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Optimization of biological nutrient removal in a SBR using simulation-based iterative dynamic programming

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Abstract

The purpose of this study was to simulate and optimize the nitrogen removal of a sequencing batch reactor (SBR) through the use of a simplified model derived from activated sludge model no. 1 (ASM1) and iterative dynamic programming (IDP), while meeting the treatment requirements. A new performance index for SBR optimization is proposed on the basis of minimum area criteria that consider the minimum batch time and the maximum nitrogen removal so as to minimize the energy consumption. Choosing area as the performance index simplifies the optimization problem and the use of appropriate weights in the performance index makes it possible to minimize the time and energy of the SBR simultaneously. In the optimized system, the optimal set-point of dissolved oxygen affects both the batch time and energy savings. For four different influent loadings, simulation results by IDP-based SBR optimizations suggest that batch scheduling, the set-point trajectory of dissolved oxygen concentration and the amount of external carbon all require supervisory control in order to achieve the optimal energy-saving concentration of total nitrogen in the effluent. Simulation results of the SBR show that the total energy cost can be reduced by up to 20% for the aerobic phase and 10% for the anoxic phase with maximum nitrogen removal.

Keywords: Activated sludge model; Dissolved oxygen; Iterative dynamic programming; Optimal control; Sequencing batch reactor; Simulation

1. Introduction

Sequencing batch reactor (SBR) processes have proved particularly suitable for the treatment of wastewater, which is characterized by high nutrient content and frequent changes in composition. The major advantages of SBR processes are attributable to their ability to adjust the duration of the different processing phases. Real-time control of the SBR process can contribute to this. A possible control strategy is based on the identification of the endpoint of a biological reaction. Switching to the next phase shortly after the detection of the reaction endpoint optimizes both the process performance and the economics of the plant [1–6].

There are many ways to ensure the optimal operation of an SBR, including optimal control using inexpensive online sensors to monitor dissolved oxygen (DO), pH and oxidation reduction potential [1,4,6] and model-based optimization [7–15]. To date, the most successful model and the industrial standard in biological wastewater treatment plant have been activated sludge models (ASMs), such as ASM1, ASM2 and ASM2d [16]. These models have proven to be an effective for carbonaceous, nitrogenous and phosphorous nutrient removal processes in such plants. The model-based optimization of the SBR has been used in the development and testing of optimal operation strategies for biological nitrogen and phosphorous removal [9–15,17]. Sin et al. [14] summarized the historical works of the optimization of the SBRs: the stepwise feeding of the influent [13], intermittent aeration [7], using the oxygen set-point in the aerobic reaction phase to regulate the extent of simultaneous nitrification and denitrification in the SBR [6,13,18] and the durations of the anaerobic, aerobic and anoxic phases [2,13,17].

Nonlinear models of ASMs have rarely been used for SBR optimization. The much more common linearized models some-

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Nomenclature

A_{NH}	total area under the trajectory of ammonium concentration (i.e., integration of nitrate concentration during the aerobic phase)
A_{NO}	the area under the trajectory of nitrate concentration (instead of A_{NH} (the area under the trajectory of ammonium concentration))
A_O	total area of oxygen utilization (i.e., integration of dissolved oxygen concentration during the aerobic phase)
A_S	total area under the consumed external carbon addition
C_O	cost of oxygen
E_C	energy consumption
E_Q	effluent equality
J	performance index
M	number of allowable control points
N	number of allowable grid points
Q	weighting factor of nitrate accumulation area
R	weighting factor of oxygen utilization area
S_{NH}	ammonia concentration
S_{NO}	nitrate concentration
S_O	dissolved oxygen concentration
T	batch time cost
t_f	final batch time

Greek letter

γ	region contraction factor

times predict unrealistically high effluent concentrations of nitrogen and phosphorous, while full model-based optimization can generally control the nitrogen and phosphorous dynamics by controlling the duration of the aerobic phase. Since such optimizations are sensitive to large mismatches between model and real data and may not function properly, the application of linearized models to wastewater treatment optimization should be approached with caution [9–11,17]. However, Sin et al. [14] used a full ASM model for SBR optimization to analyze various scenarios of single-input and single-output perturbations and several fixed-duration aerobic and anoxic sequences. A scenario-based analysis requires many simulations (e.g., hundreds) and hence is time consuming and does not allow for variable durations of the aerobic and anoxic sequences, despite SBRs being subject to dynamic input conditions.

Latest studies into the optimal control of SBRs have focused on minimizing the batch time rather than optimizing the control policy of the process variables [19]. Determining the optimal control trajectory from a microbiological point of view is much more complex and hence there are few guidelines for determining optimal control trajectories [18–21]. The primary aim of the present study is to determine the optimal batch trajectory of the aerobic and anoxic phases in an SBR.

