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Combined ILC and PI regulator for wastewater treatment plants

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ABSTRACT

Due to high nonlinearity with features of large time constants, delays, and interaction among variables, control of the wastewater treatment plants (WWTPs) is a very challenging task. Modern control strategies such as model predictive controllers or artificial neural networks can be used to deal with the non-linearity. Another characteristic of this system should be considered is that it works repetitively. Iterative learning control (ILC) is a potential candidate for such a demanding task. This paper proposes a method using ILC for WWTPs to achieve new results. By exploiting data from the previous iterations, the learning control algorithm can improve gradually tracking control performance for the next runs, and hence outperforms conventional control approaches such as feedback controller and model predictive control (MPC). The benchmark simulation model No.1-BSM1 has been used as a standard for performance assessment and evaluation of the control strategy. Control of the Dissolved Oxygen in the aerated reactors has been performed using the PD-type ILC algorithms. The obtained results show the advantages of ILC over a classical PI control concerning the control quality indexes, IEA and ISE, of the system. Besides, the conventional feedback regulator is designed in a combination with the iterative learning control to deal with uncertainty. Simulation results demonstrate the potential benefits of the proposed method.

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1. INTRODUCTION

A wastewater treatment plant (WWTP) is an industrial system encompassing mechanical, physical, chemical and biological processes in order to remove pollutants from the inlet wastewater [1]. The complexity of the biological and biochemical processes and the strong fluctuations of the influent flow rate make the control problem of the WWTPs very challenging [2]. The technology using the activated sludge process (ASP) is applied widely in advanced WWTPs [3, 4]. This technology is inexpensive and can be adapted to different types of wastewater. The WWTPs using ASP is described in Figure 1 [5]. Municipal wastewater is treated in an aeration tank, then flows to a sedimentation tank, where the biomass sludge is recovered. Treated water, located at the top of the sedimentation tank, will be the output of the system. At the bottom of the tank, the sludge deposits, in which a small part is returned to the aeration tank, while the waste activated sludge is pushed out.

The schematic of the WWTP is shown in Figure 2 [6]. The biological reactor has five tanks, including two anoxic sections (pre-nitrification) and three aerated ones (nitrification) [7, 8]. The sludge is recycled from the clarifier into the anoxic tank (external recycle), and a part of the mixed liquor is also fed back to the biological reactor (internal recycle) to maintain the microbiological population. The sludge withdrawn is pumped continuously from the settler to keep the sludge concentration constant. In order to improve the ASP efficiency, there are three things we can do to control this process: the air, or aeration rate; the sludge wasting through waste activated sludge; and the sludge recirculation, either through return activated sludge and/or internal mixed liquor recycle for nutrient removal. Aeration is an important part of biological reactors because aerobic conditions will facilitate the development of a wide range of microorganisms. Aerobic conditions for the growth of biomass affect the control of DO in biological wastewater treatment by activated sludge method. Inadequate or excess oxygen in aerobic tanks will result in degradation of activated sludge. To maintain the desired aeration in the biological tank, a DO controller is implemented. Besides, the DO level in the fifth tank is controlled that manipulates the aeration coefficient for this basin K_{La}^{5}. Besides, an outer control loop is used to control the nitrate removal by manipulating the internal recycle flow-rate.

