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High-Order Iterative Learning Fault-Tolerant Control for Batch Processes with Iteration-Varying Sensor Faults

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Abstract: This work is focused on the iterative learning fault-tolerant control for linear batch process with iteration-varying sensor faults. First, high-order internal model (HOIM) is used to describe iteration-varying sensor faults. Second, a special high-order dynamic iterative learning fault-tolerant control is constructed according to the HOIM. Third, The HOIM-based iterative learning fault-tolerant control is transformed into a controller design problem for a 2D Roesser model. Fourth, a HOIM-based iterative learning fault-tolerant control design criterion is presented to achieve the asymptotic stability. Finally, a numerical example is given to illustrate the efficiency of the proposed HOIM-based iterative learning fault tolerant control.

Key Words: High-Order Internal Model, Iteration-Varying Faults, Fault Tolerant Control

1 Introduction

With the development of manufacturing industry, batch processes play an increasingly important role in our life, such as chemical industry, medicine productivity, injection molding process and so on. Batch process repeats the same process by iteration, then iterative learning control (ILC), which can be traced back to 1984[1], has been widely studied in batch process control. In decades, scientists and engineers published abundant accomplishments[2, 3].

Due to the complicated structures and delicate components, batch processes suffers sensor/actuator faults the same with continuous processes. Fault detection and diagnosis (FDD) and fault tolerant control (FTC) for continuous process [2-5] have been studied for decades. While for batch processes, FTC for batch processes has just attracted increasingly attention in about the past 10 years. In this area, Y. Wang et al. [6-8] presented a serious FTC solutions for batch process with sensor and actuator faults based on iterative learning control. Based on an equivalent 2D FM model, L. Wang et al. proposed an optimal fault-tolerant guaranteed cost control scheme[9] as well as a closed-loop robust iterative learning fault-tolerant guaranteed cost control scheme[10] for batch processes with actuator failures. Tao et al.[11] developed a fault-tolerant iterative learning control law for a class of linear time-delay differential batch processes with actuator faults in 2014. Zhang et al.[12] presented a state space model predictive fault tolerant control scheme for batch processes with unknown disturbances and partial actuator faults.

All the existing results of FTC for batch processes have the same assumption: the fault is invariant by iteration. However, in practical batch processes, system components wear out batch by batch, then the faults in sensor/actuator can be iteration-varying.

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With the consideration of iteration-varying faults, in this paper, the authors use an approximate periodic oscillation model to generate the sensor problem. A high order ILC law is presented, then the system is transformed into a high-order 2D Roesser model. Based on 2D stability theory, the design criterion satisfying the asymptotic convergence condition is proposed.

The main contributions of this work lie in the following:

(1) An approximate periodic oscillation model of iteration-varying sensor faults for batch processes is used as an extension of the previous fault tolerant control.

(2) The control law is presented in a high order 2D dynamic form which contains history information to achieve better performance.

(3) The asymptotic stability criterion is given to achieve the asymptotic stability.

This article is organized as follows. The descriptions of the iteration-varying sensor faults is introduced in Section2. In Section 3, high order iterative learning control is introduced for iteration-varying sensor faults. Then the design criterion is presented to achieve the asymptotic stability in Section 4. Furthermore, an example is considered in Section 5.

2 Problem Formulation

A typical state-space model to describe batch process can be written as following:

$$\begin{cases} x(t+1,k) = Ax(t,k) + Bu(t,k) \\ y(t,k) = C_y x(t,k) \\ z(t,k) = C_z x(t,k) \end{cases} \tag{1}$$

$$t = 0,1,\cdots,T; k = 1,2,\cdots,$$

where t is the time axis, k denotes iterative axis, $x(t,k)\in R^n$, $u(t,k)\in R^p$, $z(t,k)\in R^q$, and $y(t,k)=[y_1(t,k),y_2(t,k),\cdots,y_l(t,k)]\in R^l$ denote the state, the input, the measured output, and the controlled output, respectively. $A\in R^{n\times n}$, $B\in R^{n\times p}$, $C\in R^{l\times n}$ are the system matrices with appropriate dimensions. For simplicity, we choose $C_y=C_z$ and denote $C=C_y=C_z$.

