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An Enhanced 2D-PID Adaptive Strategy for Batch Processes through Set-point-Tuning Indirect Iterative Learning Control

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Abstract

To optimize productivity growth in batch processes, it's imperative to effectively manage nonlinearities and dynamically shifting process parameters. A cutting-edge approach to tackle this challenge involves integrating an auto-tuning-neuron-based proportional-integral-derivative (ANPID) system with an indirect PID-type iterative learning control (ILC) method, resulting in an innovative two dimension proportional-integral-derivative (2D-PID) adaptive recipe. This intensified two-dimensional (2D) control strategy offers a robust solution for addressing the complexities inherent in batch processes, ultimately fostering enhanced efficiency and performance. This method targets industrial processes characterized by nonlinearities and time variations across multiple batches. The ANPID addresses intra-batch nonlinearities and time variations autonomously. Additionally, an adjustable set-point-related PID-type ILC improves local tracking capability between batches. Historical batch data iteratively informs productivity improvements. Initial PID and ILC parameters are optimized via Particle Swarm Optimization (PSO) procedure. A fermenting reactor simulation illustrates the proposed concept's potential application. The performance metric "Average Absolute Tracking Errors" (ATE) is frequently used in batch processes to evaluate the efficacy of tracking control. Comparing the enhanced 2D-PID to the conventional 2D-PID, which has an ETA of 0.0223, the latter has the lowest ETA, and the conventional 2D-PID demonstrates superior tracking and control effects by 0.0389. The finding indicates that enhanced 2D-PID adaptive controller adapts more effectively to the dynamic conditions of the process, a property that could be further exploited to optimize batch cycle times and throughput

1. Introduction

Through the inherent characteristics of batch processing, the multi-batch industrial procedure can systematically replicate the production of a defined number of product batches within a specified timeframe. This approach sees extensive utilization in high-value manufacturing sectors, including bio-fermentation processing, plastics production, the food-medical and pharmaceutical industries, fine chemical polymerization, integrated circuit design, and various other industrial domains [1]. The effectiveness and excellence of production in the process industry hinge on the precision of process control. Nevertheless, the batch operation's non-stationary features result in a pronounced nonlinearity and dynamically changing nature. Additionally, the challenges arise due to the difficulty in timely modeling to derive an accurate mechanism model, posing formidable complexities and obstacles to process control [2], [3].

Given the finite duration of batch processes and their recurring operational patterns, a thorough understanding necessitates incorporating both time and batch dimensions. This integrated approach optimizes process control [4], [5]. Control strategies for intermittent processes primarily focus on intra-batch online control and inter-batch learning control. Intra-batch control dynamically adjusts controller parameters or prediction models to adapt to evolving production targets, mitigating challenges like nonlinearity and uncertainty within the batch [6]. Conversely, inter-batch control aims to improve local or overall control performance across batches by leveraging repetitive features. It employs learning algorithms to adjust control parameters continuously, enhancing control performance throughout the batch sequence [7].

On-line control within a batch of batch processes aims at solving the problems of process nonlinearity, parameter time-variation and uncertain disturbances, and even mismatch of mechanistic models that exist in a process within a batch [6], [7]. From simple PID strategies to complex control methods, advanced control technologies are emerging day by day. Scholars have made a lot of research and attempts, on the one hand, model-based control methods represented by Neural Network Control [8] (NNC) and Model Predictive Control [9] (MPC) have been developed; furthermore, mechanism models have been established by data-based neural network or nonlinear prediction methods, and real-time data have been used to update the models online. To update the model online using real-time data to cope with the non-stationary state caused by the change of product formulation, to realize the adaptive control of the process [10]. On the other hand, they have developed different forms of adaptive PID control techniques [11] and Model Free Adaptive Control [12] (MFAC) methods, such as neural network-based adaptive PID and data-driven MFAC, by investigating the basic structure and the essential connotation of PID; the resulting adaptive methods are usually based on the information of historical time periods such as tracking deviation, input deviation and output deviation of the process, continuously and automatically adjusting the controller parameters for the next time period, overcoming the uncertainty disturbances such as nonlinearity and time-varying nature of the process, and enabling the process to be automatically controlled online [13].

The key to batch process inter-batch learning control is to take advantage of the repetitive nature of batch production to regulate local controllers within a batch by developing a batch-to-batch learning strategy, in order to achieve the expectation that the process under control continuously improves the tracking performance along the direction of the batch, and, ultimately, to realize a batch-by-batch convergence of the control effect [14], [15]. Iterative learning control (ILC) is an effective mainstream coping tool for batch production processes with repetitive operation characteristics [16]. It is a control attempt to solve the repetitive trajectory problem proposed by Zhang et al, through an iterative learning process that utilizes previous operation information (including trajectory error and input information, etc.) to make corrections to the current operation input. Thus, the goal of ILC is to achieve a production trajectory in which the entire batch is able to perfectly approximate the desired target during the production cycle in which it is located [17], [18].

Although the simple PID-type ILC has the advantages of simple structure, less required information and easy realization, however, the adaptive ability of its control mechanism is relatively weak because the learning gain cannot be changed dynamically [19]. It should be noted that in the ILC, the introduction of other mechanism algorithms or control methods, so that they are organically combined to produce a new control strategy [20], [21], [22]. In recent years, the algorithm development and application research of iterative learning control have been increasing day by day, and researchers have proposed most of adaptive ILC [23], [24], [25], [26], [27], ILC for two-dimensional systems [28], [29], [30], [31], [32], and mixed-strategy ILC in response to the current situation [33], [34], [35], [36], [37]. Among them, the hybrid control strategy includes the combination of methods such as internal mode control (IMC) [38], [39], PID control [40], [41], NNC [42], [43], MPC [44], [45], and data-driven control with ILC [46], [47], and a class of control strategies combining ILC, and feedback control is proposed.

