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Energy efficiency in activated sludge process using adaptive iterative learning control with PI ABAC

Maimun Huja Husin[1], Mohamad Faizrizwan Mohd Sabri[1], Kismet Anak Hong Ping[1], Norazlina Bateni[2], Shamsiah Suhaili[1]
[1]Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Malaysia Sarawak, Sarawak, Malaysia
[2]Department of Civil Engineering, Faculty of Engineering, Universiti Malaysia Sarawak, Sarawak, Malaysia

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ABSTRACT

This paper proposed an iterative learning control (ILC) with a feedback regulator based on proportional integral ammonium-based aeration control (PI ABAC) to improve dissolved oxygen control through data learning of iteration data. The proposed controller's performance is evaluated using benchmark simulation model no. 1. (BSM1). The assessments focused on four main areas: effluent violation, effluent quality, aeration energy, and overall cost index. The proposed ILC PI ABAC controller's effectiveness is evaluated by comparing the performance of the activated sludge process to the BSM1 PI and feedback PI ABAC under three different weather conditions: dry, rain, and storm. The improvement of the proposed method over BSM1 PI is demonstrated by a reduction in aeration energy of up to 24%. In conclusion, if the proposed ILC PI ABAC controller is given enough information, it can be quite successful in achieving energy efficiency.

Corresponding Author:

Maimun Huja Husin
Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Malaysia Sarawak
94300 Kota Samarahan, Sarawak, Malaysia
Email: hhmaimun@unimas.my

1. INTRODUCTION

Access to clean water is a necessity for both humans and the environment. Maintaining water supplies and guarding the nature for a sustainable future is the most important contribution of wastewater treatment plants (WWTPs) to protecting public health. To achieve this, more stringent effluent regulations have been established for WWTPs. These stricter requirements force WWTP operators to improve their control strategies. The main issue for WWTP operators is to reduce operating costs, especially energy for aeration while maintaining high effluent quality. Aeration is an energy-intensive process where energy consumption can be as high as 67.2% [1]–[3]. Wastewater quality discharged into rivers from treatment plants that do not meet standards is subject to a fine.

Advanced control systems have proven to be a practical solution to the above problem to improve wastewater quality discharged and minimize energy use compared to traditional proportional, integral and derivative (PID) controllers. However, advanced control systems like model predictive control (MPC), need a strong predictive model to forecast the plant's future response. It is challenging to develop good predictive control because the biological process of wastewater treatment is extremely complex, confusing, and unexpected. Modelling the activated sludge process is also complicated by issues of nonlinearity, fluctuations in influent flow, and significant disturbances [4]–[7].

Proportional-integral (PI) controls are the traditional controls that are still routinely employed to control the activated sludge process in WWTPs. This is primarily due to the significant expense of upgrading the control system of the existing WWTPs. The use of PI controllers in most WWTPs has been due to their simplicity, durability, and near-perfect control. However, with the introduction of new wastewater standards, the conventional PI controller is no longer capable of adapting to changing operational conditions in the WWTP. When using the PI controller, a compromise must always be made between aeration energy and effluent quality. If the aim is rather to improve the quality of the wastewater, the cost of aeration energy is high [8]–[11]. Moreover, a typical PI controller is not able to cope with the problems of nonlinearity, fluctuation of influent and severe disturbance in the treatment plant [12]–[15].

Several studies have been conducted over the last decade to assess the effectiveness of various control methods that use dissolved oxygen (DO) to reduce aeration expenses. The feature of this control system is the availability of a DO sensor probe that can continuously measure the DO levels in the tank. The primary concept behind employing the DO sensor probe is to regulate the DO supply based on the oxygen requirement of the microorganisms in the tank. However, this technique has flaws because it is impossible to identify the exact value of the microorganism's actual oxygen consumption at any given time. As a result, the majority of the proposed DO control schemes have increased the DO set point to avoid nitrification failure. However, even with the DO control technique, aeration costs remain an issue because DO control necessitates aerators and turbines powered by electric motors, which add to the system's costs. This necessitates a paradigm shift in the methods used to address the issues of energy consumption and aeration control costs. This issue has been investigated, and a solution is provided in which the aeration process can be regulated by modifying the DO set point based on the ammonium nitrogen (SNH) concentration in the wastewater [16]–[18].

