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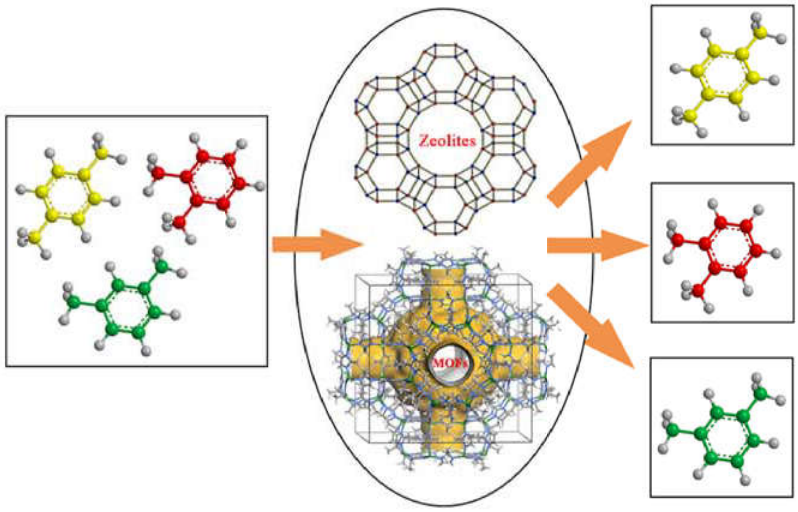

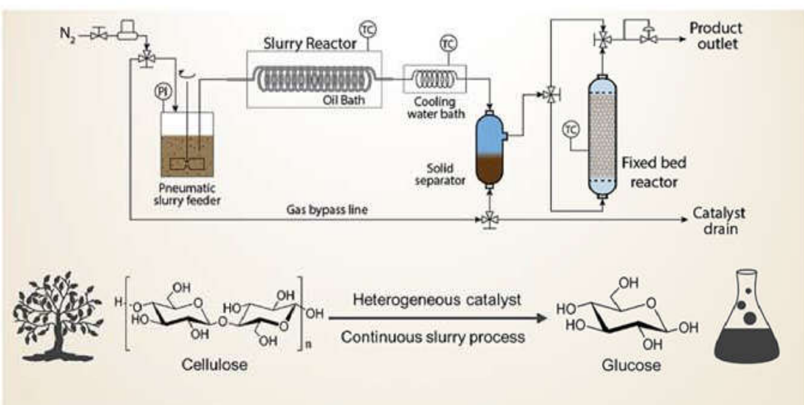

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LQG Benchmark Based Performance Assessment of IMC-PID Temperature Control System

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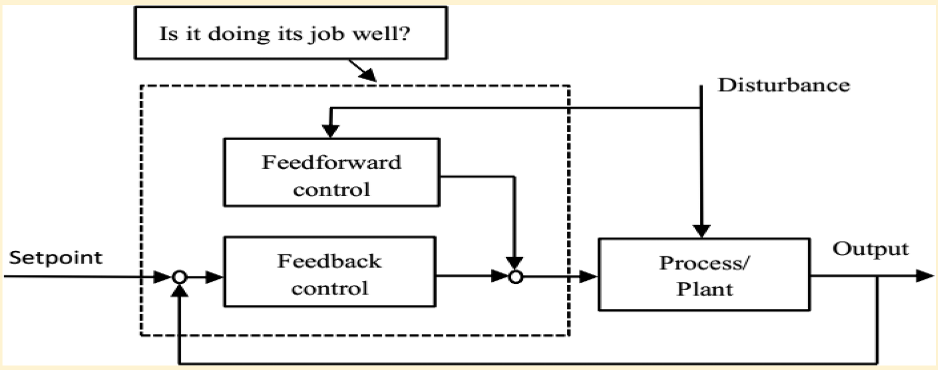

ABSTRACT: This paper focuses on the control system performance in industrial control processes and evaluates the controller performance using the assessment criterion based on linear quadratic Gaussian (LQG). The LQG performance benchmark curve is determined by the numerical calculation method, which avoids the calculation of the complex interaction matrix. This method depends on the model-based steady-state optimization technique and combines the LQG benchmark and the performance assessment of the control system. The control performance of the process system under different control strategies is described by establishing a series of the steady-state optimization problems. Compared with existing assessment algorithms, our method provides a simpler and more effective method to evaluate the performance of IMC-PID control system for both model match and model mismatch cases. Finally, the effectiveness of the method is verified by the experiments on a heating furnace.

1. INTRODUCTION

High-performance controllers are necessary for high-performance control systems, however, 60% industrial control circuits currently have a variety of performance defects such as the controller parameter design is unreasonable, the controller structure is not suitable, the process disturbance characteristics have changed during long time operation, equipment (e.g., sensors and actuators) fault, and the device is running incorrectly.[1−3] Even if the controller works normally in the initial debugging, its performance degrades because of the long-term running without parameter adjustment. With the increasing use of control systems in industrial production processes, the study of system performance assessment of controllers has attracted more and more attention.[4−8] Some of these problems can be solved by appropriate parameter adjustments, e.g., the controller parameter design, the controller structure, or the operating point of the system and so on. For some problems, the performance of a controller can be improved by adopting a new control strategy or modifying hardware devices. Because the lower control loop reduces the product quality, increases the operating costs, and shortens the service life of the equipment, it is necessary to carry out the relevant control performance assessment (CPA).[9−11]

