Proportional–Integral–Derivative Controller Performance Assessment and Retuning Based on General Process Response Data

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ABSTRACT: In this paper, the current research status of controller performance assessment is reviewed in brief. Solving the problem of proportional–integral–derivative performance assessment usually requires step response data, and several methods are combined and extended. Using the integral of signals, implicit model information contained in process response data becomes explicit, and then the least squares approach is adopted to construct a detailed low-order process model based on process response data in more general types. A one-dimensional search algorithm is used to attain better estimation of process time delay, and integral equation approach is extended to be useful for more general process response. Based on the obtained model, a performance benchmark is established by simulating model output. Appropriate retuning methods are selected when the index of absolute integral error (IAE) indicates bad performance. Simulations and experiments verify the effectiveness of the proposed method. Issues about estimation of process time delay, data preprocessing, and parameter selection are studied and discussed.

1. INTRODUCTION

With quality standards and functional demands of products getting higher and higher, industrial processes are becoming increasingly complex, and demands for control performance are also stricter. According to statistics, after controllers are put into operation for a period of time, around 60% of controllers have performance degradation issues due to inappropriate controller parameters, wear of actuator, and change of the external environment. However, an engineer usually maintains 201–500 control loops, and operators need time and experience skills to maintain controllers. In addition, as system complexity continues to increase, the maintenance costs of the system cannot be neglected.

The goal of controller performance assessment (CPA) is to assess how far the current controller performance from the desired benchmark and also retune controller parameters with routine operating data, which could provide operators with controller health status and related suggestions. CPA has attracted great attention and research in the past 30 years since Harris proposed the minimum variance control (MVC) index. Shockingly, the 2016 survey showed that the control loop problem was the same as in 1989, and the problem of inappropriate parameters is still prominent.

CPA can be divided into model-based methods and data-driven methods. The performance assessment method based on historical benchmark is a kind of data-based approach. First, select or train a benchmark model with satisfying process data from daily operation. When a new data set comes, compare it with the trained model or trained threshold to determine whether its performance is good or not. The method of evaluating controller performance based on historical benchmarks has been successfully applied in single-loop and multiloop control systems of industrial processes.

Multivariate statistical process monitoring has been a research hotspot in the past 25 years, and partial least squares and principal component analysis methods are the most commonly used. Yu and Qin (2008) propose statistical methods based on generalized eigenvalue analysis for performance monitoring of multiple input multiple output processes, which could locate the bottom control loops that cause performance degradation. The tuned proportional–integral–derivative parameters are directly obtained by solving the convex optimization problem of...
approaching a reference model through set-point changes in data.

Most of the data-driven methods are used to complete the task of control performance monitoring at the system level and require a lot of process variables to determine whether the system status is normal or abnormal. However, data-driven methods mostly build a black box system, and it is difficult to analyze and master the mechanisms of the actual system. In addition, this kind of data-driven method is usually not helpful for proportional–integral–derivative (PID) tuning. While, model-based methods are clear and direct for PID tuning, and there are scores of mature research studies on model-based controller tuning.

The model-based method mostly considers the performance evaluation of a single control loop. Integrals or sums of control loop variables such as integrated absolute error (IAE) are usually selected as performance benchmarks, and these indicators can be fused, such as by the way of producing or weighting, to form an overall benchmark. The linear quadratic Gaussian (LQG) method determines the performance benchmark in the form of a trade-off curve by balancing control performance and controller effort. Now the LQG method, generally implemented based on predictive control, has been extended to discrete processes. However, this method requires an explicit model and a relatively high computation. Moreover, the LQG performance benchmark is not applicable to PID directly due to the limitation of the controller structure. For the typical FBC/FFC control structure, Huang et al. (1999, 2000) solve the problem because of the feedforward controller or the feedback controller when the current control effect is not good.

The performance assessment of the PID controller follows the concepts of the abovementioned method, but it should be simple and practical. Swanda and Seborg simply adopt a well-designed IMC controller as the performance benchmark and compare the actual PID controller with it to evaluate the control performance. The method of reachable PID MVC performance assessment draws on the idea of LQG and takes into account the constraints of the controller. Its lower bound is much larger than that of MVC, but it can be realized. This method also requires a process model or an impulse response sequence. In actual applications, the process model may not be available.

In order to obtain process model, the integration of predefined variables with step response data can be used to estimate parameters of approximate low-order models, and the performance benchmark is established according to obtained model parameters. A semi-nonparametric approach is proposed to estimate the parameters of unknown process models and the indicators of the IAE, and the total variation of control signals (TV) are calculated to assess the performance of liner controllers. The integral equation approach (IEA) is proposed for identification of continuous-time models from step responses. The effectiveness of these modeling methods shows that implicit model information contained in daily dynamic data can be explicitly used by the integrals of control loop signals. A review on process identification from step or relay feedback test is presented.

For retuning PID when the control performance is poor, simple internal model control (SIMC) tuning and Direct Synthesis Design for Disturbance Rejection (DS-d) tuning have been used. There are abundant research studies on PID controller parameter tuning, such as the IMC tuning method, AMIGO tuning method, and so on. These tuning methods focus on different performances, and each has its own characteristics.

