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Performance Assessment Measures of Batch Processes for Iterative Learning Control

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Abstract: A new method is proposed for the assessment of the batch control system when the iterative learning control is applied. Unlike the continuous process, the performance assessment of the batch process requires particular attention to both disturbance changes and setpoint changes. Because of the intrinsically dynamic operations and the nonlinear behavior of batch processes, the conventional approach of the controller assessment cannot be directly applied. The bounds at each time point are derived and computed for the controlled output variance to create simple monitoring charts. They can help tracking the progress in each batch run to monitor the occurrence of the observable upsets. Simulation cases are used to demonstrate the advantages of the proposed strategies.

1. INTRODUCTION

Interest in research and development of batch control based on iterative learning control (ILC) has increased steadily since the term, ILC, was first presented (Arimoto et al., 1984). The control design in batch processes is quite different from that in continuous ones. When the process is operated continuously, there is a variety of methodologies in the feedback control loop system to ensure closed-loop stability and to achieve acceptable steady-state performance with respect to setpoint and disturbance inputs. Because of the intrinsically dynamic operations of batch processes, the conventional approach of the controller assessment cannot be directly applied. ILC of batch operation allows the extraction of information from the past batches to refine the new batch run and to improve the performance of tracking control for product quality. ILC utilizes a feedback controller for stabilizing the closed-loop system. It also uses a feedforward controller for designing the transient response of the operating profile. Numerous ILC schemes have been developed in the past decades. They enhanced the control performance over a fixed time interval iteratively (Chen et al., 1997; Moore, 1993; Lucibello, 1992). The effect of ILC on a continuous controlled system has been investigated to improve the performance (Tan et al., 2006; Ratcliffe et al., 2005). Comprehensive review of this topic is shown in the references (Xu and Tan, 2003; Moore, 1993). The webpage for iterative learning control research is linked (http://www.ece.usu.edu/csois/ilc/ILC/index.html). However, these control research papers focused mainly on design strategies. They did not show how good the current controller performance of the batch operation was in comparison with benchmark control. If the deterioration of controller performance cannot be identified in time, the malfunction would cause inconsistent product quality and monetary loss.

The performance assessment of the control loop based on the minimum variance was first presented by Harris (1989). Several techniques using the minimum variance have been proven useful in prioritizing the activities of process engineers, including monitoring and assessing the controller performance (Huang et al., 2000; Desborough & Harris 1993). However, the controller performance of the batch operation is influenced not only by the unmeasured disturbance but also by the deterministic regulation which is defined by the setpoint changes. Since the deterministic regulation is very different from the stochastic one, their achievable performance bounds should be separated (Isaksson et al., 2003; Swanda and Seborg, 1999). Although there were many research papers on assessing continuous control systems, to our best knowledge, the assessment of the batch control system has not been mentioned.

In this paper, two issues are addressed to assess the controller performance of the batch operation. First, the minimum variance performance bound is developed for batch operation systems. The performance bound can subsequently be used for the performance assessment of the batch system control loop. The remaining paper is structured as follows: The performance assessment of the control loop in the batch operation system is defined in Section 2. In Section 3, the performance assessment bounds of the batch control system are derived. The effectiveness of the proposed method and its potential applications are demonstrated through two computer simulation problems, including a simple linear system and a nonlinear batch reactor in Section 4. Finally, concluding remarks are made.

2. ILC STRUCTURE OF BATCH

Suppose there is an operation of a batch run (i).The feedback control structure for the batch system is shown in Fig. 1. A discrete linear time-variant (LTV) process is used to represent a batch operation system. Its form which is any linear time-invariant process governed by the transfer function models is given by

$$y(i,k) = G_p(q^{-1},k)u(i,k) + G_w(q^{-1},k)w(k) \tag{1}$$

where the controlled output $y(i,k)$ at time point (k) can be expressed as the sum of two terms, one for the deterministic manipulated input ($u(i,k)$) and the other for the white noise disturbance ($w(k)$). The process ($G_P(q^{-1},k)$) and the disturbance ($G_W(q^{-1},k)$) transfer functions vary with time. In the block diagram of Fig. 1, when the set point ($x^{sp}(i,k)$) and the disturbance ($w(k)$) changes occur, the output ($y(i,k)$) under closed-loop control can be obtained:

$$y(i,k) = \frac{G_W(q^{-1},k)}{1+G_P(q^{-1},k)G_C(q^{-1},k)}w(i,k) + \frac{G_P(q^{-1},k)G_C(q^{-1},k)}{1+G_P(q^{-1},k)G_C(q^{-1},k)}x^{sp}(i,k) \tag{2}$$

In Fig. 1, the dashed block represents lumping of all the elements in the feedback process. The batch control system aims not only at achieving disturbance rejection but also at tracking the desired reference.

