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Cascade control of effluent nitrate and ammonium in an activated sludge process

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ABSTRACT

We propose a new cascade control structure using a systematic tuning rule to enhance the treatment performance of nitrogen and ammonium removal in a predenitrifying activated sludge process. The primary outer control loop has a model predictive control (MPC) controller and the secondary inner loop utilizes two proportional–integral (PI) controllers, which form a cascade MPC–PI controller. The control objective is to simultaneously control the nitrate and ammonium concentrations in the effluent, which can decrease the effects of influent disturbances existing in a wastewater treatment process while maintaining better effluent quality. The prediction error method is employed to identity an accurate process model for the MPC controller design. Moreover, the control performance assessment (CPA) technique is proposed to tune the parameters of the outer MPC controller. Three tuning scenarios with different output weights in the MPC controllers are considered and the best tuning parameter is obtained using a closed-loop potential approach in the field of CPA. The results of the plant performances with respect to the three tuning cases demonstrate the effectiveness of the proposed controller tuning method based on CPA.

Keywords: Cascade control structure; Control performance assessment; Effluent ammonium control; Model predictive control; Wastewater treatment process

1. Introduction

At present, effective control and modeling of wastewater treatment plants (WWTPs) have become a subject of intense interest [1–3]. The main control objectives in WWTPs are (1) meeting stricter effluent quality standards, (2) maintaining high-control performance under changing influent loads and other external disturbances, and (3) minimizing energy consumption [1]. Many control strategies, such as dissolved oxygen (DO) control, volume control, and advanced control, have been proposed and applied in both simulation and full-scale studies [4].

Phosphorus and nitrogen are main nutrients of concern in wastewater discharges. Several studies have been conducted to control the nitrogen levels. Cho et al. [5] proposed a cascade proportional–integral (PI) control strategy to simultaneously control the nitrate concentrations in the second anoxic reactor and the last biological reactor in a WWTP, where external carbon dosage was used to control nitrate concentrations.

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This cascade control structure has a key advantage that it could significantly decrease the fluctuation in the effluent nitrate concentrations. Zarrad et al. [6] proposed two advanced control strategies to improve the monitoring of an activated sludge process. The first strategy was an optimal linear quadratic Gaussian controller and the second one was a disturbance-accommodating controller. Wahab et al. [7] investigated a multivariable PI control structure to improve closed-loop control performance and to reduce loop interactions for a WWTP with a predenitrifying step. In addition, a simple tuning method based on step and frequency response tests was proposed for the designing of the multivariable PI controllers.

Model predictive control (MPC), which is a widely used advanced control strategy in many industrial processes, has also been applied to the control of WWTPs as reported in a considerable amount of literature [8–13]. Stare et al. [8] compared and evaluated several control strategies, including constant manipulated variables control, PI controllers with and without feed-forward control, and MPC controllers, for the nitrogen removal in a WWTP. Their research indicated that the MPC strategy is advantageous only when the influence of an influent disturbance to the plant is huge and tight effluent standards are imposed. Holenda et al. [9] investigated the effects of MPC-tuning parameters including sampling time, prediction horizon, and input weight on the aeration control performance of an activated sludge wastewater treatment process. Nonlinear MPC and MPC with feed-forward compensation control structures have been proposed and compared for a wastewater treatment process [10,11]. In addition, Liu and Yoo [12] proposed a cascade MPC controller to reduce the effluent nitrate concentration of a WWTP. Ostace et al. [13] proposed to use MPC for the advanced control of a WWTP on the basis of an enhanced activated sludge model no. 1 (ASM1) and a reactive secondary settler. In the current work, a modified cascade control structure with an MPC controller, which can be directly extended from a single-input–single-output (SISO) process to a multi-input–multi-output (MIMO) process, is employed to simultaneously control more process variables in an activated sludge process.

Most studies in the literature focus on the control problems of nitrate and phosphorus removal in WWTPs. Gernaey and Jorgensen [14] developed a new benchmark model for anaerobic–anoxic–oxic processes (A^2/O). The A^2/O benchmark can model the removal process of biological nitrogen and biological phosphorus with a similar plant layout to the benchmark simulation model 1 (BSM1) [15]. However, the effluent ammonium should also be effectively controlled because this component is another important compound that not only reduces DO levels, but also is toxic to the animals near polluted rivers. Carlsson and Rehnstrom [16] developed a cascade PI controller to control the effluent ammonium concentrations in BSM1. Making use of the A^2/O benchmark model, Liu et al. [17] proposed a multi-objective optimization (MOO) approach to determine the optimal set points of a cascade PI controller used for controlling the effluent ammonium concentrations.

In this study, a new cascade MPC control strategy is proposed to maintain the concentrations of effluent nitrate and effluent ammonium within their limits in a simulated wastewater treatment process. The proposed cascade controller consists of a multivariate MPC controller as the primary controller and two PI controllers as secondary controllers. On the basis of the routine closed-loop data and the variance of output errors, control performance assessment (CPA) technique is used to evaluate the MPC-tuning parameters.

