Korean J. Chem. Eng., **28**(3), 667-673 (2011)
DOI: 10.1007/s11814-010-0442-x

Performance assessment of cascade controllers for nitrate control in a wastewater treatment process

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(*Received 17 August 2010 • accepted 2 October 2010*)

Abstract−A cascade control strategy is proposed to the benchmark simulation model 1 (BSM1) to enhance the treatment performance of nitrogen removal in a biological wastewater treatment plant. The proposed control approach consists of two control loops, a primary outer loop and a secondary inner loop. The method has two controllers of which the primary loop has a model predictive control (MPC) controller and the secondary loop has a proportional-integral-derivative (PID) controller, which is a cascade MPC-PID controller. The primary MPC controller is to control the nitrate concentration in the effluent, and the secondary PID controller is to control the nitrate concentration in the final anoxic compartment. The proposed method controls the nitrate concentrations in the effluent as well as in the final anoxic reactor simultaneously to strictly satisfy the quality of the effluent as well as to remove the effects of disturbances more quickly by manipulating the external carbon dosage rate. Because the control performance assessment (CPA) technique has the features of determining the capability of the current controller and locating the best achievable performance, the other novelty of this paper is to suggest a relative closed-loop potential index (RCPI) which updates the CPA technology into a closed-loop cascade controller. The proposed method is compared with a cascade PID-PID control strategy and the original PID controller in BSM1 and an improved performance of the suggested cascade MPC-PID controller is obtained by using the CPA approach.

Key words: Control Performance Assessment, Cascade Control, Model Predictive Control, Wastewater Treatment Process, BSM1 Benchmark

INTRODUCTION

Nitrogen compound is the main nutrient of concern in treated wastewater discharges. Its removal can be divided into two subprocesses, where ammonia is first converted to nitrate via nitrite (nitrification) by autotrophic bacteria under aerobic condition and the nitrate is further transformed to nitrogen gas (denitrification) by heterotrophic bacteria in the anoxic tanks. Denitrification requires a reducing agent, such as external carbon source. Methanol and ethanol have been used widely as external carbon sources in the denitrification subprocess [1,2]. Combining nitrification with predenitrification, the benchmark simulation model 1 (BSM1) [3,4] has been used most commonly for nitrogen removal. In the default BSM1 configuration, the conventional PID control strategy is proposed to test the benchmark: its aim is to control the nitrate level in the last anoxic tank by manipulation of the internal recycle flow rate and to control the dissolved oxygen level in the final compartment of the reactor by manipulation of the oxygen transfer coefficient [5].

As is reported by Alex et al. [3], the performance of the nitrate controller is not as good as the oxygen controller, mainly because of the large time delay and large disturbance. Since the external carbon source can efficiently promote the nitrogen removal, some researchers [6-9] have designed a nitrate controller by manipulating the external carbon flow rate. From the point of directly reducing the nitrate concentration in effluent, Cho et al. [10] proposed a cascade PID-PID control strategy to control the nitrate concentrations in the fifth compartment as well as in the final anoxic reactor simultaneously by manipulating the external carbon dosage. Since model predictive control (MPC) is the most widely used advanced control strategy, it is suitable to design a cascade MPC-PID controller which has an MPC controller as its primary controller to control the nitrate concentration in the effluent and a conventional PID controller as its secondary controller to control the nitrate concentration in the final anoxic unit.

The performance evaluation of the controllers in the wastewater treatment process (WWTP) is a complex activity especially under the BSM1 simulation environment which defines a large number of assessment criteria such as integral of the absolute error, integral of the squared error, maximal deviation from set points, error variance, limits constraint violations on some concentrations, effluent quality, operational costs, and so on [5]. Aiming at evaluating controller performance from routine closed-loop data, control performance assessment (CPA), as a relatively young branch of research, has attracted growing interest in control system monitoring and maintenance in the past few years. Based on the variance of the output error, CPA techniques are used to find how current controller performance compares to the ideal controller performance. A large number of applications have appeared in the fields of pulp and paper-making mills, refining, petrochemicals, and chemicals [11].

The purpose of this research is to develop the CPA technology of a WWTP based on the cascade MPC-PID control strategy. The remainder of this paper is organized as follows: the first section introduces the basics of the BSM1 and then proposed cascade MPC-

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PID control strategy and CPA approach are described. Results and discussion section contains set-point tracking and disturbance rejection of the proposed cascade controller and its control performance assessment analysis. Finally, the conclusions of this article are addressed.