This kind of model-based PID CPA usually uses low-order models to approximate high-order processes and applies the obtained models to attain performance evaluation and parameter tuning. To get low-order models, the data used for parameters estimation are usually obtained through identification tests or extracted from daily operation data. However, in practice, it is generally not allowed to add identification test signals to prevent the impact on industrial production and safety, and the identification test consumes considerable time and resources. In addition, some model-based methods for CPA are derived from the ideal step response, but the actual signal is generally not the step type. Furthermore, the step response is not always available in the daily operation. Some systems may be stable in a working condition for a long time, which is unfavorable for online evaluation of controller performance.

The proposed approach combines and extends several methods to accomplish the task of deterministic performance assessment and retuning of PID controllers based on process response data in more general types. The general process dynamic data means response data of a closed-loop control system stimulated by step input or nonideal step input, meaning system response with constrained controller outputs or under measurement noise. With integral signals, the least squares approach is adopted to construct a detailed low-order process model with process dynamic data in more general types. Because of the using of integral signals, the form of exciting signals is not so important. A one-dimensional search algorithm is used to attain better estimation of process time delay, and IEA is extended to be useful for more general process response. Based on the obtained model, PID parameters are determined and performance benchmark used for performance assessment is established by simulating model output. Appropriate retuning methods are selected when the index of absolute integral error (IAE) indicates bad performance. Because the presented method is based integral of signals, it is inherently robust to uncertain noise. It is worth noting that controller performance can be divided into deterministic performance and stochastic performance from the perspective of control tasks. Moreover, the proposed method in this article focuses on the deterministic performance.

The organizational structure of this paper is as follows. Section 2 introduces the principle of process modeling. PID tuning and performance assessment are expounded in Section 3. Section 4 proves the effectiveness of the algorithm through several simulations. The applications of temperature control on the Tennessee Eastman process (TEP) and water level control on intelligent process control test facility (IPC-TF) verify the validity of the method in Section 5. The last section summarizes the work of this paper.

2. PROCESS MODELING

The proposed method is mainly divided into two parts, one is process modeling, and the other is PID tuning and performance evaluation. First, the principles and specific implementation of process modeling will be introduced.

2.1. Problem Formulation. A simple unity-feedback control system is shown in Figure 1. $C(s)$ is the controller in the form of PID, and $D(s)$ is the disturbance process. $P(s)$ is
the controlled process, which is a single-in single-out self-regulating process. The signal \( r \) is the set point, \( d \) is the measured process variable, \( e \) is the control error, \( u \) is the controller output, and \( y \) is the disturbance.

There are several forms of PID controllers, and different forms can be transformed. The form adopted in this article is the ideal form as eq 1. Of course, a filter should be added to the differential part in practical applications as \( T_\text{d} + 1 \), and \( N \) can be selected as 10.

\[
C(s) = K_p \left( 1 + \frac{1}{T_\text{d}s} + T_\text{d}s \right)
\]

In order to conveniently study PID tuning and performance evaluation, for the real process as eq 2, it can be approximated to the first-order plus dead time (FOPDT) model (eq 3) or second order plus dead time (SOPDT) model (eq 4). For actual low-order systems such as first-order plants, FOPDT model should be used. For a more complex high-order system, “Half Rule” can be used to approximate it to a SOPDT model.

\[
P(s) = \frac{\prod_j (T_\text{d}s + 1)}{\prod_i (T_\text{i}s + 1)} e^{-\theta_0}
\]

\[
P_1(s) = \frac{\mu}{\tau_i + 1} e^{-\theta_0}
\]

\[
P_2(s) = \frac{\mu}{(\tau_i s + 1)(\tau_i s + 1)} e^{-\theta_0}
\]

In practical applications, if the process model is known in a high-order form, it can be approximated as a low-order system through approximation rules. Otherwise, it can be considered that the model structure is known, and the model parameters should be solved.

### 2.2. Estimation of Process Time Delay

The correct estimation of process delay has a great influence on the accuracy of process modeling. Process time delay is common, but 90% of industrial control loops in practical applications are PID control types without delay compensation, which will cause the actual PID control performance far from theoretical benchmarks such as MVC-based benchmarks, no matter how the parameters are tuned. The problem of process delay estimation is solved by the fixed model variable regressors proposed by Elnaggar. For process dynamic response with sampling period \( T \), the original process output sequence \( y(k) \) and process input sequence \( u(k) \) are obtained, \( k = 1, 2, 3, \ldots, M \), and \( M \) is recommended above 500. First, subtract the initial values from the original data to get \( y(k) \) and \( u(k) \). With the preprocessed data, \( d \), the number of sampling intervals corresponding to the process delay can be solved with the eq 5, where \( E \) represents the mathematical expectation, and \( k \) represents the k-th sampling point. Multiply \( d \) corresponding to the maximum \( E_1 \) by the sampling period \( T \) to obtain process time delay \( \theta \).

\[
E_1 = E[(y(k) - y(k - 1)) \cdot u(k - d)]
\]

\[
\hat{d} = \max_d E_1
\]

\[
\theta = \hat{d} \cdot T
\]

### 2.3. Estimation of Process Gain and Time Constants.

For the SOPDT model, the estimation of process gain and time constant will be described below. In addition, the procedures for the FOPDT model can be easily derived similarly. After preprocessing of raw data and estimating process time delay as above, take the sequence of \( u(1), \ldots, u(M - \hat{d}), \ldots, y(M) \) to construct the process response without time delay to estimate parameters of eq 6. Then, eq 6 can be transformed into the form of the integral equation as eq 7, and then, eq 8 is obtained through the inverse Laplace transform, which can be written as the matrix form as eq 9.

