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The Local-Symmetrical-Double-Integral-Type Iterative Learning Control for Dynamics of Industrial Processes with Time Delay in Steady-State Optimization[1)]

RUAN Xiao-E[1] LI Huan-Qin[1] WAN Bai-Wu[2]

[1](*Faculty of Science, Xi'an Jiaotong University, Xi'an* 710049)

[2](*Systems Engineering Institute, Xi'an Jiaotong University, Xi'an* 710049)

(E-mail: wruanxe@mail.xjtu.edu.cn)

Abstract The weighted leading local-symmetrical-double-integral-type iterative learning control algorithm is studied for dynamics of industrial processes with time delay in steady-state optimizing. Based on the desired trajectory and real output dynamical information of the control system, a basic iterative learning control algorithm is suggested, its ε-convergence is derived, and the interval length of local symmetrical double integral is determined. Digital simulations show that the iterative learning control algorithm can effectively eliminate the influence of the noise on output signal and can remarkably improve the dynamical performance of the control systems in steady-state optimizing, such as to decrease the overshoot, shorten the settling time, accelerate the response, etc.

Key words Local-symmetrical-double-integral, iterative learning control, time delay

1 Introduction

In the course of steady-state hierarchical optimizing for large-scale industrial processes, the model-reality difference exists due to the complexity and uncertainty of the control systems. In this situation, the coordinator in the upper level computes out a series of controller's step set-point changes with different magnitudes. Then each set-point is imposed on the real process and a conventional PID controller adjusts the system. But the system dynamical performance is usually not satisfying because of the complexity and uncertainty of the control system, such as excessive overshooting, slow response, long settling time, etc. This seriously influences the quality and quantity of industrial production. How to improve the dynamic performance of transient response is an urgent problem to be solved in on-line steady-state optimization[1].

Because of the measurement noise, the algorithms with derivative term in the literatures are not used in practice though their theoretical conclusions are perfect[2,3]. Hence, the measurement noise should be smoothed off before the iterative learning control strategy is adopted. The local-symmetrical-integral-type iterative learning control algorithms for repeated control systems are suggested in [4,5] to smooth output with noise, but the signal-noise ratio would be enlarged since the error between un-smoothed output and desired trajectory is used to update the iterative input, and the overflow sometimes appears when un-smoothed error is amplified by the proportion and derivative terms in the iterative learning control algorithm, particularly, the derivative term would greatly enlarge high frequency noise signal. This leads to the limited use of iterative learning control in practice.

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In this paper, the local-symmetrical-double-integral is firstly suggested to smooth off the noise, and then in successive steady-state optimization iterations, the responding leading weighted local-symmetrical-double-integral iterative learning control is discussed for dynamics of linear industrial processes with time delay in steady-state optimizing to improve its dynamical performance.

2 Control structure and algorithm

The basic control structure is shown in Fig. 1, where ILC means the iterative learning unit, $n(t)$ is random white noise, $G_c(s)$, $G_p(s)e^{-\tau s}$ and $H^2(s)$ are the transfer function of PID controller, industrial process with time delay, and local-symmetrical-double-integral operator, respectively. The closed-loop stable control system is described as

