



Comparative evaluation of PID controller performance for dissolved oxygen control in flow-through aquaculture systems

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ABSTRACT

Flow-through aquaculture systems are highly sensitive to continuous water inflow and outflow, causing dissolved oxygen (DO) to fluctuate with influent water quality, fish oxygen consumption, and oxygen supply conditions. Consequently, maintaining adequate oxygen remains challenging. Most farms still rely on fixed oxygen input or simple on/off control, often resulting in oxygen oversupply and poor maintenance of the target DO range. This study compared the DO control performances of P, PI, PD, and PID controllers in a flow-through aquaculture system to assess their relative control effectiveness and practical applicability. Using water-quality and oxygen flow-rate data collected from an operating farm, a measured-data-based dynamic DO model was developed using a mass-balance equation based on the continuous stirred-tank reactor framework. The internal model control method was then employed to derive controller parameters using the identification dataset, and the selected controller gains were subsequently evaluated on a separate held-out validation period. Under held-out validation, PI and PID controllers maintained 100% of simulated DO within $\pm 5\%$ of the 10 mg/L target at controller update intervals of 1, 10, and 20 min. At 20 min, the corresponding within-band percentages of P and PD decreased to 25.86% and 26.13%, respectively. However, all controller structures deteriorated markedly at 30- and 60-min update intervals, indicating that sparse controller updating can become a dominant limitation. These results demonstrate that integral action is important for correcting persistent DO deviation under short-to-moderate update intervals, while the controller update interval itself must also be appropriately selected.

1. Introduction

1.1. Background

Global aquaculture is becoming increasingly important for food supply and protein production (Khurshed et al., 2023), and precise management of rearing environments is essential for ensuring stable production. Among various water-quality parameters, dissolved oxygen (DO) is a critical factor that directly affects fish growth, feed utilization, metabolic stability, and survival, and is widely recognized as a representative environmental variable that determines both the productivity and operational stability of aquaculture systems (Pichavant et al., 2001; Abdel-Tawwab et al., 2019; Chen et al., 2025; Azevedo et al., 2026). Therefore, maintaining DO at an appropriate level is fundamental to aquaculture operations.

DO in aquaculture systems fluctuates in real time under the influence of multiple factors, including water temperature, salinity, biomass,

oxygen consumption rate, feeding activity, influent DO, and hydraulic retention characteristics (Kim and Cho, 1999; Zhou et al., 2022; Nugraha and Desnanjaya, 2025; Yu et al., 2026). Immediately after feeding, oxygen consumption can increase rapidly because of enhanced digestion and metabolic activity (Chabot et al., 2016), whereas increases in water temperature or stocking density may further accelerate DO depletion (Ananias et al., 2025; Jiang et al., 2021). In addition, even when the same amount of oxygen is supplied, the actual DO maintenance performance may vary depending on tank mixing conditions and influent–effluent hydraulics, making it difficult to precisely maintain a target concentration under field conditions (Trujillo-Rogel et al., 2025). This challenge is particularly pronounced in flow-through aquaculture systems, where continuous water inflow and discharge cause tank DO to be strongly affected by the quality and flow conditions of the incoming water. Under such conditions, excessive oxygen injection may be lost directly through the effluent, resulting in substantial oxygen waste (McLean et al., 1993; Tahar et al., 2018; Xu et al., 2023). Therefore, in

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flow-through systems, it is important to prevent hypoxia and establish a control strategy capable of maintaining DO stably within a target range.

In actual field operations, a fixed oxygen supply rate or a simple threshold-based on/off control scheme is commonly adopted because of its operational simplicity and the need to secure a safety margin (Zhou et al., 2022; Li et al., 2022). However, such approaches have limited ability to respond precisely to time-varying oxygen demand, which may cause the system to deviate from the target DO level and induce excessive oxygen supply. In addition, because on/off control operates inherently in a discrete manner, frequent switching may occur near the setpoint, and the control response may become irregular depending on variations in influent water quality or fish activity levels (Domański, 2022; Zhong et al., 2026). Therefore, to effectively cope with DO variability in flow-through aquaculture systems, it is necessary to systematically examine the applicability of feedback control approaches.

1.2. Literature review

Research on the importance of DO has long been conducted in relation to fish physiology and growth. Pichavant et al. (2001), in a comparative study on the effects of long-term hypoxia exposure in juvenile turbot and European sea bass, reported that hypoxic conditions negatively affected growth, feed intake, and oxygen consumption, with the magnitude of these effects varying by species. Tran-Duy et al. (2008) investigated the effects of DO concentration and body weight on maximum feed intake, growth, and hematological indicators in Nile tilapia, and found that reductions in DO led to decreased feed intake and growth performance, with this tendency being more pronounced in larger individuals. In addition, Chabot et al. (2016) reported that oxygen consumption can increase rapidly after feeding because of enhanced digestive and metabolic activity, and emphasized that a quantitative understanding of oxygen consumption and metabolic responses is essential for evaluating fish physiology and environmental stress. Collectively, these studies suggest that DO is not merely one of many water-quality variables, but rather a key factor that determines the productivity and health status of cultured organisms.

Meanwhile, DO has also been treated as a major variable in studies aimed at understanding the production carrying capacity and operational limitations of aquaculture systems. Colt and Orwicz (1991), in modeling the production carrying capacity of freshwater aquaculture systems, identified water-quality parameters such as DO as major factors limiting production; in particular, DO can act as a critical limiting factor in aquaculture systems. Lawson (1995), from an aquacultural engineering perspective, summarized the principles and design concepts of oxygen supply and aeration, and explained that an appropriate oxygen supply is essential for maintaining both system operational efficiency and productivity. These studies further support the view that DO management is a critical technical component in the design and operation of aquaculture systems.

More recently, with advances in sensor technologies and data-driven approaches, active research has been conducted to monitor and predict DO and overall water quality in aquaculture systems in real time (Vo et al., 2021). Lin et al. (2021) developed a wireless multi-sensor system capable of simultaneously measuring water temperature, pH, DO, and electrical conductivity, and proposed a low-cost monitoring framework for real-time collection and transmission of water-quality conditions in aquaculture farms. Elias and Ajmal (2020) proposed a hybrid DO prediction model based on aquaculture time-series data and demonstrated the potential to support DO early warning and operational decision-making through improved predictive performance compared with conventional single-model approaches. Ren et al. (2020) developed a deep belief network-based DO prediction model for a recirculating aquaculture system (RAS) and showed that it could effectively predict DO fluctuations characterized by strong nonlinearity and time-lag effects. In addition, Chen et al. (2025) proposed a two-stage hybrid model linking prediction and control, thereby suggesting the potential to

predict DO variations more precisely and incorporate such predictions into control strategies.

Along with these developments, studies on control techniques for maintaining stable DO levels have also advanced steadily. Zhou et al. (2022) combined a mechanistic DO model reflecting oxygen transfer, reaeration, and biological oxygen consumption within the system with an adaptive PID controller in an RAS. They demonstrated that DO could be maintained with high precision. Chai et al. (2024), noting that fish oxygen consumption varies according to circadian rhythms, proposed a DO model incorporating circadian rhythm analysis together with a Gain-scheduling model predictive control (GSMPC) controller, and suggested its potential for precise control and energy savings, with high goodness of fit. Moreover, Li et al. (2024) and Yu et al. (2026), through their respective reviews of recent DO prediction and control technologies in aquaculture systems, summarized that mechanistic modeling, machine learning, deep learning, intelligent control, and Internet of Things-based real-time monitoring technologies have emerged as major research directions in DO management.

Existing studies have generally focused on the physiological importance of DO itself, improving prediction accuracy, or enhancing controller performance; however, limitations remain in the applicability of real-time decision-making and operational strategies based on DO to actual aquaculture system operation. In particular, many prediction studies have primarily emphasized improvements in accuracy, whereas relatively few have directly linked prediction outcomes to actual aeration control or operational optimization in aquaculture farms. In addition, control-related studies have mainly been conducted in RAS environments, indicating the need for further examination of their generalizability and field applicability under diverse aquaculture system conditions.

1.3. Research scope and goals

The scope of this study is as follows. First, the performance of the on/off control method currently applied in an actual flow-through aquaculture farm was evaluated, and a mass-balance-based dynamic DO model was developed using water-quality and oxygen flow-rate data collected from the field. Subsequently, a time-varying oxygen consumption term was calibrated so that the model predictions were consistent with the measured DO values. Second, based on the field-acquired operational data and the calibrated oxygen consumption term, P, PI, PD, and PID controllers were simulated under identical conditions, and their performances were comparatively analyzed in terms of target DO maintenance rate, error, mean DO, deviation characteristics, and oxygen consumption, with comparisons conducted both against the on/off control method and among the P, PI, PD, and PID control strategies themselves.