Controller performance assessment has become one of the important directions in the research field. In 1970, Astrom[12] and Box and Jenkins[13] established the minimum variance control (MVC) theory. In 1978, DeVries and Wu[14] proposed the idea of control performance assessment. However, people began to gradually recognize the importance of control performance assessment when Shinskey,[15] Ender,[16] and Bialkowski[17] surveyed the problems of the control performance in the process industry. In 1989, Harris[18] first proposed a method to evaluate the performance of single-loop control based on the MVC with the Harris index. Subsequently, Desborgough and Harris[19] and Stanfelj et al.[20] extended the MVC benchmark to include a feedforward/feedback control loop system. In 1995, Tyler and Morari[21] extended the Harris indicators to unstable and nonminimum phase systems. In 1996, Lynch and Dumont[22] proposed the use of the Laguerre network to evaluate performance index. In 2000, Ko and Edgar[23] extended the MVC benchmark to the cascade control

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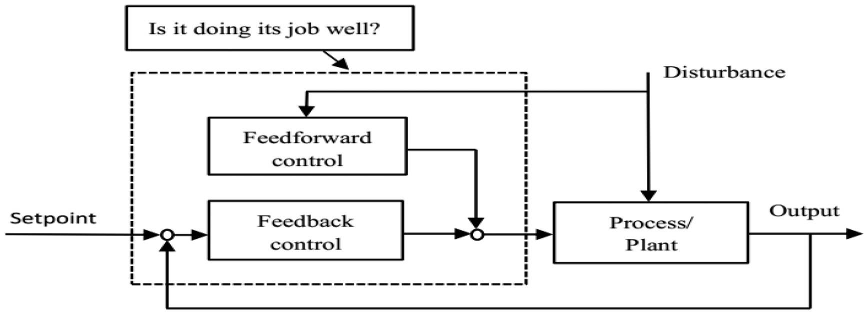

Figure 1. Typical closed-loop process.

loop. However, because of too much MVC control action and poor robustness, the practical use is very limited. In 1999, Huang et al.[24] proposed a linear quadratic Gaussian (LQG) optimal control based on MVC as a benchmark for performance assessment, which considers the input and output and provides a practical lower bound of performance. In 2002, Kadali et al.[25] proposed a method based on the closed-loop subspace method to calculate the LQG benchmarks. By setting the closed-loop data obtained by the point excitation sampling, the control law can be obtained directly. To improve the accuracy of the LQG benchmark, Danesh et al.[26] proposed a noise uniformity estimate for closed-loop subspace identification in 2009. In 2010, Danesh et al.[27] extended the LQG benchmark to the cascade control loop. In 2012, Liu et al.[28] applied an equidistant LQG benchmark for performance assessment and optimization of two-layer model predictive control (MPC). In 2015, Wei et al.[29] introduced a two-dimensional LQG benchmark for the control performance assessment of the iterative learning control (ILC) of batch processes. On the basis of these results, there are many companies that have already presented relevant performance assessment and monitoring software products, e.g., Matrikon's ProcessDoctor, ABB's Optimize[IT] Loop Performance Manager (LPM), Honeywell's Loop Scout, Metso Automation's LoopBrowser, and so on. Reference 4 shows the detailed information on these products.

The internal model control (IMC) in the control system design was established by Garcia et al.[30] and has been studied and applied widely.[31−33] With the continuous development and improvement, the study of IMC and other control algorithms can promote their development on the one hand and help to analyze other control algorithms on the other hand.[34,35] There is a corresponding relationship between the IMC and PID control such that clear analytical results can be obtained if the PID controller is converted into the IMC frame, which reduces the complexity of parameter tuning and randomness.[36] Rivera et al.[37] first introduced the idea of IMC into the design of the PID controller and established the relationship between the filter parameters and the PID controller parameters. Compared with classical PID control, the relationship between the parameters adjustment and the dynamic quality, the robustness of the system is clearer. Because PID has a wide range of applications, its performance assessment has important practical significance. Ko and Edgar,[38,39] Jain and Lakshminarayanan,[40] and Sendjaja and Kariwala et al.[41] used the MVC benchmark to evaluate the performance of the control loop by calculating the minimum variance that can be achieved by the PID/PI controller.

Although control system performance assessment techniques have achieved some results in both theoretical and industrial applications in recent years, most of the existing assessment algorithms are based on the minimum variance control system performance assessment methods.[42,43] The algorithm is based on the assumption that the input variance can be infinitely large, and the complexity of the algorithm is greatly increased due to the calculation of the interaction matrix, which limits the practicability of the algorithm to a certain extent. Compared with the minimum variance benchmark, the LQG benchmark takes into account the variance of the system control variables and the output variables, which is more in line with the actual process requirements. At the same time, although Grimble,[44] Huang,[45] and Horton et al.[46] evaluated the control performance of the PID/PI controller with LQG benchmark, these assessment methods did not consider the model match and mismatch in the industrial processes, and thus the performance assessment results are one-sided.

To solve the above problems, this paper proposes an assessment method based on LQG benchmark for IMC-PID control. The control strategy depends on the model-based steady-state optimization technology and combines the LQG benchmark and the performance assessment of the control system together. The control performance of the control system under different control strategies is described by establishment of a series of steady-state optimization problem. The method is simpler and more effective than the existing assessment algorithms. On the basis of the established model, we established the LQG benchmark by the method proposed in this paper and evaluated the IMC-PID controller in case of the model match and the model mismatch on the heating furnace. This provides the basis for the improvement of the performance of the heating furnace control system. This article mainly illustrates the following aspects:

(1) The establishment of the generalized internal closed-loop model through the internal model controller to set the PID parameters.
(2) According to the established generalized closed-loop model, we proposed an improved LQG process assessment method, where the model match and the model mismatch can be assessed.
(3) The experiment in the industrial heating furnace is further done to verify the effectiveness of the above method.