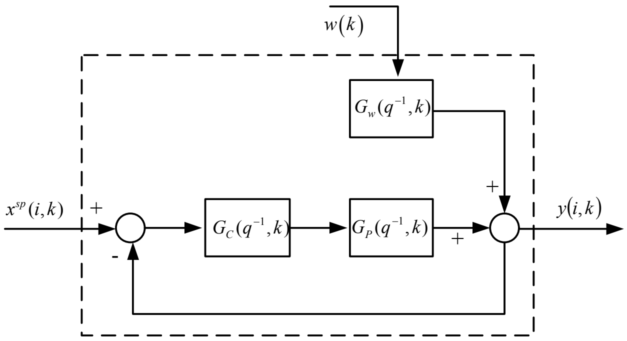


Fig. 1. Block diagram of feedback control for the batch system.

To complement this, the iterative improvement strategy in a structure with two-degree of freedom is widely applied to tracking errors by improving its control action estimates. In Fig. 2, a block diagram interpretation of the ILC scheme is shown. The dashed block in Fig. 1 denotes the feedback process for the time-varying closed loop system at a particular run in Fig. 2. The principle of ILC makes use of the measurement ($y(i,k)$) and the reference signal ($x^{sp}(i,k)$) of the previous batch run for control during the current batch ($i+1$) under the disturbance input ($w(k)$). The feedback controller ($G_c(q^{-1},k)$) undertakes correction based on non-deterministic disturbances and modeling errors. The feedforward controller ($G_f(q^{-1},k)$) adjusts the reference based on the modeling errors. Based on both controllers, the new reference signal ($x^{sp}(i+1,k)$) is designed.

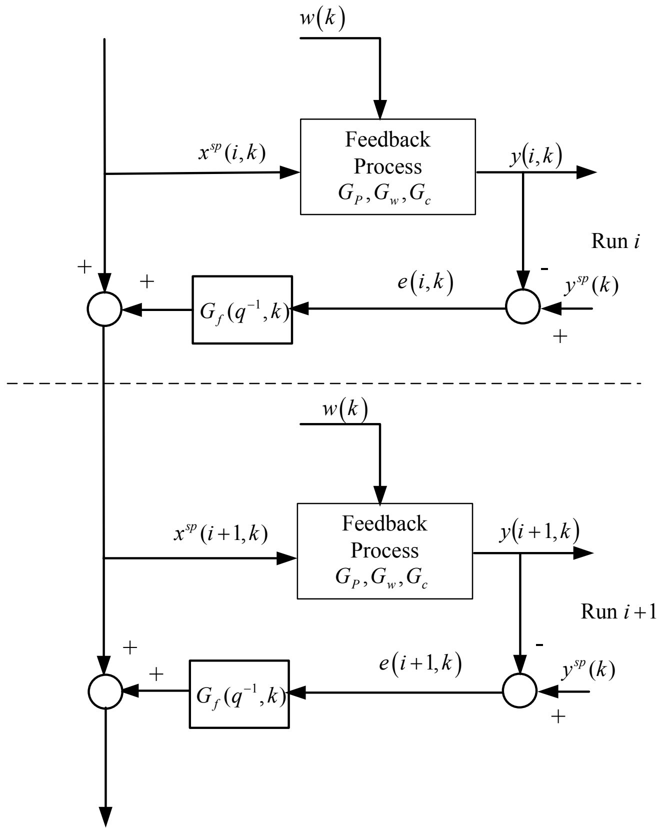


Fig. 2. The schematics of ILC with the feedback controller ($G_c(q^{-1},k)$) and the feedforward controller ($G_f(q^{-1},k)$).