In this study, our objective was to compare the DO regulation performance and oxygen-use efficiency of PID-based control strategies in a flow-through aquaculture system, and thereby evaluate which control structure is more suitable for field application. To this end, a model capable of reproducing the dynamic behavior of DO was first established using actual operational data and a mass-balance equation. Thereafter, the oxygen supply process was approximated as a first-order plus dead-time (FOPDT) system, and the controller parameters were derived using the internal model control (IMC) method. Based on these results, simulations were conducted at different control intervals to systematically compare the performances of the P, PI, PD, and PID controllers. The present study evaluates DO-regulation performance and oxygen-use characteristics only; fish growth, welfare, feed utilization, and production performance were not measured and are therefore discussed solely as biological motivation for the importance of DO management rather than as outcomes of the present study.

2. Materials and Methods

2.1. Flow-through aquaculture system

A flow-through aquaculture system is an open aquaculture system that operates by continuously pumping in water from the external environment and discharging it back out (Goo et al., 2023). The tank environment can be maintained in a relatively stable state when influent water quality remains stable, as continuous water supply in this system minimizes the accumulation of ammonia and fecal matter generated by fish metabolism (Shin et al., 2025). However, because the internal tank conditions are directly influenced by the state of the external water source (Park et al., 2025; Shin et al., 2026), this system is highly susceptible to environmental variability, and water-quality control becomes relatively difficult when the temperature and DO of the source water change rapidly. Therefore, maintaining stable water quality is essential in flow-through aquaculture systems.

2.2. Target system

The system used in this study was implemented at a flow-through aquaculture farm located in Songji-myeon, Haenam-gun, Jeollanam-do, Republic of Korea, and data were collected from one tank selected among the entire set of culture tanks. The experiment was conducted in a 40-t concrete tank (10 × 10 m; water depth, 40 cm) containing approximately 2200 fish at the time of the study (Fig. 1). Influent water was supplied following pretreatment filtration, and the system was operated at 12 turnovers per day. Liquid oxygen was used, and oxygen was delivered to the tank through an oxygen cone. A digital flow meter was installed on the oxygen supply line, allowing the supplied oxygen flow rate to be monitored in real time. The oxygen flow rate was

controlled by an on/off scheme based on the DO sensor readings in the tank, through an opening-and-closing device installed on the oxygen supply line.

2.3. Data collection and preprocessing

2.3.1. Collected variables and preprocessing

To secure the input data required for the mass-balance-based DO model and control simulations, water-quality, oxygen flow-rate, and culture-related data were collected from October 23, 2025, to November 8, 2025. The water-quality dataset included tank DO, influent DO, water temperature, and salinity, whereas the oxygen flow-rate dataset included oxygen supply rate and control status. In addition, culture and system-related information, including the number of fish, body weight, feed amount, feeding time, tank size, and turnover rate, was compiled. Missing values were corrected using linear interpolation, and outliers were detected and removed based on the interquartile range criterion. Each input variable was used for estimating the inflow and outflow terms, oxygen supply term, and oxygen consumption term in the mass-balance equation, as well as for defining disturbance inputs in the control simulations.

The collected variables were broadly classified into water-quality, oxygen-supply, and culture-related data, and each category was used for model parameterization and input construction. Table 1 summarizes the major variables used in this study.

2.3.2. Baseline operating characteristics under the existing on/off control

Analysis of the measured data showed that the mean DO concentration in the culture tank was 11.18 mg/L, with continuous fluctuations observed around the target DO of 10.0 mg/L. In this study, an allowable range of $\pm 5\%$ of the target value was adopted, and thus, 9.5–10.5 mg/L

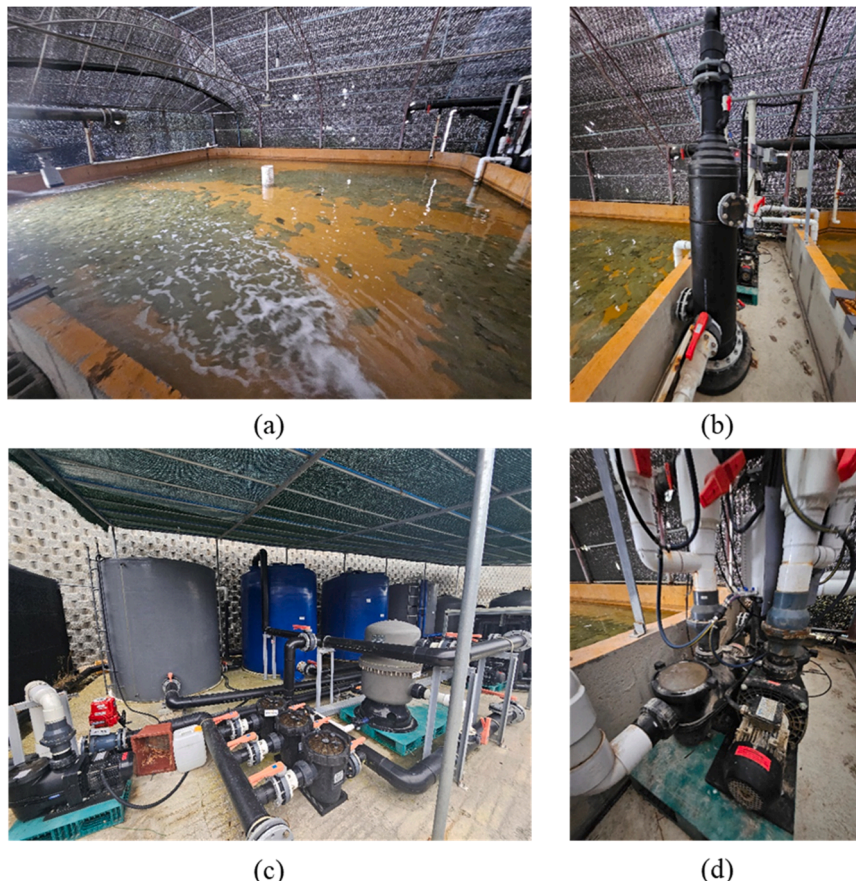


Fig. 1. Target testbed: (a) Aquaculture tank; (b) Oxygenator; (c) Circulation and filtering system; (d) Circulation pump.

Table 1
Data Types Utilized in Model Development.

Water quality data	System data	Culture-related data
Dissolved oxygen (Tank)	Oxygen flow rate	Fish number
Dissolved oxygen (Inflow)	Tank quantity	Fish weight
Temperature	Tank size	Feed amount
Salinity	Turnover rate	Feed time

was defined as the target maintenance range. The proportion of time during which the measured DO remained within this range was 21.9% over the entire observation period. In addition, the measured DO repeatedly decreased to approximately 9 mg/L and increased to above 13 mg/L.

From the perspective of oxygen supply, the baseline oxygen supply rate was 7.72 L/min. These operational data reflect DO variability and oxygen-supply characteristics formed under actual field conditions, and were subsequently used as baseline data for inverse estimation of the oxygen consumption term and for comparative evaluation of controller performance. Fig. 2 presents the results describing the actual DO behavior observed in the testbed.

During the observation period, water temperature ranged from 17.66 to 22.11 °C, while salinity was approximately 35 ppt. Based on the temperature- and salinity-dependent oxygen-solubility relationship (Garcia and Gordon, 1992), the corresponding dissolved oxygen concentration at equilibrium with atmospheric air was approximately 7.12–7.73 mg/L. Therefore, the 10 mg/L control setpoint corresponded to approximately 129–140% of air-equilibrium saturation and represented a supersaturated condition. However, the investigated facility supplied liquid oxygen through an oxygen cone rather than relying solely on conventional air aeration. Thus, DO concentrations above air-equilibrium saturation were operationally achievable. This was also supported by the field measurements, in which the mean tank DO was 11.18 mg/L and DO repeatedly exceeded 13 mg/L. Nevertheless, the existing on/off control maintained DO within the 9.5–10.5 mg/L target band for only 21.9% of the observation period, indicating that the principal limitation was stable maintenance of the target rather than its physical attainability.