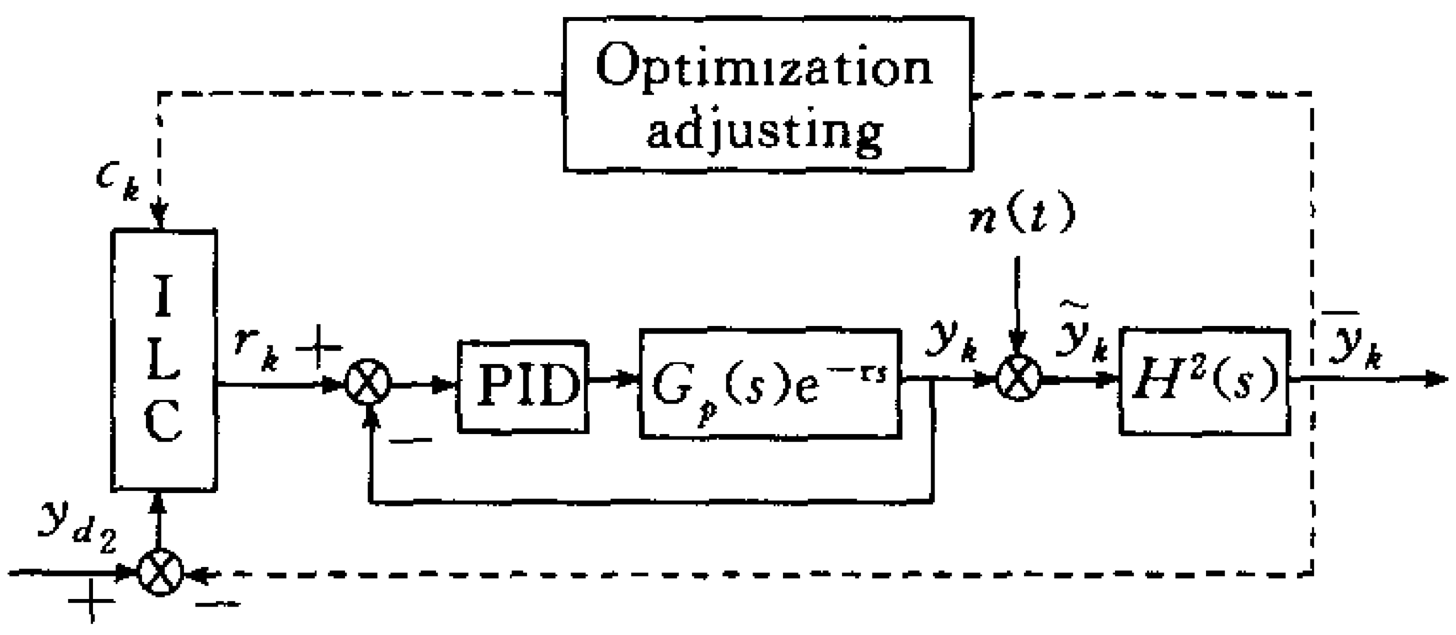

Fig. 1 Iterative learning control structure

$$Y(s) = \frac{G_{cp}(s)e^{-\tau s}}{1+G_{cp}(s)e^{-\tau s}}R(s) \tag{1}$$

where $G_{cp}(s)=G_c(s)G_p(s)$, $R(s)$ represents the input and $Y(s)$ is the precise output.

In steady-state optimizing, the step set-point change series $c_1, c_2, \cdots, c_k, \cdots$ with different magnitudes are obtained from upper optimization level and the iterative learning control strategy is adopted when each c_k is imposed on the real process. The weighted leading local-symmetrical-double-integral iterative learning control algorithm is in the following form:

$$r_{k+1}(t) = \alpha_{k+1}r_k(t) + \alpha_{k+1}\Gamma_p e_k(t+\tau) + \alpha_{k+1}\Gamma_d \dot{e}_k(t+\tau) \tag{2}$$

where $\alpha_{k+1}=c_{k+1}/c_k$ is the weighting coefficient, k represents the iteration number, $r_{k+1}(t)$ is the control input, Γ_p and Γ_d are the proportional and derivative learning gains, respectively, $e_k(t)=\bar{y}_k(t)-y_{d_k}(t)$, $y_{d_k}(t)$ is the desired trajectory with perfect dynamic performance with respect to c_k and $\bar{y}_k(t)=\frac{1}{4T_l^2}\int_{t-T_l}^{t+T_l}\int_{\varphi-T_l}^{\varphi+T_l}\tilde{y}_k(\mu)\mathrm{d}\mu\mathrm{d}\varphi$ expresses noise-smoothed output. When algorithm (2) is imposed on control system(1), the corresponding system dynamics can be described by the following transfer function:

$$Y_{k+1}(s) = \frac{G_{cp}(s)e^{-\tau s}}{1+G_{cp}(s)e^{-\tau s}}R_{k+1}(s) \tag{3}$$

Definition 1. Algorithm (2) is said to be ε-convergent with respect to system(1) means that the noise-smoothed value $\bar{y}_k(t)$ of $\tilde{y}_k(t)$ satisfies $|y_{d_k}(t)-\bar{y}_k(t)|<\varepsilon$ as $k\to\infty$, where $t\in[0,T]$, ε is a suitable positive constant, and T is the adjusting time.