Iterative dynamic programming (IDP) has not previously been used to determine the optimal trajectory of an SBR in wastewater processing. The main research objectives of this study are to determine (1) the optimal operation trajectory of DO at the aerobic phase of the SBR for different loading conditions, (2) a new performance index for SBR optimization based on minimum area criteria that consider the minimum batch time and the maximum nitrogen removal so as to minimize the energy consumption and (3) the minimum amount of external carbon required at the anoxic phase of the SBR for different loading conditions.

This paper is organized as follows. Section 2 provides a brief explanation of the IDP algorithm, the simplified model of the SBR from ASM1 for nitrogen removal and then presents the SBR optimization by IDP for maximizing nitrogen removal and minimizing the energy consumption based on a simple performance index. Section 3 describes how the SBR optimization results at several influent loading scenarios are obtained using the optimal DO trajectory in the aerobic phase and external carbon addition in the anoxic phase. Finally, conclusions are drawn in Section 4.

2. Theory

2.1. Iterative dynamic programming (IDP)

The nonlinear method of IDP reported by Luus [22] has been effective in optimizing the control of batch and fed-batch reactors, in which the entire batch process is divided into P stages of equal duration. In this method the performance index can be minimized by applying piecewise constant control over the P time stages [22–24].

IDP is a useful tool for determining the optimal control policy for batch processes [22]. To explain the optimal control problem of IDP, let us consider the nonlinear dynamic system

$$\frac{d\mathbf{x}}{dt} = f(\mathbf{x}, \mathbf{u}, t) \tag{1}$$

with initial state $\mathbf{x}(0)$ given, where $\mathbf{x}$ is an state vector and $\mathbf{u}$ is a control vector bounded by $\alpha_j \leq u_j \leq \beta_j$, $j = 1, 2, \ldots, m$. The performance index (PI) associated with this system is a scalar function of the state at final time t_f given by

$$\mathrm{PI}[\mathbf{x}(0), t_f] = \Psi(\mathbf{x}(t_f)) + \int_0^{t_f} \phi(\mathbf{x}, \mathbf{u}, t)\, dt \tag{2}$$

The optimal control problem is to simultaneously determine the control policy $\mathbf{u}(t)$ in the time interval $0 \leq t \leq t_f$ and the final time, t_f, that maximize PI [23].

The main advantage of IDP lies in its robustness in obtaining the global optimum. IDP iteratively applies the principle of optimality in dynamic programming for obtaining the optimal control of complex systems such as an SBR. IDP breaks up a problem into multiple stages and assumes that the performance index can always be expressed explicitly in terms of the state variables at the last stage. This provides a scheme that can be solved backwards in a systematic manner, with optimization performed at each stage [23].

There are many ways of implementing IDP and choosing the allowable values for system control [24]. The following list details the use of a piecewise linear control law in IDP that is applied in this study:

1. Divide the time interval $[0,t_f]$ into P time stages, each of duration $L = t_f/P$.
2. Choose the number of allowable control (M) and grid (N) points. Choose an initial control policy $\mathbf{u}(0)$, initial region size r and region contraction factor γ.
3. Using the initial control policy, integrate Eq. (1) from $t = 0$ to t_f to generate the x grid points for each time stage.
4. Starting at the beginning of the last time stage P, corresponding to time $t_f - L$, for each x grid point integrate the differential equation in Eq. (2) from $t_f - L$ to t_f with each of the M allowable control values. Store the control value that gives the minimum value of PI.
5. Proceed to time stage P-1, corresponding to time $t_f - 2L$. For each x grid point integrate the differential equation with each of the allowable control values. To continue integration from $t_f - L$ to t_f, choose the control from step 4 that corresponds to the grid point that is closest to the resulting $\mathbf{x}$ at $t_f - L$. Store the control value that gives the minimum of the M values of PI.
6. Repeat the procedure for stages P-2, P-3, ..., to stage 1, which corresponds to the initial time $t = 0$. Store the control policy that gives the minimum value of PI.
7. Reduce region size r by a factor γ; i.e.,

$$r^{(j+1)} = \gamma r^{(j)} \tag{3}$$

where j is the iteration index.

8. Use the best control policy and initial control policy from step 6 and go to step 3 [23–24]. Fig. 1 shows the basic schemes of iterative dynamic programming to find the best control policy, where $\mathbf{x}$ is an state vector and $\mathbf{u}$ is a control vector bounded (u_H and u_L).