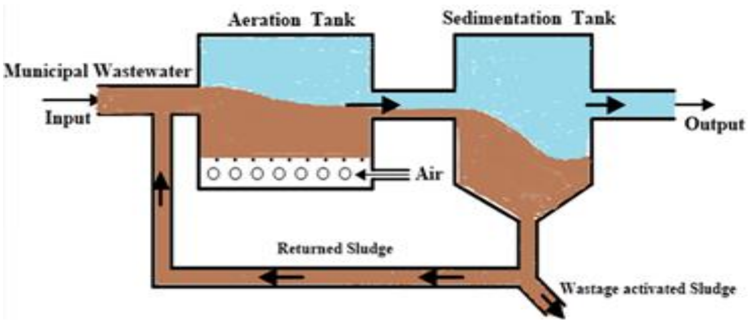

Figure 1. Municipal wastewater treatment by activated sludge process

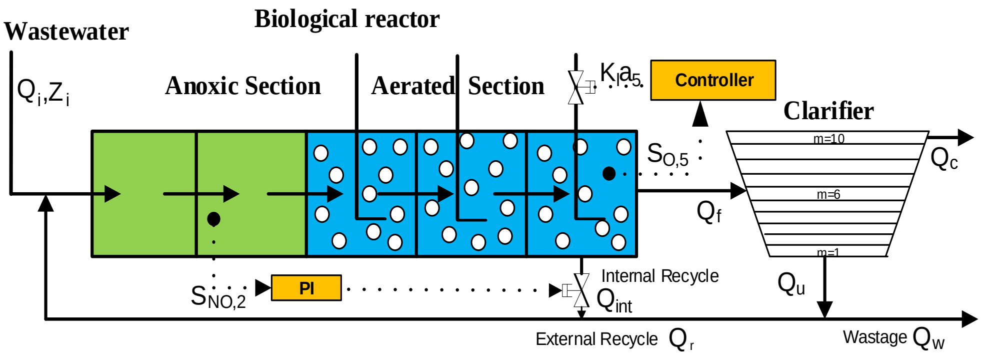

Figure 2. schematic representation of the WWTPs

To keep favorable processing conditions for the required treatment results and cost-effectiveness, different control strategies are applied. For example, in the aeration section, the aeration is controlled based on the difference between DO desired value and the measured output. Besides, control algorithms are designed to adjust the position of the aeration valve and the operation of the air compressor. Practically, conventional PID is the most used controller in wastewater treatment [9], because of its simplicity and capability of providing acceptable performance. Its disadvantage, however, is that correction is active only when the measured output differs from the setpoint. A combination of feedforward and feedback regulator has been proposed for DO concentration control [10, 11]. This method can provide a more stable, responsive, and reliable control system. The basic idea of feedforward control is based on the notion that major disturbances are measured and compensated before they have time to upset the system. In WWTPs, however, it is very difficult to measure disturbances as well as to derive a mathematical model.

To increase the efficiency and reduce costs, a number of advanced controllers have been proposed such as cascade control loops [12], intelligent controllers based on Hedge algebras [13], fuzzy logic control [14, 15], Model predictive control [16, 17]. These aforementioned methods, however, are non-learning algorithms. Artificial neural networks are proposed in [18]. Neural network learning, however, modifies the controller parameters. Therefore, modifying large networks of nonlinear neurons requires extensive training data. Whereas, ILC is another type of learning strategy that adjusts the control input, which is a signal, by gathering data from previous executions [19]. WWTPs work in a repetitive manner. Therefore, if the same manipulated variables are used for every iteration, the control performance cannot be improved. Therefore, data from previous runs is wasted. The main idea of ILC is that the performance of a system that operates in repetitive/repeatable maneuvers can be enhanced by incorporating and learning information from previous iterations. To our best knowledge, ILC has not been deployed in such systems. This paper aims to propose a method using ILC for WWTPs to achieve new results in DO control performance. Compared to feedback, feedforward controllers, ILC has some advantages [20]. A feedback regulator has to react to inputs and disturbance, results in a transient tracking lag. To eliminate this lag, a feedforward controller can be used, but only for measurable or known signals. ILC is anticipatory and able to compensate for exogenous signals, such as repetitive disturbances by learning from previous operations. In ILC, the exogenous signals are not required to be known or measured but repeated from iteration to iteration. Due to ILC cannot address unanticipated and nonrepeating disturbances, a combination of feedback regulator and with ILC is proposed to use. The remainder of this paper is organized as follows. The proposed control algorithm is introduced in section 2. Then, a combined ILC and PI regulator for WWTPs is derived in section 3. Next, section 4 presents simulation results and discussion. Finally, the conclusion is given in Section 5.