2. LQG BENCHMARK

Figure 1 is a typical closed-loop process. The weighted input/output variances are used to represent the lower bound of the performance of the linear controller in the LQG benchmark, which can be described in the mathematical form as when $\mathrm{Var}(U_k) = \alpha$, $\mathrm{Var}(Y_k)$, how much is the minimum $\mathrm{Var}(Y_k)$?

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Through the performance trade-off curve that is also known as the performance limit curve, the optimal performance can be achieved. This performance trade-off curve can be solved by solving the problem:

$$J_{\mathrm{LQG}} = \mathrm{Var}(Y_k) + \rho \mathrm{Var}(U_k) \tag{1}$$

Under the condition of varying the weighting factor, the different optimal input and output variance can be obtained. The performance trade-off curve can be drawn with the optimal input variance as the horizontal axis and the optimal output variance as the vertical axis, then we can get the lower limit of the linear controller performance and the performance index of the input and output variance (see Figure 2).

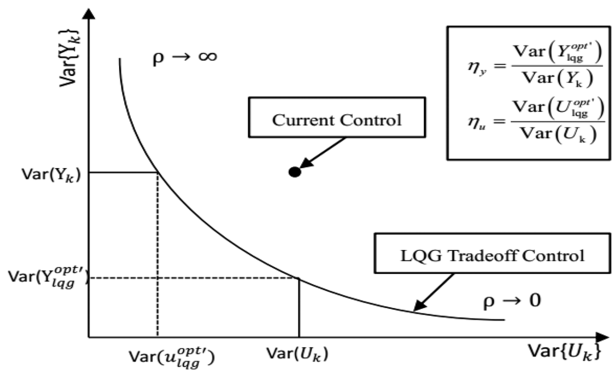

Figure 2. Limit curve based on LQG performance.

Depending on the existence and the form of the system model, the method of solving the LQG optimal control law can be divided into the following four types. When the model is a state space model, the classical state space model based algorithm or the MPC algorithm can be used. When the model is an autoregressive moving average with exogenous (ARMAX) model, the polynomial algorithm can be used. When the model is unknown or the model parameters are difficult to obtain, the closed-loop subspace method is used. This paper focuses on the LQG benchmark algorithm for the case with known system models.

2.1. LQG Benchmark Algorithm. The LQG performance benchmark is an extension of the MVC benchmark, which takes into account the variance of the system output and the control input. Therefore, the LQG performance benchmark can provide more information on the controller performance. The computational burden of the Riccati equation is very large when the LQG is used as the performance benchmark. Therefore, when the prediction horizon and the control horizon are approaching infinite, the LQG benchmark is solved by the approximation of solving the MPC, which can simplify the acquisition of the trade-off curve and is briefly described herein.[47]

Consider the single-input single-output discrete-time processes:

$$Y_k = G_p(z^{-1})U_k + G_d(z^{-1})a_k \tag{2}$$

where, Y_k and U_k are the process output and input, respectively, z^{-1} is the back-shift operator, and $\{a_k\}$ is the variance of discrete white noise sequence with the zero mean value. The transfer function of the process and disturbance are described as follows:

$$G_p(z^{-1}) = \frac{z^{-d}\omega(z^{-1})}{\delta(z^{-1})}, \quad G_d(z^{-1}) = \frac{\theta(z^{-1})}{\phi(z^{-1})\nabla} \tag{3}$$

where the polynomials $\omega(z^{-1})$, $\delta(z^{-1})$, $\theta(z^{-1})$, and $\phi(z^{-1})$ are defined as

$$\begin{aligned} \omega(z^{-1}) &= \omega_0 - \omega_1 z^{-1} - \cdots - \omega_s z^{-s} \\ \delta(z^{-1}) &= 1 - \delta_1 z^{-1} - \cdots - \delta_r z^{-r} \\ \theta(z^{-1}) &= 1 - \theta_1 z^{-1} - \cdots - \theta_q z^{-q} \\ \phi(z^{-1}) &= 1 - \phi_1 z^{-1} - \cdots - \phi_p z^{-p} \end{aligned} \tag{4}$$

where, d is the time delay of the system, and $\nabla = 1 - z^{-1}$ is the difference operator.

A quadratic optimization function is usually adopted in the infinite time-domain MPC, and the structure is as follows:

$$J_{\mathrm{MPC}} = \lim_{N\to\infty} \frac{1}{N} \sum_{j=1}^{N} (Y_{k+j|k}^2 + \rho \nabla U_{k+j-1}^2) \tag{5}$$

where N is the prediction horizon, ρ is the weighting factor, $Y_{k+j|k}$ is the predicted value for the future time $k + j$ at current time k. ∇U_{k+j-k} is the control input for the future time $k + j - 1$.

Here, $Y_{k+j|k}$ can be calculated by the following simplified perturbation model:

$$Y_k = G_{p0}(z^{-1})U_k + G_{d0}(z^{-1})a_k = \frac{z^{-d}\omega_0(z^{-1})}{\delta_0(z^{-1})}U_k + \frac{1}{\nabla}a_k \tag{6}$$

where the subscript "0" indicates the parameters in the controller with the perfect process model.

On the basis of MPC, the closed-loop output of the system can be described as

$$U_k = -G_c(z^{-1})Y_k \tag{7}$$

where $G_c(z^{-1})$ is the transfer function.

$$G_c(z^{-1}) = \frac{G_{cn}(z^{-1})}{\nabla G_{cd}(z^{-1})} \tag{8}$$

Here, $G_{cn}(z^{-1})$ and $G_{cd}(z^{-1})$ have the same forms as $\omega(z^{-1})$ in eq 4.