2.2. Mathematical modeling of nitrogen removal in an SBR

Nitrogen removal incorporates nitrification and denitrification governed by nitrifying and denitrifying microorganisms that take place under aerobic and anoxic conditions, respectively. Nitrifying microorganisms are autotrophic and lithotrophic bacteria that aerobically oxidize ammonia to nitrite (*Nitrosomonas* is the predominant genus of this group) and, subsequently, nitrite to nitrate (a reaction step that is mediated by *Nitrobacter* species) [20]. This study focuses on the nitrogen removal reaction. In the SBR, carbon removal and nitrification during the aerobic phase

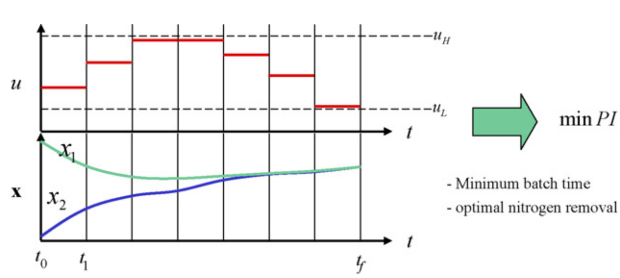

Fig. 1. Basic scheme of iterative dynamic programming (IDP).

and denitrification during the anoxic phase occur in the same reactor. Nitrogen removal involves two sequential steps: (1) the aerobic growth of autotrophs that consumes inorganic carbon, ammonia and DO to produce extra biomass and nitrates and (2) the anoxic growth of heterotrophs that consumes oxygen and increases nitrates to produce extra biomass and nitrogen gas [2,20].

The following mathematical description of SBR processes is useful for identifying significant operational parameters and interpreting the system performance [8,13]:

$$\frac{dS_i}{dt} = \frac{q_{in}}{V}(S_{i,in} - S_i) + r_i \tag{4}$$

where V is the volume, q_{in} the inflow rate, S_i the substrate concentration (of carbon and nitrogen), $S_{i,in}$ the influent concentration and r is the reaction rate.

In this paper, a simplified mathematical model based on ASM1 is used for the nitrogen removal optimization of the SBR. Table 1 lists the six components and five reactions in a simplified model of the ASM, which are selected from ASM1 relating to carbon and nitrogen removal. Mass balances for all components related to carbon and nitrogen removal are formulated as nonlinear ordinary differential equations, where the components are carbon (S_s), ammonia (S_{NH}), nitrate (S_{NO}), DO (S_O) and autotrophic (X_A) and heterotrophic biomass (X_H) and the related reactions are carbon oxidation, nitrification and denitrification [8]. The rate term can be obtained from stoichiometry and the reaction kinetics of Table 1. During the constant-volume reaction phase, the SBR components are completely mixed and the mass balances can be simply expressed as

$$\frac{dS_i}{dt} = r_i \tag{5}$$

where S_i is each component and r_i is the corresponding reaction rate of each component.

2.3. Optimal control formulation of the SBR for nitrogen removal

2.3.1. Understanding SBR dynamics and area

The minimal-time problem in optimal control theory generally leads to a time-varying bang-bang control law [25]. The issues include how to specify the final time and the aerobic and anoxic reaction times in the SBR, information that is necessary for minimizing the required energy. Another issue is determining the optimal trajectory of DO control in the aerobic phase and the minimum amount of external carbon in the anoxic phase.

The optimal operational strategies of the SBR are investigated using an IDP algorithm that calculates the minimum batch time, the optimal trajectory of DO control in the aerobic phase and the minimum amount of external carbon added in the anoxic phase. In the aerobic phase, the optimal set-point trajectory of DO and the minimum batch time are important variables for the SBR optimization. In the anoxic phase, the concentration of soluble carbon is used as a control variable. The step feeding of external carbon is used as an optimization variable. In both phases, the objective function involves energy minimization while consid-

Table 1
Kinetics of carbon and nitrogen removal in a simplified ASM model

Process	Components						Kinetics
	S_s	S_O	S_{NH}	S_{NO}	X_H	X_A	
Aerobic growth of heterotrophs	$-1/Y_H$	$(Y_H-1)/Y_H$	$-i_{XB}$		1		$\mu_H(S_S/(K_S+S_S))(S_O/(K_{OH}+S_O))X_H$
Anoxic growth of heterotrophs	$-1/Y_H$		$-i_{XB}$	$(Y_H-1)/2.86Y_H$	1		$\mu_H(S_S/(K_S+S_S))(K_{O,H}/(K_{OH}+S_O)) \times (S_{NO}/(K_{NO}+S_{NO}))\eta_g X_H$
Aerobic growth of autotrophs		$(Y_A-4.57)/Y_A$	$-i_{XB}-(1/Y_A)$	$1/Y_A$		1	$\mu_A(S_{SH}/(K_{NH}+S_{SH}))(S_O/(K_{OA}+S_O))X_A$
Decay of heterotrophs	$1-f_P$		$i_{XB}-f_P i_{XP}$		-1		$b_H X_H$
Decay of autotrophs	$1-f_P$		$i_{XB}-f_P i_{XP}$			-1	$b_A X_A$