In order to overcome the problem posed by the non-stationary characteristics of the intermittent process and the dependence of the corresponding mechanism model, this study proposes an improved two-dimensional (2D) control strategy that combines auto-tuning-neuron-based proportional-integral-derivative (ANPID) and set-point-adjusted ILC. First, the adaptive control of the process is realized by employing ANPID within the batch of the intermittent process; further, a learning algorithm is designed to continuously modify the local ANPID control set-point along the batch direction, focusing on the batch repetitive characteristics of the intermittent process, in combination with the set-point-dependent indirect PID-type iterative learning control. In addition, it is worth stating that the initial parameters of ANPID and ILC can be easily optimized and obtained by PSO alone [48].

Recent advancements in two dimension proportional-integral-derivative (2D-PID) control strategies have shown promise in addressing complex process dynamics. However, existing literature highlights significant gaps and shortcomings, such as limited adaptability to varying operating conditions and inadequate performance in non-linear systems. Therefore, this study seeks to bridge these gaps by proposing a comprehensive solution that leverages adaptive control mechanisms, setting a benchmark for future developments in batch process control.

2. Problem Formulation and Preliminaries

Examining batch processes characterized by single-input and single-output (SISO) dynamics, wherein uncertainties evolve over time and across batches, as outlined in the following discrete-time formulation [46], [47].

$$y_{k+1}(t+1) = f_{n\text{-}l}(y_{k+1}(t), y_{k+1}(t-1),\ldots, y_{k+1}(t-n_1), u_k(t), u_k(t-1),\ldots, u_k(t-n_2), v_k(t), v_k(t-1),\ldots, v_k(t-n_3)) \tag{1}$$

in which, $k \in N_k$ and $t \in Z_t$ respectively represents the inter-batch cycle number and the time intra-batch instant of batch processes, here, $N_k = 1,2,3,\ldots,T_k$, $Z_t = 1,2,3,\ldots,T_f$. In addition, $y_k(t) \in R$ denotes the variable of the process output and $u_k(t) \in R$ expresses the variable of the process input. And the third variable have to be defined is $v_k(t)$, shows as the vector of the external disturbance in the batch process. Among them, a series of real numbers is referred as R; n_1, n_2, n_3 are all positive integers to indicate the forward time instant; $f_{n\text{-}l}(\ldots)$ is inferred as the unknown function with dissimilar nonlinearities.

It is important to emphasize that selecting batch processes as the focal point of research implies that nonlinear processes (1) replicate identical operations, maintaining a consistent time interval between successive batches. In this context, the assumption is made that the manipulation of the input variable $u_k(t)$ can effectively govern the output variable $y_k(t)$ in a rational manner. To attain peak production efficiency and adhere to the ultimate quality standards, a basic PID control framework with a single output is employed to characterize the complete process within a batch, as depicted in Fig. 1.

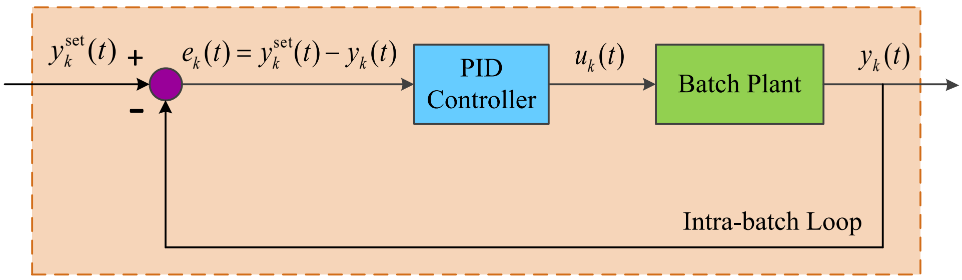

Fig. 1 *The straightforward PID framework design of the intra-batch process with a single-input and single-output configuration*

If k =1 is considered, the batch process PID block diagram depicted in Fig. 1 illustrates the intra-batch control loop for the batch process. In the below, the control regulation of the PID controller within the intra-batch process is presented, showcasing the feedback relationship between input variables and output deviations [49], [50].

$$u_k(t) = K_p[e_k(t) + \frac{1}{T_i}\int_0^t e_k(\tau)d\tau + T_d\frac{d}{dt}e_k(t)] \tag{2}$$

$$e_k(t) = y_k^{set}(t) - y_k(t) \tag{3}$$

where, $y_k^{\text{set}}(t)$ represents the target for tracking in the k-th batch of the batch process at the t-th moment, while $e_k(t)$ signifies the tracking error during the same period. The control constants, denoted as K_{p}, T_{i} and T_{d}, refer to the proportional, integral, and differential gain coefficients, respectively.

In the case of existing a sampling time represented by t_{s}, the expression for the PID control law can be articulated as follows:

$$u_k(t) = u_k(t-1) + K_{\text{p}}[e_k(t) - e_k(t-1)] + K_{\text{i}} e_k(t) + K_{\text{d}}[e_k(t) - 2e_k(t-1) + e_k(t-2)] \tag{4}$$

In this context, there exists an expression for T_{i} and T_{d}, which can be extended as an equation with respect to K_{p} and t_{s}, so that $K_{\text{i}} = K_{\text{p}} t_{\text{s}} T_{\text{i}}^{-1}$ intends to the integral gain, while $K_{\text{d}} = K_{\text{p}} T_{\text{d}} t_{\text{s}}^{-1}$ means to the differential gain.

3. Intra-batch Adaptive Mechanism

Within this framework, a technique termed auto-tuning neuron PID is employed to the adaptive control of the intra-batch process. Neurons, constituting the most basic structure in a neural network, are characterized by input I, threshold θ, and internal activation states net, in which the expression of the net is given as [50]:

$$net = I - \theta \tag{5}$$

Upon the confirmation of a neuron's valid activation state, the description of the neuron's output can be articulated as:

$$O = g(net) = \frac{a\,[1 - \exp(-b\,net)]}{[1 + \exp(-b\,net)]} \tag{6}$$

where, the hyperbolic tangent function, denoted as $g(\ldots)$, generates the nonlinear output O of the neuron, with a and b serving as the saturation and slope coefficients in the neuron's nonlinear function. The combined effect of these coefficients shapes the geometric configuration of the neuron function. As a result, the adaptive mechanism of the self-adjusting neuron PID relies on harnessing the nonlinear capability of the neuron function $g(\ldots)$. This allows for continual online adjustment of control parameters (K_{p}, T_{i} and T_{d}) based on tracking error information from the controlled process, facilitating adaptive control of the system.