If the time delay d is known, the LQG performance index can be achieved while minimizing the objective function in the optimization algorithm, as pointed out by Huang and Shah:[24]

$$J_{\mathrm{LQG}} = \mathrm{Var}(Y_k) + \rho \mathrm{Var}(U_k) \tag{9}$$

Therefore, the LQG optimization problem is solved by spectral decomposition[48] and the exact expression of MPC controller can be obtained:

$$G_c(z^{-1}) = \frac{G_{cn}(z^{-1})}{\nabla G_{cd}(z^{-1})} = \frac{\delta_0(z^{-1})}{\gamma(z^{-1}) - z^{-d}\omega_0(z^{-1})} \tag{10}$$

where the polynomial $\gamma(z^{-1})$ is a reversible factor for spectral decomposition, satisfying:

$$\gamma(z^{-1})\gamma(z) = \omega_0(z^{-1})\omega_0(z) + \rho(1 - z^{-1})\delta_0(z^{-1})\delta_0(z) \times (1 - z) \tag{11}$$

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For the design of the controller, only the simplified process model is used.

For convenience, the operator z^{-1} is omitted from the following formula.

According to eqs 2, 7, and 8, we can obtain

$$Y_k = \frac{\theta\delta G_{cd}}{\phi(\delta G_{cd}\nabla + z^{-d}\omega G_{cn})}a_k \tag{12}$$

$$U_k = \frac{\theta\delta G_{cd}}{\nabla\phi(\delta G_{cd}\nabla + z^{-d}\omega G_{cn})}a_k \tag{13}$$

On the basis of the Parseval theory, the variance of the control input and the output of the closed-loop system can be obtained by the following operations:

$$\mathrm{Var}(Y_{\mathrm{lqg}}^{\mathrm{opt}}) = \sigma_Y^2 = \frac{\sigma_a^2}{2\pi j}\oint_{|z|=1}\left|\frac{\theta\delta G_{cd}}{\phi(\delta G_{cd}\nabla + z^{-d}\omega G_{cn})}\right|^2 \frac{\mathrm{d}z}{z} \tag{14}$$

$$\mathrm{Var}(U_{\mathrm{lqg}}^{\mathrm{opt}}) = \sigma_U^2 = \frac{\sigma_a^2}{2\pi j}\oint_{|z|=1}\left|\frac{\theta\delta G_{cd}}{\nabla\phi(\delta G_{cd}\nabla + z^{-d}\omega G_{cn})}\right|^2 \frac{\mathrm{d}z}{z} \tag{15}$$

2.2. Trade-off Curves and the Indicators. For the range $[0 + \infty)$ and according to the above algorithm, we can get different $\mathrm{Var}(U_{\mathrm{lqg}}^{\mathrm{opt}})$ and $\mathrm{Var}(Y_{\mathrm{lqg}}^{\mathrm{opt}})$ values for different ρ values. Then we can draw the trade-off curve that presents the control performance limit for which the PID, MPC and other linear controllers can only operate in the right area above the curve in Figure 2.

Assume that the current input and output variances are $\mathrm{Var}(U_k)$ and $\mathrm{Var}(Y_k)$, the optimal output variance of $\mathrm{Var}(Y_k)$ corresponding to the trade-off curve is $\mathrm{Var}(Y_{\mathrm{lqg}}^{\mathrm{opt}\prime})$, and the optimal output variance of $\mathrm{Var}(U_k)$ corresponding to the trade-off curve is $\mathrm{Var}(U_{\mathrm{lqg}}^{\mathrm{opt}\prime})$, then the current control performance can be reflected by defining two indicators of the input and output variances:

$$\eta_y = \frac{\mathrm{Var}(Y_{\mathrm{lqg}}^{\mathrm{opt}'})}{\mathrm{Var}(Y_k)}, \quad \eta_u = \frac{\mathrm{Var}(U_{\mathrm{lqg}}^{\mathrm{opt}'})}{\mathrm{Var}(U_k)} \tag{16}$$

Obviously, both η_y and η_u vary between 0 and 1. In case $\eta_y = 1$, it means that for a given input variance, the controller achieves the optimal output variance; otherwise, there is room for improvement in the process output accordingly. Similarly, in case $\eta_u = 1$, it means that for a given output variance, the controller produces an optimal input variance; otherwise, there is room for reduction.

3. PROCESS MODEL ESTABLISHMENT AND IMC-PID PRINCIPLE

3.1. Process Model Establishment. In industrial process control, the two-point method is a commonly used modeling method.[49,50] By analyzing the time domain response curve of the system, the response parameters of the system can be obtained, which can be described as the first-order plus dead time (FOPDT)

$$G_p(s) = \frac{y(s)}{u(s)} = \frac{K}{Ts + 1}\mathrm{e}^{-\tau s} \tag{17}$$

where $G_p(s)$ is the transfer function, $y(s)$ and $u(s)$ are the Laplace transforms of the output $y(t)$ and input $u(t)$, respectively, K is the gain of the process, T is the system time constant which needs to be identified and determined by the system itself, and τ is the time delay.

The time domain response of FOPDT can be described as follows:

$$y(t) = \begin{cases} 0, & t < \tau \\ K - Ke^{-t-\tau/T}, & t \geq \tau \end{cases} \tag{18}$$

Denote $y(\infty)$ as the steady value of $y(t)$ and U as the input step signal change. The steady process gain K is then calculated as $K = \frac{y(\infty) - y(0)}{U}$.

Selecting two special points with the gain ratio coefficient of t_1 and t_2, respectively, we can obtain through the system response curve that

$$\begin{aligned} y(t_1) &= 0.39(y(\infty) - y(0)) + y(0) \\ y(t_2) &= 0.63(y(\infty) - y(0)) + y(0) \end{aligned} \tag{19}$$

So, the system time constant T and the system delay time τ are given as

$$\begin{aligned} T &= 2(t_2 - t_1) \\ \tau &= 2t_1 - t_2 \end{aligned} \tag{20}$$

Through the above two-point modeling method, we have established the FOPDT model as eq 17.