2. THE PROPOSED CONTROL ALGORITHM

The main idea of ILC is to utilize the situation that the control system carries out the same task over and over again. Based on that, the performance of the control system could be improved gradually by using the results from the previous iterations when updating the input signal for the next iteration. Figure 3 shows the basic structure of an ILC. The input signal $U_j(s)$ and the error signal $E_j(s)$ between the reference trajectory $Y_d(s)$ and system output $Y_j(s)$ are stored in memory. The input signal for the next iteration is computed based on $U_j(s)$ and $E_j(s)$ to improve the system performance. That is: $U_{j+1}(s) = f(U_j(s), E_j(s))$. A popular ILC algorithm is [21]:

$$U_{j+1}(s) = U_j(s) + L_e(s)E_j(s) \tag{1}$$

where $L_e(s)$ is a learning function.

It should be mentioned that ILC is an open-loop approach and has no feedback mechanism to deal with nonrepeating and unanticipated disturbances. Therefore, we proposed to use a feedback regulator combined with ILC for the DO control in tank 5, as shown in Figure 4. The basic idea here is that the system performs the same movement repeatedly, and a correction signal ΔU_j is updated after each iteration. In Figure 4, *C* is a feedback PI regulator, and *P* is the plant.

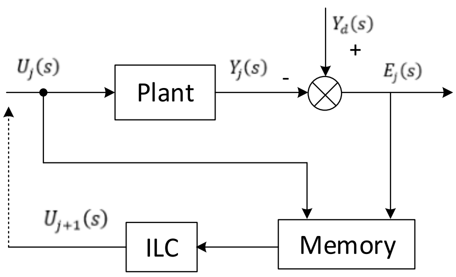

Figure 3. Block diagram of basic iterative learning control

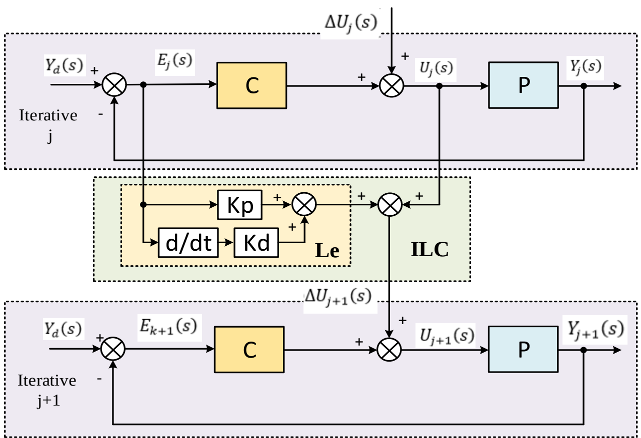

Figure 4. ILC combined with a feedback regulator

From the block diagram, the input signal is given by:

$$U_j(s) = G_c(s).\left(Y_d(s) - Y_j(s)\right) + \Delta U_j(s) \quad (2)$$

in which $G_c(s)$ is a feedback transfer function. So, the output of the closed-loop system:

$$Y_j(s) = \frac{G_p(s)}{1+G_c(s).G_p(s)}\left(G_c(s).Y_d(s) + \Delta U_j(s)\right) \quad (3)$$

where G_p (s) is the plant transfer function. The update equation:

$$\Delta U_j(s) = U_j(s) + L_e(s).E_j(s) \quad (4)$$

in which the learning function is PD-typed as following : $L_e(s) = K_p + K_d s$

Convergence is a major issue in ILC. Convergence means that the iterative update of the input signal converges to a signal giving a good performance. In the following, conditions for convergence to zero error will be derived. From Figure 4, the error signal of the iterative j is defined:

$$E_j(s) = Y_d(s) - Y_j(s) \quad (5)$$

inserting (3) into (5) gives:

$$E_j(s) = G(s).G_c{}^{-1}(s).\left(G_p{}^{-1}(s).Y_d(s) - \Delta U_j(s)\right) \quad (6)$$

where:

$$G(s) = \frac{G_c(s).G_p(s)}{1+G_c(s).G_p(s)} \quad (7)$$

is the closed-loop transfer function. At the iterative j+1, the control signal is:

$$U_{j+1}(s) = U_j(s) + L_e(s).E_j(s) \quad (8)$$

similar to (6), we have:

$$E_{j+1}(s) = G(s).G_c{}^{-1}(s).\left(G_p{}^{-1}(s).Y_d(s) - \Delta U_{j+1}(s)\right) \quad (9)$$

inserting (8) into (9) gives:

$$E_{j+1}(s) = E_j(s) - G(s).G_c{}^{-1}(s).L_e(s).E_j(s) \quad (10)$$

hence:

$$E_{j+1}(s) = \left(1 - G(s).G_c{}^{-1}(s).L_e(s)\right)E_j(s) \quad (11)$$

we see that with $|1 - G(s).G_c{}^{-1}(s).L_e(s)| < 1 \quad \forall\, \omega$, the error will tend to zero, and hence to output signal will follow the reference exactly. The condition in (11) means that the Nyquist diagram $G(j\omega)G_c{}^{-1}(j\omega)L(j\omega)$ has to be inside a circle of radius one with the center at one. This circle is denoted learning circle.

3. COMBINED ILC WITH A PI REGULATOR FOR WWTPs

In this project, the proposed method is applied to the BSM1, which is based on the most popular Activated Sludge Model No.1 (ASM1) developed by the International Association on Water Pollution Research and Control. The BSM1 is the standard model [7] to model, assess performance, and evaluate control strategies [8].

Figure 5 shows the Simulink model, including a nitrate controller and a DO controller. In former, a PI controller is pre-implemented. In the latter, another pre-designed PI controller is applied in the first iteration, then ILC combined with a PI regulator will be used in next iterations. In the first iteration, $\Delta U_j(s) = 0$, so only the PI feedback regulator is active. The control signal U_last and the measured output $O2\_meas$ are sent to the workspace in Matlab. In Matlab programming, the updating control signal is designed and calculated according to (4), then sent back to the Simulink model using input terminals $Delta\_u$ to run the next iteration.