The indices 1, 2, and 3 associated with the neuron output O correspond to the three dimensions of control parameters, namely the proportional coefficient K_{p}, integral coefficient T_{i}, and differential coefficient T_{d}. Throughout the period of a batch cycle, varying control parameters K_{p}, T_{i} and T_{d} at different time points are analogous to the time-dependent neuron outputs $O_k^1(t)$, $O_k^2(t)$, and $O_k^3(t)$. By combining equations (5) and (6), one can deduce that the neuron's output is ultimately updated through θ, a and b to facilitate its adaptive regulation process.

$$a_{t+1}^c = a_t^c + \eta_t^c \cdot \left[e_t \cdot \text{sgn}(\frac{\partial y_t}{\partial u_t}) \right] \frac{\partial u_t}{\partial O_t^c} \frac{\partial O_t^c}{\partial a_t^c} \tag{7}$$

$$b_{t+1}^c = b_t^c + \eta_t^c \cdot \left[e_t \cdot \text{sgn}(\frac{\partial y_t}{\partial u_t}) \right] \frac{\partial u_t}{\partial O_t^c} \times \frac{a_t^c \cdot net_t^c}{2} (1 + \frac{O_t^c}{a_t^c})(1 - \frac{O_t^c}{a_t^c}) \tag{8}$$

$$\theta_{t+1}^c = \theta_t^c - \eta_t^c \cdot \left[e_t \cdot \text{sgn}(\frac{\partial y_t}{\partial u_t}) \right] \frac{\partial u_t}{\partial O_t^c} \times \frac{a_t^c \cdot b_t^c}{2} (1 + \frac{O_t^c}{a_t^c})(1 - \frac{O_t^c}{a_t^c}) \tag{9}$$

In which, the variable $c = 1, 2, 3.$ denotes the dimension associated with the three PID control parameters. To streamline, the term "O_t^c" is utilized to represent $O_k^c(t)$ in the intra-batch dimension of batch processes. "η_t^c" denotes the learning rate of neurons, signifying a minute positive value. The determination of the value for $\partial y_t / \partial u_t$ is outlined as follows:

$$\theta_{t+1}^c = \theta_t^c - \eta_t^c \cdot \left[e_t \cdot \text{sgn}(\frac{\partial y_t}{\partial u_t}) \right] \frac{\partial u_t}{\partial O_t^c} \times \frac{a_t^c \cdot b_t^c}{2} (1 + \frac{O_t^c}{a_t^c})(1 - \frac{O_t^c}{a_t^c}) \tag{10}$$

The ANPID control framework in the intra-batch process is shown in Fig. 2. According to literature review, the corresponding adaptive control law and details of the other parameters involved are known [50].

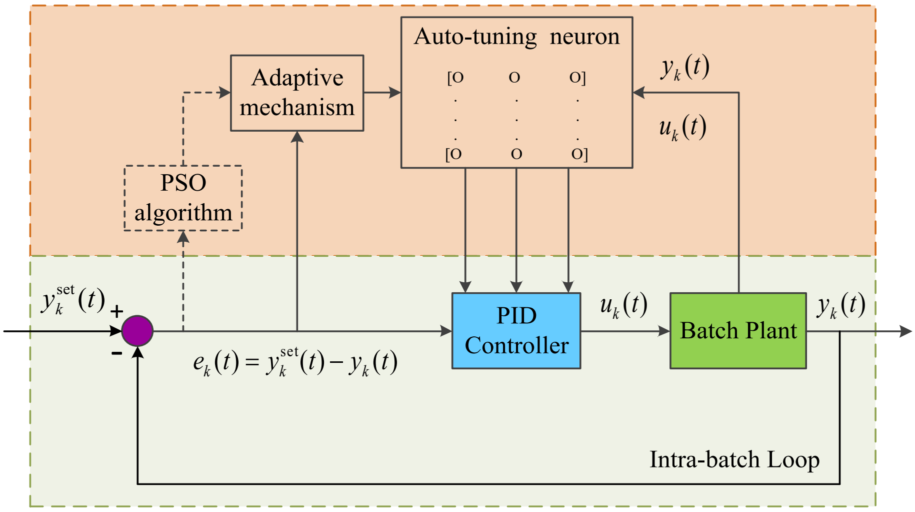

Fig. 2 *The block diagram of auto tuning PID scheme in the intra-batch process*

4. Enhanced 2D-PID of Inter-batch Processes

The central focus of this study is the exploration of the control objective, specifically addressing batch processes characterized by nonlinearities. The aim is to achieve precise tracking of the process's output value up to a specified target, even when encountering disturbances like uncertainty and time-varying parameters.

In order to enhance the tracking performance of the local controller in the intra-batch of the batch process, the objective of the strategy design is to devise an inter-batch set-point control that facilitates batch-by-batch tracking of target set points. To achieve this, through the integration of PID-type iterative learning control with set value adjustment in the outer loop, the ANPID is expanded into a control method within a two-dimensional framework, alternatively referred to as an enhanced 2D-PID adaptive approach. It is evident from Fig. 3 that the framework of the enhanced 2D-PID adaptive control strategy for intermittent processes is illustrated.