Ammonium-based aeration control (ABAC) is a control strategy that uses SNH as a response variable in addition to or instead of DO. ABAC is a method that helps improve effluent quality while keeping aeration energy low by using real ammonium measurement [19]–[24]. The study shows that the neural network ABAC reduced aeration energy by up to 23% while improving wastewater quality by 1.9% [19], [21]. Up to 43% of the aeration cost can be saved in [22]. The impact of ABAC on energy consumption is observed after a comprehensive implementation of ABAC at a regional water treatment plant, which achieved an average energy savings of 5%, equivalent to an average savings of 10% in total electricity costs per month [23].

Despite the fact that ABAC has been on the market for a number of years, most pilot or real-world plants employ the PI controller in their ABAC configurations. The PI controllers used are set up to be disseminated. This arrangement is advantageous because the coupling problem in a multiple-input multiple-output (MIMO) system is avoided. A PI controller, on the other hand, is infamous for being prone to interference and/or operational state variations. On the other hand, several investigations have demonstrated that sophisticated control systems outperform PI controllers. MPC, for example, is known to be computationally demanding [25]–[27]. As a result, a leaner control method with less complexity is preferable, particularly if the controller will be utilized in a real or pilot plant.

To increase the effectiveness of the control system by providing an adjustment system that helps to deal with the nonlinearity of the wastewater inflow, an iterative learning control (ILC) is introduced in this study. ILC is a type of tracking control that allows the system to operate in a recurrent mode. There are very few published results on the implementation of ILC in WWTPs [5], [28]–[30]. The data-driven indirect ILC scheme was suitable for the case where no mechanistic model of the complex system was available [30]. The learning control algorithm can gradually enhance the performance of the tracking control for the next runs by applying ILC, which effectively uses the data from past iterations, surpassing conventional control systems such as feedback controllers and model predictive control [5]. The proportional iterative learning control (P-ILC) algorithm is employed in the aeration basin of oxygen input connection with consideration of data producing omission by altering the algorithm to totally regulate the aeration tank of oxygen, obtaining the best wastewater treatment efficiency [29].

In this study, a combination of ILC and PI ABAC is proposed with the aim that the proposed controller can better adapt to the changes in the inflow. To verify the efficiency of the proposed controller, its performance is evaluated with two other control configurations, namely the standard benchmark simulation model no. 1 (BSM1) PI [31] and the feedback controller PI ABAC [8].

2. METHOD

BSM1 consists of 5 activated sludge reactors with two anoxic basins and three aerobic basins. A secondary clarifier follows the active sludge reactor. Figure 1 depicts an in-depth diagram of the BSM1 plant. The basic control technique for BSM1 is to first manipulate the internal recycling flow rate to control nitrate levels in the anoxic final tank, and second, the oxygen transfer coefficient to regulate DO levels in the aerobic final tank. The primary control objectives for the standard BSM1 PI controller are to regulate the nitrate concentration in the second anoxic tank at a preset setpoint of 1 g.m^{-3} and the DO concentration in the final aerobic tank at a preset setpoint of 2 g(-COD).m^{-3}.

The BSM1 is designed for an average biodegradable chemical oxygen demand (COD) in the influent of 300 g.m^{-3} and an average dry weather influent of 18446 m^3.d^{-1}. The hydraulic retention time is 14.4 hours. Both the biological reactor and the settler have a volume of 6000 m^3. The age of the biomass sludge is about nine days, as the discharge rate is 385 m^3.d^{-1}. Three files representing dry, rain and storm weather are used to determine the dynamics of the inflow. The performance of the suggested controller is evaluated in terms of the impact of the control strategy on the plant process. The limit shown in Table 1 should be met by the flow-weighted average effluent concentrations across the three evaluation periods.