2.4. Predicting fish oxygen consumption

2.4.1. Mass balance equation for dissolved oxygen

A dynamic model capable of describing how DO in the culture tank varies over time is required to perform oxygen control simulations. The DO dynamics in the tank are primarily determined by the oxygen supplied to the system, the oxygen consumed within the tank, and the concentration difference between the influent water and the tank water DO (Khater et al., 2021). Accordingly, this study employed a mass-balance equation based on the continuous stirred-tank reactor (CSTR) concept. The CSTR equation represents the system using a single spatially uniform concentration under the assumption of complete

mixing (Arratia et al., 2004). For this reason, the CSTR framework is intuitive and well-suited for describing the mixed DO behavior observed in actual aquaculture tanks. A mass-balance equation establishes the relationship among the amount entering the system, the amount leaving the system, the amount accumulated within the system, and the amount generated or consumed. In this context, the mass-balance concept provides a useful framework for incorporating inflow and outflow processes, thereby allowing DO variation in actual aquaculture tanks to be interpreted as a function of influent and effluent flow rates. Accordingly, previous studies have also applied mass-balance equations to dynamic DO models while incorporating oxygen consumption as a time-varying term (Royer et al., 2021; Zhou et al., 2022; Chai et al., 2024). The equation describing DO behavior based on the mass-balance framework is given as follows.

$$\frac{dDO}{dt} = \frac{O_{\text{sup}}(t) - O_{\text{con}}(t)}{V} + k_{\text{ex}}(t)(DO_{\text{in}}(t) - DO(t)) \quad (1)$$

The temporal variation of DO in the culture tank can be described as the sum of two major components: the net oxygen input within a tank of volume (V), represented by the difference between the oxygen supply rate to the tank (O_{sup}), and the oxygen consumption rate within the tank (O_{con}), and the exchange term between the current tank DO concentration ($DO(t)$), and the DO concentration of the external influent water ($DO_{\text{in}}(t)$), governed by a time-varying DO exchange-rate constant ($k_{\text{ex}}(t)$). Based on these components, the resulting equation constitutes a dynamic model that describes the temporal rate of change in DO ($\frac{dDO}{dt}$).

2.4.2. Derivation of fish oxygen consumption from measured DO profiles

To use the consumption term as a disturbance input in the control simulations, the time-varying oxygen consumption rate was inversely estimated from the measured DO time series and the mass-balance equation. Specifically, the inflow, outflow, and oxygen supply terms in the mass-balance equation were first calculated using the tank volume, influent DO, oxygen supply rate, and turnover-rate data. The equation was then rearranged with respect to the consumption term to estimate the oxygen consumption rate on a minute-by-minute basis. In other words, the oxygen consumption term used in this study was not derived through a simple theoretical application, but rather through a calibration process in which the consumption term was adjusted so that the model predictions were consistent with the measured DO values. The resulting time-varying consumption term was subsequently used as a disturbance input in the control simulations to represent the oxygen demand in the tank.

To avoid circular validation arising from the use of the same measured DO data for both model calibration and evaluation, the complete dataset was chronologically divided into an identification period (October 23–November 3, 2025) and a held-out validation period (November 4–8, 2025). The mass-balance model was implemented using the actual operating condition of 12 water turnovers per day.

The time-varying oxygen-demand term was reconstructed using only the identification-period data. The reconstructed demand was subsequently represented using a 24-h periodic model,

$$r_{\text{base}}(t) = 0.09238 - 0.00341 \sin\left(\frac{2\pi h}{24}\right) - 2.00213 \cos\left(\frac{2\pi h}{24}\right) \quad (2)$$

where h denotes the hour of day. The coefficients of this model were fixed before application to the held-out validation period. No Tank DO measurement from the validation period was used to re-estimate or recalibrate the oxygen-demand term. During validation, measured influent DO, temperature, salinity, and oxygen-supply conditions were used as exogenous operating inputs, whereas measured Tank DO was reserved exclusively for evaluating model prediction accuracy.

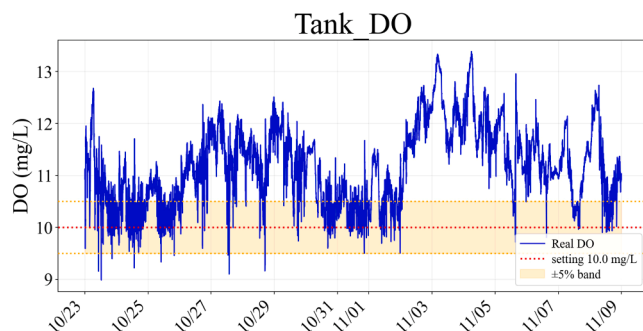


Fig. 2. DO variation in the testbed tank.

2.5. PID control

PID control is a representative feedback control technique that combines proportional, integral, and derivative actions to minimize the error between the setpoint and the measured value. A PID controller can substantially improve the response speed, steady-state accuracy, and stability of the controlled system by simultaneously determining the output based on the magnitude of the current error, the accumulated value of past errors, and the rate of change in error. The equations corresponding to each component of the PID control structure are as follows (Borase et al., 2021).

$$u(t) = K_p e(t) + K_i \int e(t) dt + K_d \frac{de(t)}{dt} \quad (3)$$

where, $u(t)$ denotes the control output, which in this study corresponds to the output generated by the PID controller.

$$P = K_p e(t) \quad (4)$$

$$PI = K_p e(t) + K_i \int e(t) dt \quad (5)$$

$$PD = K_p e(t) + K_d \frac{de(t)}{dt} \quad (6)$$

The equations for the P, PI, and PD control structures are as follows. The parameter K_p represents the proportional gain, K_i the integral gain, and K_d the derivative gain (Goud et al., 2025). Proportional control generates a control input in proportion to the current error, and therefore has the advantages of rapid response and structural simplicity. However, proportional control alone may not eliminate steady-state error. Integral control reflects the accumulated error over time, making it effective in removing residual error and improving steady-state performance. In contrast, excessive integral action may increase overshoot and oscillation. Derivative control considers the rate of change of the error and thus responds preemptively to future error trends, which is advantageous for mitigating transient responses and enhancing system stability. However, it is also limited by its sensitivity to measurement noise. For this reason, PID control has been widely applied in various fields, including industrial processes, motor control, temperature regulation, and water-quality control, because it can simultaneously achieve fast response characteristics, reduced steady-state error, and suppression of oscillation (Zhao et al., 2025). Nevertheless, because control performance strongly depends on the settings of the proportional, integral, and derivative gains, parameter tuning appropriate to the characteristics of the target system is essential.

2.5.1. FOPDT with IMC tuning

DO in the culture tank does not change immediately upon the application of control action, but rather responds after a certain time delay. In addition, the dissolution of supplied oxygen into the tank water is not linear but nonlinear, and this behavior varies depending on water temperature and salinity. The objective of the present model is not simply to achieve rapid tracking of the setpoint, but rather to maintain DO stably within a target range while suppressing excessive fluctuations in oxygen flow rate. Therefore, a tuning method capable of ensuring stable regulation was required. The IMC tuning method was considered suitable for this system because it can simultaneously reflect process delay and the desired response speed, making it appropriate for applications in which stable DO maintenance is more important than rapid tracking. Accordingly, IMC was selected for controller tuning, as it explicitly accounts for both the process model and time delay, and allows the control tendency to be adjusted conservatively through the parameter λ , thereby facilitating stable control implementation. In addition, the same IMC-based tuning framework was applied consistently to all controller structures so that the comparison focused on differences among the P, PI, PD, and PID control structures rather than

on differences arising from the tuning methodology.

The most distinctive feature of IMC-based tuning is that the process is first represented by a simplified dynamic model, and the controller is then designed on the basis of that model (Zhao et al., 2011; Schwenzer et al., 2021). In general, the process is approximated by an FOPDT model characterized by process gain (K), time constant (τ), and dead time (θ), and an additional parameter (λ), representing the desired response speed, is specified to adjust the aggressiveness or conservativeness of the controller. In other words, IMC provides a framework in which the designer can directly determine the speed at which the system follows the target. When a larger λ is selected, the response becomes somewhat slower, but stability and robustness are improved; in contrast, when a smaller λ is used, the controller responds more rapidly, although the risk of oscillation and overshoot increases. Thus, unlike empirical approaches that rely on repeatedly increasing gains through trial and error, IMC offers the advantage of enabling the gains K_p , K_i , and K_d to be determined in a relatively systematic manner by reflecting both the dynamic characteristics of the process and the control objective. The IMC tuning procedure consists of identifying the process as an FOPDT model to estimate K , τ , and θ , and then substituting these values into the IMC tuning equations to calculate K_p , K_i , and K_d . The FOPDT model used for IMC tuning is given as follows (Arya & Chakrabarty, 2022).

$$G(s) = \frac{Ke^{-\theta s}}{\tau s + 1} \quad (7)$$

In Eq. (7), θ represents the effective input–output dead time of the oxygen-supply process. Based on the open-loop step-response analysis, the dead time was determined to be 5 min. With $K = 0.383$, $\tau = 121$ min, and $\theta = 5$ min, the identified FOPDT model was expressed as

$$G(s) = \frac{0.383e^{-5s}}{121s + 1}$$

The dynamic characteristics of the oxygen-supply process were approximated using an FOPDT model incorporating first-order lag behavior and dead time. The FOPDT parameters were identified through a numerical open-loop step-response test conducted using the model-based oxygen-supply process. During this identification test, the on/off feedback controller was not active, and the oxygen-supply input was imposed directly on the model.

The physical oxygen-supply input was stepped from 0 to 22 L/min. For FOPDT identification, the manipulated input u was normalized by the available oxygen-supply capacity, such that 0 L/min corresponded to $u = 0$ and 22 L/min corresponded to $u = 1$. Thus, the applied full-scale step was $u: 0 \rightarrow 1$, corresponding equivalently to 0–100% of the available oxygen-supply capacity, and $\Delta u = 1$ was used in the process-gain calculation. Tank DO concentration (mg/L) was used as the process output, and the numerical response was evaluated at 1-min intervals under the actual operating condition of 12 water turnovers per day.

