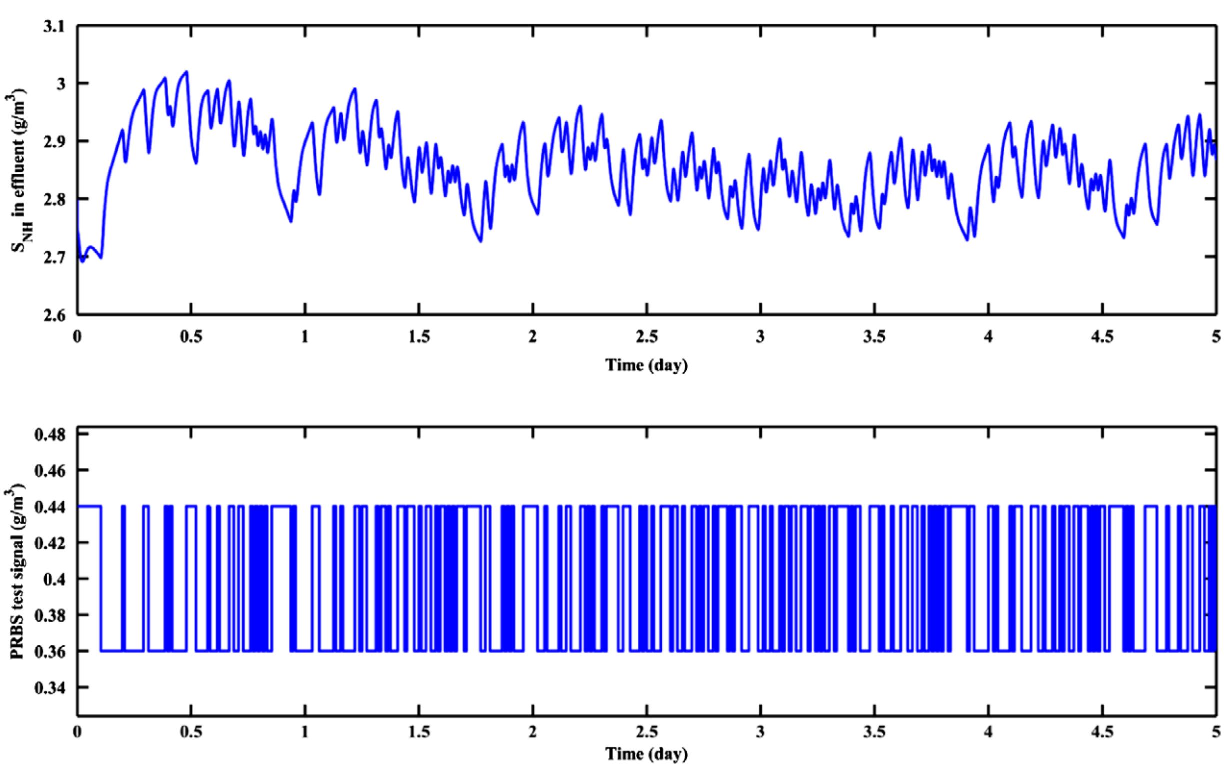

Fig. 5. PRBS test signals for identifying effluent ammonia concentration dynamics.

tion was carried out to obtain a system model for tuning controller parameters.

To capture the dynamic properties of the process, the sampling time of identification was chosen to be 15 min. Besides, considering the energy cost of input equipments (such as pumps) and persistent excitation [22] during the identification test, the magnitude of the PRBS test signal should be determined appropriately. A high value of PRBS magnitude will unnecessarily increase the energy consumption or even cause the process to be unstable if this value is set too high. On the other hand, a too low value of the PRBS magnitude will not provide persistent excitation for the identification. Therefore, the PRBS magnitude was set to 10% of the steady-state value in this study.

The data used for the process identification are shown in Fig. 5. A fourth-order PEM model could result in a satisfactory accuracy as shown in Fig. 6. This PEM model was validated using a different set of validation data. Over 95% fitting accuracy to the validation data was observed by using the PEM method. So the accuracy of the model achieved was satisfactory and this identified model can be used for the controller tuning. Finally, all the parameters of three PI controllers obtained are shown in Table 1.

Set point tracking and disturbance rejection experiments were conducted to test the control performance of tuned PI controllers. The process control response to the set point change is shown in Fig. 7(a). The proposed cascade controller exhibits the faster response and the overshoot to the set point change is small. Therefore, the closed-loop response for a set point change is satisfactory. By using an inner loop and two feedback PI controllers, cascade control can improve the response to a set point change effectively.