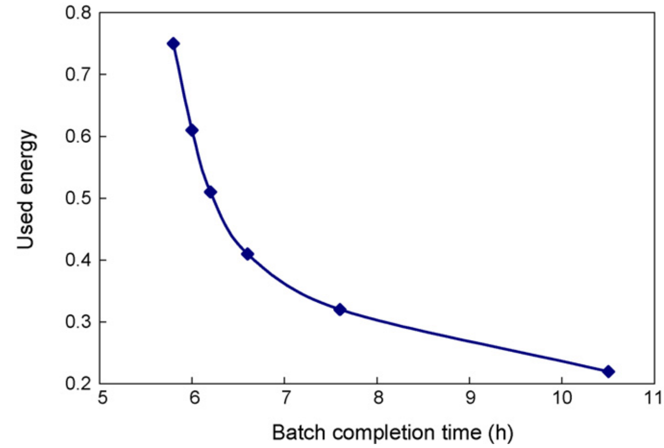

Fig. 2. Relationship between the used energy and batch completion time.

ering the maximum nitrogen removal and the minimum batch time.

The dependence of the used aeration energy on the batch completion time of nitrogen removal in the aerobic phase is shown in Fig. 2, which indicates that the value of T (the final batch time) greatly affects the consumed energy. There is a trade-off between the consumed energy and final batch time, since the energy required for nitrogen removal is inversely proportional to the batch time required for the nitrogen removal. It should be noted that this trade-off should consider both the elapsed time and the used energy, which can be incorporated into the performance index.

Fig. 3 shows the areas of the ammonium nitrogen and oxygen concentrations for a constant aeration rate, where A_O is the area under the trajectory of DO concentration and A_{NH} is the area under the trajectory of the nitrate concentration (S_{NH}). A_O is proportional to energy consumption and A_{NH} is proportional to the minimum time of the batch processing and the effluent quality. Minimizing the energy consumption and aerobic reac-

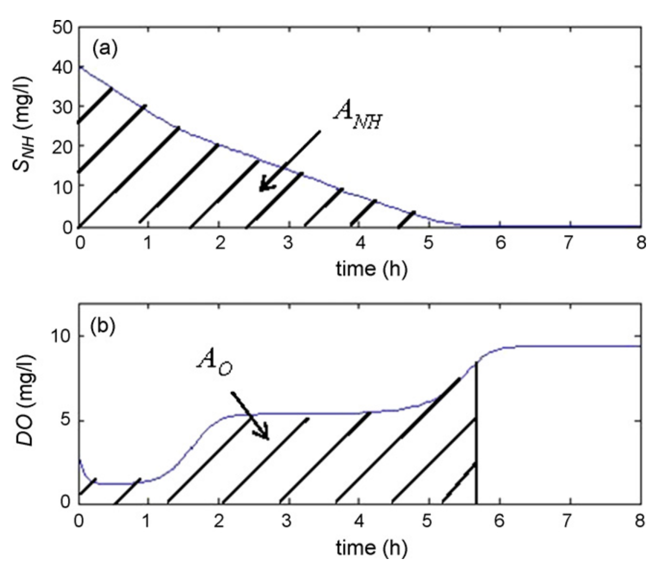

Fig. 3. Areas of the ammonium (A_{NH}) and oxygen concentrations under a constant aeration rate (A_O).

tion time can be used as objective functions for the removal of nitrogen. In the aeration phase, the optimal batch trajectory of DO control is determined in order to optimize nitrogen removal. The optimal DO trajectory is based on minimizing A_O, since the area under the graph of time versus the optimal DO is proportional to the amount of oxygen used. That is, a large A_O is associated with high oxygen usage and energy consumption.

2.3.2. Nitrogen optimization of the SBR in the aerobic phase

Previous section indicates that A_O and A_{NH} can be used to derive a new performance index using the weighted combination of elapsed time and used energy based on area minimization while considering the dynamic responses of the ammonium and oxygen concentrations in the aerobic phase and the external carbon in the anoxic phase:

$$J = \sum_{k=0}^{N} (QS_{NH}(K)L + RU_{Do}(k)L) \quad (6)$$

$$Q = aT + bE_Q, \qquad R = cE_C + dC_O \quad (7)$$

where Q and R are weights, L the time interval, T the batch time cost, E_Q the effluent quality, E_C the energy consumption, C_O the cost of oxygen and a, b, c and d are weight constants. The batch time can be reduced by increasing Q relative to R and the energy consumption can be reduced by increasing R relative to Q. Therefore, a performance index can be based on the trade-off between energy usage and the batch time through the weighting of Eq. (6).