2. Materials and methods

2.1. *Effluent cascade controller in a modified BSM1*

BSM1 is a useful simulation platform for designing and testing new control strategies in wastewater treatment processes [15]. This benchmark consists of five biological reactors and one secondary settler (Fig. 1). The first two reactors are anoxic reactors used for denitrification and the next three reactors are oxic reactors used for the nitrification of ammonium to nitrate. The reactor model is based on the activated sludge model 1 (ASM1) [18], and the settler model is based on Takacs double-exponential settling velocity model [19]. A strong disturbance from wastewater influent has a significant effect on control performance. Fig. 2 displays the dry weather influent measurements for the flow rate, readily biodegradable substrate concentration, and ammonium concentration in BSM1. More details of this simulation benchmark can be found on the website of the COST working group (http://www.benchmarkwwtp.org).

A cascade control structure is especially useful for the systems like WWTPs that suffer from intense external and internal disturbances. The cascade controller implemented in BSM1 is also shown in Fig. 1. The cascade controller contains two control loops: a secondary inner loop and a primary outer loop. The secondary loop consists of two PI controllers that individually control the nitrate concentration in the second reactor and the DO concentration in the last reactor. The external carbon flow rate is used as the manipulated variable in the nitrate PI controller. The primary

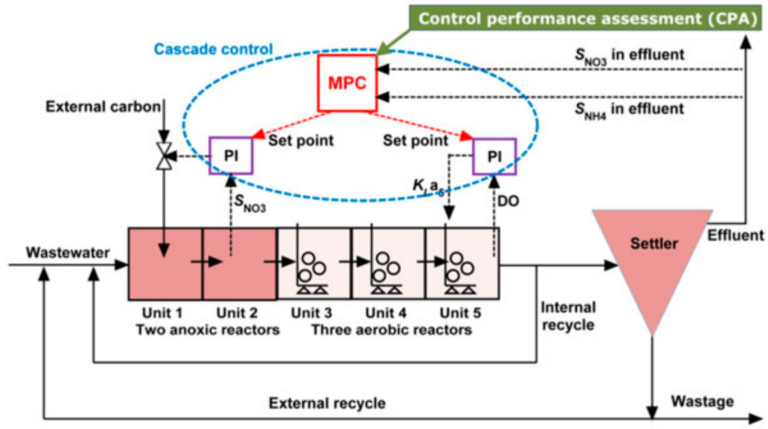

Fig. 1. BSM1 layout with the proposed cascade MPC–PI controller.

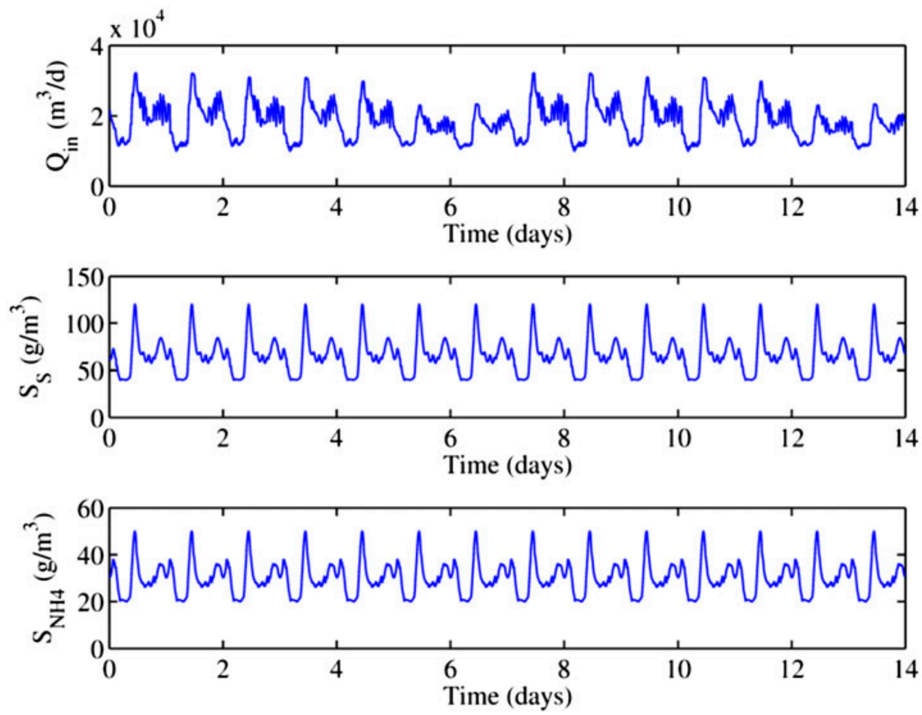

Fig. 2. Dry weather influent data defined in BSM1.

loop has a multivariate MPC controller used to control the effluent nitrate and effluent ammonium concentrations simultaneously by adjusting two set points of the inner PI controllers.