The process gain was calculated as $K = \Delta y / \Delta u$, where Δy represents the change in Tank DO between the initial and final response levels. Because the input was expressed in the dimensionless 0–1 normalized form, the process gain is expressed as mg/L per unit normalized input. The dead time, θ , was determined as the elapsed time between application of the input step and the onset of the DO response, whereas the time constant, τ , was determined as the time required, after the dead time, for the response to reach 63.2% of its final change. This procedure yielded $K = 0.383$ mg/L per unit normalized input, $\tau = 121$ min, and $\theta = 5$ min. To avoid implying excessive precision, the process gain is reported as $K = 0.383$ mg/L per unit normalized input, while the full numerical value was retained for the controller-tuning calculations. Because the FOPDT identification was based on a single numerical step-response analysis rather than repeated independent step tests, between-test variability and confidence intervals for K , τ , and θ could not be estimated. Accordingly, these parameters are reported with limited numerical precision and should be interpreted as nominal parameters

used for the local FOPDT approximation and IMC controller tuning.

It should be emphasized that the FOPDT representation was used only as a local input–output approximation for IMC controller tuning and was not used as a separate closed-loop simulation plant. The closed-loop simulations were performed using the mass-balance model in Eq. (1), together with the explicitly modeled oxygen-supply actuator dynamics and measurement delay. In this context, K represents the steady-state sensitivity of tank DO to the manipulated oxygen-supply input, τ represents the dominant dynamic response associated with oxygen transfer and tank mixing, and θ represents the effective delay between an input change and the observable DO response.

2.5.2. Determination of controller gains

To avoid selecting and evaluating the controller tuning parameter on the same dataset, the complete dataset was divided chronologically into an identification period and a held-out validation period. The identification period covered October 23 through November 3, 2025, whereas November 4 through November 8, 2025 was reserved exclusively for validation.

For each controller structure, the IMC tuning parameter was expressed in normalized form as

$$\lambda_{\text{norm}} = \frac{\lambda}{\tau + \theta} \quad (8)$$

Candidate λ values were evaluated using only the identification dataset under the 1-min controller update condition. A coarse search was first conducted over normalized λ values from 0.005 to 0.300 at increments of 0.005. A subsequent local search was performed within ± 0.005 of the best coarse candidate using increments of 0.001. Candidate values were ranked by maximizing the percentage of time for which DO remained within the $\pm 5\%$ target band (9.5–10.5 mg/L). RMSE was used as the secondary criterion, and the larger λ was selected if an exact tie remained.

After the optimal λ was selected for each controller structure, the corresponding controller gains were calculated using the IMC equations. The resulting λ and controller gains were then fixed before the validation analysis and were not retuned using the validation dataset.

Based on the selected λ , the corresponding IMC tuning equations for each controller structure are given as follows

$$K_p = \frac{\tau + 0.5\theta}{K(\lambda + 0.5\theta)} \quad (9)$$

$$K_i = \frac{K_p}{T_i} \quad (10)$$

$$K_d = K_p T_d \quad (11)$$

At this point,

$$T_i = \tau + 0.5\theta \quad (12)$$

$$T_d = \frac{\tau\theta}{2\tau + \theta} \quad (13)$$

Given the derived values, the equation is as follows:

$$T_i = 123.5 \quad (14)$$

$$T_d \approx 2.4494 \quad (15)$$

Table 2 presents the final K_p , K_i , and K_d values obtained for each control method.

2.5.3. Performance evaluation under different control intervals

In this study, the performances of the P, PI, PD, and PID controllers were comparatively evaluated under different control intervals of 1, 10, 20, 30, and 60 min to enable a more comprehensive assessment of their control characteristics. This approach was adopted because the response

Table 2

P, PI, PD, and PID Components (values are reported as used in simulation).

	P	PI	PD	PID
Kp	71.314936	41.331911	80.273742	43.439203
Ki	-	0.334671	-	0.351734
Kd	-	-	196.621918	106.399668
Normalized lambda(λ)	0.016	0.042	0.012	0.039
Lambda(λ)	2.016	5.292	1.512	4.914

characteristics of the controllers and their ability to compensate for accumulated error may differ substantially between shorter and longer control intervals. All evaluations were conducted based on a target DO of 10 mg/L and an allowable range of $\pm 5\%$ (9.5–10.5 mg/L). The controller-performance evaluation was distinct from the predictive validation of the mass-balance model. The P, PI, PD, and PID controllers were not evaluated according to their ability to reproduce the measured Tank DO trajectory. Instead, controller performance was evaluated relative to the prescribed DO setpoint of 10.0 mg/L and the acceptable range of $\pm 5\%$ (9.5–10.5 mg/L).

Accordingly, all tracking-error metrics were calculated from the deviation between simulated DO and the prescribed setpoint over the common held-out validation period. Measured Tank DO from the validation period was used exclusively to assess the predictive validity of the mass-balance model and was not used as the reference trajectory for controller-performance calculations.

The controller update interval, T_s , was set to 1, 10, 20, 30, or 60 min. To ensure a consistent discrete-time implementation across these intervals, the integral and derivative actions were explicitly scaled by T_s . For PI and PID control, the integral state was updated as

$$I_k = I_{k-1} + K_i e_k T_s \quad (16)$$

where e_k is the control error at the k -th controller update. For PD and PID control, the derivative term was calculated from the measured DO rather than from the error:

$$D_k = -K_d (y_k - y_{k-1}) / T_s \quad (17)$$

thereby avoiding derivative kick associated with abrupt setpoint changes. The controller output calculated at each update instant was held constant until the next update using a zero-order hold. In contrast, the actuator dynamics, the effective 5-min input–output delay represented by θ , and the mass-balance-based plant dynamics were numerically updated at a fixed 1-min simulation step. Anti-windup was applied only to controllers containing integral action (PI and PID), whereas P and PD controllers did not retain an integral state.

Because the identified process time constant was 121 min, the ratio between the controller update interval and the process dynamics became increasingly unfavorable as T_s increased. In particular, a 60-min update interval corresponds to only approximately two controller updates per process time constant. Therefore, the long-interval cases were interpreted not only in terms of controller structure but also in terms of the influence of sparse controller updating and zero-order-hold behavior.

Control performance was quantified using the within-band percentage, integral absolute error (IAE), mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE). With $e_k = SP - y_k$, these metrics were calculated as $IAE = \sum |e_k| \Delta t$, $MAE = N^{-1} \sum |e_k|$, $MAPE = 100N^{-1} \sum \left| \frac{e_k}{SP} \right|$, and $RMSE = [N^{-1} \sum e_k^2]^{1/2}$. The within-band percentage was defined as the proportion of samples satisfying $9.5 \leq DO \leq 10.5$ mg/L. These control-error metrics were calculated over the same complete held-out validation period using a common 1-min numerical simulation grid for all controllers and update intervals. Mean DO, DO standard deviation, and upper- and lower-band excursions were used as stability metrics, whereas total injected oxygen, daily injected oxygen, and mean oxygen flow rate were used to char-

acterize oxygen use. To account for temporal dependence in the validation time series and to quantify uncertainty in the reported controller-performance metrics, a moving-block bootstrap analysis was performed. Consecutive 120-min blocks were resampled with replacement to generate 1000 bootstrap replicates for each controller structure and update interval. For each bootstrap replicate, the within-band percentage and RMSE were recalculated. The 2.5th and 97.5th percentiles of the bootstrap distributions were used as the 95% confidence intervals.

3. Results and discussion

3.1. Independent validation of the mass-balance DO model

The predictive validity of the calibrated mass-balance model was evaluated using the held-out period from November 4 to November 8, 2025. For the continuous free-running validation, only the first measured Tank DO value at the beginning of the validation period was used to initialize the model state. Subsequent measured Tank DO values were not used to correct the simulated state or to recalibrate the oxygen-demand term.

Over the full 5-day free-running validation period, the model achieved an MAE of 0.452 mg/L, an RMSE of 0.570 mg/L, a mean prediction bias of -0.258 mg/L, and an R^2 of 0.283. The correlation coefficient between the measured and predicted DO trajectories was 0.657.

These results indicate that the calibrated mass-balance model retained useful short-term predictive capability on data not used for model identification. However, relatively large deviations were observed during some periods, particularly when the measured DO exhibited rapid fluctuations, whereas the predicted DO trajectory remained comparatively smooth. The oxygen-demand term used for validation was represented by a fixed 24-h periodic function derived from the identification period. Therefore, it could reproduce the average daily pattern but could not fully represent irregular short-term disturbances during the validation period. Such disturbances may include feeding-related changes in fish activity and metabolic oxygen demand, temporary variations in influent or hydraulic conditions, local mixing effects around the DO sensor, and short-term changes in oxygen-supply effectiveness. Because detailed event-level operational records were not available for all deviation periods, these factors could not be individually verified and should be regarded as plausible explanations rather than confirmed causes. Accordingly, the discrepancies in Fig. 3 demonstrate a limitation of the fixed periodic oxygen-demand model in reproducing non-periodic field disturbances. The model was therefore used primarily as a common simulation framework for comparative controller evaluation, and its multi-day predictive limitations were considered when interpreting the controller results. Fig. 3 compares the

measured and predicted DO trajectories during the held-out validation period.