METHODS

1. Description of the BSM1

Effective control of the WWTP has become a subject of intense interest. Many control strategies such as dissolved oxygen control, sludge inventory control, respirometry-based control and advanced nutrient removal control, have been proposed in this process [12]. However, it is difficult to evaluate and compare these methods, partly due to the variability of the influent, the complexity of the biological and hydrodynamic phenomena, the large range of lime constants (from a few minutes to several days, even weeks), and the lack of standard evaluationa1 criteria. Based on the most popular activated sludge model 1 (ASM1) [13,14] and the double exponential settling velocity model [15], the BSM1 has been used widely as a standard simulation environment. The purpose of BSM1 is to provide a platform-independent simulation environment which defines the plant layout, a detailed description of the influent disturbances, simulation models and parameters, and evaluation criteria to determine the effectiveness of control strategies. For more detailed information about this benchmark, refer to the website of the COST working group (http://www.ensic.u-nancy.fr/COSTWWTP).

It is stated that the disturbances used to test a particular control strategy play a critical role in the evaluation. There are three influent disturbances and each is meant to be representative of a different weather condition: dry weather, stormy weather (which contains one week of dry weather and two storms during the second week) and rainy weather (which contains one week of dry weather and a long rain event during the second week) [16]. Each file contains 14 days of influent data at 15-minute intervals. Fig. 1 presents the basic dry weather wastewater data for influent flow rate, readily biodegradable substrate concentration and ammonium concentration. Their average values are 18,446 m^3/d, 65 g/m^3 and 30 g/m^3, respectively.

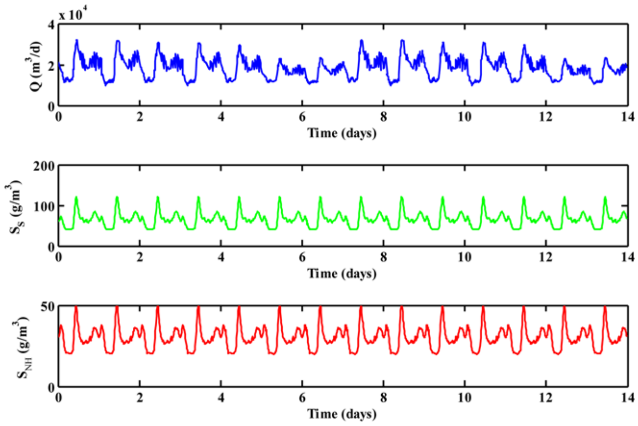


Fig. 1. Dry weather influent disturbance.

2. Proposed Cascade MPC-PID Control Strategy

It is well-known that a cascade control scheme can dramatically improve the closed loop performance by rejecting the disturbances very fast. Cascade control, which was first introduced by Franks and Worley [17] many years ago, is one of the strategies that can be used to improve the system performance particularly in the presence of disturbances. In conventional single feedback control, the corrective action for disturbances does not begin until the controlled variable deviates from the setpoint. A cascade control structure consists of two control loops, a secondary inner loop and a primary outer loop. The idea of cascade structure is that the disturbances introduced in the inner loop are reduced to a greater extent in the inner loop before they extend into the outer loop.

Traditionally, industrial processes have relied strictly on regulatory loops that are designed to stabilize operation of the process. These loops are generally based on PID regulatory control. When implementing an advanced control system, such as MPC, on a process with regulatory PID loops, one is faced with the following two options [18]: the first option is called direct MPC control, which