For measured output $y_i(t,k)(i=1,2,\cdots,l)$, the following fault model is adopted to describe the sensor gain fault

$$y_i^F(t,k)=\alpha_i y_i(t,k), i=1,2,\cdots,l, k\ge m-1 \tag{2}$$

Where

$$0\le \underline{\alpha}_i\le \alpha_i\le \bar{\alpha}_i, i=1,2,\cdots,l \tag{3}$$

$\underline{\alpha}_i\le 1$ and $\bar{\alpha}_i\ge 1$ are known constant parameters.

Remark 1. Fault model (2) is widely used[13, 14], usually α_i remains the same value for different batches. However, the sensor may wear out batch by batch, then the sensor faults can be iteration-varying. To describe the iteration-varying sensor fault clearer, a high order fault model is introduced based on (2) as

$$\alpha_i(k+1)=H(q^{-1})\alpha_i(k)+\beta, k\ge m-1 \tag{4}$$

where $H(q^{-1})=h_{r,1}+h_{r,2}q^{-1}+\cdots+h_{r,m}q^{-m+1}(h_{r,j}\in R)$, m denotes the order, q denotes the shift operator in the iteration domain satisfying $q^{-1}\alpha_i(k+1)=\alpha_i(k)$. β is a known constant parameter. If $H(q^{-1})=1$ and $\beta=0$, the fault is iteration-invariant.

Denote

$$\begin{aligned} y^F &= [y_1^F, y_2^F,\cdots,y_l^F]^T \\ \alpha(k) &= diag\{\alpha_1(k),\alpha_2(k),\cdots,\alpha_l(k)\} \end{aligned} \tag{5}$$

Then a batch process with sensor faults may be described by

$$\Sigma_{BPF}:\begin{cases} x(t+1,k)=Ax(t,k)+Bu(t,k) \\ y^F(t,k)=\alpha(k)C_y x(t,k) \\ z(t,k)=C_z x(t,k) \end{cases} \tag{6}$$

The control objective is to determine a fault-tolerant control law such that the resulting closed-loop system is asymptotically stable not only when the sensor is health, but also when there exists batch-varying sensor faults.

The following notations are introduced:

$$\begin{aligned} &\Gamma_j = diag\{\Gamma_{j1},\Gamma_{j2},\cdots,\Gamma_{jl}\}, \\ &\Gamma_{ji} = \underline{\alpha}_i or \bar{\alpha}_i, j=1,2,\cdots 2^l, i=1,2,\cdots,l \end{aligned} \tag{7}$$

Especially,

$$\begin{aligned} &\Gamma_0 = diag\{\Gamma_{01},\Gamma_{02},\cdots,\Gamma_{0l}\}, \\ &\Gamma_{0i} = \frac{\underline{\alpha}_i+\bar{\alpha}_i}{2}, i=1,2,\cdots,l \end{aligned} \tag{8}$$

Then, all fault gain matrix satisfying (3) must be contained in the following polyhedron

$$\alpha(k)\in\left\{\sum_{j=1}^{2^l}a_j\Gamma_j \,\middle|\, 0\le a_j\le 1, \sum_{j=1}^{2^l}a_j=1\right\} \tag{9}$$

Γ_0 is the center of this polyhedron. For convenience, this polyhedron is called fault gain polyhedron.

3 HO-ILC for iteration-varying sensor faults

In this section, the system is firstly transformed into HOIM 2D model, then a high order iterative learning control is introduced for iteration-varying sensor faults.