2.3.3. Minimizing the amount of external carbon added in the anoxic phase

The optimal control strategy of the SBR in the anoxic phase involves determining the minimum amount of external carbon that will remove sufficient nitrate in the anoxic phase. In IDP this involves determining the $P+1$ values of $S_s(k)$, $k=0, 1, 2, \ldots, P$, that maximize the nitrogen removal and minimize the amount of external carbon added at the end of anoxic phase such that the proposed performance index in Eq. (6) is minimized:

$$J = \sum_{k=0}^{N} (QS_{NO}(K)L + RU_S(k)L) \quad (8)$$

where the parameters have the similar meaning as the aerobic phase.

3. Results and discussion

3.1. System conditions of the SBR

The simulated data are obtained using the simplified ASM model of an SBR which considers the complete one-step nitrification and denitrification with only a kind of nitrification biomass (autotrophic biomass) and denitrification biomass (heterotrophic biomass). A fill-and-draw SBR with a 12.5-l working volume is simulated during 120 h reaction comprising aerobic and anoxic phases. Similar to those in municipal-like sewage, the influent wastewater simulated at 150 of chemical oxygen demand (COD) and 40 mg/l concentration of ammonium (NH_4^+-N), respectively [8]. The SBR was operated with fixed time control (FTC) with a total batch reaction time of 12 h (aerobic and anoxic times of 8 and 4 h, respectively). Since nitrogen removal occurs only during the reaction phase of aerobic and anoxic phase, here, the total batch time represents the total reaction times of the aerobic and anoxic phases. The initial and operating conditions of the SBR are listed in Table 2. Fig. 4 illustrates typical concentration profiles associated with the cyclic operation of the SBR in the steady state.

Table 2
Initial and operating conditions of an SBR simulation

	Value
Operational conditions	
Reactor volume (l)	12.5
Total batch reaction time (h)	12
Aerobic reaction time (h)	8
Anoxic reaction time (h)	4
Initial conditions	
COD concentration (mg/l)	150
Ammonium concentration (mg N/l)	40
Nitrate concentration	0
Dissolved oxygen concentration (mg/l)	3
Heterotrophic microorganism concentration (mg/l)	400
Autotrophic microorganism concentration (mg/l)	40

IDP is implemented in a simulated data of a SBR using a simplified model of the ASM1, which focuses on nitrogen removal. The selection of the number of grid points, P, is important in IDP, since the accuracy increases linearly but the simulation time increases exponentially with P (which therefore needs to be selected appropriately). The simulation times are about 5 and 23 min with $P=24$ and $P=40$, respectively. A number of simulations revealed that the reasonable number of grid points was three and that the region contraction factor was 0.8 for allowable control value.

3.2. Optimal trajectory of the SBR in the aerobic phase

In the aerobic phase, the optimal trajectory of the DO concentration greatly affects nitrogen removal and energy minimization

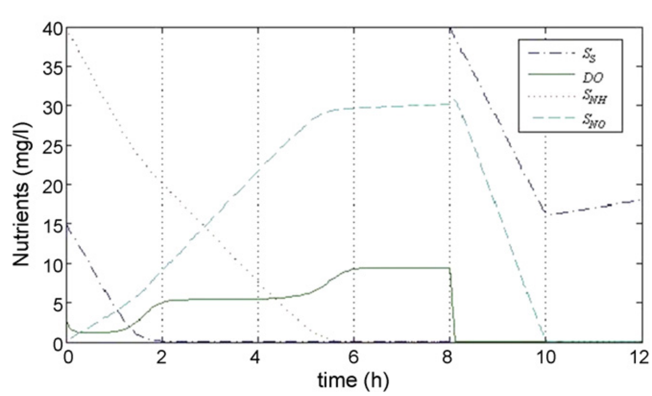

Fig. 4. Typical concentration profiles associated with the cyclic operation of the SBR in the steady state.

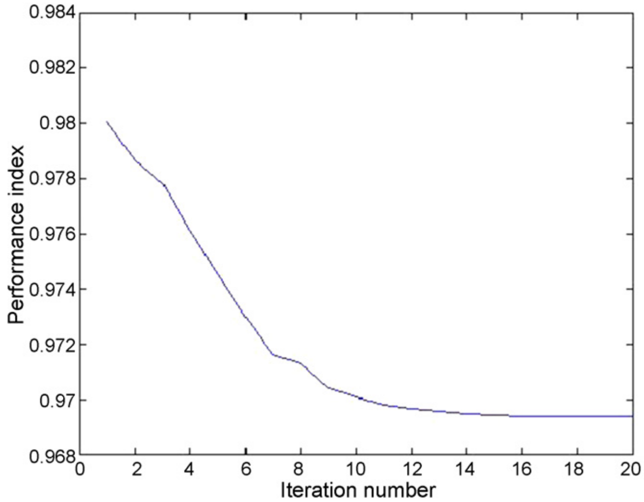

Fig. 5. Performance index versus the number of IDP iterations.