3.2. Comparison of P, PI, PD, and PID controllers

In this section, the DO control performances of the P, PI, PD, and PID controllers were compared from three perspectives: control performance, stability and deviation characteristics, and oxygen-use characteristics. At the 1-min update interval, all PID-based controller structures showed improved target-band maintenance compared with the conventional on/off control, while PI and PID provided the lowest tracking errors.

3.2.1. Control performance

Under held-out validation, a clear difference in control performance was observed as the controller update interval increased. At the 1-min interval, all controller structures maintained DO within the $\pm 5\%$ target band for most of the validation period, with within-band percentages of 99.04%, 100.00%, 99.63%, and 100.00% for P, PI, PD, and PID, respectively. However, the tracking errors of PI and PID were substantially lower than those of P and PD. The RMSE values were 0.438 mg/L for P and 0.390 mg/L for PD, compared with only 0.024 mg/L for PI and 0.023 mg/L for PID.

The influence of controller structure became more pronounced at moderate update intervals. At 10 min, the within-band percentages of P and PD decreased to 42.31% and 46.33%, respectively, whereas PI and PID both maintained 100%. At 20 min, P and PD further decreased to 25.86% and 26.13%, whereas PI and PID continued to maintain 100% of the simulated DO within the target band.

A marked deterioration occurred when the controller update interval increased to 30 min. The within-band percentage fell to 16.90%, 19.03%, 16.86%, and 18.60% for P, PI, PD, and PID, respectively. At 60 min, all four controller structures showed poor target-band maintenance, ranging from 9.43% to 10.67%. Correspondingly, RMSE increased to approximately 3.44–3.53 mg/L across all controllers.

These results indicate that integral action provided a clear advantage at update intervals up to 20 min; however, at 30 and 60 min, sparse controller updating became the dominant limitation, substantially reducing the differences among controller structures.

Table 3 and Figs. 4–7 present the control performance of the P, PI, PD, and PID controllers during the held-out validation period. Moving-block bootstrap analysis showed that the clear performance separation between controllers with and without integral action was maintained at moderate update intervals. In contrast, the confidence intervals of PI and PID largely overlapped, indicating that their small numerical differences should not be interpreted as evidence of statistically established

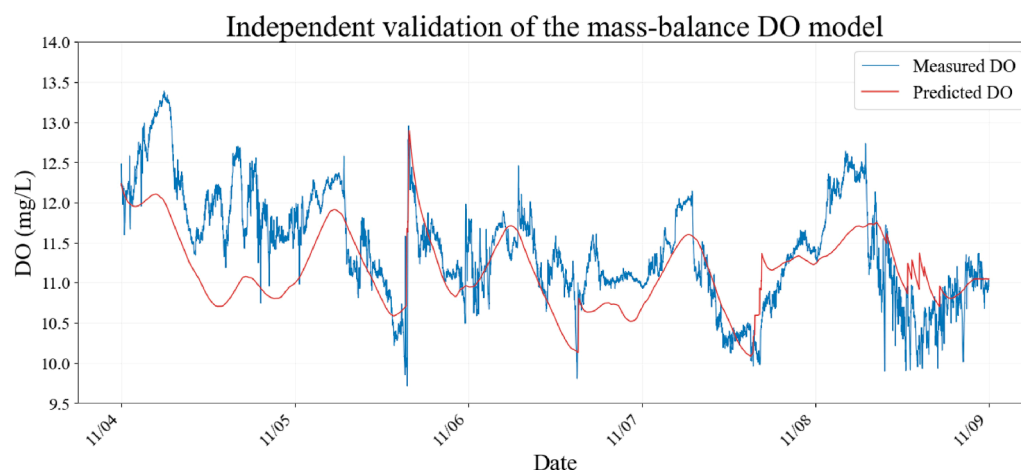


Fig. 3. Comparison of measured and predicted DO during the held-out validation period.

Table 3
Control performance of P, PI, PD, and PID controllers.

Control	Interval (min)	Within-band (%)	IAE (mg/L-min)	MAE (mg/L)	MAPE (%)	RMSE (mg/L)
P	1	99.04	3138.56	0.436	4.359	0.438
	10	42.31	4456.87	0.619	6.190	0.720
	20	25.86	7057.35	0.980	9.802	1.141
	30	16.90	11149.14	1.548	15.485	1.819
	60	9.43	21271.15	2.954	29.543	3.530
PI	1	100.00	156.34	0.022	0.217	0.024
	10	100.00	158.14	0.022	0.220	0.026
	20	100.00	170.72	0.024	0.237	0.029
	30	19.03	10600.63	1.472	14.723	1.741
	60	10.18	20887.72	2.901	29.011	3.491
PD	1	99.63	2798.98	0.389	3.887	0.390
	10	46.33	3764.67	0.523	5.229	0.598
	20	26.13	7160.91	0.995	9.946	1.166
	30	16.86	11296.33	1.569	15.689	1.852
	60	10.36	20812.27	2.891	28.906	3.513
PID	1	100.00	151.69	0.021	0.211	0.023
	10	100.00	156.71	0.022	0.218	0.026
	20	100.00	202.86	0.028	0.282	0.036
	30	18.60	10781.87	1.497	14.975	1.769
	60	10.67	20344.80	2.826	28.257	3.444

superiority. Detailed 95% confidence intervals are provided in [Supplementary Table S1](#).

3.2.2. Stability and excursion characteristics

The stability characteristics showed a similar transition with increasing controller update interval. At 1–20 min, the PI and PID controllers maintained mean DO values essentially equal to the 10 mg/L setpoint, ranging from 9.998 to 10.001 mg/L, with standard deviations no greater than 0.036 mg/L. In contrast, the variability of P and PD increased substantially as the update interval increased; at 20 min, their standard deviations reached 1.129 and 1.162 mg/L, respectively.

At the 30-min interval, the standard deviation increased markedly for all controller structures, reaching 1.789, 1.717, 1.806, and 1.740 mg/L for P, PI, PD, and PID, respectively. At 60 min, the values further increased to approximately 3.29–3.43 mg/L. Mean DO also shifted above the target, with values of 10.846, 10.890, 11.038, and 11.008 mg/L for P, PI, PD, and PID, respectively.

Upper- and lower-band excursions also increased sharply at long update intervals. Whereas PI and PID exhibited no excursion outside the target band at 1–20 min, all controller structures showed substantial excursions at 30 and 60 min. These findings confirm that the control stability achieved at short and moderate update intervals was lost when controller updates became excessively sparse.

[Table 4](#) and [Figs. 8 and 9](#) illustrate the stability and excursion characteristics.

3.2.3. Oxygen-use efficiency

Oxygen consumption showed a comparatively smaller variation among controller structures than did DO-control performance. Under the 1-min interval, the daily injected oxygen amounts were 12.23, 12.70, 12.28, and 12.70 kg/day for P, PI, PD, and PID, respectively. Although P and PD consumed slightly less oxygen than PI and PID, their tracking errors were considerably larger, particularly when RMSE and mean DO were considered.

As the controller update interval increased, oxygen use generally increased for all controller structures. At 60 min, daily oxygen consumption reached 13.51 kg/day for P, 13.78 kg/day for PI, 13.93 kg/day for PD, and 13.69 kg/day for PID. The corresponding mean oxygen flow rates ranged from 7.553 to 7.788 L/min.

These results indicate that oxygen-use efficiency should not be interpreted solely on the basis of the amount of oxygen injected. Rather, oxygen consumption should be considered together with the achieved DO-control quality. In this respect, PI and PID provided substantially better control quality at 1–20 min while requiring oxygen input of a magnitude comparable to that of P and PD.

[Table 5](#) and [Figs. 10 and 11](#) present the oxygen-use characteristics of the four controller structures.