As we know, WWTP happens to confront various influent changes with respect to the changing loads and the toxic load. It is of great interest to study how

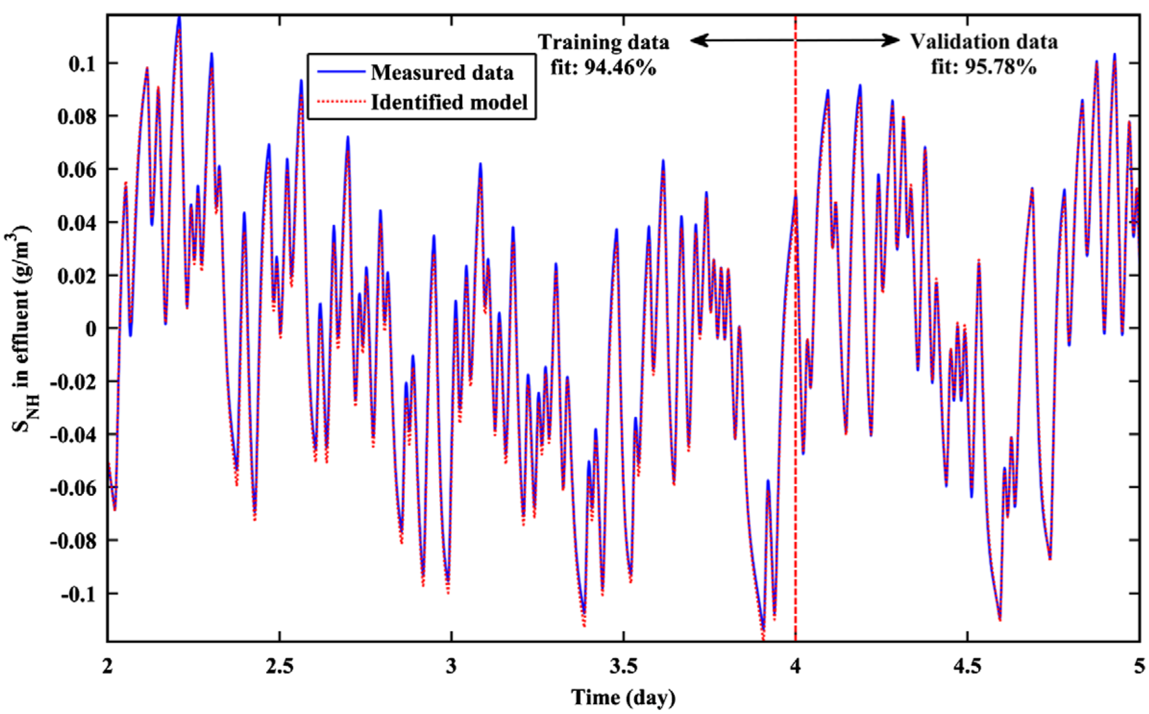

Fig. 6. Comparison between the identified model data and the measured data.

Table 1
Tuned parameters of PI controllers in the AAO plant

PI controller parameters	Cascade controller		Nitrate PI controller
	Secondary PI controller	Primary PI controller	
Proportional gain, K_p	100	−4	10,000
Integral time constant, T_i, d	0.002	0.02	0.015
Anti-windup time constant, T_t, d	0.001	0.01	0.01