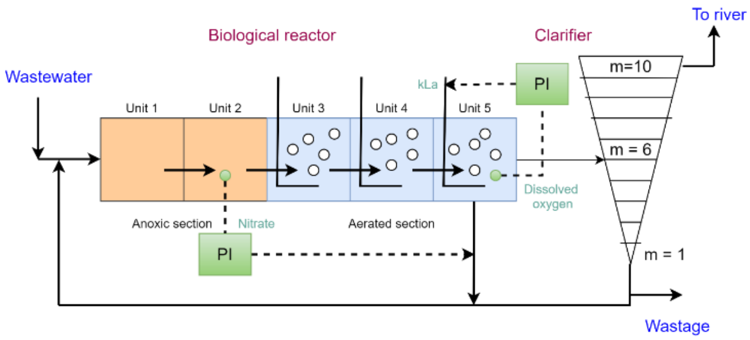

Figure 1. General overview of the BSM1 plant

Table 1. The effluent limit

Variable	Value
Total nitrogen (Ntot)	18 g.N.m^{-3}
COD	100 g.COD.m^{-3}
Ammonium nitrogen (SNH)	4 g.N.m^{-3}
Total suspended solids (TSS)	30 g.SS.m^{-3}
Biological oxygen demand (BOD)	10 g.BOD.m^{-3}

2.1. Feedback PI ABAC

Single-input-single-output (SISO) PI ABAC feedback is used for comparison. In PI ABAC feedback, the PI controller is cascaded with the existing PI controller to manipulate the DO setpoint, as shown in Figure 2. This configuration is used in most pilot or real plants. In this control structure, a SISO configuration is used where the SNH concentration at the end of the vented section is determined and evaluated to the desired SNH setpoint. Based on the error values between these two measurements, the first PI controller calculates the DO setpoint for the second PI controller. The second SISO PI controller then calculates the required airflow rate based on the DO setpoint calculated by the first PI controller.

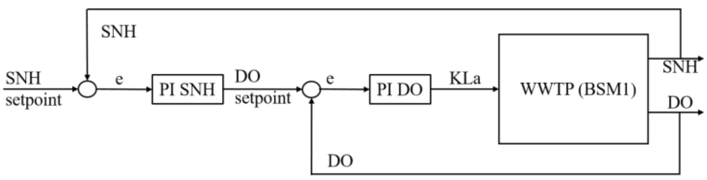

Figure 2. Feedback PI ABAC control system

2.2. ILC PI ABAC

A combination of PI-ABAC with ILC is proposed to create an adaptive control system and achieve new results in the control performance of DO. ILC is a learning system whose purpose is to enhance the operation of the control system by repeatedly analyzing and calculating the results of previous iterations to improve the data when generating the new iteration. Figure 3 shows the basic control system of iterative learning control.

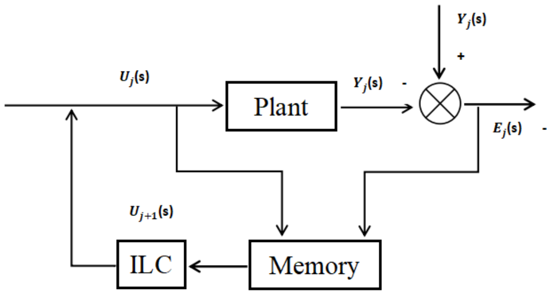

Figure 3. Block diagram of ILC

Based on Figure 3, the ILC system store both the input signal U_j(s) and the error signal E_j(s) in memory. U_j(s) is the previous iteration result meanwhile E_j(s) is the output or error signal between the system output Y_j(s) and the reference trajectory Y_d(s). Both data stored in memory will be used in the generation of the next output iteration signal. ILC mathematical expression is given as (1):

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

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

The implementation of the ILC PI ABAC control system was designed using MATLAB/Simulink. The design included a Simulink module consisting of a MATLAB function and a feedback system. The ILC Simulink model involves the use of MATLAB functions that consist of the mathematical equations required to process the iteration data. The main input to the system is the iteration data. The main output is the reference trajectory. The unit delay acts as a storage system that manages the iteration data. The Simulink model of the ILC is shown in Figure 4.