Define

$$\delta x(t,k)=x(t-1,k+1)-H(q^{-1})x(t-1,k) \tag{10}$$

$$\delta u(t,k)=u(t,k+1)-H(q^{-1})u(t,k) \tag{11}$$

From (6) , we can obtain the following 2D high order model

$$\Sigma_{2D}:\begin{cases} \begin{bmatrix}\delta x(t+1,k)\\ \hat{z}(t,k+1)\end{bmatrix}=\tilde{A}X_1(t,k)+\tilde{B}\delta u(t-1,k) \\ Y(t,k)=\hat{y}_f(t,k)=\tilde{C}_y X_1(t,k) \\ \hat{z}(t,k)=\tilde{C}_z X_1(t,k) \end{cases} \tag{12}$$

$$X_1(t,k)=\begin{bmatrix}\delta x(t,k)\\ \hat{z}(t,k)\end{bmatrix},$$

$$\hat{z}(t,k)=\begin{bmatrix} z(t,k)\\ z(t,k-1)\\ \vdots \\ z(t,k-m+1)\end{bmatrix}\in R^{m\times q},$$

$$\hat{y}_f(t,k)=\begin{bmatrix} y_f(t,k) \\ y_f(t,k-1) \\ \vdots \\ y_f(t,k-m+1) \end{bmatrix},\ \tilde{B}=\begin{bmatrix} B \\ CB \\ 0 \\ \vdots \\ 0 \end{bmatrix} \triangleq \begin{bmatrix} \tilde{B}_{11} \\ \tilde{B}_{12} \end{bmatrix},$$

$$\tilde{A}=\left[\begin{array}{c|cccc} A & 0 & \cdots & 0 & 0 \\ \hline CA & h_{r,1}I_q & \cdots & h_{r,m-1}I_q & h_{r,m}I_q \\ 0 & I_q & \cdots & 0 & 0 \\ 0 & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I_q & 0 \end{array}\right] \triangleq \begin{bmatrix} \tilde{A}_{11} & \tilde{A}_{12} \\ \tilde{A}_{21} & \tilde{A}_{22} \end{bmatrix},$$

$$\tilde{C}_y=\left[\begin{array}{c|cccc} 0 & \alpha(k) & 0 & \cdots & 0 \\ 0 & 0 & \alpha(k-1) & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ 0 & 0 & \cdots & 0 & \alpha(k-m+1) \end{array}\right]$$
$$\triangleq \begin{bmatrix} \tilde{C}_{y11} & \tilde{C}_{y12} \end{bmatrix} = \begin{bmatrix} 0 & \hat{\alpha} \end{bmatrix},$$

$$\tilde{C}_z=\begin{bmatrix} 0 & I & 0 & \cdots & 0 \\ 0 & 0 & I & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ 0 & 0 & \cdots & 0 & I \end{bmatrix}.$$

The model in (12) is a typical 2D-Roesser model with sensor fault. Therefore, it is clear that design of updating law for system is equivalent to design a fault-tolerant control law $\delta u(t,k)$ for model (12).

Design a dynamic output feedback controller as following

$$\begin{cases} x_{c1}(t+1,k)=A_{c11}x_{c1}(t,k)+A_{c12}x_{c2}(t,k)+B_{c1}Y(t,k) \\ x_{c2}(t,k+1)=A_{c21}x_{c1}(t,k)+A_{c22}x_{c2}(t,k)+B_{c2}Y(t,k) \\ \delta u(t-1,k)=C_{c1}x_{c1}(t,k)+C_{c2}x_{c2}(t,k)+D_cY(t,k) \end{cases} \quad (13)$$

where $x_{ci}(t,k)$ are the internal state of the controller and $\{A_{ci},B_{ci},C_{ci},D_{ci}\}, i=1,2$ are controller parameters to be determined with appropriate dimensions.