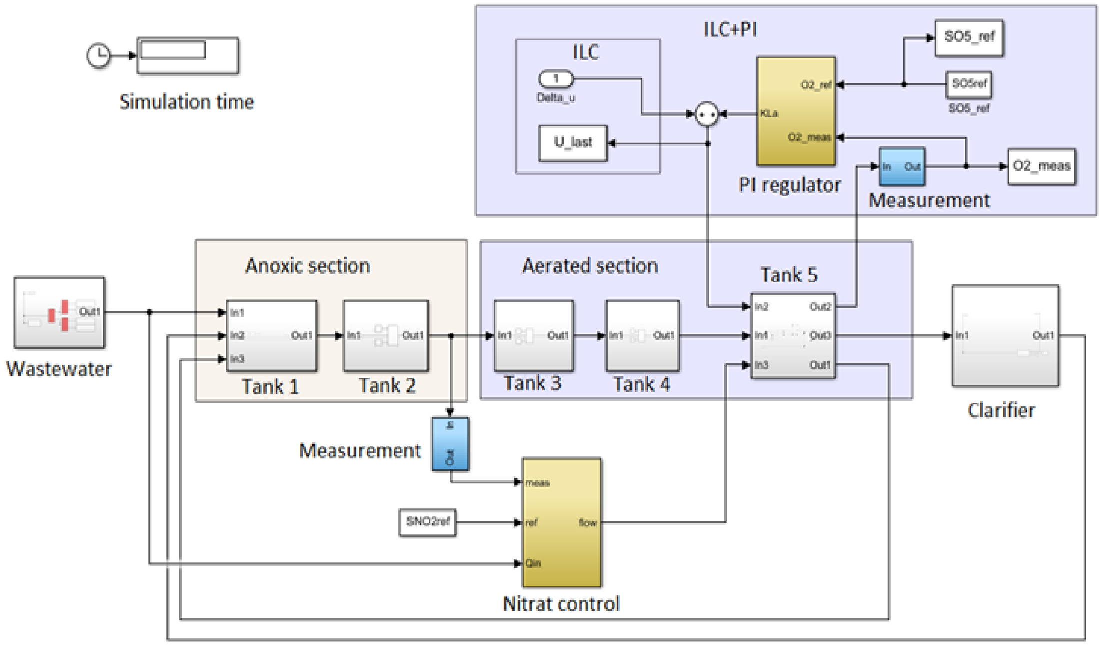

Figure 5. Simulation model

To evaluate the performance of the system, control quality evaluation will be used. In ILC, the converged error $E_\infty(s)$ and the initial error $E_0(s)$ is compared, using the differential integration method (IAE) and integrating the square of control deviation [7], in which:

$$IAE_j = \int_{t_0}^{t_f} |E_j| dt \text{ and } ISE_j = \int_{t_0}^{t_f} E_j^2 dt \tag{12}$$

to evaluate the performance of the system, operating cost index (OCI) and output wastewater quality index (EQI) are used, according to [8]:

$$EQI = \frac{1}{T.1000} \int_{t=0\ day}^{t=14\ days} A.Q_e(t)dt \tag{13}$$

where:

$$A = B_{TSS}.TSS_e(t) + B_{COD}.COD_e(t) + B_{TKN}.TKN_e(t) + B_{NO}.S_{NO_e}(t) + B_{BOD5}.BOD_e(t)$$

In which TSS_e, COD_e, TKN_e, S_{NO_e}, and BOD_e are the total amount of solids, the demand of the chemical oxygen, the total amount of nitrogen, the demand of the nitrate concentration and biological oxygen in the outlet, respectively. $Q_e(t)$ is the flow rate of outlet, and T is time (14 days in simulation) $B_{TSS} = 2, B_{COD} = 1, B_{TKN} = 30,\ B_{NO} = 10$, and $B_{BOD5} = 2$ are coefficients.

$$OCI = AE + PE + 5.SP + 3.EC + ME \tag{14}$$

where AE is aeration energy, EC is the mixing energy, EC is the consumption of external carbon source, PE is the pump energy and SP is the total amount of discharged sludge [7].

4. RESULTS AND ANALYSIS

Figure 6 demonstrates the simulation result of the DO control responding to a constant setpoint, in dry weather, with a PI controller, and with the proposed ILC controller. The Figure show that while a PI controller still gives a large tracking error, up to about 2.5 [g.(COD)/m3], the ILC combined PI gives a much better tracking control in the second iteration, and to nearly zero error after 10 iterations. This leads to very small control quality indexes