The learning control objective is to determine the controllers, $G_c(q^{-1},k)$ and $G_f(q^{-1},k)$, and generate an appropriate control input time history to produce a detailed output history through iterative trails. In minimum variance control, the minimum variance bound of the ILC system for all batch runs is defined as

$$\min_{\substack{G_c(q^{-1},k)\\ G_f(q^{-1},k)}} J = \min_{\substack{G_c(q^{-1},k)\\ G_f(q^{-1},k)}} E\left[\sum_{k=1}^{T} e(i,k)^2\right] \tag{3}$$

where $e(i,k) = y^{sp}(k) - y(i,k)$, T is the duration of each batch run, and $E[\bullet]$ is the expectation operator. In the above definition, the expected performance bound of $\sum_k e(i,k)^2$ is computed based on all batches. It is apparent that the variance of $\sum_k e(i,k)^2$ depends on all the system controller functions, $G_c(q^{-1},k)$ and $G_f(q^{-1},k)$. The calculation described by Eq. (3) is also provided for examination.

3. PERFORMANCE ASSESSMENT MEASURES OF ILC

When ILC is applied to the process, the output error ($e(i,k)$) at the time point (k) can be represented by

$$\begin{aligned} e(i,k) &= y^{sp}(k) - y(i,k) \\ &= \underbrace{G^{\det}(q^{-1},k)y^{sp}(k)}_{\text{deteriministic}} - \underbrace{G^{sto}(q^{-1},k)w(i,k)}_{\text{stochastic}} \end{aligned} \tag{4}$$

$e(i,k)$, the measurement of the output error variable at time k for a particular batch i, is represented by a deterministic dynamics ($G^{\det}(q^{-1},k)$) plus a stochastic disturbance ($G^{sto}(q^{-1},k)$). The stochastic disturbance is often called the unexplained measurement error. It is resulted from the uncertain variations and disturbances among the lurking variables. The deterministic dynamics, which is explainable, is the function of $y^{sp}(k)$, that keeps the mean constant trajectory. Thus, the performance bound (J) in Eq. (3) can be expressed by two parts: the stochastic effect ($J_{\text{Disturbance}}$) from unmeasured disturbance in the feedback loop and the deterministic effect (J_{Setpoint}) from the desired setpoint trajectory in the feedforward loop,

$$\begin{aligned} J &= E\left[\sum_k e(i,k)^2\right] \\ &= J_{\text{Setpoint}}(G_C,G_f) + J_{\text{Disturbance}}(G_C,G_f) \end{aligned} \tag{5}$$

To achieve the minimum bound, Eq. (5) will be

$$\min_{G_C,G_f} J = \min_{G_C,G_f} E\left[\sum_k e(i,k)^2\right] = J^*_{\text{Disturbance}} + J^*_{\text{Setpoint}} \tag{6}$$

where $J^*_{\text{Disturbance}} = \min_{G_C,G_f} J_{\text{Disturbance}}$ and $J^*_{\text{Setpoint}} = \min_{G_C,G_f} J_{\text{Setpoint}}$. J^*_{Setpoint} can be identically zero under perfect control. This means that the final output error is zero over the whole batch duration if there is no disturbance.

Thus, the feedforward learning controller ($G_f(q^{-1},k)$) can be obtained

$$G_f(q^{-1},k) = \frac{1 + G_P(q^{-1},k)G_C(q^{-1},k)}{G_P(q^{-1},k)G_C(q^{-1},k)} \tag{7}$$

$J_{\text{Disturbance}}$ can be regrouped into controller-invariant and controller-dependent terms. Using the Diophantine identity,

$$G_w(q^{-1},k) = Q(q^{-1},k) + q^{-d}R(q^{-1},k) \tag{8}$$

where Q is LTV polynomials of degree $d-1$ and R is a proper LTV transfer function. After substituting the feedforward controller (Eq. (7)) and the Diophantine identity (Eq. (8)) into Eq. (5), the output error will come from the disturbance only. To achieve $J^*_{\text{Disturbance}}$, the controller dependent term must be zero. The feedback controller ($G_C(q^{-1},k)$) can be obtained

$$G_C(q^{-1},k) = \frac{R(q^{-1},k)}{G^*_P(q^{-1},k)Q(q^{-1},k)} \tag{9}$$

where $G^*_P(q^{-1},k)$ is the process model without any time delay. Hence, the minimum variance (MV) of the performance bound can be derived into