Applying (13) into(12),

$$\begin{bmatrix} X_2(t+1,k) \\ Z(t,k+1) \end{bmatrix}=\begin{bmatrix} \bar{A}_{11} & \bar{A}_{12} \\ \bar{A}_{21} & \bar{A}_{22} \end{bmatrix}\begin{bmatrix} X_2(t,k) \\ Z(t,k) \end{bmatrix} \quad (14)$$

$$X_2(t,k)=\begin{bmatrix} \delta x(t,k) \\ x_{c1}(t,k) \end{bmatrix}, Z(t,k)=\begin{bmatrix} \hat{z}(t,k) \\ x_{c2}(t,k) \end{bmatrix},$$

$$\bar{A}_{11}=\begin{bmatrix} \tilde{A}_{11} & \tilde{B}_{11}C_{c1} \\ 0 & A_{c11} \end{bmatrix},\ \bar{A}_{12}=\begin{bmatrix} \tilde{B}_{11}D_c\hat{\alpha} & \tilde{B}_{11}C_{c2} \\ B_{c1}\hat{\alpha} & A_{c12} \end{bmatrix},$$

$$\bar{A}_{21}=\begin{bmatrix} \tilde{A}_{21} & \tilde{B}_{12}C_{c1} \\ 0 & A_{c21} \end{bmatrix},\ \bar{A}_{22}=\begin{bmatrix} \tilde{A}_{22}+\tilde{B}_{12}D_c\hat{\alpha} & \tilde{B}_{12}C_{c2} \\ B_{c2}\hat{\alpha} & A_{c22} \end{bmatrix}.$$

Design objective. For batch process (6) with sensor faults described in Eqs. (2) and (4), select matrices $\{A_c,B_c,C_c,D_c\}$ such that the system is always be stable and monotonically convergent for all $\alpha(k)$ satisfying Eq.(4).

4 Convergence of HOILC using 2D stability theory

In this subsection, the asymptotic stability theory of 2-D system is utilized to address the convergence of the ILC (13) against the iteration-varying sensor gain faults. First we introduce three lemmas.

Lemma 1[15]. *Consider a 2D Roesser model*

$$\begin{bmatrix} \bar{x}^h_{i+1,j} \\ \bar{x}^v_{i,j+1} \end{bmatrix}=\begin{bmatrix} \hat{A}_{11} & \hat{A}_{12} \\ \hat{A}_{21} & \hat{A}_{22} \end{bmatrix}\begin{bmatrix} \bar{x}^h_{i,j} \\ \bar{x}^v_{i,j} \end{bmatrix} \quad (15)$$

where $i\in[1,T]$, $j\geq 0$, $\bar{x}=\begin{bmatrix} \bar{x}^{hT} & \bar{x}^{vT} \end{bmatrix}^T \in R^n$ *is the state and if* $\hat{A}_{11}$, $\hat{A}_{12}$, $\hat{A}_{21}$, $\hat{A}_{22}$ *are appropriate dimensional real matrices, and the boundary conditions for the system* (12) *satisfy* $\bar{x}^v(i,0)$ *is finite for* $i\in[1,T]$ *,then* $\lim_{j\to\infty}\bar{x}(i,j)=0$ *holds for all* $i\in[1,T]$ *if and only if the matrix* $\hat{A}_{22}$ *is stable, i.e. the spectral radius of matrix* $\hat{A}_{22}$ *fulfills* $\rho(\hat{A}_{22})<1$.

Lemma 2[16] *(Schur Complement). Assume that* W, L, *and* V *are given matrixes with appropriate dimensions, where* W *and* V *are positive definite matrixes, then*

$$L^TVL-W<0 \quad (16)$$

if and only if

$$\begin{bmatrix} -W & L^T \\ L & -V^{-1} \end{bmatrix}<0 \quad (17)$$

or

$$\begin{bmatrix} -V^{-1} & L \\ L^T & -W \end{bmatrix}<0 \quad (18)$$

Theorem 1. *Consider the system* (12). *The system output* $z(t,k)$ *converges to 0 for all* $t\in[1,T]$ *as* $k\to\infty$ *if the learning gains* $\{A_{ci},B_{ci},C_{ci},D_c\}$, $i=1,2$ *can be designed such that*

$$\Psi_j \triangleq \begin{bmatrix} -X & -I & X\tilde{A}^T_{22}+\tilde{C}_{c2}\tilde{B}^T_{12} & \tilde{A}_{c2} \\ * & -Y & \tilde{A}^T_{22}+\Gamma_j\tilde{D}^T_c\tilde{B}^T_{12} & \tilde{A}^T_{22}Y+\tilde{B}^T_{c2} \\ * & * & -X & -I \\ * & * & * & -Y \end{bmatrix}<0 \quad (19)$$