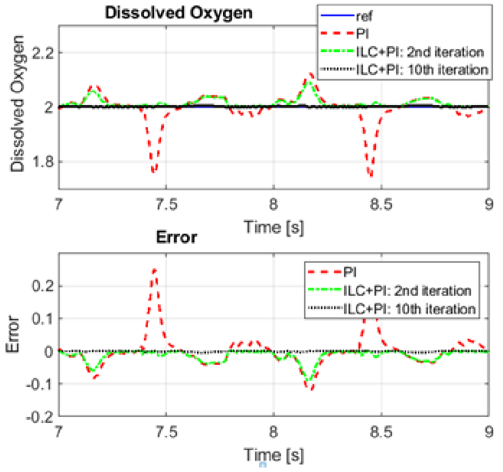

Figure 6. Control performance with constant setpoint

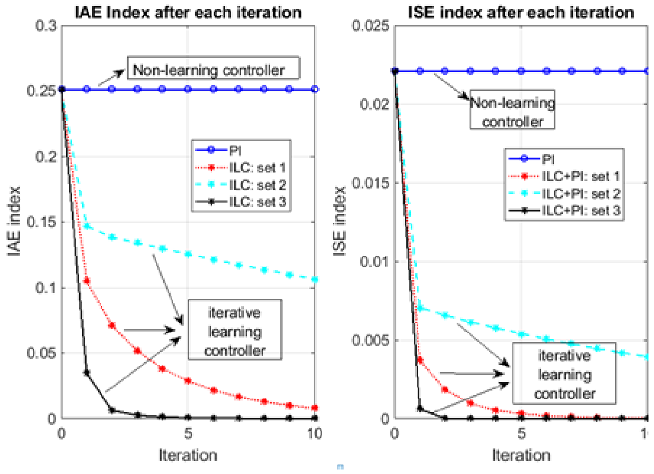

Figure 7. Learning process with different sets of K_{p_ilc}, K_{d_ilc}

Simulation result of the learning process is given in Figure 7, with 3 different sets of learning coefficients: *set* 1: $K_{p\_ilc} = 5, K_{d\_ilc} = 2$; *set* 2: $K_{p\_ilc} = 0.5, K_{d\_ilc} = 0.2$; and *set* 3: $K_{p\_ilc} = 40, K_{d\_ilc} = 10$. The figure illustrates that both *IAE* and *ISE* decrease significantly after each iteration. The rate of decreasing can be influenced by K_{p_ilc} and K_{d_ilc} of the learning function $L_e(s)$.

An importance aspect needs to be considered when applying ILC is the convergence. That is, the iterative update of the control signal converges to a signal giving a good performance. In [22], a detail of convergence issues was discussed, and some convergence criteria were derived. In this project, the learning process can be continued until the desired performance is reached.

Different weather conditions are also used to investigate the advantage of the proposed controller concerning disturbance rejection. Table 1 gives a comparison of the proposed controller with a PI-only regulator and with the method using a model predictive controller combined a feedforward [2] in term of control quality indexes. The Table shows that the proposed controller gives the best control performance with the smallest *IAE* and *ISE* indexes in all three considered weather conditions.

Table 1. Comparison of quality indexes of different controllers in dry weather

Indexes / Method	Dry weather		Rainy weather		Stormy weather	
	IAE	*ISE*	*IAE*	*ISE*	*IAE*	*ISE*
PI	0.25105	0.022085	0.2299	0.0177	0.2601	0.0217
MPC+FF [2]	0.047	0.00067	-	0.0013	-	0.0018
PI+ILC	0.0098	0.000078	0.0082	0.000054	0.0081	0.000058

To improve the system performance, a hierarchical control is proposed by some investigations [2, 4]. Higher-level control is designed to regulate the DO set-points, using states of the process, usually S_{NH4} and S_{NO} concentration values in any tank or the inlet [23, 24] or DO in other basins [25, 26]. The simulation of the proposed control algorithm for a regulated setpoint is given in Figure 8. Similar to a constant setpoint, the tracking control performance with a regulated setpoint is also nearly zero error. Table 2 compares the system quality indexes (OCI and EQI) of the DO control using constant setpoint and regulated setpoint. The table illustrates that using regulated setpoint, not only OCI but also EQI are decreased significantly comparing those using the constant setpoint in all three considered weather conditions.

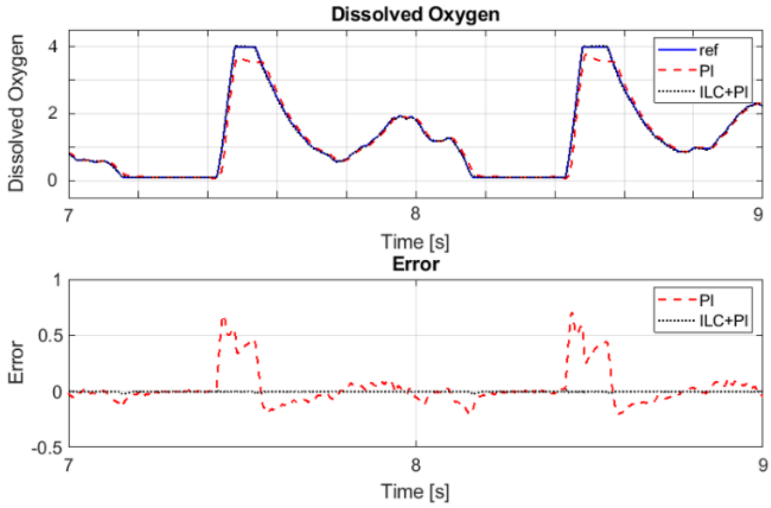

Figure 8. Control performance with regulated setpoint

Table 2. Comparison of quality indexes of different controllers in all three weather