\[
P_2(s) = \frac{Y(s)}{U(s)} = \frac{b_0}{s^2 + a_1s + a_0}
\]

\[
Y(s) + a_1Y(s) + a_0Y(s) = b_0 U(s)
\]

\[
y(t) + a_1y_1(t) + a_0y_2(t) = b_0 u_1(t)
\]

\[
z = H\theta
\]

The meaning of symbols as are in eqs 10 and 11. Using the least squares method to solve the available parameters \( a_0, a_1, b_0 \), the unbiased estimation vector \( \bar{\theta} \) is shown in eq 12.

\[
y_1(t) = \int_0^t y(r)dr
\]

\[
y_2(t) = \int_0^t \int_0^r y(\rho)d\rho dr
\]

\[
u_2(t) = \int_0^t \int_0^r u(\rho)d\rho dr
\]

\[
H = [h(n)h(n + 1) \ldots h(L)]^T
\]

\[
h(t) = [-y_1(t) - y_2(t)u_2(t)]^T
\]

\[
z = [y(n)y(n + 1) \ldots y(L)]^T
\]

\[
\bar{\theta} = [a_0, a_1, b_0]
\]

\[
\bar{\theta} = (HH^T)^{-1}H^T z
\]

The process time constant \( \tau_1 \) and \( \tau_2 \) and the process static gain \( \mu \) can be obtained by factorization and simple conversion as eq 13. \( \tau_1 \geq \tau_2 \) will be ensured by exchanging them if the result is not obtained.
\[
\mu = \frac{b_0}{a_0}
\]
\[
\tau_2 = \frac{a_1 - \sqrt{a_1^2 - 4a_0}}{2a_0}
\]
\[
\tau_1 = \frac{1}{a_0a_2}
\]  

(13)

After the model is established, the model output sequence \( \hat{y} \) can be simulated. Model accuracy can be evaluated by the model fitness index \( Q \) as eq 14, where \( y \) represents the actual measured output, \( \hat{y} \) represents the model output, \( \bar{Y} \) represents the average value of the actual output, and \( M \) represents the length of data sequence. When \( Q \) is close to 1, it indicates that the established model is accurate. The length of the data sequence is recommended to be greater than 500.

\[
Q = 1 - \frac{\sum_{i=1}^{M} [y(i) - \hat{y}(i)]^2}{\sum_{i=1}^{M} [y(i) - \bar{Y}]^2} 
\]  

(14)

Remark 1. Note that the data sequences \( u \) and \( y \) used in the above calculation are the deviations of the actual input and output data, that is, the initial value has been subtracted. This can avoid the influence of the initial state of the system on the parameters estimation. For a transient response without a clear system initial steady-state value, the way of preprocessing is to consider the initial steady-state value as an unknown variable for transient response. By integrating eq 8 on both sides to increase the number of equations, the unknown steady-state value is solved. However, multiple integrations will increase the error, and the solution effect may not be good.

Remark 2. The accurate estimation of time delay is the key to ensuring the accuracy of the process model because the estimation of time delay will affect the correct estimation of process gain and time constants. Another empirical approach is to estimate process delay from step response. The process delay is the time when the measurements of process variable is to estimate process delay from step response. The process gain and time constants. Another empirical approach is to estimate process delay from step response. The process gain and time constants. Another empirical approach is to estimate process delay from step response. The process gain and time constants.

Remark 3. Implicit model information contained in daily dynamic data can be explicit by using the integral equation approach (IEA), without designing test signals to conduct system identification tests. The proposed modeling method is the upgraded version of approaches and more general. It can be seen from the derivation process that this method is easy to be extended to higher-order systems such as the third order and fourth order. In addition, this method is not only effective for step response data but also for more general process dynamic data, and the identification accuracy is enough. In practice, the integral is usually approximated by the sum of rectangular divisions, and trapezoidal divisions can be used to obtain higher calculation accuracy.

Since integration can eliminate the influence of white noise, this method is inherently robust. Regarding colored noise, variants of the least squares method such as the instrumental variable method can be used to solve model parameters.

Remark 4. In practical applications, if there is a process model, it can be approximated as a low-order system through approximation rules. If there is no process model, the FOPDT model should be used for modeling first; if the model fitness \( Q \) exceeds 85%, FOPDT is appropriate to be used. Otherwise, then try to use the SOPDT model for modeling. Systems of the third order and above can be extended by the above method, but the complexity and computation will also increase. In fact, in order to analyze and study process dynamics accurately, more precise process models may be required. Then, the model order should be determined first. For example, after estimating the process time delay, the number of system poles from 1 to 10 and the number of system zeros from 1 to 10 are arranged and combined, and the process model can be solved cyclically. The number of poles and zeros of the process model can be determined when the model fits \( Q \) is the maximum, and the parameters of the model can be determined simultaneously.

Remark 5. Here is a brief introduction on how to use the obtained model to simulate the output. For MATLAB, you can use the built-in function “lsim” to implement easily. For the python implementation, use the “inverse_laplace_transform” module in the SYMPY library to perform the inverse Laplace transform, and then use the “signal.convolve” function in the SCIPY library to facilitate the implementation. Note that the input parameters supposed to be of the same data type of one function should be guaranteed in the same data type; otherwise, the running speed of the program will be very slow. For other language implementations, you need to construct the function yourself. Use the known transfer function to perform the inverse Laplace transform to obtain the impulse response sequence, and convolve the input sequence with the impulse response function to obtain the model output sequence.