3.3. Discussion

PI and PID exhibited a clear performance advantage over P and PD at update intervals of 1–20 min. However, these differences narrowed markedly at 30 and 60 min as sparse controller updating became the dominant limitation. PI and PID showed similarly favorable control performance under the evaluated conditions. The small numerical differences between the two controller structures were not considered

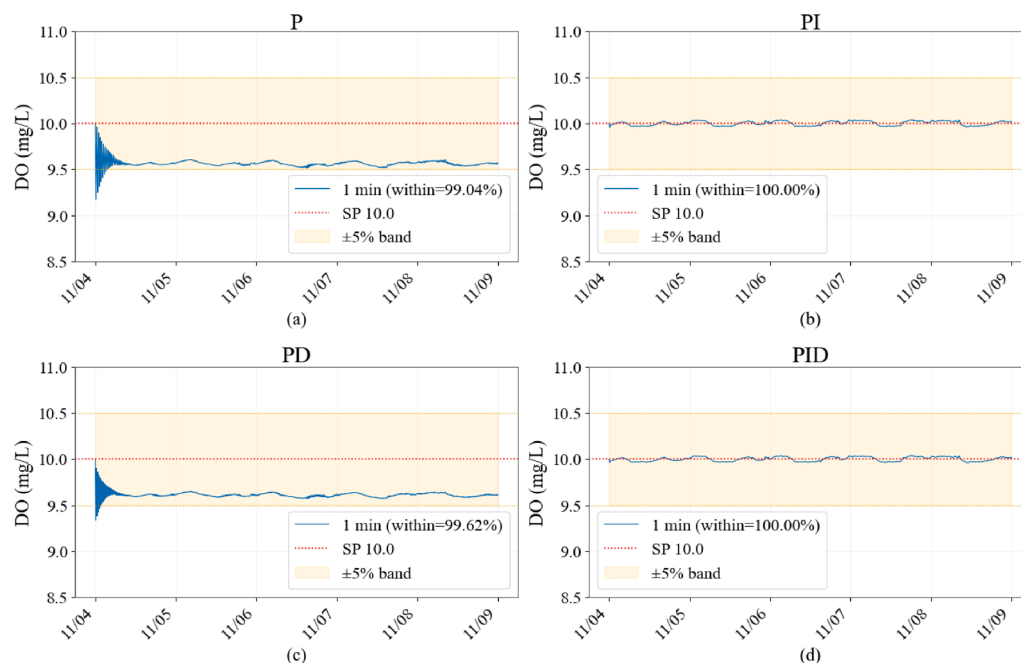


Fig. 4. DO comparison by control period (1 min): (a) P; (b) PI; (c) PD; (d) PID.

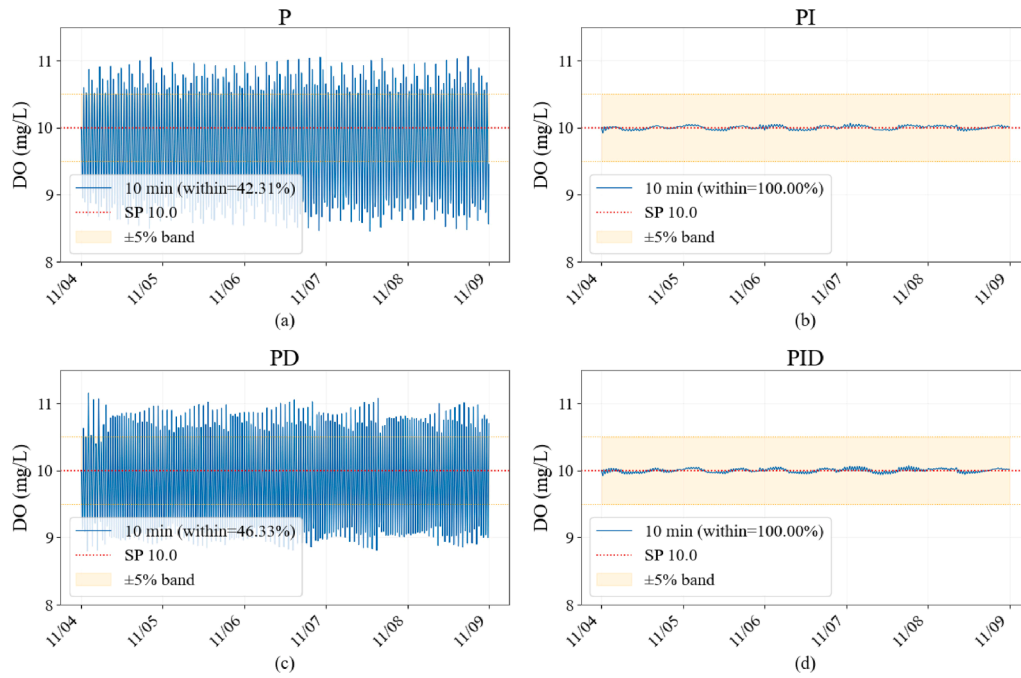


Fig. 5. DO comparison by control period (10 min): (a) P; (b) PI; (c) PD; (d) PID.

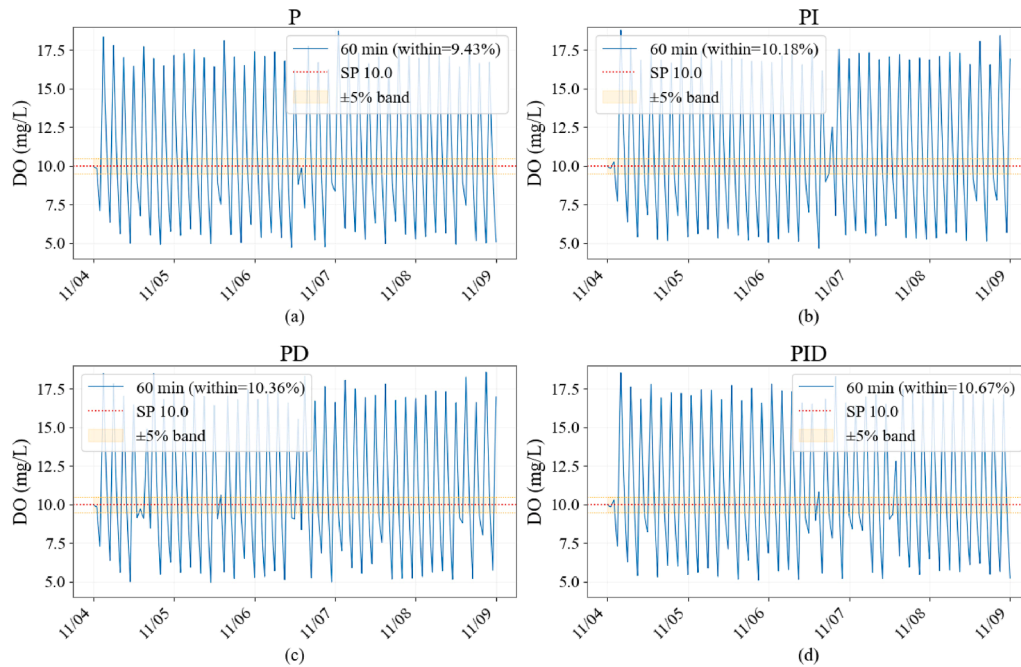


Fig. 6. DO comparison by control period (60 min): (a) P; (b) PI; (c) PD; (d) PID.

sufficient to establish the general superiority of either PI or PID. These results therefore suggest that the inclusion of integral action, rather than the additional derivative term itself, was the principal factor contributing to improved DO regulation.

At update intervals of 1–20 min, PI and PID showed substantially lower tracking errors than P and PD, demonstrating the benefit of integral action under adequately sampled control conditions. However, when the update interval increased to 30 and 60 min, the performance of all controller structures deteriorated markedly and the differences among controller structures became considerably smaller. The upward shift in mean DO observed under these coarse update conditions should

therefore not be attributed to error accumulation in proportional control alone. Rather, the one-sided oxygen-supply actuator, which can add but cannot actively remove oxygen, combined with long zero-order-hold intervals, caused previously calculated oxygen commands to remain active even after DO approached or crossed the setpoint. These results indicate that sparse controller updating became a dominant limitation at long update intervals, partially overriding the advantages associated with controller structure. The oxygen-supply actuator was one-sided and constrained to 0–22 L/min; therefore, oxygen could be added but could not be actively removed. When this constraint was combined with long zero-order-hold intervals, controller commands frequently reached the

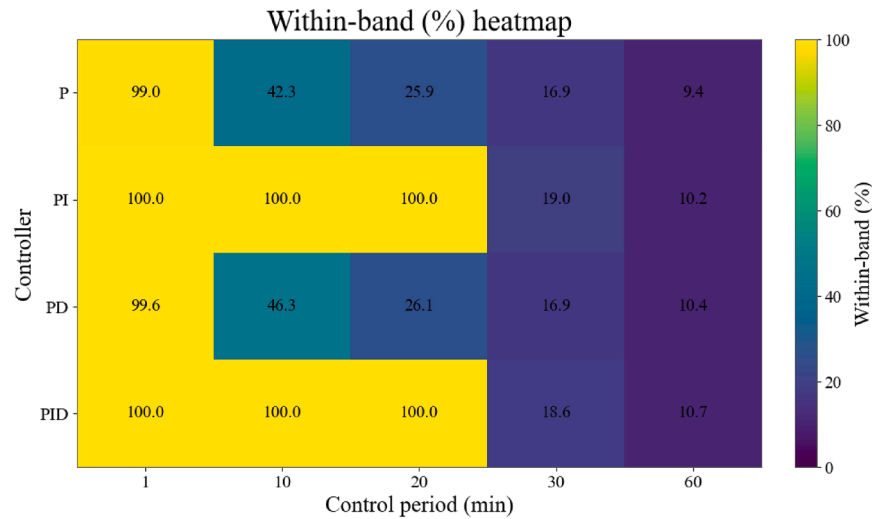


Fig. 7. Within-band heatmap for P, PI, PD, and PID controllers.