and hence the DO trajectory was chosen as a control variable in this phase. The cost of energy, nitrogen removal and the minimum reaction time is assessed in the following four scenarios with different weights for time (Q) and energy (R): (1) Q:R = 0.6:0.1, (2) Q:R = 0.5:0.2, (3) Q:R = 0.35:0.35 and (4) Q:R = 0.2:0.5. The constraint used is

$$0.5 \leq U_{\mathrm{DO}} \leq 3\,(\mathrm{mg/l}) \tag{9}$$

Simulation conditions are as follows: the initial control policy (i.e., $\mathbf{u}(0)$) is 1.5, the region size is 2 and the number of iterations is 20, P is 24, where piecewise constant control is used to solve Eq. (6). Fig. 5 shows how the performance index varied with the number of IDP iterations.

For comparison, the operation case as FTC with a constant aeration rate (standard case, $A_{\mathrm{O}} = 0.725$) is defined, where the DO concentration was maintained at 3 mg/l. note that since A_{O} is directly proportional to energy consumption, the energy consumption can be compared with the area under the trajectory of DO concentration (A_{O}). Fig. 6 shows the optimal control results of the SBR using IDP for the four scenarios: Fig. 6(a–c) shows the optimal trajectory of DO in the aerobic phase, the optimal trajectory of S_{s} in the anoxic phase and the resulting nutrient concentration profiles, respectively.

The top three panels of Fig. 6 show the results for scenario 1, for which the aerobic time for nutrient completion was 5.8 h, $A_{\mathrm{O}} = 0.6728$ and $J = 2.4446$. The energy consumption of scenario 1 was 7.2% lower than that in FTC, there was no difference in the aerobic reaction time and the total cost decreased by 11.7% (from 2.7692 to 2.4446). Scenario 2 focused on effluent quality rather than energy consumption (data not shown). The aerobic reaction time was 6.2 h, $A_{\mathrm{O}} = 0.6411$ and $J = 2.1145$. The total cost decreased by 23.6% and the energy consumption decreased by 11.6%. In scenario 3, Q and R had the same weight (data not shown) and the aerobic reaction time was 6.6 h, $A_{\mathrm{O}} = 0.571$, $J = 1.6097$. The total cost decreased by 41.9%, the energy consumption decreased by 21% and the aerobic time increased by 0.8 h. The bottom three panels of Fig. 6 show the results for scenario 4, which focused on energy consumption. The aerobic

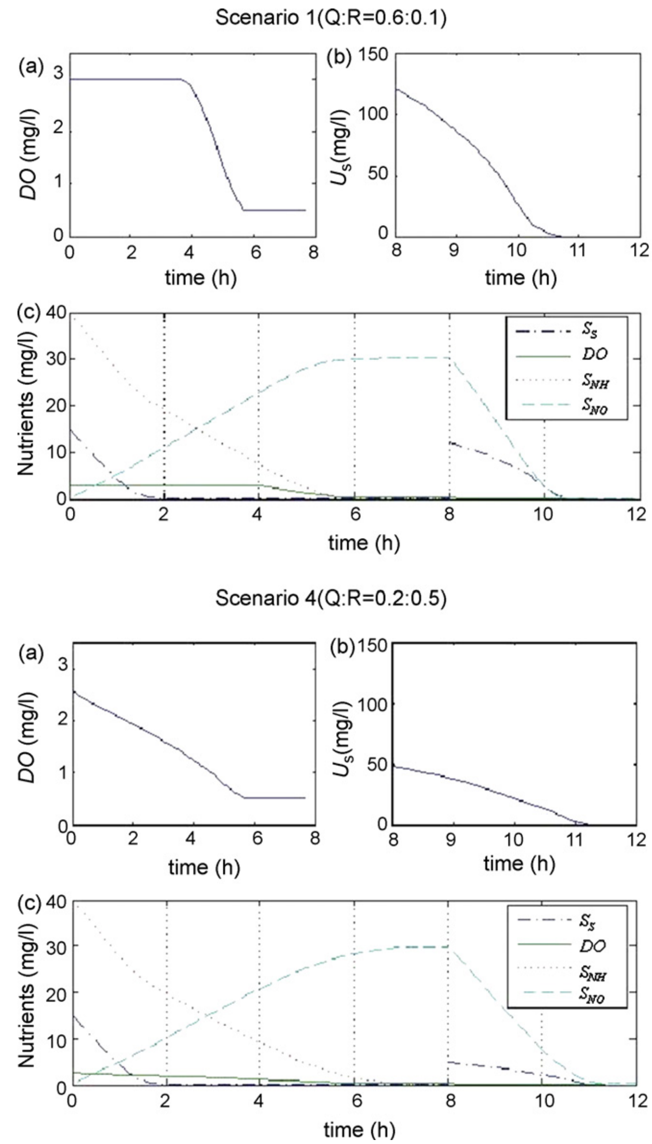

Fig. 6. Optimal control results of the SBR using IDP for (top panels) scenario 1 (Q:R = 0.6:0.1) and (bottom panels) scenario 4 (Q:R = 0.2:0.5): (a) optimal trajectory of DO in the aerobic phase, (b) optimal trajectory of S_{s} in the anoxic phase and (c) nutrient concentration profiles.