The performance criteria consisted of the effluent quality index (EQI), the aeration energy (AE), the pumping energy (PE), the average daily sludge production for disposal (P_{sludge}), average external carbon addition, and some main effluent concentration variables. As the EQI value represents the levies or fines to be paid due to the discharge of wastewater pollutants, a good control strategy should have a small EQI value from a strict environmental protection point of view. In BSM1, EQI is defined as follows [15]:

$$\begin{aligned}\mathrm{EQI} = \frac{1}{1000(t_f - t_0)} \int_{t_0}^{t_f} & [\beta_{TSS} \cdot \mathrm{TSS}(t) + \beta_{COD} \cdot \mathrm{COD}(t) \\ & + \beta_{BOD} \cdot \mathrm{BOD}(t) + \beta_{TKN} \cdot \mathrm{TKN}(t) \\ & + \beta_{NO_3} \cdot \mathrm{NO_3}(t)] Q_e(t)\, dt \end{aligned} \quad (1)$$

where t_0 and t_f stand for the starting and ending time, respectively; Q_e is the effluent flow rate; COD, BOD, TKN, and NO_3 can be calculated using the mathematical expressions explained in more detail in the BSM1 official report [15]. The weighting factors used in this work were set as $\beta_{TSS} = 2$, $\beta_{COD} = 1$, $\beta_{BOD} = 2$, $\beta_{TKN} = 20$, and $\beta_{NO3} = 20$, which are in accordance with those proposed by Gernaey and Jorgensen [14].

The operational costs (OC) transforming several criteria into a single monetary unit are useful for evaluating the plant performances of the developed control strategies, and they were calculated using Eq. (2) [20,21]:

$$\mathrm{OC} = \gamma_1(\mathrm{AE} + \mathrm{PE}) + \gamma_2\mathrm{EC} + \gamma_3\mathrm{SP} + \mathrm{EF} \tag{2}$$

where EC is an external carbon addition, SP is the sludge production, and EF means effluent fines. The weights γ_1, γ_2, and γ_3 were set as 0.1 €/kWh, 0.5 €/kg, and 0.3 €/kg, respectively [8]. The calculation equations for AE, PE, EC, SP, and EF can be found in the literature [20,21].

2.2. MPC for cascade controller design

For the last 20 years, MPC has become an effective control method successfully applied in many areas [22]. MPC is an intuitive control approach mainly used for multivariate and constrained systems. It has two major advantages compared with the multi-loop PI control strategy. First, it is a multivariate control strategy; therefore, the optimal solutions can be obtained by online solving of an optimization problem at each sampling instance. This feature makes it more suitable for controlling MIMO plants where strong interactions may exist among the process variables. In contrast, a multi-loop PI control strategy for a MIMO process usually needs additional decoupling controllers to reduce control loop interactions. In addition, the selection of different manipulated and controlled variables is a difficult task for multi-loop PI controllers.

The second benefit is that MPC can explicitly take into account of the constraints of controlled or manipulated variables, whereas a multi-loop PI control strategy cannot directly deal with system constraints. MPC is based on the receding horizon control principle. At each sampling instance, a finite constrained horizon optimal control problem is solved over a certain prediction horizon and only the first optimal control variable solution is utilized to control the process. The comprehensive review by Qin and Badgwell [23] is suggested for a better understanding of the evolution of the MPC technique.

A generic MPC algorithm is given by solving the following quadratic cost function (Eq. (3)) under the constraints expressed by Eq. (4):

$$\begin{aligned} J = {} & \sum_{i=1}^{H_p} (\hat{y}(k+i) - r(k+i))^{\mathrm{T}} \boldsymbol{Q} (\hat{y}(k+i) - r(k+i)) \\ & + \sum_{i=1}^{H_u} (u(k+i) - u_0)^{\mathrm{T}} \boldsymbol{R}_u (u(k+i) - u_0) \\ & + \sum_{i=1}^{H_u} \Delta u(k+i)^{\mathrm{T}} \boldsymbol{R}_{\Delta u} \Delta u(k+i) \end{aligned} \tag{3}$$

$$\begin{aligned} & y_{\min} \le y \le y_{\max} \\ & u_{\min} \le u \le u_{\max} \\ & \Delta u_{\min} \le \Delta u \le \Delta u_{\max} \end{aligned} \tag{4}$$

where k is the sampling instant, $\hat{y}$ is the predicted output variable, r is the set point, u is the input variable, Δu is the input rate variable, u_0 is the steady-state input value, H_p is the prediction horizon, H_u is the control horizon, $\boldsymbol{Q}$ is the output weighing matrix, $\boldsymbol{R}_u$ is the input weighing matrix, and $\boldsymbol{R}_{\Delta u}$ is the input rate weighing matrix.

2.3. Control performance assessment

Many factors, such as inappropriate control structure, inadequate controller tuning, and equipment malfunction, may result in poor control performance in industrial processes. It has been reported that more than 50% of industrial controllers undergo control performance problems. Hence, evaluating the level of controller performance using a CPA has become an important research topic during the past two decades [24–26]. The basic roles of a CPA are to evaluate whether the controller is doing its job satisfactorily and to recommend the improvement potential, as shown in Fig. 3 [27]. Many CPA methods, such as minimum variance control [28] and linear quadratic Gaussian [29], can be found in the literature. Huang et al. [30] proposed to use a closed-loop potential index to tune an MPC controller in a distillation column, and recently, Liu and Yoo [12] applied the closed-loop potential algorithm to evaluate the control performance of a series of cascade control structures in a wastewater treatment process. The main steps of calculating prediction error and closed-loop potential defined in Huang et al. [30] are revisited below.