3. PID TUNING AND PERFORMANCE ASSESSMENT

In practical applications, the control tasks of set point tracking and load disturbance rejection are very common. In order to facilitate understanding and direct application of this method in practice, the following will specifically introduce the performance assessment of set point tracking response and load disturbance rejecting response with the SOPDT model. In addition, the procedures for the FOPDT model can be easily derived similarly.
3.1. Set Point Tracking Task. After obtaining the process model such as the SOPDT model, the SIMC tuning method\textsuperscript{20} can be used to make the desired closed-loop transfer function as eq 16. In practical applications, $\tau_c$ can be selected according to specific performance requirements. The literature\textsuperscript{17,26} describes some research studies on the selection of this parameter. A second-order reference model was proposed to achieve better control performance.\textsuperscript{8}

Without considering the disturbance process, the closed-loop transfer function in Figure 1 is given as eq 17. In addition, the PID benchmark parameters can be determined with $e^{-\theta t} = 1 - \theta t$ for the SOPDT model as given in eq 18.

$$\begin{align*}
\frac{Y(s)}{R(s)} &= \frac{e^{-\theta t}}{\tau^2 + 1} \\
Y(s) &= \frac{P_2(s)C(s)}{1 + P_2(s)C(s)}
\end{align*}$$

For the FOPDT model, the PI controller can be determined (19).

\begin{align*}
K_p &= \frac{\tau}{\mu(\tau_c + \theta)} \\
T_i &= \min\{\tau, 4(\tau \theta)\}
\end{align*} \hspace{1cm} (19)

In order to make a balance between set point tracking task and load disturbance rejecting requirement, performance, and robustness, a compromise parameter can be selected as $\tau_c = \theta$.

For step response with amplitude $A_d$ the theoretical approximate absolute integral error benchmark $IAE_d$ can be derived (eq 20). This approximate expression is easy to implement and has a low computation. A more accurate $IAE$ can be obtained by simulating model outputs.

$$IAE_d = \int_0^{\infty} (r(t) - y(t))dt \approx 2A_d\theta$$ \hspace{1cm} (20)

The set point tracking performance index $\eta_s$ is calculated (21), where $t$ is the time for the process to reach a steady state. When $\eta_s$ is lower than the preset threshold, it indicates poor set point following performance. If the performance is poor, the PID retuning is applied (18).

Note that for nonideal step signals such as set point changes of ramp-up first and then saturation, it is difficult to use the formula to calculate the approximate performance benchmark $IAE_d$. At this time, the desired closed-loop transfer function model can be used to simulate the expected output sequence. This method is more reasonable in practice because the input is generally not an ideal step signal.

3.2. Load Disturbance Rejecting Task. For step disturbance with an amplitude of $A_d$, the literature\textsuperscript{3} gives the DS-d tuning method for the PID controller. For the SOPDT model, in order to achieve the desired disturbance closed-loop transfer function as in eq 22, the PID parameter can be obtained (eq 23) with $\tau_c = \theta$. Use the desired closed-loop transfer function to predict the expected output, calculate the ideal $IAE$ as the evaluation criterion of load disturbance rejecting performance, and compare it with the actual response to obtain the performance index $\eta_d$. In practice, the size of step disturbance may be unknown and $A_d = -\frac{K_c}{\tau} \int_0^t e(\nu)d\nu$ can be used to estimate the size of the step disturbance.

$$\begin{align*}
\frac{Y(s)}{D(s)} &= \frac{T_1}{K_p (\tau_\theta + 1)^3} \\
K_p &= \frac{\tau_1 + \tau_2}{(\tau_\theta + \theta)\mu} \\
T_i &= \frac{\tau_1 + \tau_2}{\tau_1 + \tau_2} \\
T_D &= \frac{\tau_1 \tau_2}{\tau_1 + \tau_2}
\end{align*}$$

For the FOPDT model, the PI controller can be determined (19).

$$\begin{align*}
K_p &= \frac{4\theta^2(\tau_1 + \tau_2) + 4\theta\tau_1\tau_2 - 4\theta^3}{8\theta^3} \\
T_i &= \frac{4\theta^2(\tau_1 + \tau_2) + 4\theta\tau_1\tau_2 - 4\theta^3}{\tau_1 \tau_2 + \theta(\tau_1 + \tau_2) + \theta^2} \\
T_D &= \frac{7\theta^2\tau_1\tau_2 - 2\theta(\tau_1 + \tau_2) - \theta^4}{4\theta^2(\tau_1 + \tau_2) + 4\theta\tau_1\tau_2 - 4\theta^3}
\end{align*}$$

For the FOPDT model, the PI controller can be determined (19).
The literature\textsuperscript{26} gives a simple and usable performance evaluation benchmark for step disturbance, which is easy to apply in engineering practice. That is, the integral error value IE is used as the performance index benchmark IAEd because the integral error value is less than or equal to the absolute integral error value (24).

\[ IAE = \int_0^\infty |e(t)|dt \geq \int_0^\infty e(t)dt = IE \]  
\[(24)\]

**Remark 6.** For set point tracking task, the PID tuning rules of SIMC\textsuperscript{26} and DS-d\textsuperscript{21} are the same when the condition $\tau_1 \leq 4(\tau_c + \theta)$ is true for SOPDT model. However, SIMC tuning considers more when the condition is false. For load disturbance rejecting task, the simulations in Section 4 show that DS-d method is much better than SIMC. Therefore, SIMC tuning is suggested for the control task of set point tracking, and DS-d tuning is advised for load disturbance rejecting task. Besides, for the sake of safety and practical operation, the way of selecting $\tau_c$ is presented as follows. First, $\tau_c$ can be solved to make the tuned proportional coefficient $K_p$ approach to the original proportional coefficient. Then, change $\tau_c$ a little at a time. Apply the tuned PID to check whether control performance becomes better or not. A smaller $\tau_c$ can attain fast speed of response and good disturbance rejection, while a larger one is better for small input variation and can enhance stability and robustness of the system.