Table 4

Stability and excursion of P, PI, PD, and PID controllers.

Control	Interval (min)	Upper-band excursion (mg/L)	Lower-band excursion (mg/L)	Mean DO (mg/L)	Std DO (mg/L)
P	1	0.000	0.328	9.564	0.038
	10	0.562	1.043	9.709	0.658
	20	1.781	1.988	9.836	1.129
	30	3.577	2.879	10.331	1.789
	60	8.230	4.770	10.846	3.428
PI	1	0.000	0.000	10.001	0.024
	10	0.000	0.000	10.000	0.026
	20	0.000	0.000	9.998	0.029
	30	3.348	2.591	10.284	1.717
	60	8.267	4.826	10.890	3.376
PD	1	0.000	0.165	9.611	0.028
	10	0.654	0.705	9.832	0.574
	20	2.219	1.978	10.093	1.162
	30	3.913	2.676	10.410	1.806
	60	8.058	4.538	11.038	3.356
PID	1	0.000	0.000	10.000	0.023
	10	0.000	0.000	9.999	0.026
	20	0.000	0.000	9.999	0.036
	30	3.669	2.527	10.325	1.740
	60	8.019	4.415	11.008	3.293

lower and upper actuator limits. This asymmetric saturation behavior, together with sparse controller updating, explains the positive shift in mean DO observed at long update intervals. This appears to be closely related to the fact that, unlike variables such as flow rate that change more instantaneously (Park et al., 2025), DO in aquaculture systems is a state variable formed through the temporal accumulation of influent water conditions, oxygen supply, and biological oxygen consumption. In particular, because flow-through systems are characterized by continuous inflow and outflow, disturbances are persistently imposed on the system, and part of the supplied oxygen may be immediately lost through discharge. Under such conditions, proportional or proportional-derivative control alone is insufficient to adequately eliminate persistent deviations arising under long control intervals. At update intervals of 1–20 min, PI and PID control benefited from integral action and maintained DO more stably around the target (Borase et al., 2021). However, at 30- and 60-min update intervals, sparse updating and actuator constraints became dominant limitations, substantially reducing this advantage.

These findings are consistent in direction with the results of Zhou et al. (2022), who reported high DO control precision in an RAS

environment using adaptive PID control, and they also share a similar context with the recent work of [Chai et al. \(2024\)](#), who presented precise DO control based on GSMPC. However, whereas previous studies have mainly focused on RAS environments or advanced control techniques, the present study provides a more fundamental benchmark for field application by comparatively evaluating the relative performances of basic PID structures under actual operating conditions in a flow-through aquaculture system. Furthermore, the limited performance difference observed between the PI and PID controllers suggests that, in actual field settings, PI control may also serve as a sufficiently practical alternative when tuning burden and implementation complexity are taken into consideration. [Table 6](#) summarizes the comparative performance of the on/off control method and the P, PD, PI, and PID controllers. For direct comparison, the on/off control metrics in [Table 6](#) were recalculated over the same held-out validation period used for the PID-based controller evaluations.

4. Limitations and future work

4.1. Practical scope of the PID-based comparison

This study compared the P, PI, PD, and PID controllers to evaluate which basic feedback characteristics are more suitable for DO control in flow-through aquaculture systems. PID control is a classical feedback control method that has been used for a relatively long time. Nevertheless, it offers several practical advantages, including a simple structure, relatively low computational burden, and ease of implementation, as it can be readily applied when only an input signal derived from sensors and an output signal linked to a control device are available, without requiring high-performance computing hardware or the introduction of highly complex system architectures ([Joseph et al., 2022](#); [Çelik et al., 2026](#)). For this reason, although many advanced feedback control mechanisms have since been developed ([Brogliato and Lozano, 1994](#); [Grimm et al., 2007](#); [Kaloust and Qu, 1997](#); [Lazar and Heemels, 2009](#); [Mayne et al., 2006](#)), PID-based control remains an appropriate baseline for examining field applicability in actual aquaculture operations because of its relatively low operational complexity. In particular, when field conditions are considered—such as limited sensor infrastructure, simple hardware configuration, ease of maintenance, and the operator's ability to intuitively adjust controller parameters—a PID-based comparison carries substantial practical significance. The performance of PID-based controllers can also depend on the tuning method used to determine the controller gains. In the present study, IMC-based tuning was consistently applied to all controller structures

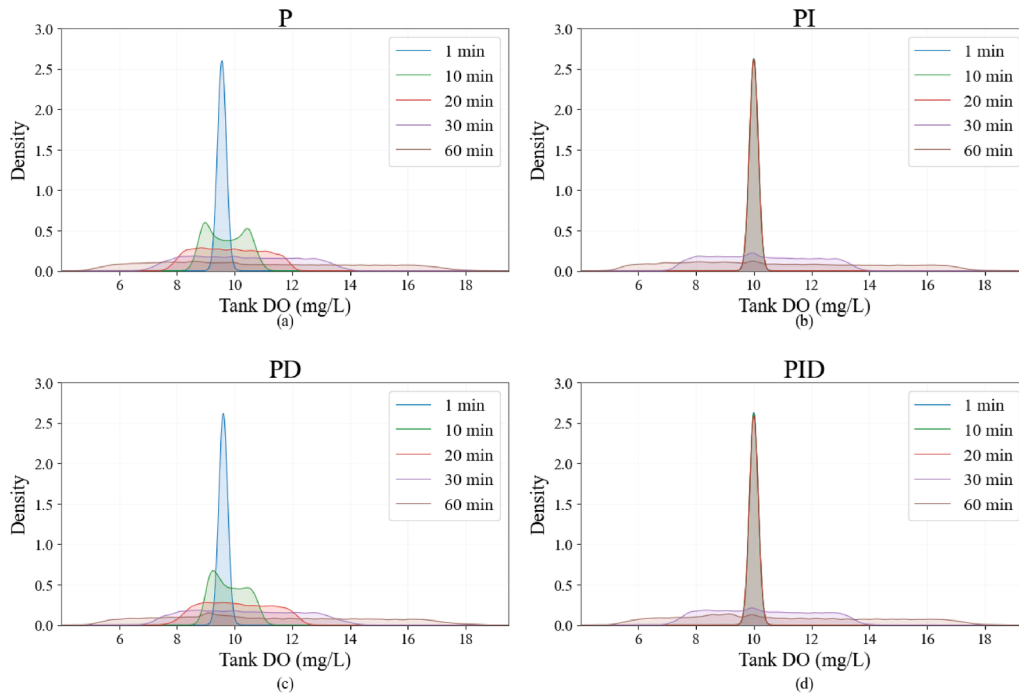


Fig. 8. Tank DO distribution of P, PI, PD, and PID controllers: (a) P; (b) PI; (c) PD; (d) PID.

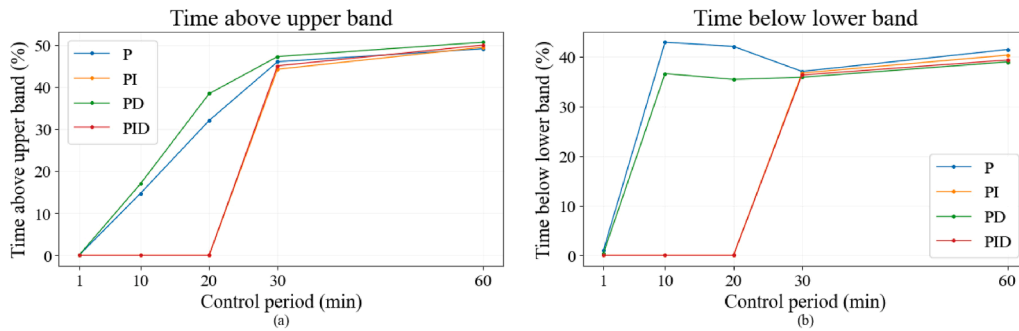


Fig. 9. Time above upper band and Time below lower band by control period: (a) Time above upper band; (b) Time below lower band.

Table 5
Oxygen-use metrics of P, PI, PD, and PID controllers.