For a multivariable process, the closed-loop output with a zero set point driven by white noise can be expressed using a time-series model:

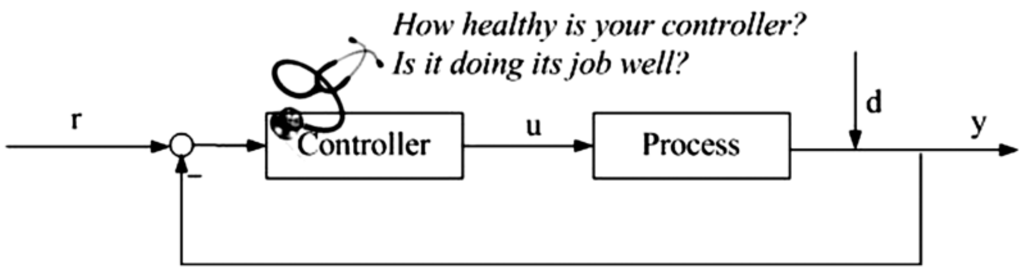

Fig. 3. A conceptual scheme of the performance assessment problem, where r is a set point, u is a manipulated variable generated from the controller, d is a disturbance signal, and y is an output variable.

$$Y_t = G_{\mathrm{cl}} a_t \tag{5}$$

where G_{cl} is the closed-loop time-series model and a_t is the white noise signal.

The above time-series model can be transferred to a moving average (MA) form with infinite order:

$$\begin{aligned} Y_t &= \sum_{k=0}^{\infty} F_k a_{(t-k)} \\ &= F_0 a_t + F_1 a_{t-1} + \ldots + F_{i-1} a_{t-(i-1)} + F_i a_{t-i} \end{aligned} \tag{6}$$

where F_0, F_1, …, F_i are the impulse response matrices of the closed-loop time-series model.

Then, we can obtain the optimal ith step prediction:

$$Y_{t|t-i} = F_i a_{t-i} + F_{i+1} a_{t-(i+1)} + \ldots \tag{7}$$

and the prediction error can be calculated as follows:

$$e_{t|t-i} = Y_t - Y_{t|t-i} = F_0 a_t + F_1 a_{t-1} + \ldots + F_{i-1} a_{t-(i-1)} \tag{8}$$

The covariance of $e_{t\,|\,t-i}$ can be calculated from the following equation:

$$\mathrm{cov}(e_{t|t-i}) = F_0 \Sigma_a F_0^{\mathrm{T}} + F_1 \Sigma_a F_1^{\mathrm{T}} + \ldots + F_{i-1} \Sigma_a F_{i-1}^{\mathrm{T}} \tag{9}$$

where Σ_a is the covariance of the white noise signal a_t.

A scalar measure s_i can be defined as follows:

$$\begin{aligned} s_i &= \mathrm{tr}(\mathrm{cov}(e_{t|t-i})) \\ &= \mathrm{tr}(F_0 \Sigma_a F_0^{\mathrm{T}} + F_1 \Sigma_a F_1^{\mathrm{T}} + \ldots + F_{i-1} \Sigma_a F_{i-1}^{\mathrm{T}}) \end{aligned} \tag{10}$$

Finally, the closed-loop potential p_i defined in Huang et al. [30] is shown below:

$$p_i = \frac{s_\infty - s_i}{s_\infty} \tag{11}$$

An interpretation of the closed-loop potential index p_i was given by Huang et al. [30] as follows: if a dead-beat control action is applied from time i, then the sum of squared error of the process output can be reduced by $100 \times p_i$ percent. A larger closed-loop potential p_i reveals that the controller has more potential that can be improved. In other words, a faster reduction of the closed-loop potential index p_i indicates a lower possibility of improving the performance of the related controller.

2.4. Steps for evaluating MPC controller performance

The procedure for tuning a cascade MPC controller using a CPA is shown in Fig. 4. Before setting up an MPC controller, the parameters of the secondary PI controllers should be determined first. These parameters can be obtained from the literature. The DO PI controller is the same as the original one in the BSM1 [15] and the nitrate PI controller is the same as the one suggested in Liu and Yoo [12]. The detailed parameters of these two PI controllers are listed in Table 1. An anti-windup time constant is introduced for further improving the control performance of the PI controller.

Then, a process identification step was implemented to get a MIMO process model for the MPC controller design. It should be noted that, in this study, the controlled variables for the MPC controller are the nitrate and ammonium concentrations in the effluent and the manipulated variables are the two set points of the secondary PI controllers (Fig. 1). The pseudo-random binary sequence (PRBS), which is widely used for model identification in practice [31], was chosen as the test signal. To identify a linear process model for the MPC controller, the prediction error method (PEM) [32] was employed. In the next step,