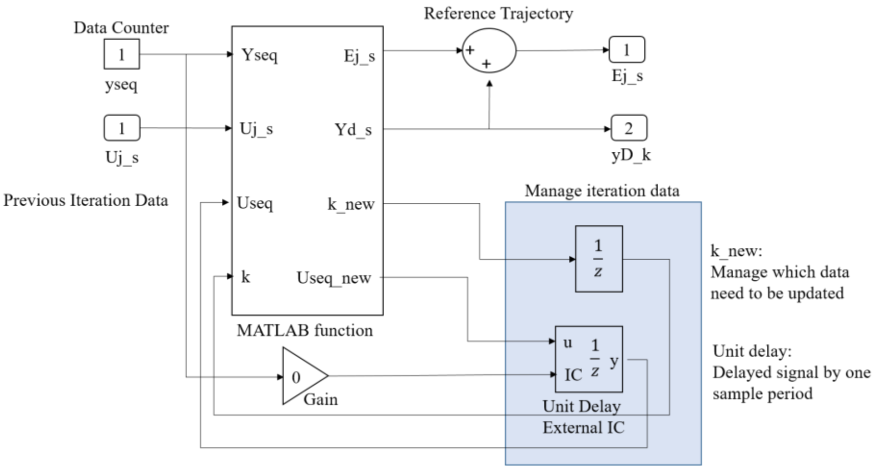

Figure 4. Simulink model of ILC

As $\Delta U_j(s) = 0$, only the PI ABAC controller is active during the first iteration. As a new iterative signal is generated, the ILC in conjunction with the PI ABAC regulator is activated and used for the next iteration. The iteration signal U_{j_s}, as well as the measured outputs DO and SNH, are sent to the MATLAB workspace as input for ILC control. The updated iteration signal is then calculated based on the data provided and returned to the Simulink model as an input terminal E_{j_s}, which is then used to improve the next iteration.

3. RESULTS AND DISCUSSION

This section explained the outcomes of the suggested control method on wastewater discharged quality and cost elements for operations such as aeration energy (AE) and overall cost index (OCI). The discussion has been made into several sub-sections.

3.1. Effect on the plant process in terms of effluent violations

The numbers of wastewater discharged quality violations under all three weather conditions are monitored and are evaluated to the default benchmark PI controller and are indicated in Tables 2–4 respectively. ILC PI ABAC has been shown to perform better in reducing SNH violations in all weather conditions. The time of SNH violation during dry, rain and storm inflow reduced by 0.9%, 3.7%, and 2.35%, respectively, compared to the controller PI. This shows that the proposed ILC PI ABAC successfully improved the nitrification process, which means that there is enough oxygen for the bacteria in the tank. Compared to the PI controller, where DO is set to a higher level just to avoid nitrification failure, the combination of PI ABAC and ILC shows that nitrification is further improved without simply setting the level high all the time.

Table 2. The number of violations under dry weather

		PI	PI ABAC	ILC PI ABAC
Ntot	%	17.86%	**15.77%**	15.8%
	Occasion	7	**7**	6
SNH	%	16.82%	16.82%	**15.9%**
	Occasion	5	5	**5**

Table 3. The number of violations under rain weather

		PI	PI ABAC	ILC PI ABAC
Ntot	%	11.01%	**9.82%**	9.97%
	Occasion	5	**5**	5
SNH	%	25.59%	31.10%	**21.9%**
	Occasion	8	11	**8**

Table 4. The number of violations under storm weather

		PI	PI ABAC	ILC PI ABAC
Ntot	%	15.48	**13.24%**	13.7%
	Occasion	7	**6**	6
SNH	%	26.34%	27.83%	**23.95%**
	Occasion	7	7	**7**

PI ABAC indicates the best outcomes in terms of Ntot violations in all weather conditions. However, the improvement is only slightly better than ILC PI ABAC. On the other hand, PI ABAC unfortunately has the worst results on SNH violations. This is particularly noticeable for rain weather, where there were 11 SNH violations, representing 31.1%. This is to be expected because better Qa manipulation was required for the Ntot violations, which means that the PI controller for the second tank must also be modified to produce better results. Qa is raised when the input SNH is elevated to reduce the output SNH. The simulation findings show that the proposed ILC PI ABAC control has enhanced plant performance by lowering Ntot and SNH effluent violations.