3.3. **General Procedure.** The procedures of process modeling and PID performance assessment and retuning are depicted as Figure 2.

After obtaining the process model such as the SOPDT model, PID tuning methods can be selected according to actual demands. For the dynamic response data of the process with the sampling period $T_s$, set point value $r_o$, process variable $y_o$, and controller output $u_o$ usually can be accessed. After the PID benchmark parameters and process parameters are determined, the control loop can be used to simulate the output. The difference between the set point value and the process variable, namely, the control error signal, is taken as the input sequence, and the theoretical output of PID controller can be simulated. For those exceeding the controller’s constraints, the output values are taken as the limit values. Then, the process output is simulated with the process model. The control performance assessment can be attained by comparing the IAE of actual variables with that of simulated variables.

When the control performance assessment index $\eta$ is close to 1 (or higher than the preset threshold), it indicates that the control performance is good. The threshold is generally set to 0.6. When it is close to 0 (or below the preset threshold), it indicates poor control performance. Then, the controller parameters need to be adjusted.

4. **SIMULATIONS**

In order to verify the effectiveness of the method proposed in this paper, the feasibility and effectiveness are verified by the simulation below. The third-order process is adopted as follows.\textsuperscript{26}

\[ P(s) = \frac{1}{(10s + 1)(5s + 1)(s + 1)}e^{-4s} \]  
\[(25)\]

**Figure 3.** Measured output and the FOPDT model output.

**Table 1. Models for Set Point Tracking Response without Measurement Noise**

| modeling methods       | model                      | fitness (%) |
|------------------------|----------------------------|-------------|
| proposed method with the FOPDT model | $\frac{1.0067}{16.2655s + 1}$ | 77.85       |
| proposed method with the SOPDT model | $(0.9999)(9.7047s + 1)(5.5998s + 1)$ | 99.05       |
| referenced method\textsuperscript{26} | $\frac{0.9852}{11.0134s + 1}$ | 72.43       |

**Figure 4.** Measured output and model outputs.

4.1. **Set Point Tracking Case.** The initial parameters of the ideal form PID used in the simulation are $K_p = 1.1$, $T_i = 11.0$, and $T_d = 0.9091$, which are consistent with the serial form PID as $K_p = 1$, $T_i = 10$, and $T_d = 1$, respectively.\textsuperscript{26} In order to be consistent with practical situation, the controller output is limited between $-1$ and $3$.

4.1.1. **Step without Measurement Noise.** Without considering the measurement noise, the sampling period is set to 0.1 s, and the total simulation time is 200 s. The set point input $r$ changes from 0 to 1 after a sampling period, and the disturbance input signal $d$ remains at zero. Using the
obtained step response data, the FOPDT model is first used for process modeling. The model obtained is \( P(s) = \frac{1.0067}{16.2655 + 1} e^{-4.8s} \). Based on the obtained model, the model output can be simulated with the model input and the model fit index \( Q = 77.85\% \). Figure 3 shows the measured process variable and the model output. It can be seen that the trend is basically consistent, but the accuracy of the model needs to be further improved.

Using the SOPDT model for process modeling, the model obtained is \( P(s) = \frac{0.9999}{(9.7047s + 1)(5.5998s + 1)} e^{-4.8s} \). Based on the obtained model, the model output can be simulated with the model input and the model fit index \( Q = 99.05\% \), indicating that the established model is more accurate and much better than the FOPDT model. Note that the one-dimensional search algorithm for process time delay is adopted as default. The method \(^{26}\) is also used, and \( P(s) = \frac{0.9784}{9.5524s + 1} e^{-6s} \) is obtained with model fitness 72.43%. The information of these models are concluded in Table 1, and the corresponding curves of model outputs are shown in Figure 4.

Choosing \( \tau_c = \theta_c \), the set point tracking performance index is calculated as \( \eta_r = 0.5005 \), indicating that the control performance is poor. The actual output and expected output are shown in Figure 5, consistent with the performance indicator.

After adjusting the PID parameters to \( K_p = 1.5944, T_i = 15.3045, \) and \( T_d = 3.5509 \) with \( \tau_c = \theta_c \) in eq 18, \( \eta_r = 0.7118 \) is obtained. The results show that the set point tracking performance has been significantly improved after retuning the controller parameters, as shown in Figure 6.

Based on different models, corresponding tuning methods can be chosen to determine retuned PID parameters as Table 2. The curves of process variable and control variable of different PID are shown in Figure 6.