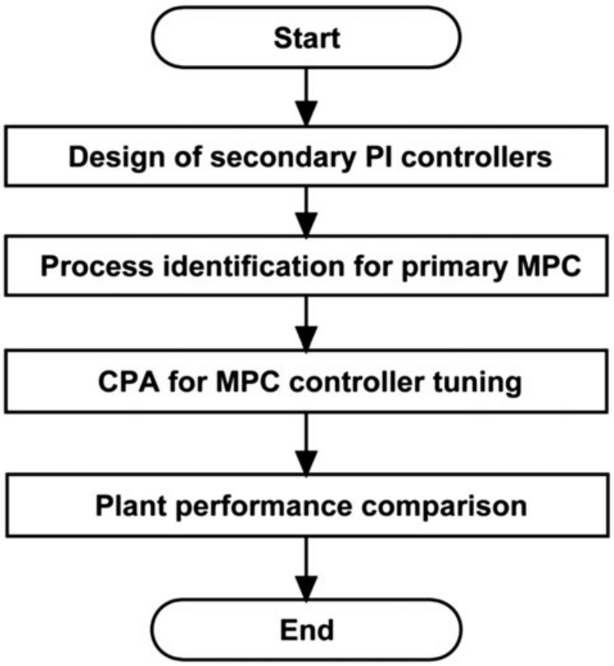

Fig. 4. Flow chart of the cascade MPC controller tuned with CPA.

the CPA technique was used to tune the output weighting matrix of the MPC controller. Finally, the plant performances of the three MPC controllers with different output weighting parameters were compared using the dry weather influent disturbance data.

3. Results and discussion

3.1. Process identification for MPC controller design

Since MPC is a model-based control strategy, an accurate process model that can be used for predicting future variations of process output variables is needed. To this end, the identification procedure was implemented to obtain this process model. The excitation input signal for identification was a PRBS-type test signal, which is shown in the lower plot of Fig. 5. Its corresponding effluent nitrate concentration response is shown in the upper plot of Fig. 5. The measurements of the first day were discarded because the initial data usually may not represent the real dynamics of the process. The data from days 2 to 4 were used for estimation and the remaining data were used for validation. Finally, a fifth-order PEM model resulted in a satisfactory identification performance. The identification accuracy of the model is shown in Fig. 6, where the goodness of the fit is calculated as follows:

$$\text{Fit} = 100 \times \left(1 - \frac{\|y - \hat{y}\|}{\|y - \text{mean}(y)\|}\right) \tag{12}$$

where y is the measurement and $\hat{y}$ is the identified model output.

PRBS can be generated using a feedback shift register. Two main parameters in the PRBS generator can affect the accuracy of identification models: the PRBS sampling time and the PRBS gain. The PRBS sampling time controls the frequency of the generated signal. In order to get a proper frequency with persistent excitation, we set this parameter to be equal to the default sampling time of 15 min in the BSM1. A big PRBS gain may make the process fluctuate too heavily, which should be avoided in real plants. In this work, the value chosen was 0.15.

The order of the identification model was determined by selecting the order with the highest fit value. The identification model with a lower order could not capture the main dynamics of the process, whereas the model with a higher order may make the system unstable. Specifically, for the fifth-order model, the fit values for the estimation and validation data of the effluent S_{NO3} were 95.4 and 92.9%, respectively; the fit values for the estimation and validation data of effluent S_{NH4} were 92.5 and 88.9%, respectively.

3.2. CPA for MPC controllers

The identified process model was then used to build the MPC controller to control effluent concentrations in the wastewater treatment process. The

Table 1
Parameters used for the secondary PI controllers

PI parameters	S_{NO3} PI controller	DO PI controller
Proportional gain, K_p	−1.4120	25
Integral time constant, T_i, d	0.0270	0.002
Anti-windup time constant, T_t, d	0.0100	0.001

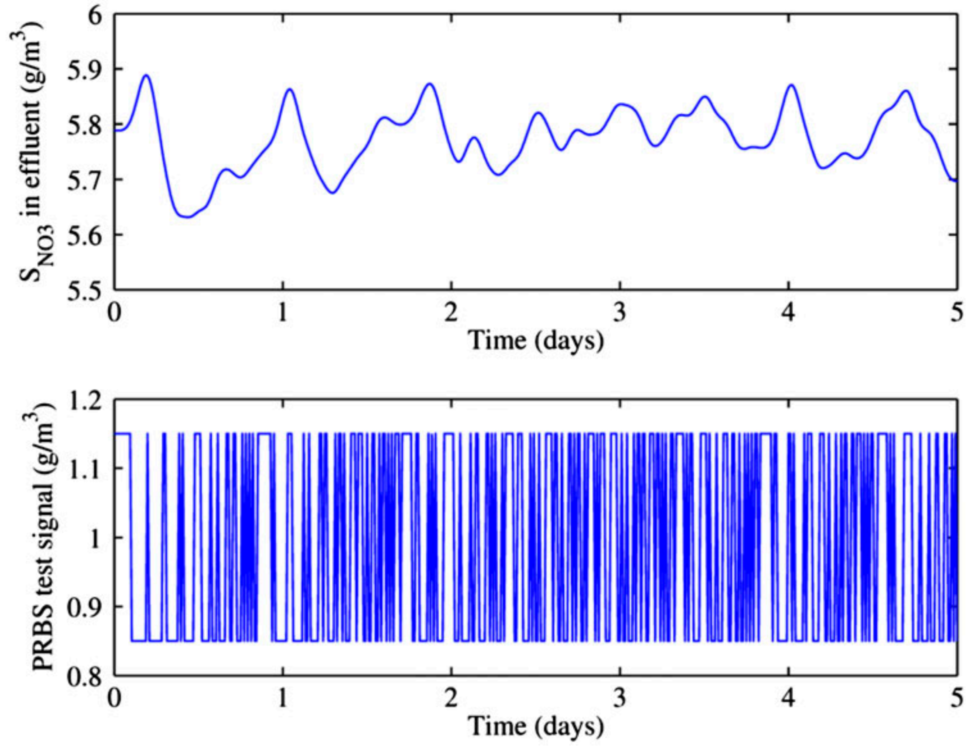

Fig. 5. Effluent nitrate concentration (top) and the corresponding PRBS test signal (bottom).