Lemma 1. Denote Laplace transmitter of function $f(t)$ as $L(f(t))=F(s)$. Then

$$L\left(\frac{1}{2T_l}\int_{t-T_l}^{t+T_l}f(\varphi)\mathrm{d}\varphi\right)=\frac{e^{T_l s}-e^{-T_l s}}{2T_l s}F(s)$$

3 Main results

Theorem 1. The local-symmetric-double-integral-type iterative learning control algorithm (2) is ε-convergent with respect to system (1) if learning gains Γ_p and Γ_d satisfy

$$P(\mathrm{j}\omega) = \left|1 - \frac{\sin^2 \omega T_l}{\omega^2 T_l^2} \frac{(\Gamma_p + \mathrm{j}\omega\Gamma_d)G_{cp}(\mathrm{j}\omega)}{1 + G_{cp}(\mathrm{j}\omega)\mathrm{e}^{-j\tau\omega}}\right| < 1$$

Proof. Denote Laplace transmitter of function $f(t)$ as $L(f(t))=F(s)$. Hence, $f(t) = L^{-1}(F(s))$. Denote $G(s)=\frac{G_{cp}(s)\mathrm{e}^{-\tau s}}{1+G_{cp}(s)\mathrm{e}^{-\tau s}}$, $H(s)=\frac{e^{T_l s}-e^{-T_l s}}{2T_l s}$ and $\tilde{y}_{k+1}(t)=y_{k+1}(t)+n_{k+1}(t)$. Then from the above Lemma 1 we have

$$\begin{aligned}
E_{k+1}(s) &= Y_{d_{k+1}}(s) - \bar{Y}_{k+1}(s) = Y_{d_{k+1}}(s) - H^2(s)(Y_{k+1}(s) + N_{k+1}(s)) = \\
&Y_{d_{k+1}}(s) - \alpha_{k+1}H^2(s)G(s)R_k(s) - H(s)N_{k+1}(s) - \alpha_{k-1}H^2(s)G(s)(\Gamma_p + \Gamma_d s)E_k(s)\mathrm{e}^{\tau s} = \\
&\alpha_{k+1}(1 - H^2(s)(\Gamma_p + \Gamma_d s)G(s)\mathrm{e}^{\tau s})E_k(s) + H(s)(\alpha_{k+1}N_k(s) - N_{k+1}(s)) = \\
&\alpha_{k+1}P(s)E_k(s) + W_{k+1}(s) = \beta_k P^k(s)E_1(s) + W_{k+1}(s) + \sum_{m=1}^{k-1}\beta_{k-m}P^{k-m}(s)W_{m+1}(s)
\end{aligned} \tag{4}$$

where

$$P(s) = 1 - H^2(s)(\Gamma_p + \Gamma_d s)G(s)\mathrm{e}^{\tau s}$$
$$W_{k+1}(s) = \alpha_{k-1}H^2(s)N_k(s) - H^2(s)N_{k+1}(s)$$
$$\beta_{k-q+2} = \alpha_{k+1}\alpha_k\cdots\alpha_q \quad (q = 2,3,\cdots,k)$$

In real industrial processes it is reasonable to suppose $|\beta_m|<\beta$ for all $m(m=1,2,\cdots,k)$ and to suppose that the spectrum width of measurement noise is limited but is much larger than the frequency width of the system, and that the measurement noise mean value is zero. Then

$$\begin{aligned}
w_m(t) &= L^{-1}(W_m(s)) = L^{-1}(H^2(s)(\alpha_m N_{m-1}(s) + N_m(s))) = \\
&\frac{1}{4T_l^2}\int_{t-T_l}^{t+T_l}\int_{\varphi-T_l}^{\varphi+T_l}(\alpha_m n_{m-1}(\mu) - n_m(\mu))\mathrm{d}\mu\mathrm{d}\varphi
\end{aligned} \tag{5}$$

and

$$\int_0^{\infty} w_i(t)\mathrm{d}t = 0$$

Denote $L^{-1}(P^k(s))=p_k(t)$; then it is obtained that

$$\begin{aligned}
|L^{-1}(P^{k-m}(s)W_{m+1}(s))| &= \left|\int_0^t p_{k-m}(t-\xi)w_{m+1}(\xi)\mathrm{d}\xi\right| \leqslant \\
&|p_{k-m}(\zeta_{k-m})|\left|\int_0^t w_{m+1}(\xi)\mathrm{d}\xi\right| \leqslant N_0|p_{k-m}(\zeta_{k-m})|
\end{aligned}$$

Particularly,

$$|L^{-1}(P^k(s)E_1(s))| \leqslant |p_k(\zeta_k)|\int_0^t |e_1(\xi)|\mathrm{d}\xi \tag{6}$$

where

$$\begin{aligned}
|p_{k-m}(\zeta_{k-m})| &= \left|\frac{1}{2\pi}\int_{-\infty}^{+\infty} P^{k-m}(\mathrm{j}\omega)\mathrm{e}^{\mathrm{j}\omega\zeta_{k-m}}\mathrm{d}\omega\right| = \\
&\left|\frac{1}{2\pi}\int_{-\infty}^{+\infty} |P^{k-m}(\mathrm{j}\omega_{\zeta_{k-m}})|\mathrm{e}^{\mathrm{j}\omega\zeta_{k-m}}\mathrm{d}\omega\right| \leqslant \frac{1}{\pi\zeta_{k-m}}|P^{k-m}(\mathrm{j}\omega_{\zeta_{k-m}})|
\end{aligned} \tag{7}$$