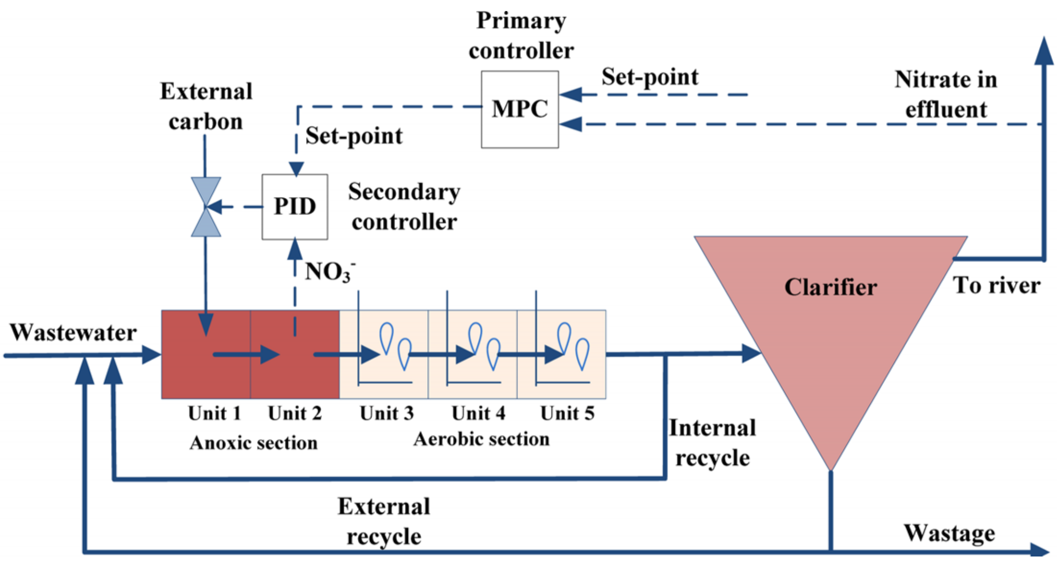


Fig. 2. BSM1 benchmark layout with the proposed cascade MPC-PID controller.

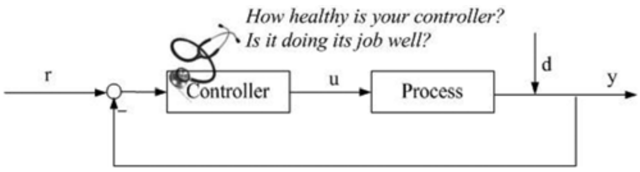


Fig. 3. A conceptual scheme of the performance assessment problem [23].

means breaking the regulatory loops and have the MPC controller to manipulate the process directly. In recent years, direct MPC control has been applied to the BSM1 [19,20]. The second option is called cascade MPC-PID control, which means leaving the loops and have the MPC controller to manipulate the set-points of these loops. Fig. 2 shows the schematic diagram of the cascade MPC-PID controller in BSM1. This control structure helps to eliminate the disturbances that occur inside the inner loop more efficiently and quickly. On the other hand, identification can be made easier since unstable or excessively slow dynamics are stabilized or made faster by inner loop PID controller.

3. Control Performance Assessment

The field of CPA began to blossom about 20 years ago with the ground-breaking work of Harris [21], in which the controlled variable variance under minimum variance control (MVC) was used as a theoretical lower bound benchmark to evaluate and diagnose the performance of single-loop controllers. The basic role of CPA is to answer if the controller is doing its job satisfactorily and further figure out the improvement potential (see Fig. 3) [11].

There are several review articles and monographs published in this field [11,22-25]. Moreover, an overview of CPA was published in a special issue of the *International Journal of Adaptive Control and Signal Processing* [26]. Generally, CPA approaches can be classified into the following benchmarkings: MVC benchmarking, linear quadratic Gaussian benchmarking, MPC benchmarking, user specified benchmarking and historical data benchmarking [27]. Among these methods, prediction error approach is one of the most promising ones which does not need the interactor matrix. Because the concepts of prediction error approach and closed-loop potentials as defined in [28] play an important role in determining the performance of nitrate cascade controllers, we describe these concepts in detail in the following part.

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

$$Y_t=G_{cl}a_t \tag{1}$$

where G_{cl} is the closed-loop time-series model and a_t is the white noise driving the process with mean zero and covariance Σ_a.

A series expansion of the above model gives the following infinite order moving average (MA) form:

$$Y_t=\sum_{k=0}^{\infty}F_k a_{(t-k)}=F_0a_t+F_1a_{t-1}+\cdots+F_{i-1}a_{t-(i-1)}+F_ia_{t-i} \tag{2}$$

where $F_0, F_1, \cdots, F_i$ are the impulse response coefficients of closed-loop model.

With this MA model, we can obtain the optimal *i*th step prediction and the prediction error:

$$Y_{t|t-i}=F_ia_{t-i}+F_{i+1}a_{t-(i+1)}+\cdots \tag{3}$$

$$e_{t|t-i}=Y_t-Y_{t|t-i}=F_0a_t+F_1a_{i-1}+\cdots+F_{i-1}a_{t-(i-1)} \tag{4}$$

The covariance of the prediction error can be calculated as:

$$\mathrm{cov}(e_{t|t-i})=F_0\Sigma_aF_0^T+F_1\Sigma_aF_1^T+\cdots+F_{i-1}\Sigma_aF_{i-1}^T \tag{5}$$

Define the scalar measure s_i and closed-loop potential p_i as:

$$s_i=tr(\mathrm{cov}(e_{t|t-i}))=tr(F_0\Sigma_aF_0^T+F_1\Sigma_aF_1^T+\cdots+F_{i-1}\Sigma_aF_{i-1}^T) \tag{6}$$

$$p_i=\frac{s_\infty-s_i}{s_\infty} \tag{7}$$

Here, p_i indicates the index of CPA of controller, that is, how much potential to improve performance if process has a time delay i. Faster decays of the potential to zero indicate less possibility to improve the control.