$$J = \begin{cases} 2\sum_{k=1}^{T}\sum_{j=0}^{k}\varphi_j^2(k)\sigma_w^2 & T \le d \\ 2\sum_{k=1}^{d}\sum_{j=0}^{k-1}\varphi_j^2(k)\sigma_w^2 + 2\sum_{k=d+1}^{T}\sum_{j=0}^{d-1}\varphi_j^2(k)\sigma_w^2 & T > d \end{cases} \tag{10}$$

where $\varphi_j(k)$ is the time-variant coefficients of the polynominal $Q(q^{-1},k)$. Here the same variance of the disturbance ($w(k)$) with a normally distributed random variable at any time and at any batch run is assumed. σ_w^2 is the variance of the unmeasured white noise. For the duration of each batch run, the variances ($\sigma^2(k)$) at time k represented by the MV benchmark controller can be obtained by

$$\sigma^2(k) = \frac{\sigma_e^2(k)}{\sigma_w^2} = \begin{cases} 2\sum_{j=0}^{k}\varphi_j^2(k) & T \le d \\ 2\sum_{j=0}^{d-1}\varphi_j^2(k) & T > d \end{cases} \tag{11}$$

where the signal-to-noise ratio ($\sigma^2(k)$) is used for simple expression.

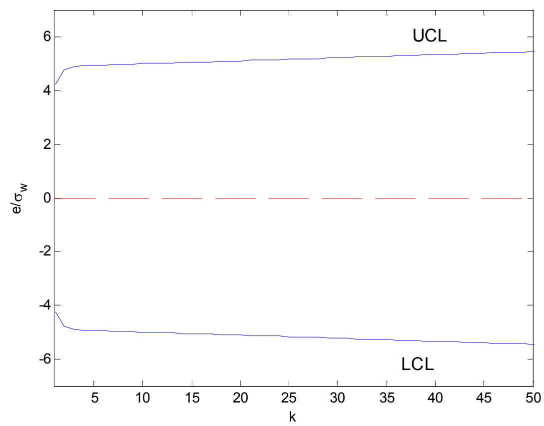
To detect if the current operations have deviations from the minimum bounds, a statistical hypothesis testing approach can be applied to the control output error at each time point. Based on the traditional statistical process control methods, the upper control limits (UCL), the center line (CL) and the lower control limits (LCL) at each time point are given

$$UCL(k) = 3\sigma(k) \tag{12}$$

$$CL(k) = 0 \tag{13}$$

$$LCL(k) = -3\sigma(k) \tag{14}$$

(a)



(b)

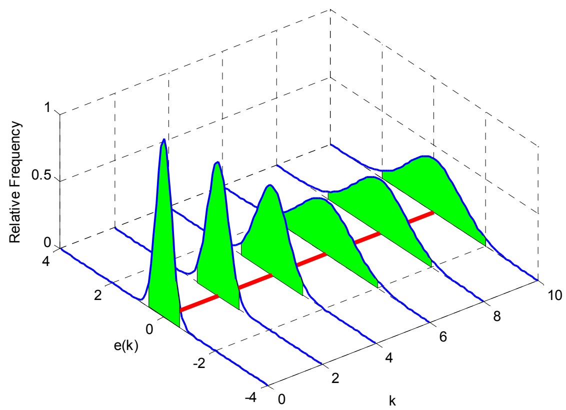


Fig. 3. (a) The batch control chart with UCL and LCL; (b) the distribution function at each time point whose shaded region represents the region in control.

where $k = 1, 2, \cdots, T$. Fig. 3(a) shows the control chart with LCL and UCL is used to compare the performance of a current control loop with that of the control loop with benchmark controllers when the benchmark's expected output errors fall on CL. Fig. 3(b) shows a pictorial display of what characteristics of the underlying distribution might be during each time point. The shaded regions covered by the upper and lower control limits at each operation time are also plotted. Thus, there is no lack of the benchmark performance when the output error falls between the control limits. Whether the current operating data from a batch run is in control with good performance can be determined.