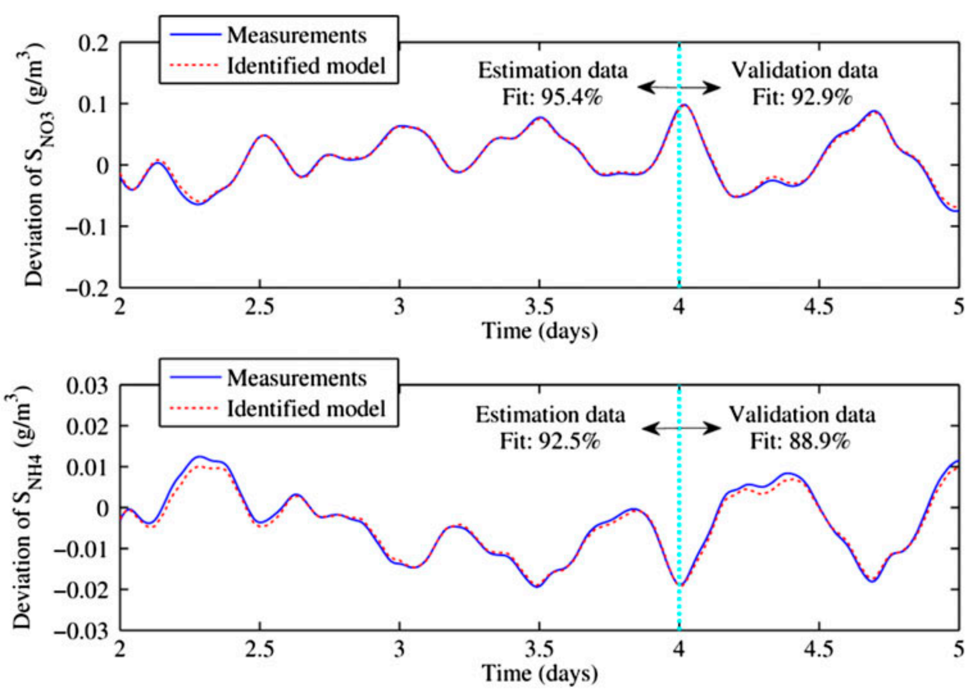

Fig. 6. Identification accuracy of the fifth-order PEM model.

parameters of the MPC controller were tuned based on our experience and the tuning guidelines from Maciejowski [22]. The following MPC parameters were used in the present work. The sampling time of the MPC controller was 15 min, which is the same as the process sampling time. The prediction horizon and the control horizon were set to 10 and 3, respectively. Both input weighting matrix and input rate weighting matrix were set to 0. Both constraints for the manipulated variables were between 0 and 5 g/m^3. The constraint for the effluent nitrate was between 3 and 12 g/m^3, and the constraint for the effluent ammonium was between 0 and 8 g/m^3.

Since output weights have direct effects on MPC controller performance, the following three tuning scenarios with different output weights were considered and the best tuning parameter was obtained using the CPA approach:

$$\boldsymbol{Q}_{\text{Tune 1}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \boldsymbol{Q}_{\text{Tune 2}} = \begin{bmatrix} 1 & 0 \\ 0 & 10 \end{bmatrix}, \quad \boldsymbol{Q}_{\text{Tune 3}} = \begin{bmatrix} 10 & 0 \\ 0 & 1 \end{bmatrix} \tag{13}$$

In each diagonal matrix of Eq. (13), the first weight was used for controlling the effluent nitrate concentration and the second one was used for controlling the effluent ammonium concentration. The physical explanation of the different tuning matrices in Eq. (13) is as follows: Tune 1 gives equal emphasis to the two output variables; Tune 2 gives more emphasis to the second output variable (S_{NH4} in the effluent); Tune 3 concentrates more on the first output variable (S_{NO3} in the effluent).

Fig. 7 shows the overall closed-loop potentials in terms of the three tuning cases. Potentials exist for all the three tuning cases, especially when the time lag is small. Furthermore, the MPC controller with Tune 1 has a greater potential to be improved, which implies that the control performance with Tune 1 is not as good as the other two tuning cases. The CPA result also indicates that the MPC controller with Tune 3 has the best control performance because it has the lowest potential to be improved.