Control	Interval (min)	Total injected O ₂ (kg)	Daily injected O ₂ (kg/day)	Mean O ₂ flow (LPM)
P	1	61.14	12.23	6.834
	10	61.91	12.38	6.921
	20	62.80	12.56	7.020
	30	65.57	13.11	7.329
	60	67.57	13.51	7.553
PI	1	63.51	12.70	7.099
	10	63.50	12.70	7.099
	20	63.49	12.70	7.097
	30	65.32	13.06	7.302
	60	68.88	13.78	7.699
PD	1	61.39	12.28	6.863
	10	62.68	12.54	7.007
	20	64.20	12.84	7.176
	30	65.99	13.20	7.376
	60	69.67	13.93	7.788
PID	1	63.51	12.70	7.099
	10	63.50	12.70	7.098
	20	63.50	12.70	7.098
	30	65.01	13.00	7.267
	60	68.45	13.69	7.651

because the primary objective was to compare the effects of controller structure under a common model-based tuning framework rather than to compare different tuning methodologies. Conventional approaches such as the Ziegler–Nichols method may result in different control characteristics, and comparative evaluation of alternative tuning methods should therefore be considered in future work.

However, it is important to consider the fact that the results of this study were obtained in a simulation environment that was based on a mass-balance model and an oxygen consumption term that was calibrated using measured data. In actual aquaculture systems, DO is simultaneously affected by various time-varying factors, including oxygen supply rate, biomass, feeding activity, water temperature, influent water quality, and biological oxygen consumption (Zhou et al., 2022; Yu et al., 2026). Accordingly, the system may exhibit complex dynamic behavior involving nonlinearity and external disturbances. Therefore, although this study is meaningful in that it provides an initial performance benchmark for field application and a relative comparison among control structures, the results cannot be regarded as fully representative of all operating conditions. From this perspective, further development and application of models that more explicitly reflect real dynamic characteristics are required. The present analysis was based on a single culture tank and a single observation period. Therefore, the results

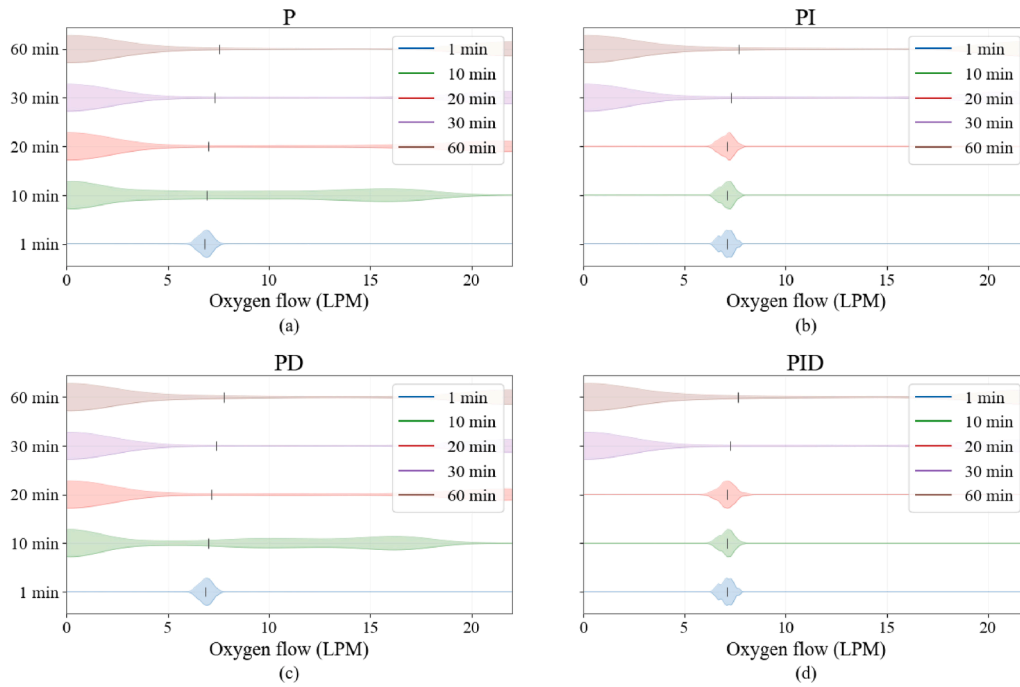


Fig. 10. Oxygen flow distribution of P, PI, PD, and PID control: (a) P; (b) PI; (c) PD; (d) PID.

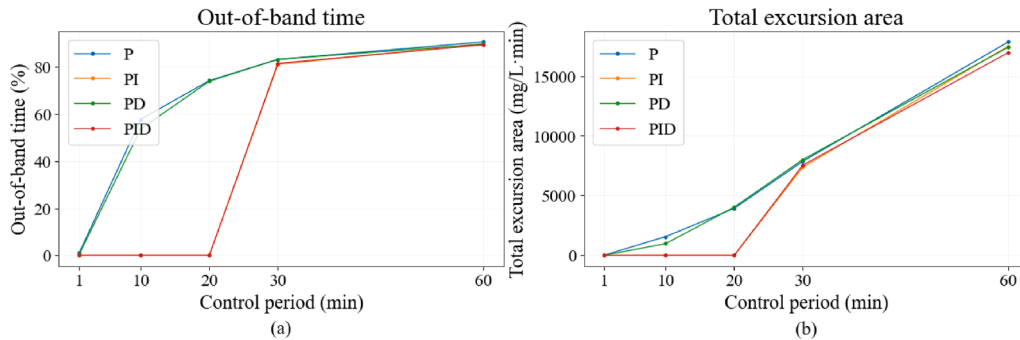


Fig. 11. Out-of-band time and Total excursion area by control period: (a) Out-of-band time; (b) Total excursion area.

Table 6

Comparison of the performance of different control strategies.

Control	On/off	P (1 min)	PI (1 min)	PD (1 min)	PID (1 min)
Mean DO (mg/L)	11.416	9.564	10.001	9.611	10.000
Within-band (%)	9.36	99.04	100.00	99.63	100.00
Mean O ₂ flow (L/min)	7.778	6.834	7.099	6.863	7.099
Daily injected O ₂ (kg/day)	13.92	12.23	12.70	12.28	12.70
Total injected O ₂ (kg)	69.6	61.1	63.5	61.4	63.5

should be interpreted as a relative comparison among controller structures under the investigated operating conditions rather than as evidence of universal superiority across tanks, seasons, or stocking conditions. In particular, small numerical differences between PI and PID should not be interpreted as statistically established differences without additional biological and temporal replication.

4.2. Advances toward predictive and adaptive control

Considering these limitations, future research should extend toward predictive or adaptive control strategies. Although PID-based control is effective in terms of field applicability and baseline performance evaluation, it may have inherent limitations with respect to future-state prediction, the incorporation of multiple constraints, and adaptability to changes in operating conditions (Schwenzer et al., 2021). In particular, because DO in flow-through aquaculture systems is strongly influenced by disturbances and non-stationary behavior, it is difficult to ensure optimal control in all situations by relying solely on responses to the current error.

Therefore, future studies should build upon the PID-based control results obtained in this study and explore the application of model predictive control, which can predict future system behavior and calculate optimal control inputs under given constraints, as well as reinforcement learning-based control, which can adaptively respond to uncertainty and non-stationary environments. A direct quantitative comparison between PID-based control and MPC was beyond the scope of the present study; however, such a comparison under variations in oxygen demand, inflow conditions, and other operational disturbances represents an important next step. Such extensions are expected to

provide more advanced control strategies for actual aquaculture systems, with improvements in DO regulation performance as well as oxygen-use efficiency, disturbance rejection capability, and long-term operational optimization.

5. Conclusion

In this study, we developed a mass-balance-based dynamic DO model for a flow-through aquaculture system and comparatively evaluated the application performance of the conventional on/off control method and the P, PI, PD, and PID controllers on the basis of actual measured data. To this end, the oxygen consumption term was calibrated using field-measured data, and the DO regulation performance and oxygen-use efficiency of each controller were assessed under identical conditions. The major findings of this study are summarized as follows.

1. Under held-out validation, PI and PID controllers showed excellent DO regulation at controller update intervals of 1–20 min. At 20 min, both controllers maintained 100% of simulated DO within the $\pm 5\%$ target band, whereas P and PD maintained only approximately 26%. This result demonstrates the importance of integral action for compensating persistent DO deviation.
2. When the controller update interval increased to 30 and 60 min, the performance of all controller structures deteriorated markedly. Within-band percentages decreased to approximately 17–19% at 30 min and approximately 9–11% at 60 min, while RMSE and DO variability increased substantially. Thus, excessively sparse controller updating can become a dominant limitation regardless of controller structure.

Overall, PI and PID control represent effective feedback strategies for DO regulation in flow-through aquaculture systems when the controller update interval is appropriately selected. The present results also indicate that controller structure and update frequency should be considered jointly when designing practical DO-control systems.

CRediT authorship contribution statement

Geonwoo Park: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Hakjong Shin:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Seng-Kyoun Jo:** Validation, Resources, Project administration, Funding acquisition. **Jae Young Jung:** Validation, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Woonjung Kim:** Validation, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.aqrep.2026.103877](https://doi.org/10.1016/j.aqrep.2026.103877).

Data Availability

The authors do not have permission to share data.

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