Under the condition of sampling time T_s, eq 17 can be discretized and then we can obtain the following model:

$$y(k) = \alpha_m y(k-1) + K(1-\alpha_m)u(k-d-1) \tag{21}$$

where the time-delay step d is an integer part of τ/T_s, $\alpha_m = \mathrm{e}^{(-T_s/T)}$.

3.2. Principle of IMC-PID. In this paper, we use IMC-PID to control the temperature of an industrial heating furnace and the control block is shown in Figure 3.

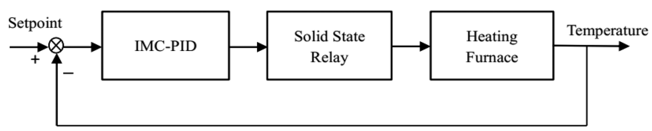

Figure 3. Block of IMC-PID for heating furnace.

According to ref 51, the relationship between the PID parameters and the internal model controller is

$$K_p = \frac{T + 0.5\tau}{K(\lambda + 0.5\tau)}, \quad T_i = T + 0.5\tau, \quad T_d = \frac{T\tau}{2T + \tau} \tag{22}$$

where, K is the system gain, K_p is the proportional coefficient, T_i is the integral coefficient, and T_d is the derivative coefficient.

4. CASE STUDY

In this paper, the process is a SXF-4-10 type temperature control system of a furnace as shown in Figure 4, and its rated voltage and rated power is 220 V and 4 kW, respectively.

4.1. Process Description. The temperature control system produces the required temperature for product heating. The process flow mainly consists of the temperature measurement

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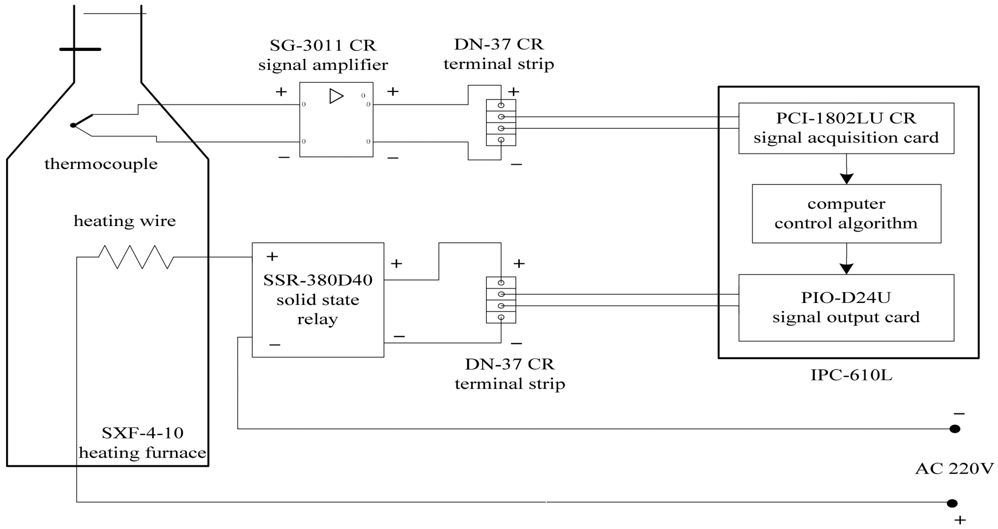

Figure 4. Process flowchart of the electric heating furnace (SXF-4-10).

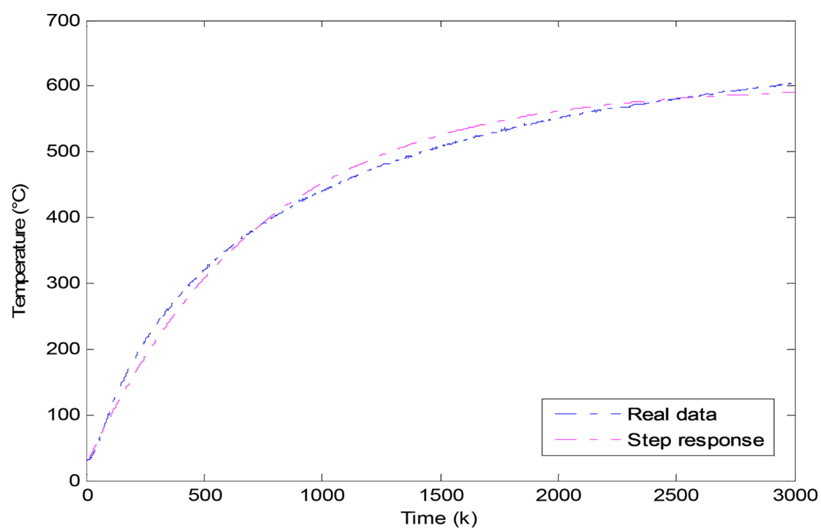

Figure 5. Step response of the furnace process.

with the K-type thermocouple, the industrial control computer, and the execution part. The temperature of the furnace is collected through the PCI-1802LU converter and sent to the industrial computers for processing. After this, the temperature is compared with the desired temperature set-point and the corresponding control algorithm in the industrial control computer will calculate the corresponding heating amount required and send this requirement to the temperature execution module for implementation with the control of the off time of the relay.