Indexes	Method	ILC+PI Constant setpoint	ILC+PI Regulated setpoint	%
Dry weather	OCI	16364.77	16298.87	- 0.4027 %
	EQI	6095.23	6002.08	- 1.5282 %
Rainy weather	OCI	15996.38	15916.48	- 0.4995 %
	EQI	8174.91	8109.56	- 0.7994 %
Stormy weather	OCI	17236.97	17188.39	- 0.2818 %
	EQI	7228.72	7124.08	- 1.4476 %

5. CONCLUSION

The presented ILC performance of the nitrate concentration in the DO concentration control in the last aerated reactor of the pre-denitrification WWTP has shown promising results compared to the traditional decentralized PI control as well as to the MPC combined with feedforward controller. The combination of ILC with a PI feedback regulator provides a significant improvement of the WWTP operation aimed at organic and ammonium pollutants removal proved in the presence of the weather disturbance. The proposed control algorithm is proven for both constant setpoint and regulated setpoint.

The proposed controller in this project has just applied at tank No. 5. For further reduction of the OCI and the EQI, similar control structures can be designed to control oxygen concentration for the other basins (tank 3 and tank 4), and the nitrate control. Furthermore, the proposed PD-typed ILC is not an optimal algorithm. Optimal ILC, robustness, and implementation of ILC in the multiple-input multiple-output (MIMO) setup are our ongoing works for controlling a larger number of the WWTP variables. As an optimal ILC may successfully work in the presence of constraints, for both manipulated and controlled variables, the proposed control design outperforms the traditional control approach and reveals incentives for its practical implementation.

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REFERENCES

[1] Rainier Hreiz, M. A. Latifi, Nicolas Roche, "Optimal design and operation of activated sludge processes: State-of-the-art," *Chemical Engineering Journal*, vol. 281, pp. 900-920, December 2015.

[2] Ignacio Santín López, "Application of control strategies in wastewater treatment plants for effluent quality improvement, costs reduction and effluent limits violations removal," PhD thesis, Department de Telecomunicaci´o i Enginyeria de Sistemes Escola d'Enginyeria, Universitat Aut`onoma de Barcelona 2015.

[3] Arun Mittal, "Biological Wastewater Treatment," Water Today, August 2011.

[4] Henri Haimi, Kristian Sahlstedt, Michela Mulas, Riku Vahala, “Teknillinen korkeakoulu advanced operation and control methods of municipal wastewater treatment processes in Finland,” *Teknillinen korkeakoulu Vesihuoltotekniikan julkaisu Helsinki University of Technology Water and Wastewater Engineering Espoo*, 2009.

[5] Yu Gao, Ning Zhao, Yongdi Deng, Minghang Wang and Boxue Du, “Effects of treatment time and temperature on the DC corona pretreatment performance of waste activated sludge,” *Plasma Science and Technology*, February 2018.

[6] Alex J., Benedetti L., Copp J., Gernaey K. V., Jeppsson U., Nopens I., Pons M. N., Rieger L., Rosen C., Steyer J. P., Vanrolleghem P., Winkler S., “Benchmark Simulation Model No. 1 (BSM1),” Dept. of Industrial Electrical Engineering and Automation, Lund University, 2008.

[7] Copp, J. B. (Ed.)., “The COST Simulation Benchmark-Description and Simulator Manual,” Office for Official Publications of the European Communities, Luxembourg, 2002.

[8] H. Henze, C. P. L. Jr. Grady, W. Gujer, G. V. R. Marais, T. Matsuo, “A general model for single-sludge Wastewater Treatmant systems,” *Wat. Res.*, vol. 21, no. 5, pp. 505-515, 1987.

[9] Henze M., van Loosdrecht M. C. C., Brdjanovic D., Ekama G. A., “Biological Wastewater Treatment: Principles Modelling and Design,” *IWA Publishing*, 2008.