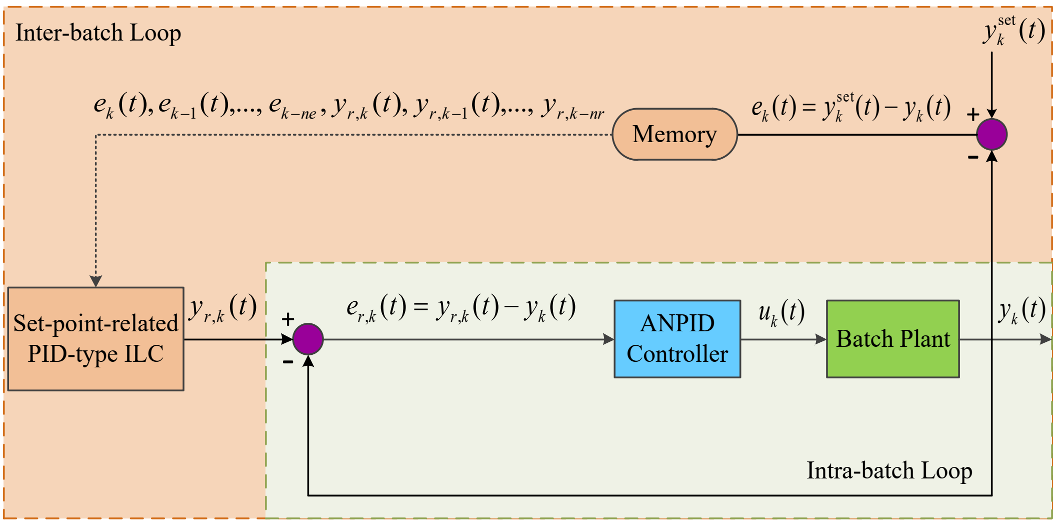

Fig. 3 *The schematic diagram of enhanced 2D-PID strategy both in the inter- and intra-batch process*

At the beginning of the study, the exploited ANPID is a method capable of automatically adjusting the parameters according to the process time-variation. Through the integration of equations (4) and (7-9), the inner-loop control ANPID in the intra-batch of the batch process can be expressed as:

$$u_k(t) = u_k(t-1) + O_k^1(t)\cdot[e_k(t) - e_k(t-1)] + O_k^2(t)\cdot e_k(t) + O_k^3(t)\cdot[e_k(t) - 2e_k(t-1) + e_k(t-2)] \tag{11}$$

For the PID-type iterative learning control with set-point tuning, the initial step involves specifying a reference virtual set-point $y_{r,k}(t)$. This set-point serves as the adaptable target for the k-th batch at the t-th moment. Furthermore, the definitions for the other variables are outlined as follows:

$$e_{r,k}(t) = y_{r,k}(t) - y_k(t) \tag{12}$$

$$Ie_k(t) = Ie_k(t-1) + e_{r,k}(t) \tag{13}$$

Here, $e_{r,k}(t)$ distinguishes itself from $e_k(t)$ as it denotes the tracking offset between the reference set-point and the actual output. The artificial set-point varies in tandem with batch changes.

Furthermore, formulating the outer loop control design for the intervals between batches in the intermittent process can be articulated as:

$$y_{r,k+1}(t) = y_{r,k}(t) + K_1 \cdot [Ie_k(t) - Ie_{k-1}(t)] + K_2 \cdot e_{k-1}(t) + K_3 \cdot [e_{r,k}(t) - e_{r,k-1}(t)] \tag{14}$$

wherein, the coefficients K_1, K_2, and K_3 represent the learning gains in the PID-type ILC.

Ultimately, a performance index J_k, denoted as "order", is formulated for the proposed enhanced 2D-PID adaptive control method:

$$J_k = 2^{-1}\sum_{t=1}^{T_f}[y_k^{\text{set}}(t) - y_k(t)]^2 = 2^{-1}\sum_{t=1}^{T_f} e_k^2(t) \tag{15}$$

To derive high-quality learning law coefficients (K_1, K_2, and K_3 in Eq. (14)) through optimization employing particle swarm algorithms [48], consider the utilization of an optimization metric as outlined below:

$$J_{k+1} < J_k \tag{16}$$

5. Case Study and Simulation Results

The research case [51] delves into the iconic fermentation process, a staple of batch processes aligned with the growth cycle of bacterial cultures, the fermentation process unfolds in distinct phases, including the stagnant adaptation period, logarithmic growth period, and stationary stable period. Each stage features specific control objectives, dominant variables, and unique process characteristics. During the growth stage of the fermentation process, effective control of the final bacterial concentration (X) can be attained by judiciously adjusting a crucial process variable—the fermentation dilution rate (D). Taking this into account, intermittent simulation of the fermentation process is conducted using a mathematical model based on the subsequent differential equations [52], [53], [54].

$$\begin{cases} \dfrac{\mathrm{d}X}{\mathrm{d}t} = -DX + \mu X \\ \dfrac{\mathrm{d}S}{\mathrm{d}t} = D(S_{\mathrm{f}} - S) - \dfrac{\mu X}{Y_{X/S}} \\ \dfrac{\mathrm{d}P}{\mathrm{d}t} = -DP + (\alpha\mu + \beta)X \end{cases} \tag{17}$$

where, the symbol "μ" signifies the growth rate of a specific bacterium, and it has the potential to experience inhibition from both substrate and product. Simultaneously, its calculation can be performed using the following formula:

$$\mu = \frac{\mu_{\mathrm{m}}(1 - P/P_{\mathrm{m}})S}{K_{\mathrm{m}} + S + S^2/K_{\mathrm{in}}} \tag{18}$$

Additionally, $Y_{X/S}$ denotes the mass yield of bacterial cells, μ_m represents the maximum growth rate of the specific bacterial cell, where α and β serve as mechanism parameters with kinetic characteristics. The dilution rate (D) and the concentration of the feed substrate (S_f) act as process inputs in the fermentation tank. The study conducted by Henson and Seborg [51], [52] facilitates the acquisition of comprehensive nominal parameters and operational conditions for the process.

Regulating the primary goal is to achieve maximum productivity in the fermenting reactor. Typically, the dilution rate (D) is chosen as the manipulated variable, and the cell concentration of substrate effluents (X), the concentration of the substrate (S), and the concentration of the product (P) are identified as state variables of the fermentation process. Opting for cell concentration (X) as the control output is a sensible choice.

To assess the efficacy of the enhanced 2D-PID adaptive iterative learning control approach in batch processes, the anticipated objective $y_k^{\text{set}}(t) \in [5.5, 6.5, 5.5, 4.5]$ for the fermentation process is employed as the trajectory for monitoring substrate cell concentration. In this context, the batch duration is defined as 80 hours, with sub-target intervals set at every 20 hours, and a sampling frequency of 0.5 hours.