reaction time was 7.2 h, $A_{\mathrm{O}} = 0.4258$ and $J = 1.0717$. The total cost decreased by 61.3%, the energy consumption decreased by 41.25% and the aerobic reaction time increased by 1.4 h. Table 3 compares the used energy and the total cost of the four scenarios in the aerobic and anoxic phases.

Liu and Tay [26] reported that reducing the aeration rate in the famine period of the SBR could effectively reduce the total energy requirement without affecting its performance or settling of aerobic sludge during long-term operation. Plots of the effects of the different parameters revealed that increasing the aeration energy did not improve the effluent quality and this was not accompanied by any decrease in the aerobic time. An increase in the aerobic time is equivalent to an increase in the oxygen setpoint and hence the used energy and total batch time decreased markedly when using an optimal operation policy of the SBR with IDP.

Table 3
Comparisons of energy consumption and total cost in the aerobic and anoxic phases

	FTC[a]	Q:R = 0.6:0.1	Q:R = 0.5:0.2	Q:R = 0.35:0.35	Q:R = 0.2:0.5
Aerobic phase					
t_1 (h)	5.8	5.8	6.2	6.6	7.2
Energy consumption	0.725	0.6728	0.6411	0.571	0.4258
Reduction of energy consumption (%)	–	7.2%	11.57%	21.24%	41.25%
Total cost	2.7692	2.4446	2.1145	1.6097	1.0717
Reduction of total cost (%)	–	11.7	23.6	41.9	61.3
Anoxic phase					
t_1 (h)	10	10.5	10.75	11	11.25
Total cost	1.01	0.989	0.928	0.7794	0.571
Reduction of total cost (%)	–	2.1	8.1	22.8	43.5

[a] FTC means fixed time control.

3.3. Optimal trajectory of the SBR in the anoxic phase

In the anoxic phase, the objective function involves minimizing the time while considering the nitrogen removal and minimum energy usage. The parameters used are $P = 16$, $r = 200$, $\mathbf{u}(0) = 200$ and 25 iterations. In the anoxic phase, the performance index considered A_{NO} (the area under the trajectory of nitrate concentration) instead of A_{NH} (the area under the trajectory of ammonium concentration) and A_{S} (the area under the consumed external carbon addition) instead of A_{DO} (the area under the consumed air flow rate). The curves in Fig. 6 from 8 to 12 h show the optimal trajectories of external carbon addition and the relating nutrient concentration profiles. In scenario 1, the reaction time increased by 30 min, the total cost decreased by 2.1% and the amount of external carbon decreased from 400 to 190 mg/l. In scenario 2 (data not shown), the reaction time increased by 45 min, the total cost decreased by 8.1% and the amount of external carbon decreased to 123 mg/l. In scenario 3 (data not shown), the reaction time increased by 1 h, the total cost decreased from 1.01 to 0.7794 and the amount of external carbon decreased to 79 mg/l. In scenario 4, the total cost decreased by 43.5%, the amount of external carbon decreased to 50 mg/l and the reaction time increased by 1.25 h.

3.4. Batch scheduling of the SBR for various influent loadings

It has been shown that a fixed batch time scheduling is not optimal since different loading influents are associated with different optimal time schedules [7,10,27]. The distribution of anoxic and oxic capacities in an SBR is based on the durations of their phases, which are generally controlled by fixed time scheduling, with variations only occurring between workdays and weekends and between summer and winter. These types of time control represent open-loop schemes that do not take into account variations in the influent load. Moreover, the time scheduling is often planned with either safety margins, which increases the waste processing time, or deficiency margins, resulting in insufficiently treated waste [8].