Substitute(5),(6) and (7) into the inverse Laplace transmitter of (4), and we have

$$|e_{k+1}(t)| \leqslant \frac{1}{\pi\zeta}\left(\int_0^t e_1(\xi)\mathrm{d}\xi\right)|P^k(\mathrm{j}\omega)| + \frac{N_0\beta}{\pi\zeta}\frac{|P(\mathrm{j}\omega)| - |P(\mathrm{j}\omega)|^k}{1 - |P(\mathrm{j}\omega)|} + N_0$$

where $\zeta = \min\limits_{l=1,\cdots,k}\zeta_l$. Thus if learning gains Γ_p and Γ_d are suitably chosen such that

$$|P(\mathrm{j}\omega)| = \left|1 - \frac{\sin^2\omega T_l}{\omega^2 T_l^2}\frac{(\Gamma_p + \mathrm{j}\omega\Gamma_d)G_{cp}(\mathrm{j}\omega)}{1 + G_{cp}(\mathrm{j}\omega)\mathrm{e}^{-\mathrm{j}\omega\tau}}\right| < 1$$

then

$$|e_{k+1}(t)| \leqslant \frac{N_0\beta}{\pi\zeta}\frac{|P(\mathrm{j}\omega)|}{1 - |P(\mathrm{j}\omega)|} + N_0$$

as $k\to\infty$. That is to say, $|e_{k+1}(t)|<\varepsilon$. □

4 Determination strategy of local symmetric integral interval length

Generally, the spectral width of local symmetric double integral operator is restricted to be no less than that of the closed-loop control system, that is to say

$$|H(j\omega_c, T_l)|^2 = \left(\frac{\sin^2\omega_c T_l}{\omega_c^2 T_l^2}\right)^2 \geqslant \frac{1}{2}$$

then $\omega_c T_l \leqslant 1.002$ is derived by solving the above inequality, where ω_c is the cut-off frequency of the closed-loop control system.

5 Numerical Simulations

Choose $G_c(s) = 2 + 1.6s$, $G_p(s) = \frac{e^{-0.2s}}{2s^2 + s}$, $\Gamma_p = 0.6$, $\Gamma_d = 0.7$, the set-point series as $c_1 = 0.9$, $c_2 = 0.8$, $c_3 = 0.7$, $c_4 = 0.6$, $c_5 = 0.5$, $\cdots$, the desired trajectory as $y_{d_{k+1}} = \alpha_{k+1}(1 - e^{-(t-0.2)})$, $k = 1, 2, \cdots$. Simulation results are shown in Fig. 2, where curve 1 represents the desired trajectory, curve 2 means noise-smoothed output without iterative learning control, and curve 3 is the noise-smoothed output with iterative learning control.