The control parameters for the improved 2D-PID method in the batch fermentation process are optimized through simulated instances using the PSO algorithm. This optimization involves the adjustment of local control parameters within batches and iterative learning parameters between batches. Initially, appropriate adjustable parameters (θ, a and b with $\eta = 0.01$) are carefully chosen for the ANPID controller within the batch. Subsequently, the optimization process for the batch of intermittent processes includes determining the corresponding initial control parameters—specifically, K_{p0}, K_{i0} and K_{d0}. These determinations are based on factors such as the cumulative sum of tracking errors within the batch and the indicator J_k, as detailed in Table 1.

Table 1 *The control parameters of the ANPID controller using PSO algorithm*

Parameter	Value	Parameter	Value
θ	[0.9070; 0.9374; 0.0576]	K_{p0}	-0.1955
a	[0.9556; 0.7115; 0.2055]	K_{i0}	-0.0221
b	[0.4603; 0.6379; 0.0387]	K_{d0}	0.0422

Additionally, to ensure $J_{k+1} < J_k$ for the performance indicator representing the cumulative sum of tracking errors between batches, optimization was performed on the PID-type iterative learning control parameters. This optimization is centered around adjusting set values between batch processes, and the optimized parameters are presented in Table 2.

Table 2 *The learning coefficients of the set-point-tuning ILC through the PSO algorithm*

Parameter	Value
K_1	-0.0007
K_2	0.0093
K_3	0.1451

In conventional practice, batch processes commonly employ the performance metric "Average Absolute Tracking Errors" (ATE) to assess the effectiveness of tracking control.

$$\text{ATE}_k = \sum_{t=1}^{T_f} \left| e_k(t) \right| / T_f \tag{19}$$

By considering the performance indexes in Table 3, it becomes apparent that the enhanced 2D-PID exhibits superior tracking and control effects. During the batch simulation, the study implemented the proposed enhanced 2D-PID adaptive control on the fermentation process, and its outcomes are depicted in Figs. 4-6.

Tab. 3 *A compared illustration of ATE indices across PID, ANPID, 2D-PID, and Enhanced 2D-PID methodology*

Method	Sources	ATE
PID	Ref. [51]	0.0855
ANPID	Ref. [11]	0.0588
2D-PID Method	Ref. [36]	0.0389
Enhanced 2D-PID	This Study Proposed	**0.0223**

From the simulations, Fig. 4 illustrates the control impact of the enhanced 2D-PID across multiple batches in comparison to the 2D-PID method introduced in literature [36], the single-batch ANPID, and the conventional PID. Furthermore, analyzing the trajectory from the 1st to the 30th batch reveals a progressively improved control effect with each subsequent batch. In batch processes, where the dynamics can change significantly over time due to varying operating conditions or material properties, PID tuning parameters may become ineffective. PID controllers are inherently linear, which may not adequately handle nonlinearities common in batch processes [55], [56]. Meanwhile ANPID requires a priori knowledge of the process dynamics to design and train the neuro-fuzzy model, which may not always be available or accurate [57]. Computationally, ANPID is intensive due to the need for neural network training and fuzzy logic inference. Tuning two sets of PID parameters in conventional 2D-PID can be challenging and time-consuming due to its limitation to systems with two-dimensional dynamics, which may not fully capture the complexity of batch processes [58]. Hence, enhanced 2D-PID adaptive strategy integrates adaptability by dynamically adjusting PID parameters according to process variations. By employing 2D control surfaces, it effectively captures the intricate dynamics, surpassing the capabilities of conventional PID. This approach demonstrates potential for enhancing performance and robustness in batch processes characterized by time-varying dynamics or nonlinearities.

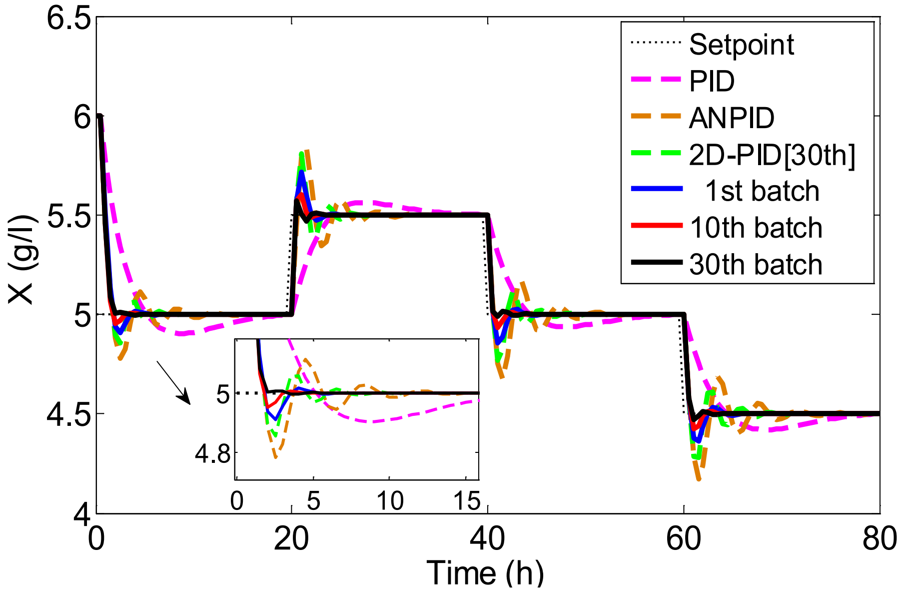

Fig. 4 *The output tracking capability of the developed enhanced 2D-PID and other similar strategies for batch processes*