[10] Yong M., Yongzhen P., Shuying W., “Feedforward-feedback control of dissolved oxygen concentration in a predenitrification system,” *Bioprocess and Biosystems Engineering*, vol. 27, no. 4, pp. 223-228, August 2005.

[11] P. Ingildsen, U. Jeppsson and G. Olsson, “Dissolved oxygen controller based on on-line measurements of ammonium combining feed-forward and feedback,” *Water Science and Technology*, vol. 45, no. 4-5, pp. 453-460, 2002.

[12] Cho J. H., Sung S. W., Lee I. B., “Cascade control strategy for external carbon dosage in predenitrifying process,” *Water science and technology*, vol. 45, no. 4-5, pp. 53-60, 2002.

[13] Binh Lam Hoang, Fei Luo, Duy Nguyen Tien, Phuong Huy Nguyen, “Dissolved Oxygen Control of the Activated Sludge Wastewater Treatment Process Using Hedge Algebraic Control,” *2014 7th International Conference on Biomedical Engineering and Informatics*, Dalian, pp. 827-832, 2014.

[14] C. H. Nguyen, N. L. Vu, X. V. Le, “Optimal hedge-algebra-based controller: Design and application,” *Fuzzy Sets and Systems*, vol. 159, no. 8, pp. 968-989, April 2008.

[15] Verbruggen H. B., Babuška R., “Fuzzy logic control: advances in applications,” World Scientific, 1999.

[16] Vasile-Mircea Cristea, Cristian Pop, Paul Serban Agachi, “Model Predictive Control of the Waste Water Treatment Plant Based on the Benchmark Simulation Model No.1-BSM1,” *18th European Symposium on Computer Aided Process Engineering –ESCAPE 18*.

[17] Camacho E. F., Bordons C., “Model Predictive Control,” *Springer*, 2004.

[18] Lingireddy S., Brion G. M., “Artificial Neural Networks in Water Supply Engineering,” *ASCE Publications*, 2005.

[19] K. L. Moore, “Iterative Learning Control for Deterministic Systems,” London: *Springer-Verlag*, 1993.

[20] Douglas A. Bristow, Marina Tharayil and Andrew G. Alleyne, “A survey of Iterative learning control, a learning method for highperformance tracking control,” *IEEE control systems magazine*, June 2006.

[21] K. L. Moore, YangQuan Chen, Hyo-sung Ahn, “An Introduction to Iterative Learning Control Theory,” CSM EGES 504/604A Colloquium Golden, CO—24 Jamuary 2006.

[22] L. Hideg, “Stability of Learning Control Systems,” PhD thesis, Oakland University, Rochester, Michigan, 1992.

[23] Ramon Vilanova, Reza Katebi, and NoraLiza Wahab, “N-removal on wastewater treatment plants: A process control approach,” *Journal of Water Resource and Protection*, 3:1-11, 2011.

[24] A. Stare, D. Vrecko, N. Hvala, and S. Strmcnick, “Comparison of control strategies for nitrogen removal in an activated sludge process in terms of operating costs: A simulation study,” *Water Research*, vol. 41, no. 9, pp. 2004-2014, 2007.

[25] George S. Ostace, Anca Gal, Vasile M. Cristea, and Paul S. Agachi, “Operational costs reduction for the WWTP by means of substrate to dissolved oxygen correlation, a simulation study,” *Proceedings of the World Congress on Engineering and Computer Science, San Francisco*, USA, 2011.

[26] Do Trung Hai, Bach Van Nam, “Design of a Fuzzy Logic Controller based on Genetic Algorithm for Controlling Dissolved Oxygen in Wasted-Water Treatment System Using Activated Sludge Method,” *The ICERA 2018 International Conference on Engineering Research and Applications*, Thai Nguyen, Vietnam, Springer Nature Switzerland AG 2019, H. Fujita et al. (Eds.): ICERA 2018, LNNS 63, pp. 217–228, 2019.