4.2. Establishment of the Heating Furnace Model. In the furnace system, a constant step input signal (20% duty cycles) was implemented until there are no significant temperature changes in the furnace, and the temperature of the heating furnace was sampled every 2 s during the heating process. The obtained temperature values are shown in Figure 5. The FOPDT model for the furnace was established using the two-point method described above:

$$G_p(s) = \frac{28.5}{735s + 1}\, e^{-100s} \tag{23}$$

Here, the sampling time T_s = 20s is chosen in the discretization of the eq 23, and the discrete form of the model is

$$G_p(z) = \frac{0.7651z^{-6}}{1 - 0.9732z^{-1}} \tag{24}$$

In the course of the experiment, the disturbance transfer function model is simulated as

$$G_d(z^{-1}) = \frac{1 + 0.2000z^{-1}}{1 - 0.9732z^{-1}} \tag{25}$$

According to the eqs 24 and 25, the discrete-time processes model of the furnace can be written as

$$Y_k = \frac{0.7651z^{-6}}{1 - 0.9732z^{-1}}U_k + \frac{1 + 0.2000z^{-1}}{1 - 0.9732z^{-1}}\alpha_k \tag{26}$$

4.3. Experimental Results. Through the experiment, we established the FOPDT model of the furnace and the discrete model. We add the white noise $\{\alpha_k\}$ disturbance with the mean value of 0 and the variance of 0.1 to the temperature control system, then change the weight within a certain range, calculate

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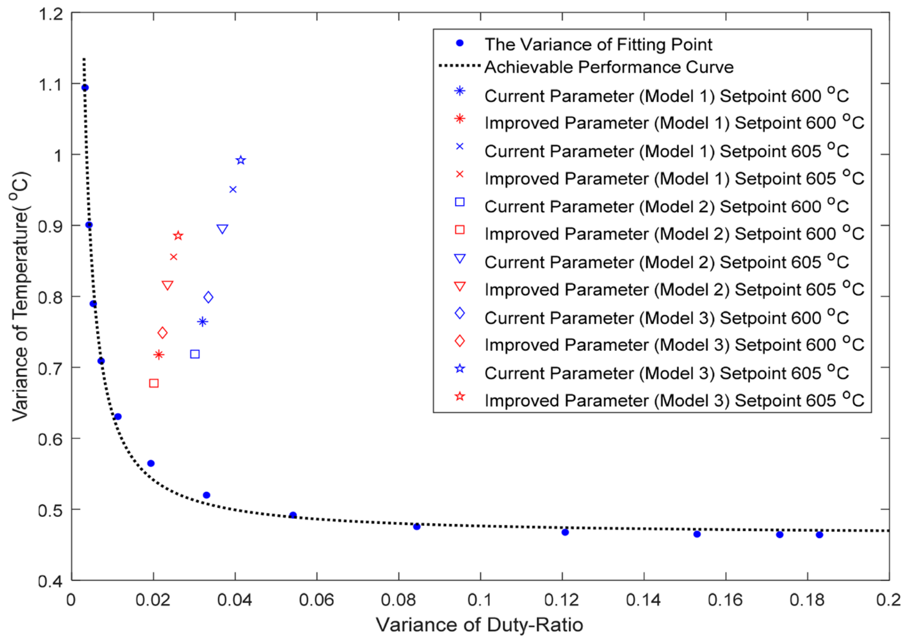

Figure 6. Limit curve based on LQG performance and actual variance of the system.

the corresponding optimal input and output variance values, and use the above LQG benchmark algorithm method to obtain the trade-off curve of the LQG benchmark, which is shown in Figure 6.

The proportional, integral, and derivative coefficients, according to the above IMC-PID principle, are

$$\lambda = 87, \quad K_p = 0.2011, \quad K_i = 0.0014, \quad K_d = 0.0235$$

Considering that the model and the actual process are difficult to match exactly in practice, we consider both the model match and the model mismatch cases in this paper, and the experimental results are shown in Figure 7a−c, with the model parameters:

$$\text{Model 1: } T = 735; \ \tau = 100; \ K = 28.5$$

$$\text{Model 2: } T = 588; \ \tau = 80; \ K = 22.8$$

$$\text{Model 3: } T = 882; \ \tau = 120; \ K = 34.2$$

According to the experimental results, the input variance and the output variance in the model match and the model mismatch are shown in Table 1. The assessment of the performance of the control system has been performed according to the performance index defined above. When the heating furnace temperature set-point is 600 °C, the performance index of the match model (Model 1) is η_u = 18.97%, ηy = 66.62%, the performance index of the mismatch model (Model 2) is η_u = 23.32%, η_y = 71.32%, and the performance index of the mismatch model (Model 3) is η_u = 16.53%, η_y = 63.48%. When the heating furnace temperature set-point is 605 °C, the performance index of the match model (Model 1) is η_u = 10.09%, η_y = 52.56%, the performance index of the mismatch model (Model 2) is η_u = 11.98%, η_y = 56.07%, and the performance index of the mismatch model (Model 3) is η_u = 8.97%, η_y = 50.20%. According to the above results, there is the relatively large room for improvement in the control performance.

According to the results of the assessment and the simulation results, here the parameter λ of the IMC-PID controller as well as the integral and the derivative coefficients are adjusted by the trial and error method. We chose one set of the controller parameters with the best control effect of the heating furnace, and the parameters are

$$\lambda = 113, \ K_p = 0.1690, \ K_i = 0.0011, \ K_d = 0.0192$$

After adjustment and recalculation of the relevant data and performance index, the simulation results of the three different model parameters are further shown in Figure 7a−c

When the heating furnace temperature set-point is 600 °C, it shows that the performance index of the match model (Model 1) is improved to η_u = 33.03%, η_y = 74.64%, the performance index of the mismatch model (Model 2) is improved to η_u = 23.94%, η_y = 77.34%, and the performance index of the mismatch model (Model 3) is improved to η_u = 36.87%, η_u = 72.23%. When the heating furnace temperature set-point is 605 °C, it shows that the performance index of the match model (Model 1) is improved to η_u = 21.15%, η_y = 61.77%, the performance index of the mismatch model (Model 2) is improved to η_u = 27.17%, η_y = 65.19%, and the performance index of the mismatch model (Model 3) is improved to η_u = 17.34%, η_y = 58.87%. By readjusting the parameters, the control performance is greatly improved for both model match and model mismatch cases, as shown in Table 2.