Due to the monotonically decreasing nature of the potentials, the area below the potential curve reflects the rate of its decaying. Therefore, it is useful to define a scalar index to monitor the change of the closed-loop potential. This index is called relative closed-loop potential index (RCPI) and can be calculated as:

$$\eta=\frac{\int p_{i,tar}-\int p_{i,ref}}{\int p_{i,ref}} \tag{8}$$

where $p_{i,ref}$ is the reference closed-loop potential and $p_{i,tar}$ is the target closed-loop potential, the integration can be calculated by summation. The value of RCPI gives the percent change of the closed-loop potential with the positive sign indicating an increased potential (a deteriorated performance) and the negative sign indicating a decreased potential (an improved performance).

4. The Procedure for Assessing the Performance of Cascade Controllers

The whole procedure for evaluating the performance of the proposed cascade controller in BSM1 is shown in Fig. 4. The BSM1 used in this paper is implemented on the Matlab/Simulink^{TM} platform. In the cascade control design phase, PID control is designed

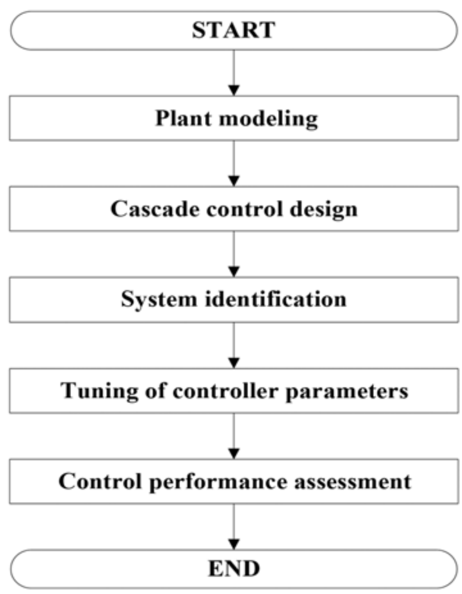


Fig. 4. Flowchart of CPA in BSM1.

for the inner control loop, and MPC is designed for the outer control loop. In the system identification phase, the following two steps are implemented sequentially. First, identify a model for the secondary PID controller. As one of the most important process activation methods for automatic tuning of a PID controller, the relay feedback method proposed by Åström and Hägglund [29] is the simplest and has been the most widely used in practice [30]. Second, identify a model for the primary MPC controller. The most important, time consuming and costly part in implementation of MPC is the process identification. In this step, a generalized binary noise (GBN) test signal [31] is used which is especially fitted to MPC applications and used widely in industry. After data preparation, the prediction error method (PEM) [32] is adopted to identify a linear process model.

To achieve the desired performance, the cascade controller parameters have to be tuned properly. For getting the parameters of the secondary PID controller, the relay feedback auto-tuning approach is applied to the secondary loop. The parameters of the primary MPC controller are tuned based on experience gained from the simulations and from the tuning rules suggested by Maciejowski [33]. In this research, the MPC controller with a sampling time of 15 minutes has been used. The prediction horizon has been of 30 and the control horizon of 5. The input weight has been set to 1. The input rate weight has been set to 0. The output weight has been set to 100. In the final CPA phase, control performances between the inner loop controller and the outer loop controller are compared using the closed-loop potential curve and RCPI number as assessment tools.

RESULTS AND DISCUSSION

1. Identification and Control Results

Relay feedback test signal and its corresponding process output are shown in Fig. 5, where the flow rate of the external carbon corresponds to the relay output (that is, process input) and the nitrate concentration in the last anoxic compartment corresponds to the process output. From the relay output and input, the ultimate gain and ultimate period of the process can be calculated directly. Then based on the Ziegler-Nichols tuning rule the parameters of this secondary PID controller can be determined as K_c=−1.4120 τ_i=0.0270.