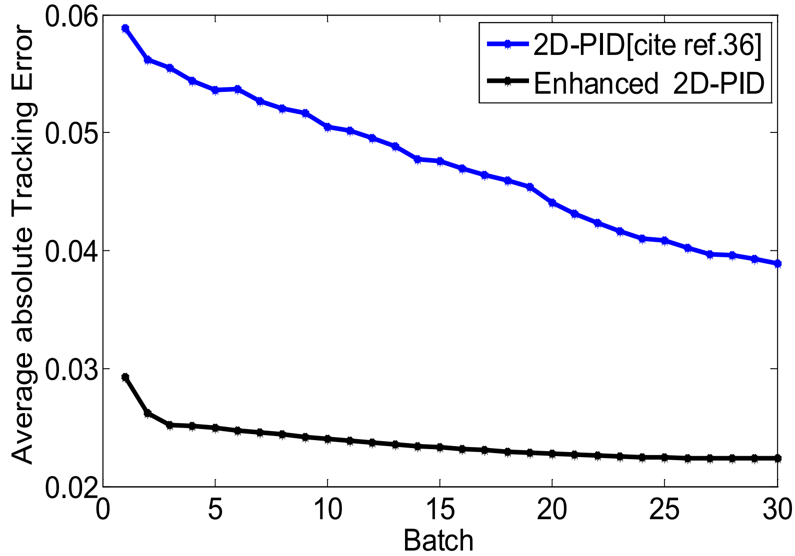

Fig. 5 *The ATE behavior index of approximate methods between enhanced 2D-PID and 2D-PID for batch processes*

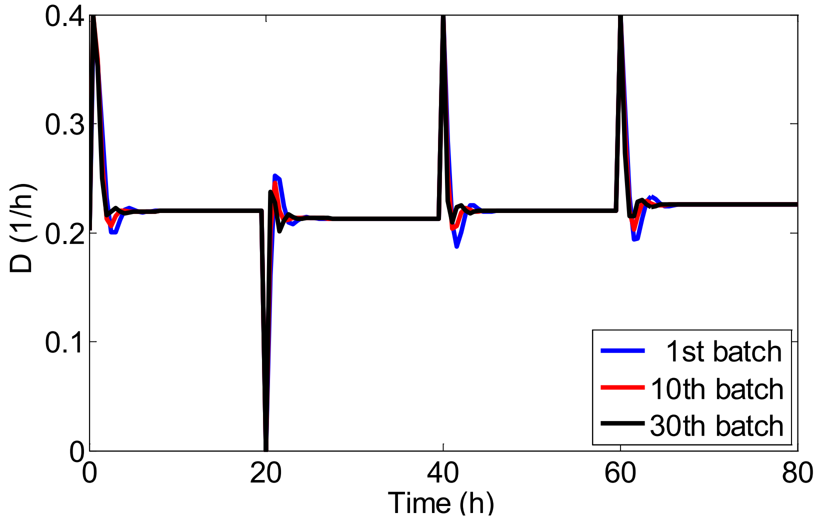

Fig. 6 *The input controlling display of the addressed enhanced 2D-PID for batch processes*

Fig. 5 presents a comparison of the convergence index ATE between the enhanced 2D-PID and analogous methods, demonstrating the enhanced control and convergence capabilities of the proposed approach. The graph presents a clear visual comparison between conventional 2D-PID and enhanced 2D-PID control strategies, where the latter shows a marked improvement in maintaining the process parameters within a tighter control range. The ETA value of enhanced 2D-PID is lower compared with conventional 2D-PID with below 0.03 for batch 1 to batch 30. However, the ETA of conventional 2D-PID is higher than 0.04 which proves that enhanced 2D-PID is significant to be applied. The combined analysis of Fig. 4 and Fig. 5 underscores that the process output of the 30th batch closely aligns with the desired target trajectory, indicating the batch-by-batch convergence effectiveness of the proposed enhanced 2D-PID adaptive control. Fig. 6 displays the actual process inputs, specifically the dilution rate (D), for various batches in the intermittent fermentation process, providing evidence for the rationality of controlling cell concentration through the adjustment of the dilution rate.

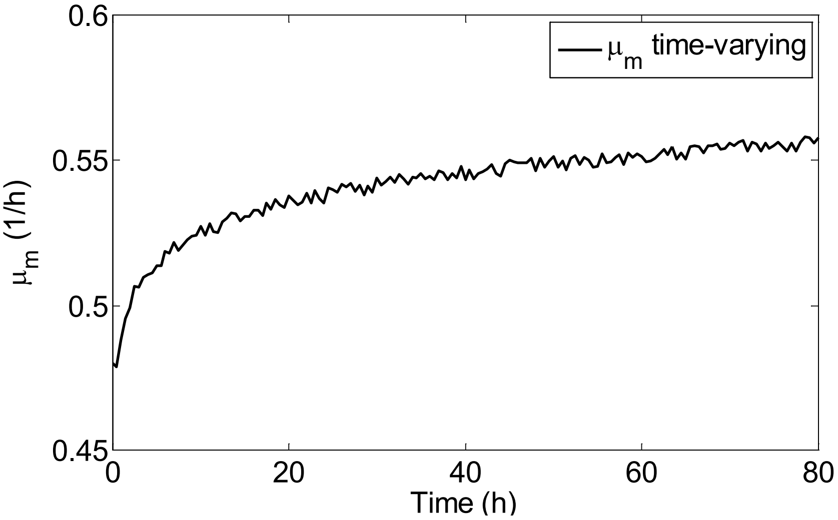

Fig. 7 *The maximum cell-growth rate* μ_m *of specific bacteria in the batch fermentation process*

It has been observed that two crucial parameters in the bio-reaction process, namely the maximum growth rate (μ_m) of the bacterial body and the bacteria's substrate inhibition coefficient ($Y_{X/S}$), play a significant role. Typically, their acceptable ranges are approximately μ_m = [0.48,0.65] and $Y_{X/S}$ = [0.3, 0.55]. Consequently, the control aspect of the proposed modified 2D-PID adaptive scheme for the intermittent fermentation process, considering the variability in parameters μ_m and $Y_{X/S}$, is explored and illustrated in Figs. 7 Specifically, Fig. 7 and Fig. 8 represent the dynamic evolution of process parameters μ_m and $Y_{X/S}$, respectively.