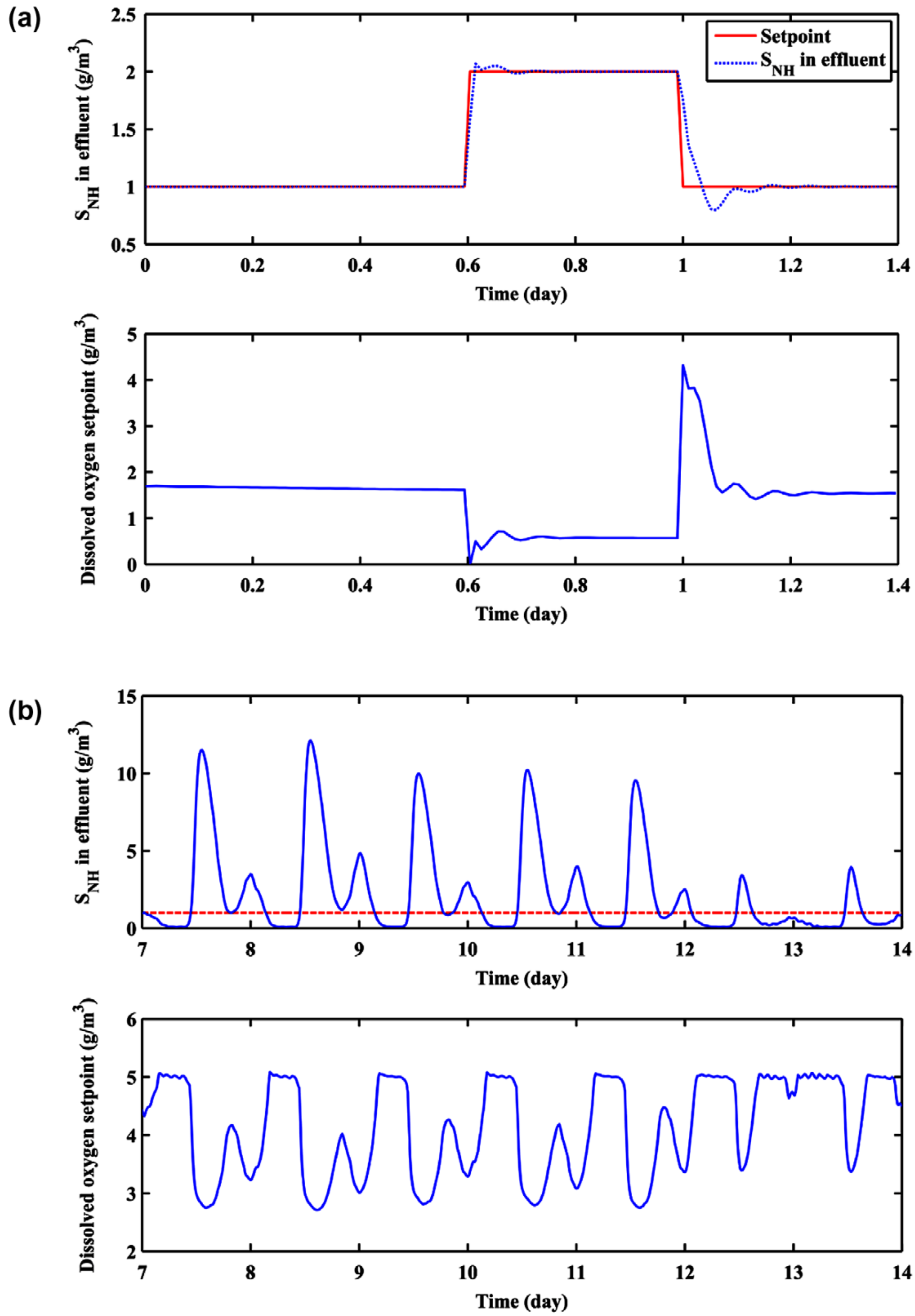

Fig. 7. Control performance of the tuned cascade controller: (a) set point tracking performance, (b) disturbance rejection performance using the dry weather data.

the controller performs under influent disturbances. The simulation result in Fig. 7(b) demonstrates that the proposed controller compensates for the dry weather disturbance in a proper manner. By employing a secondary control loop and a secondary feedback controller, the cascade control strategy can significantly improve the dynamic response to disturbances. The cascade controller could capture the process characteristics and tackle the problem of influent loading variations effectively.

3.2. MOO of controller set points

Effluent quality and energy consumption are two important aspects when designing or modifying the structure of the wastewater treatment plant. Aiming