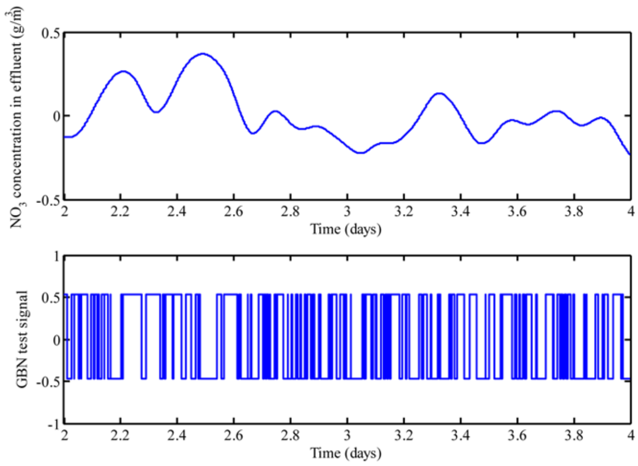


Fig. 6. Output variable and GBN input test signal for process identification.

To capture the dynamic properties of the process, the sampling time of identification was chosen to be 1 minute. Besides, the magnitude of the GBN test signal was set to 5 percent of the steady-state value. The data used for the process identification are shown in Fig. 6. To improve the accuracy of the identification model, the mean values were subtracted from the original data. The identified PEM model was validated using a different set of validation data. The model accuracy achieved is satisfactory as shown in Fig. 7.

It should be noted that some modifications are needed in order to get a better control performance. The concentration of the external carbon source was fixed at 1,200,000 g/m^3; the flow rate of the internal recycle stream was fixed at 5Q_{in}. To avoid too high effluent of suspended solids but to still get a high sludge age, the constant waste sludge flow rate (Q_w) was reduced from 385 to 300 m^3/day. The sensors are assumed to be ideal, without delay or noise. The rest of conditions are the same as in the BSM1 default configuration. The process response to the set-point change is shown in Fig. 8. The proposed cascade controller exhibits faster response and

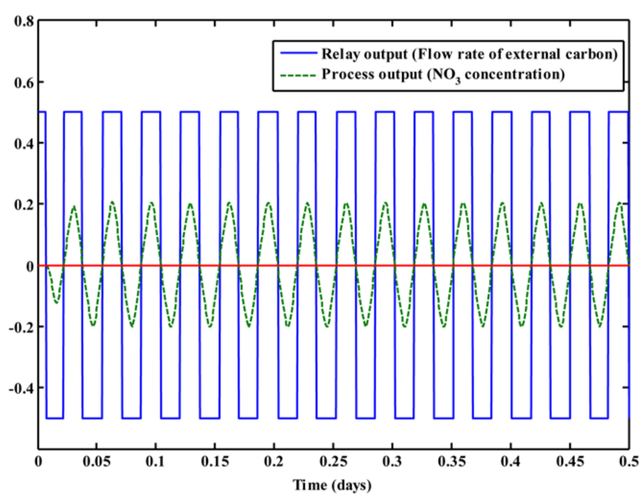


Fig. 5. Relay feedback test signal and its corresponding process output.

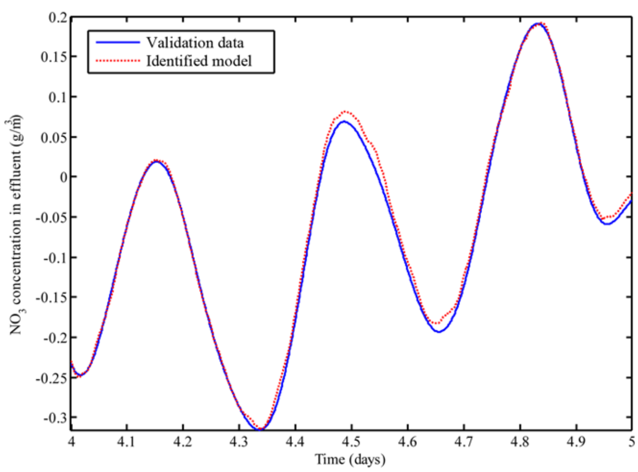


Fig. 7. Comparison between the identified model data and validation data.

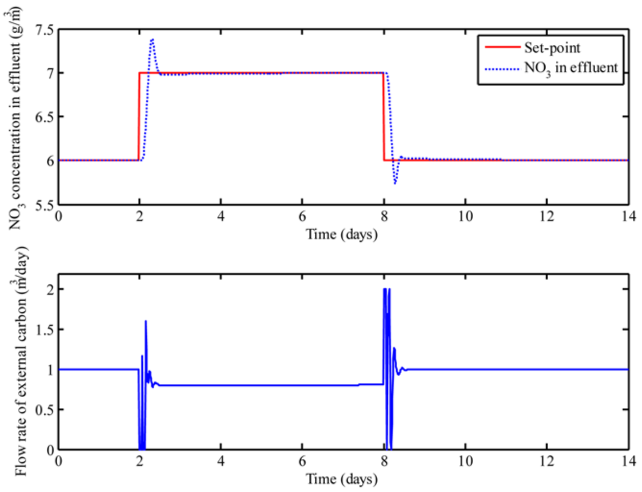


Fig. 8. Set-point tracking performance of the cascade MPC-PID controller.