3.2. The effluent quality and cost index

Effluent quality (EQ) needs to be maintained at particular standards, not just to avoid paying further penalties or levies, but also to ensure that the environment is safe and clean for all. The average energy use per day should be restrained to reduce the WWTP's operating costs. Tables 5–7 compare effluent quality and average energy use under three different weather conditions.

The EQ index (kg pollution unit d-1), according to BSM1, is defined as the average across the evaluation period established on a weighting of the wastewater released quality loads of chemicals that have a substantial impact on the river's trait. The value of levies or fines that must be paid as a result of releasing pollution into receiving water bodies is reflected in the EQ index, which is a measure of standard quality. To put it another way, high effluent quality raises levies.

Table 5. Comparative of EQ and average energy usage in dry weather

	PI	PI ABAC	ILC PI ABAC
Influent quality (IQ) index kg poll.units/d	52081.3952	52081.3952	52081.3952
EQ index kg poll.units/d	6096.1317	6081.46	**6006.832**
Average aeration energy per day (kWh/d)	3697.7019	3641.69	**2827.4923**
Total OCI	16385.8552	16317.85	**15667.60**

In the simulation of the weekly time scale, the ILC PI ABAC control strategy surpassed both PI and PI ABAC in terms of EQ index performance, as shown in Tables 5-7. ILC PI ABAC controller produced an EQ index of 6006.83 kg poll.units/d for dry weather (reduced by 1.47%), 8021.218 kg poll. units/d for rain weather (reduced by 1.54%) and 7075.189 kg poll.units/d for storm weather (reduced by 1.57%) when compared to PI controller. IQ defined the water quality incoming to the plant while EQ is the water quality leaving the plant. It can be seen that the quality of incoming water before discharge into the river has greatly improved using the proposed ILC PI ABAC control, from the original 52081.3952 kg poll.units per day.

Table 6. Comparative of EQ and average energy usage in rain weather

	PI	PI ABAC	ILC PI ABAC
IQ index kg poll.units/d	52081.3952	52081.3952	52081.3952
EQ index kg poll.units/d	8146.2177	8219.54	**8021.218**
Average aeration energy per day (kWh/d)	3671.8674	3565.74	**2827.4923**
Total OCI	15977.3599	15873.11	**15302.88**

Table 7. Comparative of EQ and average energy usage in storm weather

	PI	PI ABAC	ILC PI ABAC
IQ index kg poll.units/d	54061.497	54061.497	54061.497
EQ index kg poll.units/d	7187.2151	7244.73	**7075.189**
Average aeration energy per day (kWh/d)	3720.9099	3615.32	**2827.4923**
Total OCI	17248.7678	17140.22	**16522.75**

The average AE results indicate that the ILC PI ABAC control method is effective at lowering the energy use of WWTPs. The average AE value of the ILC PI ABAC controller as determined by simulation is the same for all weather conditions at 2827.4923 kWh/d. For dry, rain, and storm weather, the ILC PI ABAC contributed reductions of 23.5%, 23%, and 24%, respectively when compared to PI. As mentioned earlier, AE is the most important factor in the operating costs of a wastewater treatment plant. Thus, reducing AE helps to reduce the overall cost of the WWTP. ILC PI ABAC control strategies significantly improve the results of the comparison by lowering the total operational cost index. A reduction of 4.3%, 4.2%, and 4.2% for the corresponding dry, rainy, and storm weather is shown by the percentage difference between the proposed ILC PI ABAC controller and PI controller. PI controller reported the greatest total OCI index in all weather conditions. The total OCI index is calculated by taking into account all other variables of operating costs for WWTPs, such as those for pumping power, aeration power, sludge treatment and disposal, chemical usage, and effluent quality.