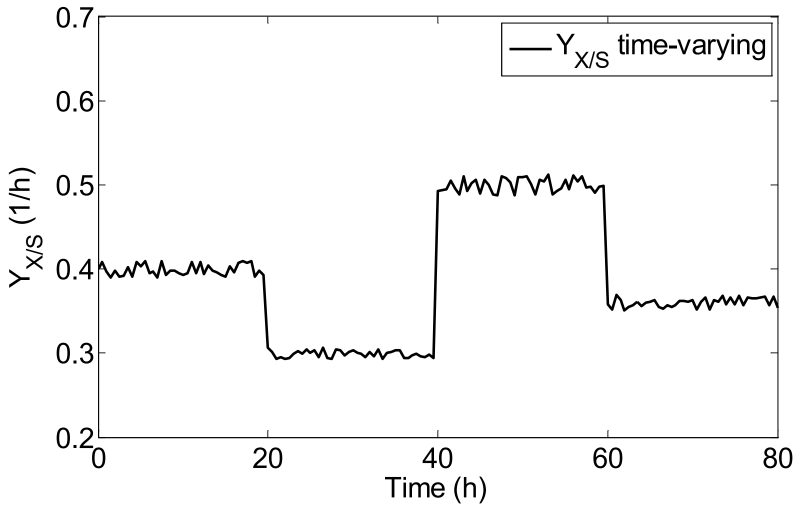

Fig. 8 *The inhibition factor* $Y_{X/S}$ *of concrete cell-mass in the batch fermentation process*

In the context of fluctuating model parameters as illustrated in Fig. 7 and Fig. 8, the proposed enhanced 2D-PID method maintains robust control performance and a capability for batch-by-batch convergence, evident in the tracking curves of diverse batches as shown in inset Fig. 9. The output tracking performance for several batch operations with time-varying features is also shown in Fig. 9. The control variable 'x(t)' is plotted against time in the graph, providing a comparison of setpoint adherence for the first, tenth, and thirty batches. Interestingly, the first batch shows a slow convergence to the setpoint that was predefined, suggesting that there is a first stabilization phase before the control system reaches its objective. On the other hand, the 10th batch shows a significantly better alignment with the setpoint, suggesting that the control system is responding adaptively to minimize short-term deviations over time. The 30th batch, which shows even more fidelity to the setpoint from the start of the batch process, provides more proof of this adaptation.

In contrast, Fig. 10 provides an analysis of the average absolute Tracking Error (ATE) performance indexes for the suggested improved 2D-PID adaptive control strategy in the batch fermentation process under the current conditions. Despite the inherent time-varying nature and uncertainties arising from variations in process parameters, the performance indexes indicating control quality exhibit a general decreasing trend with the prolonged operation of the process batch production. Furthermore, Fig. 11 details the variations in control inputs for the multi-batch intermittent process during the dynamic evolution of parameters. The control chart illustrates the stabilization effect of the enhanced 2D-PID control strategy across ten batches, maintaining parameter values within the predetermined control limits, indicating a consistent process control performance. Despite the inherent variability observed in batch processes, the application of the enhanced 2D-PID control strategy demonstrates a significant reduction in process deviation, as evidenced by the narrower control limits in comparison to the conventional 2D-PID control batches. Notably, the enhanced 2D-PID control strategy exhibits a quicker return to setpoint after disturbances, a characteristic that underscores its potential for minimizing the impact of variability in batch processing.

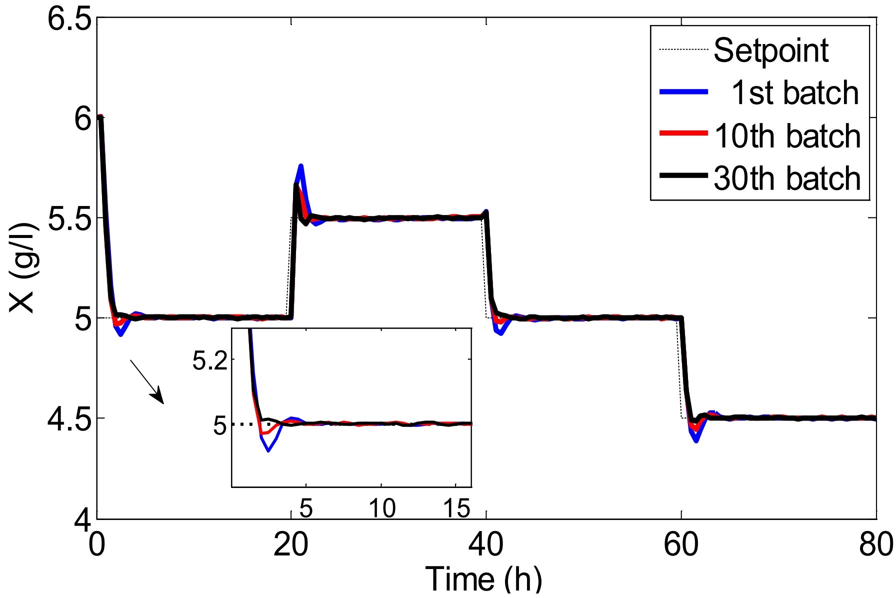

Fig. 9 *The output tracking quality of the developed enhanced 2D-PID for batch processes with time-variant features*

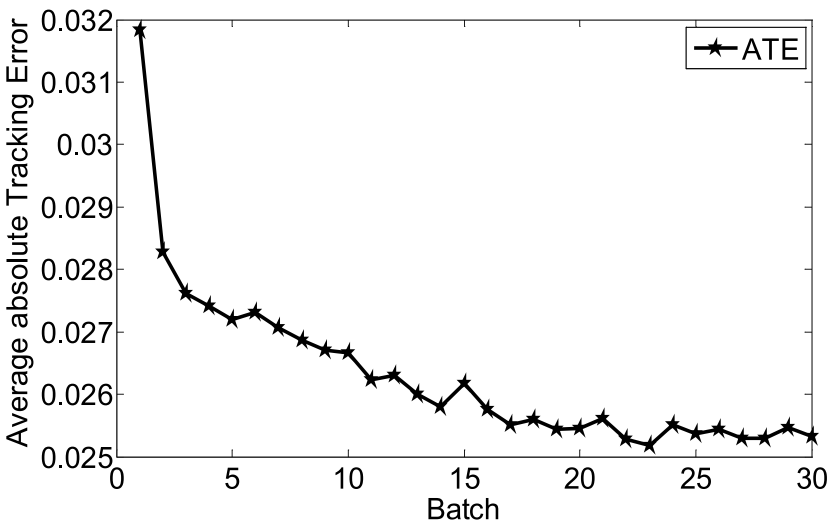

Fig. 10 *The ATE performance index of enhanced 2D-PID for batch processes with time-variant features*