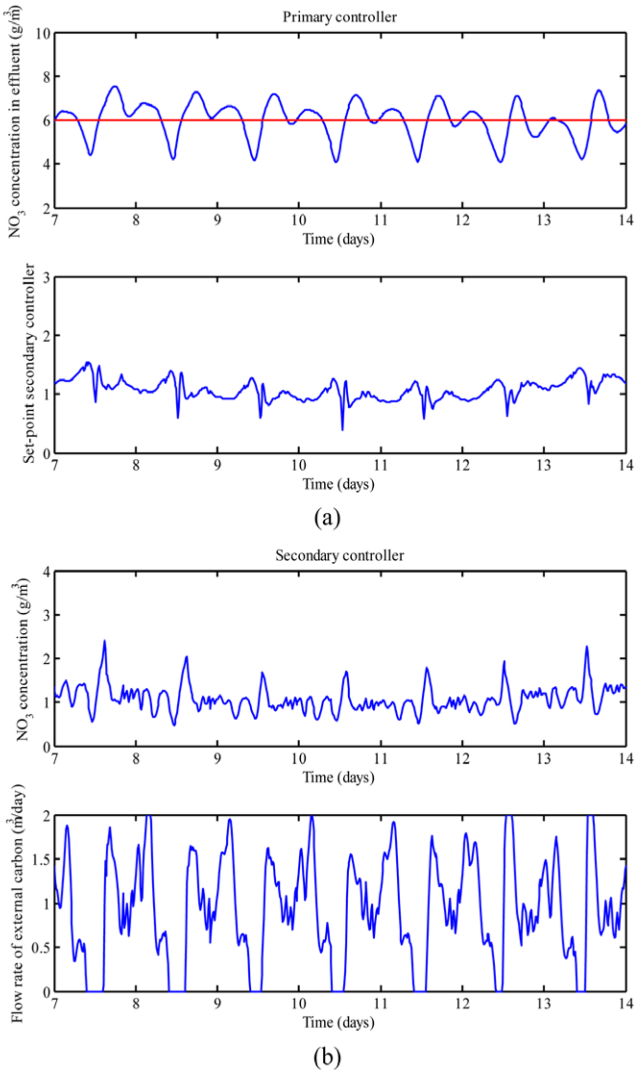


Fig. 9. Output and input data set of the cascade MPC-PID controller under dry weather influent condition in the (a) primary loop and (b) secondary loop.

the overshoot to the set-point change is small. The closed-loop response for a set-point change is satisfactory. By using an inner loop and two feedback controllers, cascade control can improve the response to a set-point change effectively.

It is of great interest to study how the controller performs under influent disturbances. The simulation result in Fig. 9 demonstrates that the proposed controller compensates for the dry weather disturbance in a well manner. By employing a secondary control loop and a secondary feedback controller, the cascade control strategy can significantly improve the dynamic response to disturbances [34]. As we know, WWTP happens to confront various influent changes following low load, high load and toxic load. The cascade controller can capture the process characteristics and tackle the problem of influent loading variations effectively.

2. Analysis and Comparison of Cascade Controllers with CPA

Once the cascade MPC-PID controller is designed properly, CPA technique is used to compare and assess the performances of the primary MPC controller and the secondary PID controller under the cascade control configuration.

Fig. 10 shows the comparison of individual closed-loop potentials between the primary MPC controller and the secondary PID controller. There exist potentials for both controllers, especially when the time lag is small. Furthermore, the primary MPC controller has more potential to improve, which implies that the MPC controller may not be well tuned or not as good as the PID controller. On the other hand, this result also indicates that the secondary PID controller in the inner loop works well under the dry weather influent distribution condition.

To compare the performance between the proposed cascade MPC-PID controller and the cascade PID-PID controller presented by Cho et al. [10], simulation results under the primary PID controller and the secondary PID controller are shown in Fig. 11(a) and Fig. 11(b), respectively. Performance between these two controllers is compared and analyzed using the CPA approach. Fig. 12 shows comparison of closed-loop potentials between the primary PID controller and the secondary PID controller. There also exists more potential for the primary PID controller to improve, which implies that the performance of the secondary PID controller is better.