Then the closed-loop system (14) *is asymptotically stable with a feasible solution as:*

$$\begin{aligned}
&D_c = \tilde{D}_c \\
&B_{c2} = N^{-1}\left(\tilde{B}_{c2}\Gamma_j - Y^T\tilde{B}_{12}\tilde{D}_c\Gamma_j\right) \\
&C_{c2} = \left(\tilde{C}_{c2}^T - D_c\Gamma_j X^T\right)M^{-T} \\
&A_{c2} = N^{-1}\left(\tilde{A}_{c2} - \Omega\right)^T M^{-T} \\
&\Omega = X\tilde{A}_{22}^T Y + X\Gamma_j D_c^T\tilde{B}_{12}^T Y + MC_{c2}^T\tilde{B}_{12}^T Y + X\Gamma_j B_{c2}^T N^T
\end{aligned} \tag{20}$$

Proof. It is obvious that $\hat{z}(t,k)$ is finite for all $t\in[0,T]$. Thus, applying **Lemma 1**, one can derive that

$$\lim_{k\to\infty}\hat{z}(t,k) = 0, \forall t\in[1,T] \tag{21}$$

if and only if

$$\rho\left(\bar{A}_{22}\right) < 1 \tag{22}$$

Note that there exists a positive definite matrix P then $\rho\left(\bar{A}_{22}\right) < 1$ is equivalent to

$$\bar{A}_{22}^T P\bar{A}_{22} - P < 0 \tag{23}$$

From **Lemma 2**, (23) is equivalent to

$$\begin{bmatrix} -P & \bar{A}_{22}^T \\ \bar{A}_{22} & -P^{-1} \end{bmatrix} < 0 \tag{24}$$

By pre- and post-multiplying $diag\{I,P\}$, we can obtain

$$\begin{bmatrix} -P & \bar{A}_{22}^T P \\ P\bar{A}_{22} & -P \end{bmatrix} < 0 \tag{25}$$

Hence, define

$$P \hat{=} \begin{bmatrix} Y & N \\ N^T & \Delta \end{bmatrix}, P^{-1} \hat{=} \begin{bmatrix} X & M \\ M^T & \Lambda \end{bmatrix}, \Pi_1 \hat{=} \begin{bmatrix} X & I \\ M^T & 0 \end{bmatrix} \tag{26}$$

where Δ, Λ are not relevant to the following discussion. It is easy to verify that

$$I - XY = MN^T \tag{27}$$

By pre- and post-multiplying nonsingular matrix $\Pi^T = diag\left\{\Pi_1^T, \Pi_1^T\right\}$ and (25) is equivalent to the following condition:

$$\begin{bmatrix} -X & -I & \Xi_1(\alpha) & \Xi_2(\alpha) \\ * & -Y & \Xi_3(\alpha) & \Xi_4(\alpha) \\ * & * & -X & -I \\ * & * & * & -Y \end{bmatrix} < 0 \tag{28}$$

where

$$\begin{aligned}
&\Xi_1(\alpha) = X\tilde{A}_{22}^T + MC_{c2}^T\tilde{B}_{12}^T + X\hat{\alpha}D_c^T\tilde{B}_{12}^T \\
&\Xi_2(\alpha) = X\tilde{A}_{22}^T Y + MC_{c2}^T\tilde{B}_{12}^T Y + MA_{c22}^T N^T \\
&\qquad + X\hat{\alpha}D_c^T\tilde{B}_{12}^T Y + X\hat{\alpha}B_{c2}^T N^T \\
&\Xi_3(\alpha) = \tilde{A}_{22}^T + \hat{\alpha}D_c^T\tilde{B}_{12}^T \\
&\Xi_4(\alpha) = \tilde{A}_{22}^T Y + \hat{\alpha}D_c^T\tilde{B}_{12}^T Y + \hat{\alpha}B_{c2}^T N^T
\end{aligned} \tag{29}$$