The result shows that the established SOPDT model is closest to the actual process, and PID parameters determined by the proposed method with the SOPDT model also

### Table 2. Retuned PID and IAE for Set Point Tracking Response without Measurement Noise

| type               | \( K_p \) | \( T_i \) | \( T_d \) | IAE       |
|--------------------|----------|----------|----------|-----------|
| initial PID        | 1.1      | 11       | 0.9091   | 19.2808   |
| proposed method with the FOPDT model | 1.6830   | 16.2655  | 21.5905  |
| proposed method with the SOPDT model | 1.5944   | 15.3045  | 13.5579  |
| referenced method with returning algorithm\(^{26}\) | 0.9315   | 11.0134  | 17.5367  |
| referenced method with formula directly\(^{26}\) | 0.9315   | 11.0134  | 19.8570  |

### Table 3. Models for Set Point Tracking Response with Measurement Noise

| modeling methods | model | fitness (%) |
|------------------|-------|-------------|
| proposed method with the FOPDT model | \( 0.9728 e^{-4.8s} \) | 77.65 |
| proposed method with the SOPDT model | \( 0.9666 e^{-4.8s} \) | 96.63 |
| referenced method\(^{26}\) | \( 0.9784 e^{-6s} \) | 41.19 |

Figure 5. Actual process output and expected output.

Figure 6. System response corresponds to different PID without measurement noise.
perform best. The model established by the referenced method is not accurate as models obtained by the proposed method. The PID parameters determined by the proposed method with the FOPDT model seem to be the worst, even poorer than the initial PID. The reason is that the real process is a third-order system, and the FOPDT model cannot approximate the actual process dynamics very well. Also, it seems that PI controller parameters determined by the proposed method are not better than the referenced method, although its model is with higher fitness. However, the result may be different if another process is adopted because we use the same tuning ruler for the PI controller, and the model built by the proposed method is with better accuracy.

4.1.2. Step with Measurement Noise. In practical applications, measurement noise is very common. This part will study the effectiveness of the proposed method under measurement noise.

After adding the measurement noise, repeat the above procedures; the model information is concluded in Table 3, and the corresponding curves of model outputs are shown in Figure 7.

Based on different models, corresponding tuning methods can be chosen to determine retuned PID parameters, as shown in Table 4. The curves of the process variable and control variable of different PID are shown in Figure 8.

The result shows that proposed method is still effective under measurement noise. The model built by the proposed method keeps good model fits. However, the model established by the referenced method is obviously poorer under the same measurement noise and the time constant is too small.

4.1.3. Ramp without Measurement Noise. Because the ideal step signal may be not practical in industry processes, set point changes of ramp-up first and then saturation are selected as system input in this test. The information of models is concluded in Table 5, and the corresponding curves of model outputs are shown in Figure 9.

Based on different models, corresponding tuning methods can be chosen to determine retuned PID parameters, as shown in Table 6. The curves of the process variable and control variable of different PIDs are shown in Figure 10.

The result shows that the proposed method is still applicable under set point changes of ramp-up first and then saturation, while the referenced method is totally ineffective.

4.1.4. Sine without Measurement Noise. Any kind of signal can be decomposed into superposition of sine waves by Fourier transform. To validate the effectiveness of the proposed method, sine signal is selected as the system input in below test. The information of models is concluded

| type | $K_p$ | $T_i$ | $T_d$ | IAE |
|------|-------|------|------|-----|
| initial PID | 1.1 | 11 | 0.9091 | 19.9525 |
| proposed method with the FOPDT model | 1.6631 | 15.8555 | 22.3445 |
| proposed method with the SOPDT model | 1.5751 | 14.9205 | 3.6223 | 14.6018 |
| referenced method with retuning algorithm | 0.7873 | 9.5524 | 2.2484 | 20.2663 |
| referenced method with formula directly | 0.7873 | 9.5524 | 21.7565 |

Figure 7. Measured output and model outputs.

Figure 8. Process variable and the control variable correspond to different PIDs.

Table 4. Retuned PID for Set Point Tracking Response with Measurement Noise

Figure 9. Measured output and model outputs.

Figure 10. Measured output and model outputs.
Table 5. Models for Set Point Tracking Response without Measurement Noise

| modeling methods       | model                                                                 | fitness (%) |
|------------------------|----------------------------------------------------------------------|-------------|
| proposed method with the FOPOT model | $\frac{1.0079}{16.9034s + 1} e^{-4.2s}$ | 77.11       |
| proposed method with the SOPOT model | $\frac{0.9998}{[(7.886 + 1.2455)s + 1][(7.886 - 1.2455)s + 1]} e^{-4.2s}$ | 97.99       |
| referenced method$^{26}$ |                                                                      |             |

Table 6. Retuned PID for Set Point Tracking Response without Measurement Noise

| type                  | $K_p$ | $T_i$ | $T_d$ | IAE   |
|-----------------------|-------|-------|-------|-------|
| initial PID           | 1.1   | 11    | 0.9091| 18.4063|
| proposed method with the FOPOT model | 1.9966 | 16.9034 | 26.0805 |
| proposed method with the SOPOT model | 1.878 | 15.7719 | 4.0413 | 9.7971 |

Table 7. Models for Set Point Tracking Response without Measurement Noise

| modeling methods       | model                                                                 | fitness (%) |
|------------------------|----------------------------------------------------------------------|-------------|
| proposed method with the FOPOT model | $\frac{1.0771}{18.3381s + 1} e^{-6.6s}$ | 75.33       |
| proposed method with the SOPOT model | $\frac{1.0009}{(9.4619s + 1)(5.7194s + 1)} e^{-4.8s}$ | 99.01       |
| referenced method$^{26}$ |                                                                      |             |

Figure 9. Measured output and model outputs.

Figure 10. Process variable and the control variable correspond to different PIDs.

Figure 11. Measured output and model outputs.