4. ILLUSTRATIVE EXAMPLES

4.1 Example 1: Linear Time Invariant System

The process and the disturbance are modelled as

$$G_P\left(q^{-1}\right) = q^{-5}\frac{0.2q^{-1} - 0.1q^{-2}}{1 - 0.9q^{-1} + 0.8q^{-2}} \tag{15}$$

$$G_w\left(q^{-1}\right) = \frac{1}{1 + 0.5q^{-1}} \tag{16}$$

where both models are linear time invariant. The unmeasured noise (w) with zero mean and unit variance enters the disturbance model. The reference profile used in this example is shown in Fig 4. A feedback controller and a feedforward one are used to control this system,

$$G_c = \frac{0.9062 - 0.6324q^{-1}}{1 - q^{-1}}$$

$$G_f = \frac{0.4138 - 0.1043q^{-1}}{1 - q^{-1}} \tag{17}$$

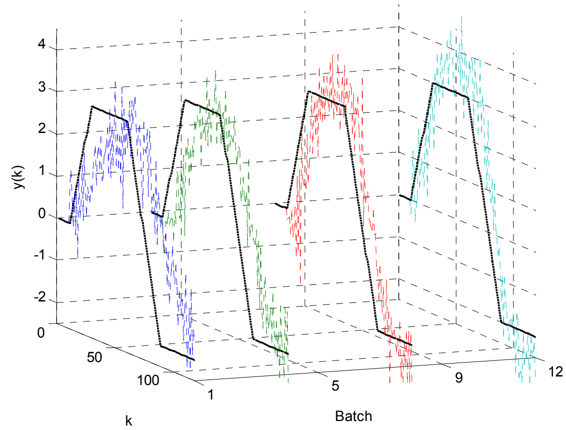


Fig. 4. The controlled outputs for the initial designed controllers in Example 1. The bold lines are the reference profiles and the dotted lines represent the controlled outputs for Batch 1, 5, 9 and 12.

Under the initial designed controllers, the responses of the output tracking to some batch runs are shown in Fig. 4. The controlled output is converged after 12 batch runs. The system under the unmeasured disturbance change seems to have some deviation from the reference setpoint; however, it is hard to evaluate the current performance from the batch output response. On the basis of the given process and the disturbance models, the minimum variance bounds for each batch can be computed using Eqs. (11)-(14). The control chart for the minimum variance performance bounds is used to test the performance of the controlled output for the batches using the controller design (Eq. (17)). Fig. 5 shows the results of the controlled error when the controller parameters are used. It is found that 55 out of the total 120 data points fall out of the performance bounds. This indicates the controllers should be tuned.

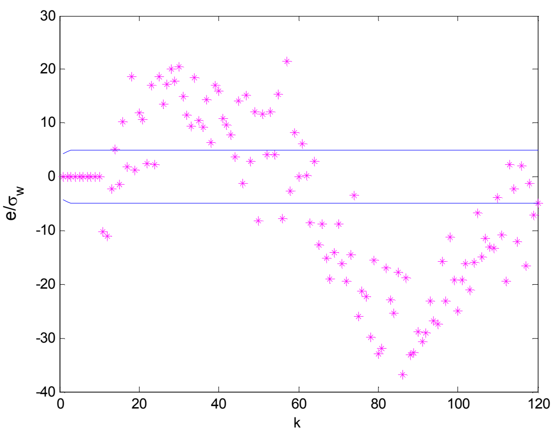


Fig. 5. The control chart with the minimum variance bounds (marked in solid line) for evaluating the control outputs (marked in asterisk).

4.2 Example 2: Nonlinear Batch Reactor

This example is intended to show how to evaluate iterative learning batch controllers for a typical exothermic chemical batch reactor. The differential equations and the parameter values describing the reaction process are referred to Luyben (1990). The reaction system involves two consecutive first-order reactions:

$$A \rightarrow B \rightarrow C$$

Two stages are run in the system. In the first (start-up) stage, the steam in the jacket initially heats up the reactor content until the exothermic heat of reaction is generated significantly enough. In the second (maintenance) stage, the cooling water in the jacket is used to remove the exothermic heats of reaction. The reactor temperature is controlled by two split-ranged control valves, a steam valve and a water valve. Thus, feedback control is used to eliminate the disturbance effect on the manipulated variables and keep the heat requirement within the batch run. The feedforward controller is used to modify the specified temperature profile from one batch to another. The duration of each batch is 250 minutes. The sampling time of each batch is 1 minute. Fig. 6 also shows the plot of the response to the controlled temperature for two operating batch runs. From the operating process data, which control system does the job better?