The numerical RCPI gives a good estimate of how much the per-

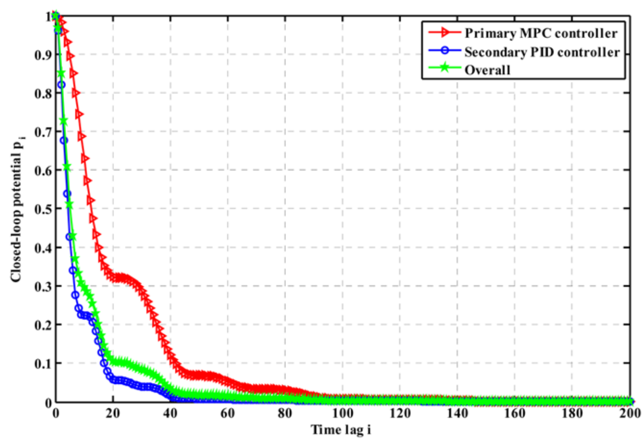
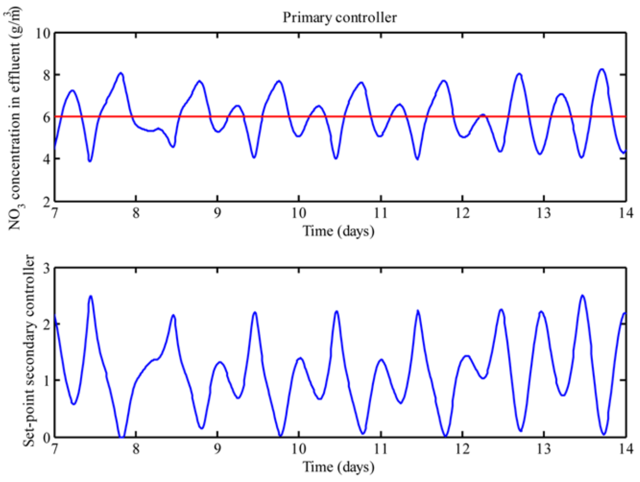
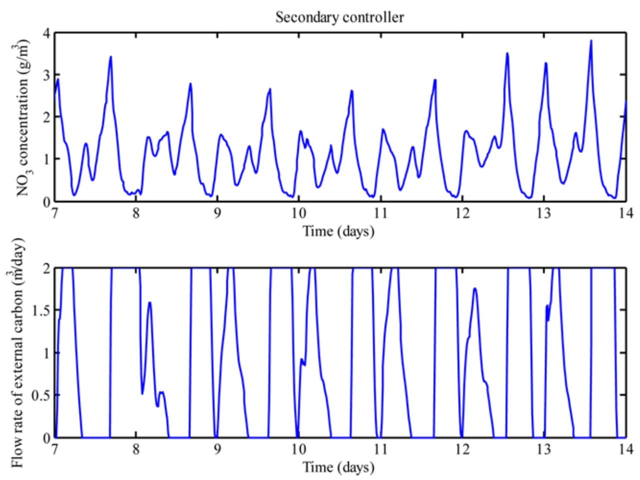


Fig. 10. Closed-loop potentials from the cascade MPC-PID controller.



(a)



(b)

Fig. 11. Output and input data set of the cascade PID-PID controller under dry weather influent condition in the (a) primary loop and (b) secondary loop.

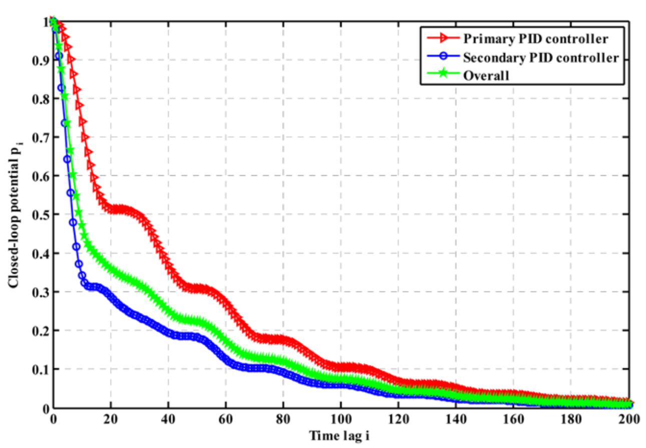


Fig. 12. Closed-loop potentials from the cascade PID-PID controller.

formance of the proposed cascade MPC-PID controller can be improved with the cascade PID-PID controller as the reference. The RCPI of overall performance listed in Table 1 is –0.6440. This RCPI

Table 1. RCPI of cascade MPC-PID controller with cascade PID-PID controller as the reference