In Table 7, and the corresponding curves of model outputs are shown in Figure 11.

Based on different models, corresponding tuning methods can be chosen to determine retuned PID parameters as Table
8. The curves of process variable and control variable of different PID are shown in Figure 12.

The result shows that the proposed method is still applicable under set point changes of the sine type, while the referenced method is totally ineffective.

4.2. Load Disturbance Rejecting Case. 4.2.1. Step without Measurement Noise. Without considering the measurement noise, the set point input $r$ remains at zero, and the disturbance input signal $d$ changes from 0 to 1 after a sampling period.

It is worth noting that the data of process dynamic response used for process modeling is the input and output of the controlled process. The information of models are concluded in Table 9, and the corresponding curves of model outputs are shown in Figure 13.

Based on different models, corresponding tuning methods can be chosen to determine retuned PID parameters, as shown in Table 10. The curves of the process variable and control variable of different PIDs are shown in Figure 14.

The result shows that proposed method is also effective for step load disturbance rejecting response even when the controller outputs are limited. The process models built by the proposed method is good and even better than ones established with set point tracking response. The model cannot be established by the referenced method when the controller output is limited. With no controller constraints, the referenced method is applicable and the obtained model is as good as the model built by the proposed method with the FOPDT model. However, Figure 14 shows the proposed method outweighs the referenced method.

4.2.2. Step with Measurement Noise. After adding the measurement noise, repeat the above procedure; the information of models is concluded in Table 11, and the corresponding curves of model outputs are shown in Figure 15.

Based on different models, corresponding tuning methods can be chosen to determine retuned PID parameters, as shown in Table 12. The curves of the process variable and control variable of different PIDs are shown in Figure 16.

The proposed method is still effective under both controller constraints and measurement noise, and the referenced method cannot accomplish the task of perform-

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Table 8. Retuned PID for Set Point Tracking Response without Measurement Noise

| type              | $K_p$ | $T_i$ | $T_d$ | IAE   |
|-------------------|-------|-------|-------|-------|
| initial PID       | 1.1   | 11    | 0.9091| 178.7505 |
| proposed method with the FOPOT model | 1.2946 | 18.3381 | 182.0859 |
| proposed method with the SOPOT model | 1.5800 | 15.1813 | 173.6559 |

Table 9. Models for Load Disturbance Rejecting Response without Measurement Noise

| modeling methods           | model                        | fitness (%) |
|-----------------------------|------------------------------|-------------|
| proposed method with the FOPOT model | $1.0050 \cdot e^{-5.46_8}$ | 82.30       |
| proposed method with the SOPOT model | $0.9962 \cdot (9.7337s + 1)(5.3877s + 1)$ | 99.26       |
| referenced method$^{26}$ (with controller limits) | $0.9847 \cdot e^{-6.46_7}$ | 83.68       |
| referenced method$^{26}$ (no controller limits) | $0.9847 \cdot e^{-6.46_7}$ | 83.68       |

Figure 12. Process variable and the control variable correspond to different PID.

Figure 13. Measured output and model outputs.

Figure 14. Process variable and control variable of different PIDs.
4.2.3. Sine without Measurement Noise. Any kind of signal can be decomposed into a superposition of sine waves by the Fourier transform. To validate the effectiveness of the proposed method, the sine signal is selected as system disturbance input in the below test.

The information of models are concluded in Table 13. Figure 17 shows the measured process variable and the model output. It can be seen that the trend is consistent.

Based on the obtained SOPDT model, tuning methods as shown in eq 23 can be chosen to determine retuned PID parameters as shown in Table 14. The curves of the process variable and control variable of different PIDs are shown in Figure 18.

The result shows that the proposed method is still applicable under the disturbance signal in the sine type.

5. APPLICATIONS

5.1. Tennessee Eastman Process. Based on the actual chemical reaction process, Eastman Chemical Company of the United States has developed an open and challenging chemical simulation platform, TEP. The process data generated by it is time-varying, strong-coupling, and non-linear. In addition, it is widely used in control tests and fault diagnosis.

The controlled process studied in this paper is the reactor temperature control loop shown in Figure 19. The PI controller is used to control the reactor temperature...
XMEAS9 by adjusting the opening XMV10 of the reactor cooling water valve.

The initial temperature of the TE reactor is 122.9\(^\circ\)C, the sampling period is 0.0005 s, the total running time is 50 s, and the set point value is changed from 122.9 to 130\(^\circ\)C at 0.02 s. The temperature change curve of TE reactor is shown in Figure 20. The random fluctuation after 25 s is caused by fault 11. Fault 11 corresponds to the cooling water inlet temperature of the reactor changing randomly.

Table 13. Models for Set Point Tracking Response without Measurement Noise

| modeling methods                  | model                                                                 |
|-----------------------------------|-----------------------------------------------------------------------|
| proposed method with the FOPDT model | \( \frac{0.9993}{(8.528s + 1)(6.484s + 1)} \) e\(^{-4.7s}\) 99.01 |
| proposed method with the SOPOT model | \( \frac{0.9993}{(8.528s + 1)(6.484s + 1)} \) e\(^{-4.7s}\) 99.01 |
| referenced method\( ^{16} \) | \( \frac{0.9993}{(8.528s + 1)(6.484s + 1)} \) e\(^{-4.7s}\) 99.01 |

Figure 16. Process variable and the control variable correspond to different PIDs.