To assess the performance of the controlled system, the benchmark of the control system should be set up first. The benchmark performance bounds are determined based on the process and disturbance models. A total of 50 batch runs of the data are collected. From the data, the dead time (d) of the processes calculated by cross-correlation analysis is three. According to the identification procedure, the process ($G_p(q^{-1},k)$) and the disturbance models can be calculated. Due to the space limitation, the detailed identification procedure is referred to Yea and Chen (2007). Thus, the estimated minimum variance bounds of the controlled output errors for a batch run can be calculated from Eqs. (12)-(14) To illustrate the control performance in Fig. 6, the control charts for these two operation batch runs are shown in Fig. 7. The charts indicate that the controller performance of the second batch run outperforms that of the first one, but the two controller designs cannot fall into the control bounds because the MV bounds, which are the minimum performance bounds, can be achieved for MV control only.

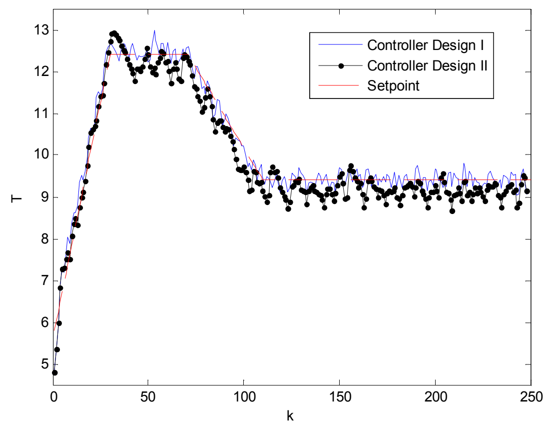
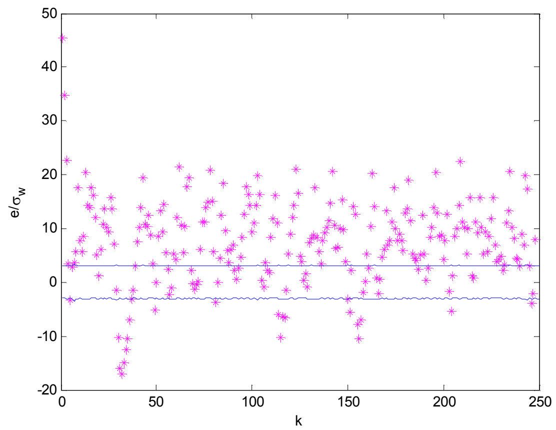


Fig. 6. The controlled outputs for two designed controllers in Example 2.

6. CONCLUSIONS

In practical operation plant, the process data can be accessible from any time period at the touch of a button because most modern chemical processes utilize computer systems in which large amounts of data is stored cheaply and efficiently. Many processes have been around for years and engineers have acquired lots of experience, but many operational problems still go undiagnosed for a prolong period of time. Thus, developing a firm grasp of the data mining technique to identify and performance assessment of the ILC system is strongly required to maintain good performance of the operating batch unit when producing products. On the basis of the operating data from the repeated tracking task which is run at a finite time interval in the time domain and an infinite repetition along the iteration domain, the performance bounds of ILC benchmark for the LTV batch operation system is developed in this paper. From the routine operation data, the advantages of the proposed method are demonstrated through simulated examples. The examples also explain how to build the performance bounds and accurately identify the control performance of the current batch operation at each time point. However, because of the aggressive control input of MV control, the lower performance bound is impractical for the general control application. Thus, the achievable minimum variance of specified control will be developed in our future research.

(a)



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(b)

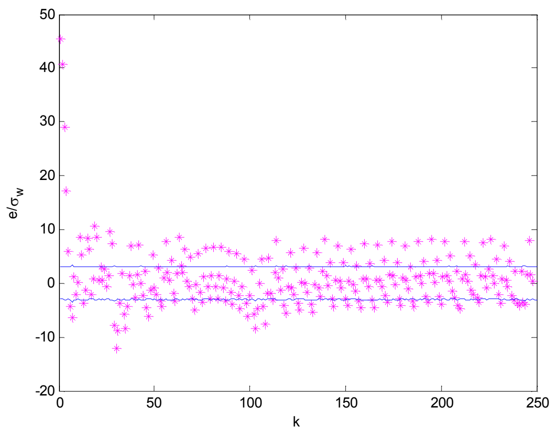

Fig. 7. The control chart with the minimum variance bounds (marked in solid line) for evaluating the control outputs (marked in asterisk) of (a) the controller design I and (b) the controller design II in Example 2.

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