Notice that

$$\begin{aligned}
&\begin{bmatrix} -X & -I & \Xi_1(\alpha) & \Xi_2(\alpha) \\ * & -Y & \Xi_3(\alpha) & \Xi_4(\alpha) \\ * & * & -X & -I \\ * & * & * & -Y \end{bmatrix} \\
&= \sum_{j=1}^{2^l}\begin{bmatrix} -X & -I & a_j\Xi_1(\Gamma_j) & a_j\Xi_2(\Gamma_j) \\ * & -Y & a_j\Xi_3(\Gamma_j) & a_j\Xi_4(\Gamma_j) \\ * & * & -X & -I \\ * & * & * & -Y \end{bmatrix} \\
&= \sum_{j=1}^{2^l} a_j\Psi_j < 0
\end{aligned} \tag{30}$$

then we can get the inequality (31) as the criterion,

$$\begin{aligned}
&\Psi_j = \begin{bmatrix} -X & -I & X\tilde{A}_{22}^T + \tilde{C}_{c2}\tilde{B}_{12}^T & \tilde{A}_{c22} \\ * & -Y & \tilde{A}_{22}^T + \Gamma_j\tilde{D}_c^T\tilde{B}_{12}^T & \tilde{A}_{22}^T Y + \tilde{B}_{c2}^T \\ * & * & -X & -I \\ * & * & * & -Y \end{bmatrix} < 0 \\
&D_c = \tilde{D}_c \\
&B_{c2} = N^{-1}\left(\tilde{B}_{c2}\Gamma_j - Y^T\tilde{B}_{12}\tilde{D}_c\Gamma_j\right) \\
&C_{c2} = \left(\tilde{C}_{c2}^T - D_c\Gamma_j X^T\right)M^{-T} \\
&A_{c22} = N^{-1}\begin{pmatrix} \tilde{A}_{c22} - X\tilde{A}_{22}^T Y - X\Gamma_j D_c^T\tilde{B}_{12}^T Y - \\ MC_{c2}^T\tilde{B}_{12}^T Y - X\Gamma_j B_{c2}^T N^T \end{pmatrix}^T M^{-T}
\end{aligned} \tag{31}$$

$\lim_{k\to\infty} z(t,k) = 0, \forall t\in[1,T]$. According to lemma 3, we can achieve the control objective by assuring $\rho\left(\bar{A}_{22}\right) < 1$. Then the asymptotic stability based ILC design criterion (19) only consider the asymptotic stability along the iterative axis k that can be achieved by only output feedback.

5 Simulation

In this section, an example was presented to illustrate the proposed HOILC design criteria.

Given a numerical system as

$$A=\begin{bmatrix}0.0672 & -0.0252\\ 0.042 & 0.63\end{bmatrix},\ B=\begin{bmatrix}0.5\\ 0.8\end{bmatrix},\ C=\begin{bmatrix}-0.2 & 0.5\end{bmatrix}. \qquad (32)$$

$0\le t\le 60, k=1,2,...,$

Choose $m=3$, the sensor fault is assumed to occur after iteration 13, and $0.5\le\alpha\le 1.5$.

$$\alpha(13)=1.2, \alpha(14)=0.7, \alpha(15)=0.6$$

Choose the parameters in (4) as $h1=1.0000$, $h2=-1.2496$, $h3=0.4804$, and $\beta=0.8$.

Then the trend of alpha can be shown in fig.1

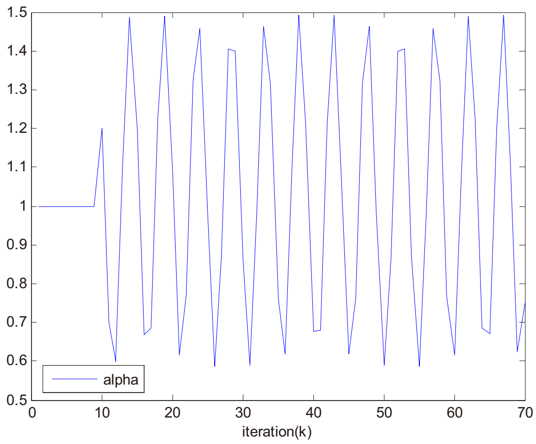

Fig. 1: The iteration-varying sensor faults.