Table 14. Retuned PID for Load Disturbance Rejecting Response without Measurement Noise

| type                | \( K_p \) | \( T_i \) | \( T_d \) | IAE     |
|---------------------|----------|----------|----------|---------|
| initial PID         | 1.1      | 11       | 0.9091   | 96.9553 |
| proposed method with the SOPOT model | 2.3503   | 13.1859  | 3.3341   | 69.1404 |

The performance index is calculated \( \eta = 0.3430 \), indicating that the control performance is quite poor. The actual output and expected output are shown in Figure 23, consistent with the performance indicator.
It can be seen from the response curve that the tracking response is slow, and it will take a long time to stabilize at the set value. In order to speed up the system response speed, a small $\tau_c$, twice the sampling period, is selected for PI tuning. With eq 19, we can get $K_p = -3.4539$ and $T_i = 0.1078$. After adjusting the PID parameters, we get $\eta = 0.5211$. The results show that the control performance has been improved after retuning the controller parameters, as shown in Figure 24.

The successful application of the TEP shows the effectiveness of the proposed method. In addition, the referenced method is also tried to be used on the above reactor temperature control system, but the model obtained is obviously wrong. The reason may be that the TEP has measurement noise, and the referenced method is invalid.

5.2. Intelligent Process Control Test Facility. The IPC-TF is established at the Wuhan University of Technology, which is developed based on the NPCTF (Nuclear Process Control Test Facility) of the CIES laboratory at the University of Western Ontario. The IPC-TF is a physical simulator that simulates typical dual-loop nuclear power plants and simplified physical processes in the general
process industry, so it can be applied in research in the fields of modeling, control, and fault diagnosis. The IPC-TF platform is shown in Figure 25.

In this study, the water level control loop used is highlighted with a red square, as shown in Figure 26. The water in the bottom water tank is pumped out by pump 2, and it flows into the spherical water tank through the water inlet valve CV1-17. By adjusting the opening of the outlet valve CV-15, the liquid level of the spherical water tank is controlled.

The initial parameters of the PID controller are $K_p = -8$ and $T_i = 50$. It is worth noting that the derivative part cannot be used in this water-level control system because the transmitter of the water level is a wireless device, and the measurement value of water level changes a lot. If the derivative part is applied, valve actuation is too frequent and abnormal voice occurs. After the water level is stable at 24 cm, the set point value changes from 24 to 20.

Using the step response data, the SOPDT model is obtained with $P(s) = \frac{-2.0516}{(1701.7s + 1)(13.6768s + 1)}$ and a good fitness of 90.91%. Figure 27 shows the measured process variable and the model output. It can be seen that the trend is well consistent.

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**Figure 22.** Measured output and fourth-order model output with later irregular data.

**Figure 23.** Actual and expected response.

**Figure 24.** Temperature and valve opening correspond to initial and proposed PID.

**Figure 25.** Intelligent process control-test facility.
Because the process time delay is zero, $\tau_c = \theta$ cannot be directly used for retuning PID, and the set point tracking process is very slow. Choosing $\tau_c = 50$, the set point tracking performance index is calculated $\eta_r = 0.3777$, indicating that the control performance is poor. The actual output and expected output are shown in Figure 28, consistent with the performance indicator.

After adjusting the PI parameters to $K_p = -17.7235$ and $T_i = 213.6768$ (eq 18), $\eta_r = 0.6567$ is obtained. The results show that the set point tracking performance has been significantly improved after retuning the controller parameters, as shown in Figure 29.

The successful application on water level control of IPC-TF shows the effectiveness of the proposed method. In addition, the referenced method is also tried to be used with the same step response data, but the model obtained is obviously wrong. The reason is that the level transmitter uses wireless device and a water level without small measurement noise. Figure 29 shows the measurement value of the water level.

6. CONCLUSIONS

In this article, to solve the problem of PID performance assessment that usually requires step response data, several methods are combined and extended. Using the integral signals, implicit model information contained in process response data becomes explicit, and then, least squares approach is adopted to construct the detailed low-order

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Figure 26. Water level control loop in red square.

Figure 27. Measured output and model output.

Figure 28. Actual process output and expected output.

Figure 29. Measurement value of the water level.
process model based on process response data in more general types. Because of the use of integral signals, the form of exciting signals is not so important. A one-dimensional search algorithm is used to attain better estimation of process time delay, and IEA is extended to be useful for more general process response. The general process response data means dynamic data of closed loop control system stimulated by step input or nonideal step input, which means system response with constrained controller outputs or under measurement noise. Based on the obtained model, PID parameters are determined and the performance benchmark used for performance assessment is established by simulating the model output. PID performance assessment can be attained by comparing the actual performance index and the expected one, and PID controller will be retuned when the performance is poor. By comparing with the referenced method, the simulation and experiment verify the effectiveness of the proposed method. The proposed method may be more practical than existing approaches in actual applications of PID CPA because step response may not happen when CPA is needed. Therefore, this proposed method may be helpful to accomplish the tasks of online PID CPA.

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Notes
The authors declare no competing financial interest.

■ NOMENCLATURE

CPA controller performance assessment
IAE absolute integral error
IMC internal model control
TEP Tennessee Eastman process
IPC-TF intelligent process control test facility

IEA the integral equation approach
SOPDT second-order plus dead time
u manipulated variable
y controlled variable
θ process time delay
μ process static gain
τ1,τ2 process constants
Q model fitness index
M length of data sequence
τc coefficient used for PID tuning

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