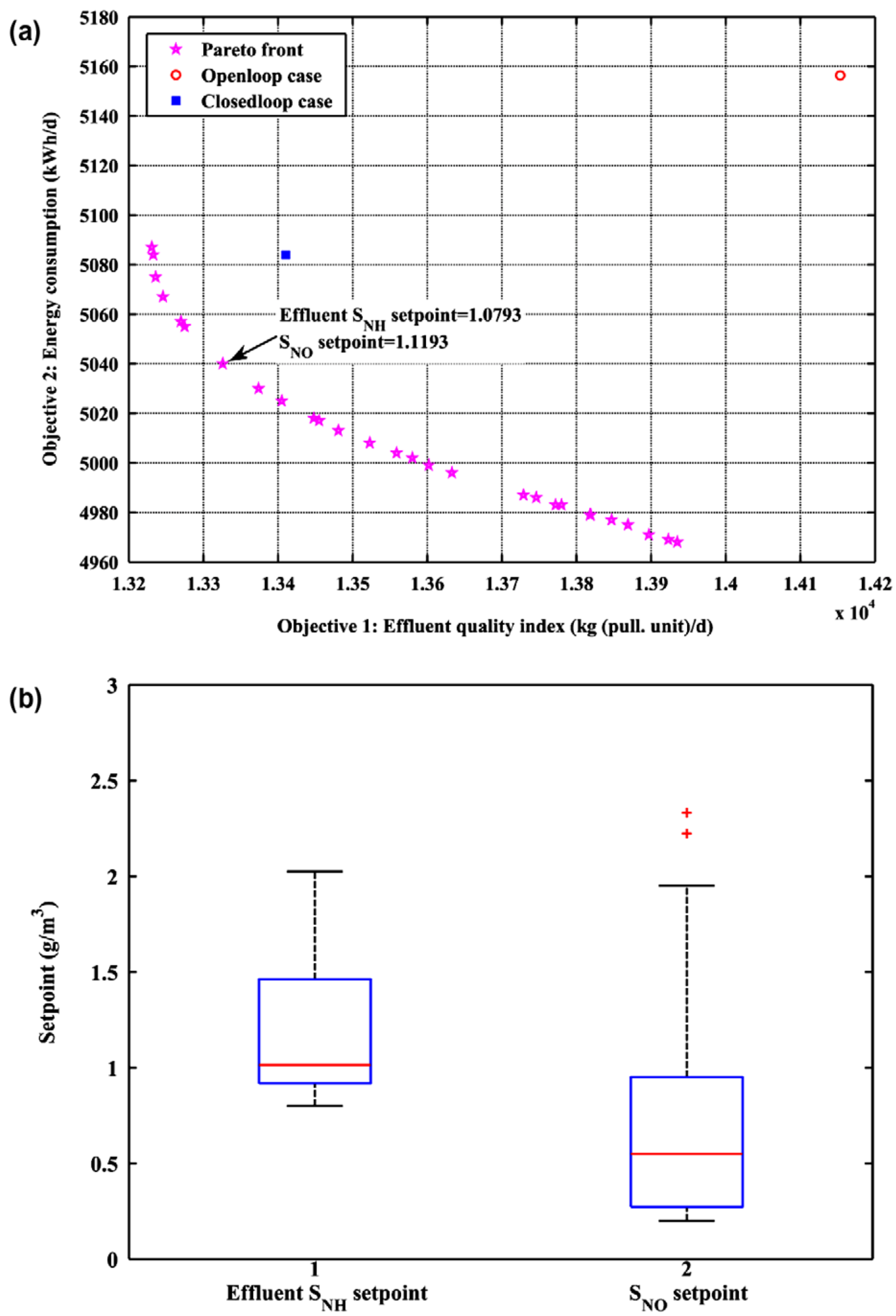

Fig. 8. (a) Pareto front curve obtained using MOGA. (b) Box plot of the final population.

Table 2
Comparison of the plant performances using dry weather disturbance influent data

Performance index	Open-loop case ($K_La_7 = 150$)	Closed-loop case ($DO = 2$; $S_{NO_3} = 1$)	Optimal set points case ($S_{NH_4} = 1.1$; $S_{NO_3} = 1.1$)
EQI (kg poll.units/d)	14,153.2286	13,410.3196	13,326.0846
AE (kWh/d)	4,915.0000	4,728.0359	4,713.5333
PE (kWh/d)	241.3520	355.9424	326.6570
P_{sludge} (kg/d)	3,286.3893	3,051.7281	3,020.0243
Effluent average ammonia conc. (g N/m^3)	8.2533	4.4991	3.9211
Effluent average nitrate conc. (g N/m^3)	10.4183	9.7277	10.9036
Effluent average total nitrate conc. (g N/m^3)	19.7216	15.2821	15.8810
Effluent average total COD conc. (g COD/m^3)	46.1026	46.1709	46.1825

at simultaneously optimizing these two plant performance indices, the MOO technique was performed to study the impact of the controller set points on plant performance.