According to the results, we obtained the actual input variance and output variance of the system under the conditions of the model match and the model mismatch before and after changing the controller parameters, whose specific values are shown in Figure 6. We can intuitively find that by adjusting the parameters of the IMC-PID, the input variance and the output variance are reduced to some extent under both the model match and the model mismatch cases and closer to the LQG trade-off curve, indicating that the control performance of the controller has been greatly improved after the parameters adjustment as expected.

In addition, for different heating furnace temperature set-points, the actual input variance and output variance of the system before and after the controller parameter adjustment are

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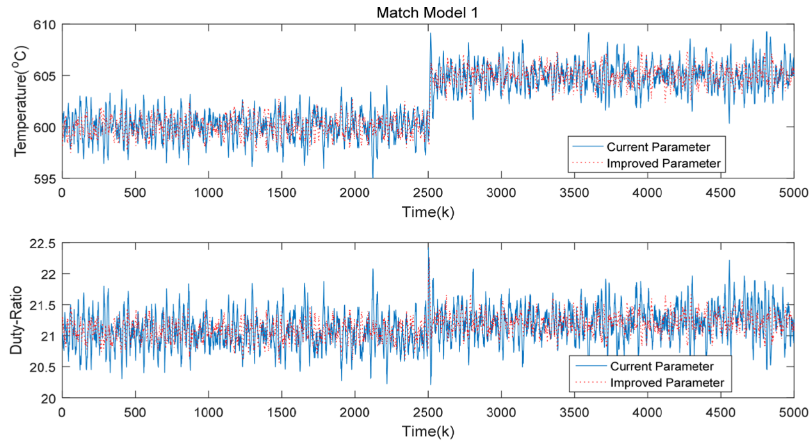
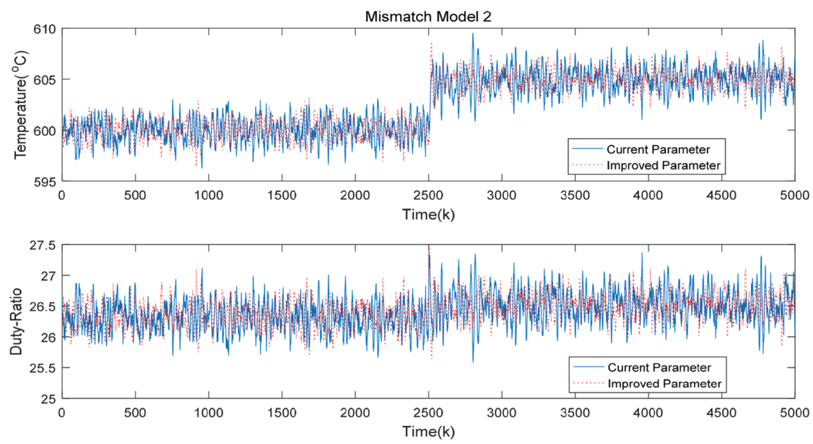
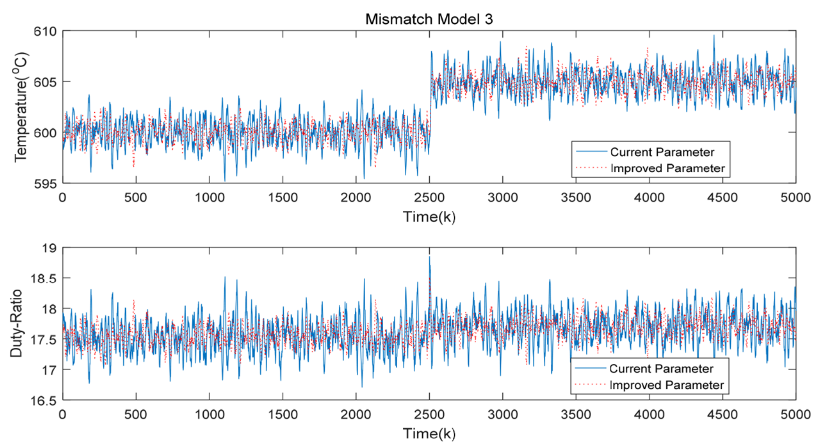


$$Model\ 1:\quad T = 735; \tau = 100; K = 28.5$$



$$Model\ 2:\quad T = 588; \tau = 80; K = 22.8$$



$$Model\ 3:\quad T = 882; \tau = 120; K = 34.2$$

Figure 7. (a) Corresponding input and output of the different parameter (Model 1). (b) Corresponding input and output of the different parameter (Model 2). (c) Corresponding input and output of the different parameter (Model 3).

compared for the model match and model mismatch cases, and the results are plotted as bar graphs in Figure 8a,b. According to the results, when the heating furnace temperature set-point is 600 °C, it is found that the corresponding input variance and output variance decrease by 14.05% and 8.02%, respectively, for the match Model 1, and those decrease 0.62% and 6.02%, respectively, for mismatch Model 2, and 20.34% and 8.75%, respectively, for mismatch Model 3.