4. CONCLUSION

In terms of energy efficiency and performance, the obtained findings demonstrate the advantages of the suggested ILC PI ABAC controller over a traditional PI and PI ABAC controller. The operation of the plant in terms of effluent violations shows fewer effluent violations in all three weather scenarios, especially in SNH violations. In addition, the plant performance in terms of EQ and overall OCI has improved significantly. For all weather scenarios, there is a significant improvement in daily energy consumption. ILC PI ABAC has helped to reduce energy consumption by about 24% and improve effluent quality by up to 1.57% compared to the BSM1 PI controller. The advantages of ILC show that it can be a promising way to control DO in a WWTP. However, it ought to be verified in a real or a pilot WWTP. Since the proposed controller was only applied to tank 5, we can extend the applicability of the method to other tanks in future work to further reduce the OCI and EQ.

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BIOGRAPHIES OF AUTHORS

Maimun Huja Husin is a senior lecturer at the Department of Electrical and Electronic Engineering, Universiti Malaysia Sarawak. Her field of specialization includes control systems and wastewater treatment control. She received B. Eng in Electronics and Telecommunication Engineering at Universiti Malaysia Sarawak in 2005 and M. Eng in Mechatronics and Automatic Control in 2008 at Universiti Teknologi Malaysia. She then completed her Ph.D. in Electrical Engineering at Universiti Teknologi Malaysia in 2022. Current research interest includes water management, control system design, and automation. She can be contacted at email: hhmaimun@unimas.my.

Mohamad Faizrizwan Mohd Sabri is an Academic at the Department of Electrical and Electronics Engineering, Faculty of Engineering, Universiti Malaysia Sarawak, Malaysia (UNIMAS) since completing his Master of Electronic Engineering at La Trobe University, Australia, in 2008. He obtained his degree in Bachelor of Electrical & Electronics Engineering from Nagasaki University, Japan in 2006 and completed his PhD in Electrical Engineering at Universiti Teknologi Malaysia (UTM) in 2019. Current research interest is in electrified vehicles and mobility, energy management and control system, smart transportation system, and electrical power system including renewable energy. He can be contacted at email: msmfaizrizwan@unimas.my.

Kismet Anak Hong Ping is an Associate Professor at the Department of Electrical and Electronic Engineering, Faculty of Engineering. He received his BEng. (Hons) (Electronics and Telecommunications) from Universiti Malaysia Sarawak, MSc in Digital Communication Systems from Loughborough University, United Kingdom and PhD in Systems Science from Nagasaki University, Japan in 1998, 2000 and 2009, respectively. His research activities are mainly focused on developing microwave image processing algorithms for medical diagnostics and antenna design. His interests include applications of microwave engineering in biomedical imaging, through-the-wall imaging (TWI), and non-destructive testing (NDT). He can be contacted at email: hpkismet@unimas.my.

Norazlina Bateni is a Senior lecturer at the Department of Civil Engineering, Faculty of Engineering, Universiti Malaysia Sarawak, Malaysia. She obtained her PhD from University of Malaya, Kuala Lumpur. Her doctoral studies focus on Water Resource Engineering in Stormwater management, emphasizing permeable pavement, with the production of StormPav a green infrastructure product of permeable pavement precast hollow detention pond structure. Her Master of Engineering is in Water Resources and Hydrology Engineering from Universiti Teknologi Malaysia (UTM), Johor, Malaysia. Her research interest includes stormwater management, water resources and supply, and coastal engineering. She can be contacted at email: bnorazlina@unimas.my.

Shamsiah Suhaili is a senior lecturer at the Department of Electrical and Electronic Engineering, Universiti Malaysia Sarawak. Shamsiah binti Suhaili received her B.Eng.(Hons.) and M.Sc. degrees in Electrical and Electronic Engineering from Universiti Sains Malaysia (USM) in 2001 and 2005 respectively. She is now with Universiti Malaysia Sarawak. Her research area of interest is the application of FPGA design. She can be contacted at email: sushamsiah@unimas.my.