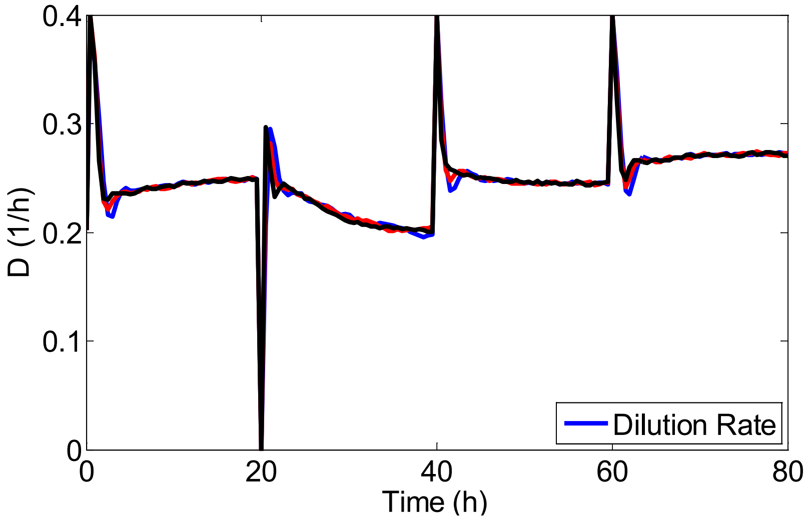

Fig. 11 *The input controlling indication of the addressed enhanced 2D-PID for batch processes with time-variant features*

The 2D-PID also can be compared with State-of-the-Art Control Approaches such as Model Predictive Control (MPC), sdaptive control strategy and machine learning based control where while MPC provides benefits in managing constraints and optimum the performance within a finite time horizon, its computational intensity and demand for precise process models can pose challenges, particularly in batch processes where obtaining accurate models may be difficult [59], [60]. Adaptive control methods, such as adaptive model-based control or adaptive sliding mode control, provide flexibility in adjusting to changing process conditions [61]. Despite their effectiveness, these approaches often necessitate significant modeling effort and computational resources. Machine learning-based control techniques, such as reinforcement learning or neural network control, have the capability to learn complex mappings between inputs and outputs without relying on explicit process models [62]. Nonetheless, these methods may encounter challenges concerning data availability, robustness, and interpretability.

To sum up, this study introduces a dual-dimensional adaptive control approach that integrates intra-batch local adaptive control and inter-batch indirect iterative learning control. The efficacy and superiority of the proposed method are validated through intermittent simulations of a representative fermentation process, involving comparisons with various methods and simulations of time-varying processes. Ultimately, the proposed enhanced 2D-PID adaptive iterative learning control method emerges as a rational and effective approach for batch control in intermittent processes. It is imperative to consider the impact of scaling up the process, as the control strategy's effectiveness demonstrated here on a smaller scale must be validated in a commercial setting where additional complexities may arise. The integration of the 2D-PID control strategy with real-time monitoring systems could pave the way for a more autonomous process control, potentially leading to a paradigm shift in batch processing industries. Recognizing the considerable practical relevance of data-driven control in batch processes, the investigation further explores this domain by integrating methodologies such as dynamic data reconciliation [63], data-driven control method and dynamic linearization techniques [64]. This comprehensive approach takes into consideration the control challenges that may arise in batch processes, especially under conditions involving desired targets, repetitive operations, and incomplete information [65], [66]. Generally, machinery comprises rotating components that encompass various elements like wheels, shafts, pulleys, and similar parts that will be issues with human error, time-consuming and inaccurate by human operating which using enhanced 2D-PID will optimize the operation of the manufacturer [67], [68].

6. Conclusions

An enhanced 2D-PID adaptive ILC is crafted specifically for batch processes, featuring dual control loops. Within the intra-batch phase, an ANPID serves as the feedback controller, followed by the application of an indirect ILC to adjust the required set-point for the intra-batch control loop. Upon comparing the performance of the improved 2D-PID controller to that of the traditional 2D-PID, which boasts an ETA of 0.0389, it becomes evident that the traditional approach achieves the lowest ETA. However, the enhanced 2D-PID controller outperforms its traditional counterpart by reducing tracking errors by 0.02223. This finding underscores the enhanced adaptability of the 2D-PID adaptive controller to the dynamic conditions inherent in the batch process. This adaptability allows the enhanced controller to respond more effectively to fluctuations, resulting in superior tracking and control outcomes. Leveraging this property presents an opportunity to optimize batch cycle times and throughput, thereby enhancing overall process efficiency and productivity. The enhanced 2D-PID adaptive strategy offers a promising approach to address the challenges faced by traditional control methods in batch processes. Its adaptability and ability to capture complex dynamics make it competitive with other state-of-the-art control approaches, providing a viable solution for improving control performance in batch processes.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

*The authors confirm contribution to the paper as follows: **study conception and design:** Zhiwen Wang, Amirul Syafiq Sadun; **data collection:** Zhiwen Wang, Amirul Syafiq Sadun; **analysis and interpretation of results:** Zhiwen Wang, Nor Anija Jalaludin, Norshuhaila Mohamed Sunar; **draft manuscript preparation:** Hairulazwan Hashim, Siti Nor Hidayah Arifin. All authors reviewed the results and approved the final version of the manuscript.*

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