Before optimization, some detailed implementation should be provided for a clear understanding of the results. Firstly, the two design variables were constrained between 0.8 and 4 g N/m^3 for the effluent ammonia controller, and between 0.2 and 4 g N/m^3 for the nitrate controller. These ranges span the normal operation periods for the set points of the concerned controllers. Besides, limiting the ranges of design variables could reduce computational load when applying the proposed MOO technique in the real plant. Secondly, for the open-loop instance, the oxygen transfer coefficients of last three reactors were set to 240, 240, and 150 d^{-1}, respectively. These values are reasonable and widely accepted by the WWTP simulation community. For the closed-loop instance, the set points of the nitrate and DO controllers were both set to 1 g N/m^3 and 2 g (–COD)/m^3, respectively. It should be noted that the default parameters for the open-loop and closed-loop simulations are the same as the values suggested by Gernaey and Jorgensen [9] for the comparison purpose.

As expected, the Pareto front curve in Fig. 8(a) shows that the optimal solutions have better effluent quality and lower energy consumption compared to the open-loop and closed-loop cases. The performance of closed-loop scenario is quite similar to that of the Pareto front solutions, but the performance of open-loop scenario is unsatisfactory in the sight of the large EQI and energy consumption value. Among all the optimal solutions, the one around the arrow mark in Fig. 8(a) is a suggested compromise between the two objectives of effluent quality and energy consumption. Furthermore, the MOO results indicate that one set of optimal set points from the Pareto curve (i.e. about 1.1 g N/m^3 for the set point of effluent ammonia concentration and about 1.1 g N/m^3 for the set point of nitrate concentration in the fourth reactor) could simultaneously reduce the energy consumption and improve the effluent quality especially when compared to the open-loop scenario.

The box plot contains information about the location, spread, and skewness of the univariate variable. So it is a useful tool to compare the distribution of several data sets in one graph visually. The box plot of the final population in Fig. 8(b) shows that (1) the major population are gathering around 1 g N/m^3 for the set point of effluent ammonia concentration and (2) the major population are gathering around 0.5 g N/m^3 for the set point of nitrate concentration in the fourth reactor.

The plant performances of the three control strategies including the open-loop case, the closed-loop case, and the optimal set points case are listed in Table 2, where the performance criteria are EQI, AE, PE, average daily sludge production for disposal (P_{sludge}), average ammonia, nitrate, total nitrate, and total COD concentrations in the effluent. Because EQI represents the levies or fines to be paid due to the discharge of pollution, a good control strategy should have small EQI from the strict regulation point of view. Compared to the open-loop and closed-loop cases, the case with optimal set points determined by MOO could obtain the smallest EQI, AE, and P_{sludge}, which further validates the effectiveness of MOO technique.

4. Conclusions

A detailed procedure containing several key steps for determining the optimal set points has been implemented in the combined biological nitrogen and phosphorus removal wastewater treatment process. A novel cascade control has been designed and properly tuned using the IMC controller tuning rule to improve the control performance of the effluent ammonia concentration. Then, the MOO based on the genetic algorithm was proposed and implemented. Finally, one set of optimal set points for the effluent ammonia concentration and the nitrate concentration was determined. The integrated technique could result in a satisfactory performance of effluent discharge and energy saving.

Acknowledgments

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Nomenclature

AAO	anaerobic-anoxic-oxic
AE	aeration energy consumption rate
ASM2d	activated sludge model No. 2d
BOD	biochemical oxygen demand
BSM1	benchmark simulation model No. 1
BSM2	benchmark simulation model No. 2
DO	dissolved oxygen
ECI	energy consumption index
EQI	effluent quality index
IMC	internal model control
MOGA	multi-objective genetic algorithm
MOO	multi-objective optimization
MPC	model predictive control
N	nitrogen
NSGA-II	non-dominated sorting genetic algorithm II
P	phosphorus
PE	pumping energy
PEM	prediction error method
PESA	Pareto envelope-based selection algorithm
PI	proportional integral
PRBS	pseudo-random binary sequence
P_{sludge}	average daily sludge production for disposal
P_{tot}	total phosphorus concentration
Q_{in}	influent flow rate
$S_{\mathrm{NH_4}}$	ammonia concentration
$S_{\mathrm{NO_3}}$	nitrate concentration
$S_{\mathrm{PO_4}}$	phosphate concentration
SPEA	strength Pareto evolutionary algorithm
TKN	total organic nitrogen
TSS	total suspended solids
VEGA	vector evaluated genetic algorithm
WWTP	wastewater treatment process
Greek	
α	cost factor
β	weighing factor

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