For $k\le 16$, design results for HO-ILC

$$A_{c11}=\begin{bmatrix}-0.0918 & 0.0126\\ -0.1993 & 0.0274\end{bmatrix},$$

$$A_{c12}=1.0e\text{-}07*\begin{bmatrix}0.1192\\ 0.0949\end{bmatrix},$$

$$A_{c21}=1.0e\text{-}08*\begin{bmatrix}-0.3147 & 0.0553\end{bmatrix},$$

$$A_{c22}=0.2500$$

For $k\ge 16$, design results for HO-ILC

$$A_{c11}=\begin{bmatrix}-0.0603 & 0.5075\\ 0.0129 & -0.1085\end{bmatrix},$$

$$A_{c12}=1.0e\text{-}15*\begin{bmatrix}-0.0606 & -0.0559 & -0.1447\\ -0.2926 & -0.2739 & -0.6999\end{bmatrix},$$

$$A_{c21}=1.0e\text{-}18*\begin{bmatrix}-0.1199 & 0.0465\\ -0.0819 & 0.1757\\ 0.0025 & 0.0050\end{bmatrix},$$

$$A_{c22}=\begin{bmatrix}0.5130 & -0.8070 & -0.1205\\ 0.8024 & 0.2500 & 0.5194\\ -0.1944 & -0.6046 & 0.2380\end{bmatrix},$$

$$B_{c1}=\begin{bmatrix}-2.1002 & 2.6244 & -1.0168\\ 2.4332 & -3.0406 & 1.1780\end{bmatrix},$$

$$C_{c1}=\begin{bmatrix}-0.2582 & 0.9636\end{bmatrix},$$

$$B_{c2}=\begin{bmatrix}-1.3958 & 1.2818 & -1.0819\\ -1.2398 & 1.1417 & -0.9586\\ 0.1954 & -0.1718 & 0.1557\end{bmatrix},$$

$$C_{c2}=\begin{bmatrix}0.0046 & 0.0011 & 0.0020\end{bmatrix},$$

$$D_c=\begin{bmatrix}-3.3333 & 4.1653 & -1.6138\end{bmatrix}.$$

The control results are shown in Fig. 2, which shows the dynamic ILC based fault tolerant control law (13) outperforms the asymptotic stability.

Performance index:

$$DT(k)\triangleq\sqrt{\sum_{t=1}^{N}z^2(t,k)} \qquad (33)$$

The smaller $DT(k)$ indicates the better convergence performance in the kth cycle.

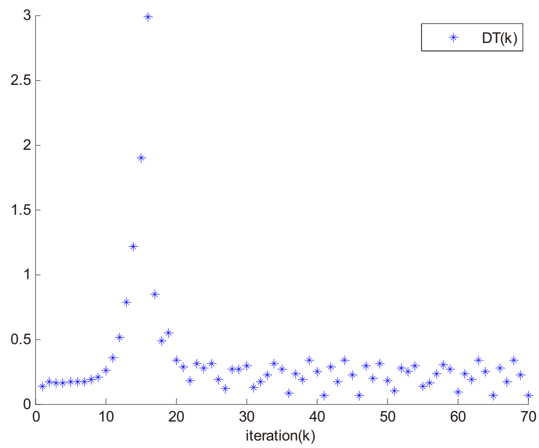

Fig. 2: The control results.

6 Conclusion

This paper proposed a novel high-order iterative learning control law for batch process with iteration-varying sensor faults, which is transformed into a 2D Roesser model. Then a HOIM-based ILC design criterion is presented by establishing the asymptotic convergence of the closed loop system. The proposed example shows the control result clearly.

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