When the heating furnace temperature set-point is 605 °C, it is found that the corresponding input variance and output variance decrease by 11.06% and 9.2%, respectively, for the match Model 1, and those decrease 15.19% and 9.12%, respectively, for mismatch Model 2, and 8.38% and 8.67%,

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Table 1. Statistical Results of Steady State Performance

set-point	⊥model	Var(u_k)	Var(y_k)	Var($u_{\mathrm{lqg}}^{\mathrm{opt}}$)	η_u (%)	Var($y_{\mathrm{lqg}}^{\mathrm{opt}}$)	η_y (%)
600 °C	model 1	0.0320	0.7644	0.0061	18.97	0.5093	66.62
	model 2	0.0301	0.7186	0.0070	23.32	0.5125	71.32
	model 3	0.0334	0.7988	0.0055	16.53	0.5071	63.48
605 °C	model 1	0.0394	0.9507	0.0040	10.09	0.4997	52.56
	model 2	0.0368	0.8964	0.0044	11.98	0.5026	56.07
	model 3	0.0413	0.9918	0.0037	8.97	0.4979	50.20

Table 2. Statistical Results of Steady State Performance

set-point	model	Var(u_k)	Var(y_k)	Var($u_{\mathrm{lqg}}^{\mathrm{opt}}$)	η_u (%)	Var($y_{\mathrm{lqg}}^{\mathrm{opt}}$)	η_y (%)
600 °C	model 1	0.0213	0.7179	0.0070	33.03	0.5359	74.64
	model 2	0.0201	0.6777	0.0082	23.94	0.5408	77.34
	model 3	0.0222	0.7487	0.0064	36.87	0.5326	72.23
605 °C	model 1	0.0249	0.8557	0.0048	21.15	0.5241	61.77
	model 2	0.0234	0.8170	0.0053	27.17	0.5285	65.19
	model 3	0.0260	0.8855	0.0045	17.34	0.5213	58.87

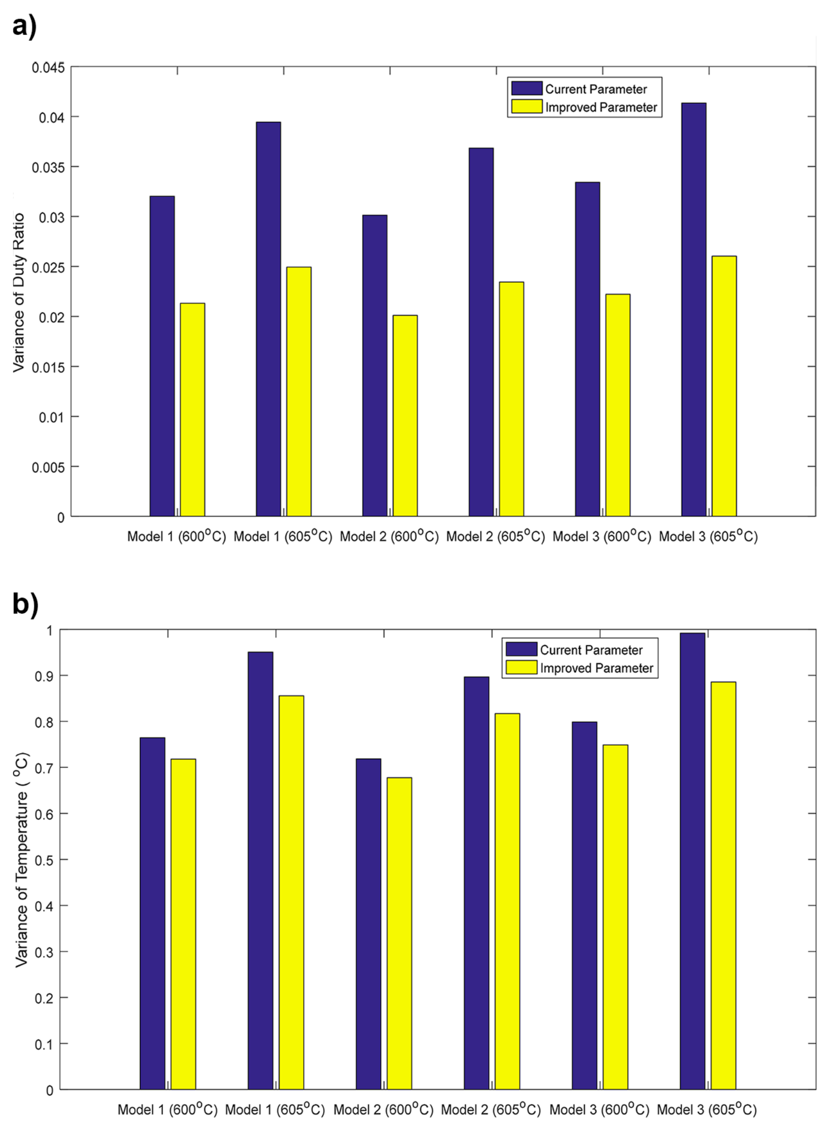

Figure 8. (a) Duty ratio's variance of the system under current/improved parameter conditions. (b) Temperature's variance of the system under current/improved parameter conditions.

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respectively, for mismatch Model 3. The decrease of the input variance is more obvious compared with that of the output variance, and the system tends to be under the control with the smallest energy. Through redesigning the controller parameters after the assessment of the system performance, the control performance of the system has been effectively improved for the model match and the model mismatch cases.

5. CONCLUSION

In this paper, we focus on the LQG benchmark based study of the control performance of model match and model mismatch of IMC-PID controller. The optimal control law is obtained by solving the linear quadratic Gaussian problem and the optimal input and output variance are determined for different weighting factors, then the performance limiting curve and the performance index of the input and the output variance are given. Finally, the performance assessment of the model match and the model mismatch based on the IMC-PID controller is carried out by using the LQG benchmark. The results show that there still exists a large room for improvement for the control performance. By readjustment of the parameters, the control performance of the controller is further improved and the lower limit of the performance of linear controller is given at the same time, which allows us to effectively evaluate the control performance of the controller when carrying out the heating furnace control experiment and to take timely measurements and adjustments.

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Notes

The authors declare no competing financial interest.

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