To show the optimal time scheduling effects of the SBR with low influent loading and nitrogen shock loading, two extreme cases is simulated, in which the influent loading concentration of organics (S_{s}, S_{NH}) in the SBR is (1) decreased to 50% and (2) increased to 200%. Table 4 compares the energy cost and batch completion time for these two-fold changes in the initial concentration of the organics. The top three panels in Fig. 7 show the optimal control result for the SBR using IDP when the initial concentration of organics is decreased to 50%. This decreased the batch completion time by 2.5 h (2 and 0.5 h in aerobic and anoxic phases, respectively), the total cost by 53.5% and the amount of external carbon to 80 mg/l. Operating an SBR with fixed phase times during low influent loading results in wastage of both energy and time, although this does satisfy the treatment required for carbon and nitrogen. The bottom three panels in Fig. 7 show the optimal control result for the SBR using IDP when the initial concentration of organics is increased twofold. This increased the batch completion time by 6.5 h (4 and 2.5 h in aerobic and anoxic phases, respectively) and the external carbon by 29.3% in order to achieve the required effluent quality. Operating an SBR with fixed phase times during high shock loading results in a degraded effluent quality with an associated wastage of treatment capacity.

Table 4
Comparisons of cost and batch completion time when the initial concentration of organics (S_{s}, S_{NH}) was decreased to 50% and increased to 200%

	When the initial concentration of organics (S_{s}, S_{NH}) is decreased to 50%		When the initial concentration of organics (S_{s}, S_{NH}) is increased to 200%	
	In aerobic phase	In anoxic phase	In aerobic phase	In anoxic phase
Cost	0.6460	0.3362	7.4401	2.57
Completion time (h)	4	+1.5	10	+3.5

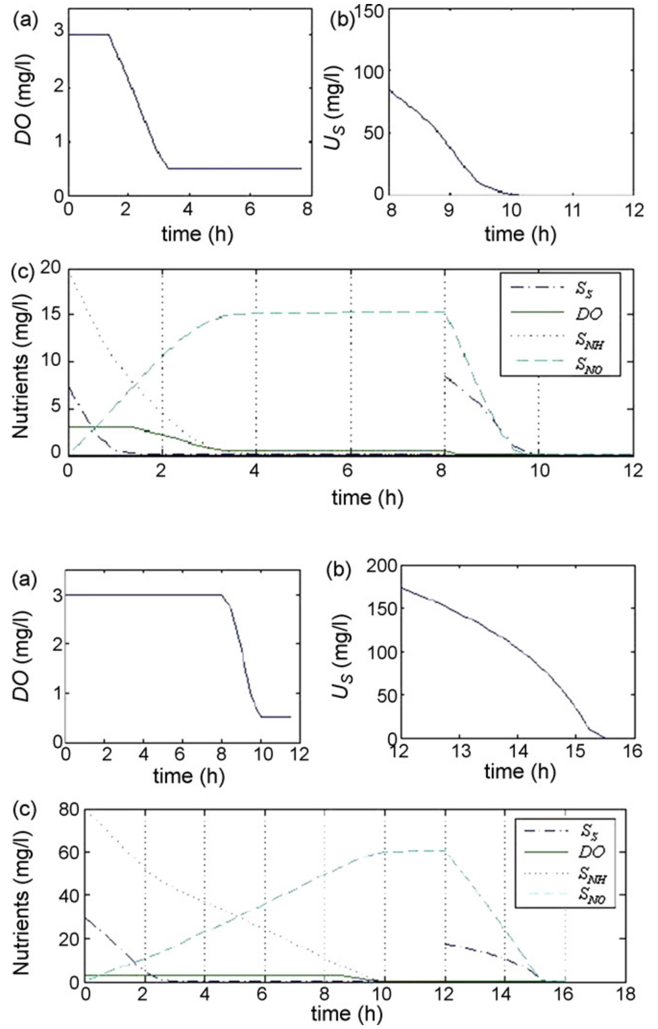

Fig. 7. Optimal control results of the SBR using IDP when the initial concentration of organics (S_s, S_{NH}) was decreased to 50% (top panels) and increased to 200%: (a) optimal trajectory of DO in the aerobic phase, (b) optimal trajectory of S_s in the anoxic phase and (c) nutrient concentration profiles.

4. Conclusions

This paper presents that IDP can be used to determine the optimal operation policy of an SBR so as to maximize the nitrogen removal and energy efficiency, based on a new performance index that incorporates the DO area and the nitrogen trajectory. The choice of area as a performance index simplifies the optimization problem and makes it more flexible, by weighting the energy and minimizing the batch time. The optimization results clearly show that our method easily determines the optimal control strategy for the phase times, the optimal trajectory of the DO controller and the optimal amount of added external carbon under various influent loading conditions. Its capabilities are mainly attributable to the use of the full nonlinear ASM model (through IDP) and the new and simple performance index. The ease of applying the proposed method to an SBR is due to there being no derivatives and no auxiliary variables in the model. However, the main drawback of the proposed method is the precision of the used simplified model of the ASM, which contains the kinetics and biological parameters. However, the model precision could be improved by applying several systematic calibration and optimization protocols to the ASM families.

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