3.3. Comparison of plant control performances

Because the set points of the MPC controller had a significant influence on plant performance, a MOO technique suggested by Liu et al. [17] was used in this work. The MOO technique is useful in finding the suitable set points of a controller for the minimization of both EQI and OC. The two set-points of the cascade

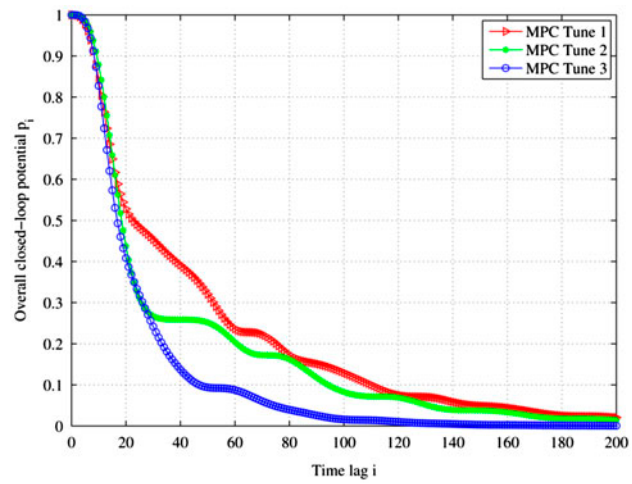

Fig. 7. Closed-loop potentials of the cascade MPC controller with three tuning parameters.

controller determined using MOO were 6 and 1 $g\,N/m^3$ for the effluent nitrate and effluent ammonium concentrations, respectively. Alternatively, the multi-criteria function based on microbiology-related failures, effluent quality, and operating costs could be used to optimize the controller set points in a WWTP [33].

Fig. 8 compares the nitrate and ammonium concentrations in the effluent with respect to the three cases with different output weights of the MPC controllers. The set points are also shown in Fig. 8. It is clear that, among the three tuning scenarios, the MPC with Tune 3 could closely track the set point of the effluent nitrate concentrations, whereas the MPC with Tune 2 shows the worst tracking performance. Besides, the concentrations of effluent nitrate controlled by the MPC with Tune 3 controller are lower than those of the other two MPC controllers in most of the simulation time. In terms of the effluent ammonium concentrations, the tracking errors of all the three MPC controllers are high due to the intense variations of the composition in the influent. MPC with Tune 2 and Tune 3 controllers have a similar tracking performance and both of these two controllers outperform the MPC with Tune 1.

A numerical index named the integral of absolute error (IAE) is useful for quantitatively comparing the control performance of different control structures, and this index can be calculated using the following equation:

$$\text{IAE} = \int_{t=7\,\text{d}}^{14\,\text{d}} |e(t)|\,dt \tag{14}$$

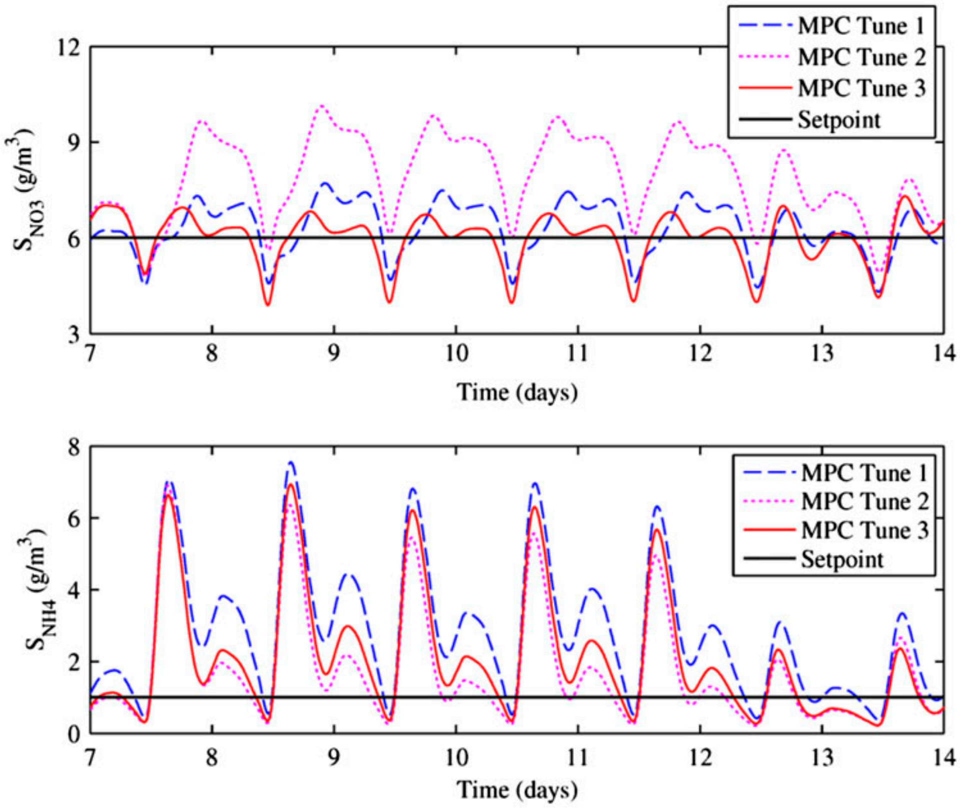

Fig. 8. Comparison of the effluent concentrations of S_{NO3} (top) and S_{NH4} (bottom) in terms of the three MPC tuning scenarios.

where t is the simulation time, e(t) is the difference between the set point and the output variable (effluent S_{NO3} or effluent S_{NH4}). The set points for the effluent S_{NO3} and effluent S_{NH4} are 6 and 1 g N/m^3, respectively. The time period for calculating IAE is from the 7th day to the 14th day.