RCPI	Primary controller	Secondary controller	Overall
Cascade MPC-PID	−0.4985	−0.6521	−0.6440

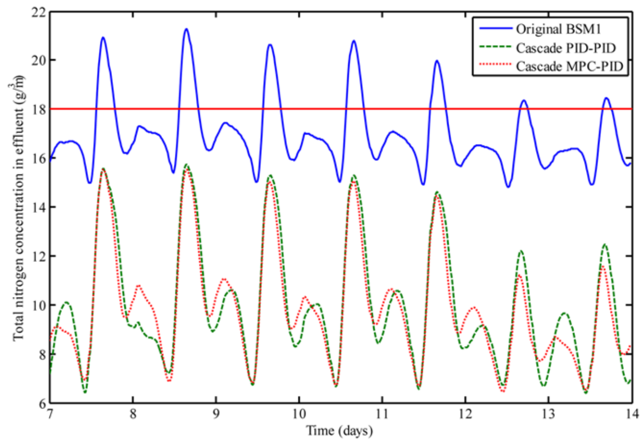


Fig. 13. Comparison of effluent total nitrogen concentration under the cascade control strategy and the original BSM1 configuration.

value shows that if the cascade PID-PID controller is replaced with the proposed cascade MPC-PID controller, then the resulting system has reduced closed-loop potential by 64.4%, indicating an improved performance.

Fig. 13 compares the effluent total nitrogen concentration between the proposed cascade control strategy and the original BSM1 configuration that uses two PI controllers. The maximum effluent total nitrogen level was violated on seven different occasions with regard to the original BSM1 configuration, whereas there is no violation with regard to the cascade structure. It also confirms that the cascade MPC-PID controller outperforms the original PID controller of BSM1.

The plant performance under the two cascade controllers with the original closed-loop conditions is presented in Table 2. The plant performance is evaluated in relation to different criteria as specified in [5]. The performance criteria shown in Table 2 are effluent quality index (EQI), average daily sludge production for disposal (P_{disp_sludge}), aeration energy (AE), pumping energy (PE), average amount of external carbon dosage, average nitrate, ammonia, total nitrate and total COD in the effluent. As 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. As can be seen from Table 2, the cascade MPC-PID controller significantly improves the quality of effluent at the cost of a little increase of P_{disp_sludge}, AE and PE. Average nitrate, ammonia and total nitrate in the effluent under the cascade MPC-PID controller decrease significantly compared with the original closed-loop case.

CONCLUSIONS

A cascade MPC-PID control strategy has been proposed and ap-

Table 2. Plant performance obtained using cascade PID-PID and cascade MPC-PID control strategy for the last seven days of simulation

Performance index	Original BSM1	Cascade PID-PID	Cascade MPC-PID
EQI (kg/d)	6115.629	4886.7948	4824.7284
P_{disp_sludge} (kg/d)	2440.7097	2598.9816	2583.6654
AE (kWh/d)	3696.6673	3885.8236	3861.4012
PE (kWh/d)	241.72	531.488	531.488
Avg. external carbon (m^3/d)	0	0.99294	0.92563
Effluent avg. nitrate (g/m^3)	12.3905	5.9183	5.9324
Effluent avg. ammonia (g/m^3) (limit=4)	2.5336	1.8872	1.7957
Effluent avg. total nitrate (g/m^3) (limit=18)	16.8891	9.9871	9.8945
Effluent avg. total COD (g/m^3) (limit=100)	48.2191	51.2295	51.1091

plied to control the nitrate concentration by adjusting the external carbon flow rate in BSM1. The proposed control structure consists of two control loops: the primary loop has an MPC controller, and the secondary loop has a PID controller. The secondary PID controller is designed using the relay feedback auto-tuning method. To design the MPC controller in the primary loop, the prediction error identification method is used. Taking advantage of the structural advantage of the cascade strategy, the proposed control strategy can control the nitrate concentration in the effluent directly and remove disturbances fast. CPA analysis shows that the proposed cascade MPC-PID controller is quite better than the cascade PID-PID controller. The proposed RCPI shows that the performance of the secondary PID controller is better than the primary MPC controller and the cascade MPC-PID controller outperforms the original PID controller and the cascade PID-PID controller.

ACKNOWLEDGEMENTS

This work was supported by the Korea Science and Engineering Foundation (KOSEF) grant funded by the Korea government (MEST) (KRF-2009-0076129) and funded by Seoul R&BD Program (CS070160). We would also like to thank Dr. Ulf Jeppsson for allowing us to use his Benchmark model implementation.

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