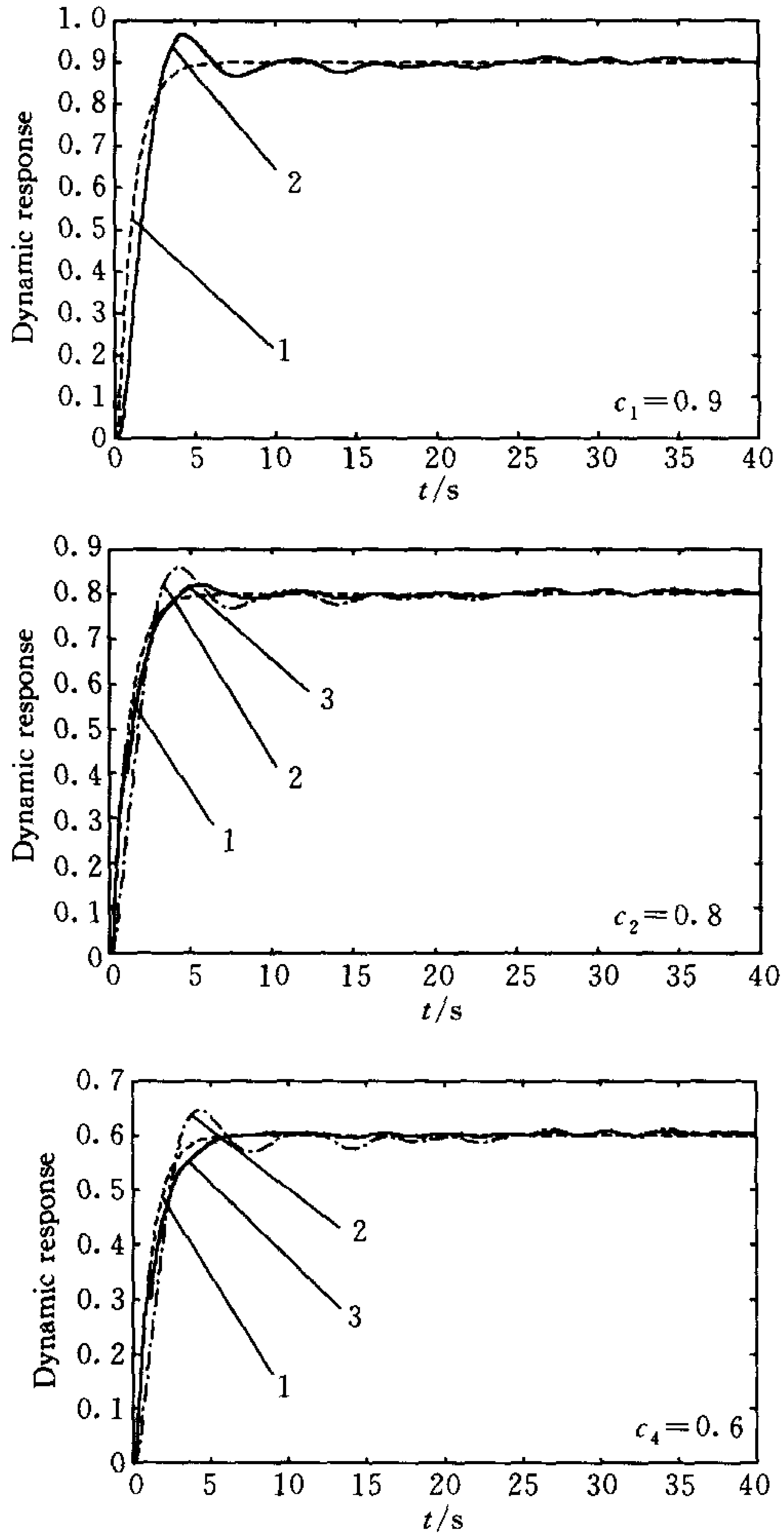

Fig. 2 Simulation results

From the simulation results it is easy to see that applying the local-symmetric-double-integral iterative learning control algorithm to industrial process can effectively decrease the overshoot, shorten the settling time, accelerate the dynamic response, etc.

6 Conclusion

This paper not only presents a theoretical basis for improving dynamic performance of industrial processes in steady-state optimizing, but also provides a practical manner for applications. The numerical simulations confirm the correction of theoretical analysis and indicate the effectiveness of the control strategy.

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RUAN Xiao-E Associate profesor in School of Science, Xi'an Jiaotong University. Obtained both Bachelor and Master's degrees from Shaanxi Normal University and received Ph. D. degree in Control Science and Engineering from Xi'an Jiaotong University. Research interests include iterative learning control for large-scale industrial processes in steady-state hierarchical optimization, product quality control, etc.

LI Huan-Qin Associate professor in School of Science, Xi'an Jiaotong University. Obtained Master's degree from Xi'an Jiaotong University. Research interests include wavelet neural network for product quaility control.

WAN Bai-Wu Professor in Systems Engineering Institute, Xi'an Jiaotong University. Research interests include theory and applications of large-scale industrial processes in steady-state hierarchical optimization, intelligent control, product quality control, etc.

滞后工业过程稳态优化进程中的局部对称双积分型迭代学习控制

阮小娥[1] 李换琴[1] 万百五[2]

[1](西安交通大学理学院 西安 710049)

[2](西安交通大学系统工程研究所 西安 710049)

(E-mail: wruanxe@mail. xjtu. edu. cn)

摘 要 对具有滞后工业过程稳态优化进程提出加权超前局部对称双积分型迭代学习控制算法. 基于理想轨线与控制系统的实际输出动态信息,提出基本的迭代学习控制算法并分析和论证算法的收敛性,给出局部对称积分区间参数的确定策略. 数字仿真表明,加权超前局部对称双积分型迭代学习控制算法能有效消除噪声对系统输出信号的影响并能改善滞后工业过程稳态优化进程中控制系统的动态品质,如减少超调,缩短过渡时间,加快响应速度等.

关键词 局部对称双积分,迭代学习控制,滞后

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