Table 2 lists the IAE values of the three MPC controllers. Numerically speaking, a controller with a lower IAE value has a higher control performance. In terms of the effluent S_{NO3}, the IAE value of the MPC with Tune 3 is 3.99 (g N/m^3) d, which is the lowest value for the three MPC controllers with different output weights. This result indicates that the MPC with Tune 3 could achieve the best control performance for the effluent S_{NO3}. The IAE value of the MPC with Tune 2 is 14.03 (g N/m^3) d, which is much higher than that of the MPC with Tune 3. In terms of the effluent S_{NH4}, the lowest IAE value is 7.53 (g N/m^3) d which corresponds to the MPC with Tune 2, but this value is still much larger than that of the MPC with Tune 3 for the case of controlling the effluent S_{NO3}. The IAE value of the MPC with Tune 3 is 9.27 (g N/m^3) d, which is slightly larger than that of the MPC with Tune 2.

The plant performances with respect to the three MPC controllers are summarized in Table 3. The total simulation time was 14 d, but only the data from the last seven days were used for calculating the performance indices, and the dry weather influent data were used to model the weather condition. Among the three MPC controllers, the MPC controller with Tune 3 produced the lowest EQI at the cost of a small increase of sludge production and external carbon addition. The total nitrogen of the MPC controller with Tune 3 was the lowest. In addition, the MPC controller with Tune 3 led to a significant reduction in effluent nitrate concentration because more control effort was imposed on the nitrate variable (refer to Eq. (13)). The OC of the MPC controller with Tune 3 and Tune 2 are similar, and both are larger than that of the MPC controller with Tune 1. The three control scenarios consumed same PE. The MPC with Tuning 1 control strategy, which has the lowest oxygen concentration in the effluent, consumed the lowest AE. Taking everything into consideration, the MPC controller with Tune 3 was optimal and therefore was suggested in this work.

Table 2
IAE values of the three MPC controllers

IAE	MPC Tuning 1	MPC Tuning 2	MPC Tuning 3
Effluent S_{NO3}, (g N/m^3) d	5.13	14.03	3.99
Effluent S_{NH4}, (g N/m^3) d	13.30	7.53	9.27

Table 3
Comparison of the plant performances using EQI, AE, PE, P_{sludge}, and carbon addition from the last seven days under the dry weather condition

Performance index	MPC Tuning 1	MPC Tuning 2	MPC Tuning 3	Unit
EQI	5,361	5,131	4,968	kg PU/d
OC	1,739	1935	1999	€/d
AE	3,403	3,922	3,672	kWh/d
PE	531	531	531	kWh/d
P_{sludge}	2,372	2,480	2,549	kg/d
Average added carbon	0.37	0.63	0.78	m^3/d
Effluent average S_O	0.53	2.23	1.34	g (-COD)/m^3
Effluent average S_{NO3}	6.20	7.82	5.91	g N/m^3
Effluent average S_{NH4}	2.80	1.82	2.13	g N/m^3
Effluent average N_{tot}	11.12	11.77	10.18	g N/m^3
Effluent average COD	50.49	50.59	50.71	g COD/m^3

Note: For the meaning of all acronyms or abbreviations in this table, see Nomenclature.

4. Conclusions

In this paper, an advanced cascade MPC control strategy has been presented and applied to simultaneously control the concentrations of effluent nitrate and effluent ammonium in the predenitrifying wastewater treatment process model. A modified BSM1 is employed as a wastewater simulation platform to test the procedure of the cascade controller design and tuning. CPA is used to evaluate the control performances of three MPC controllers with different output weighting matrices. Specifically, the closed-loop potential algorithm of CPA is used to determine the optimal controller parameters. Together with the analysis of plant performance, the MPC controller with Tune 3 which allocates more control effort to the effluent nitrate is suggested to be the best option.

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Nomenclature

AE	—	aeration energy
ASM1	—	activated sludge model no. 1
BSM1	—	benchmark simulation model no. 1
BOD	—	biochemical oxygen demand
COD	—	chemical oxygen demand
CPA	—	control performance assessment
DO	—	dissolved oxygen
EQI	—	effluent quality index
IAE	—	integral of absolute error
MIMO	—	multi-input–multi-output
MOO	—	multi-objective optimization
MPC	—	model predictive control
N	—	nitrogen
NO_3	—	nitrate
N_{tot}	—	total nitrogen
OC	—	operational costs
PE	—	pumping energy
PEM	—	prediction error method
PI	—	proportional–integral
PRBS	—	pseudo-random binary sequence
P_{sludge}	—	average daily sludge production for disposal
Q_{in}	—	influent flow rate
SISO	—	single-input–single-output
S_{NH4}	—	ammonium concentration
S_{NO3}	—	nitrate concentration

S_O — oxygen concentration
TKN — total Kjeldahl nitrogen
WWTP — wastewater treatment plant

Greek
β — weighing factor for calculating EQI
γ — weighing factor for calculating OC

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