A New Design of Predictive Functional Control Strategy for Batch Processes in the Two-Dimensional Framework

Ridong Zhang, Sheng Wu, and Jili Tao

***Abstract*—To cope with the control of batch processes under uncertainty, a novel two-dimensional (2-D) predictive functional iterative learning control (ILC) scheme is developed. By introducing a new model formulation and error compensation approach, the proposed strategy in which predictive functional control and ILC are combined through the 2-D framework compensates for the influence caused by various uncertainty gradually between cycles in the batch processes. Meanwhile, the improved state-space model is also employed effectively to enhance the control performance. Through the independent weighting on the state variables and the set-point tracking error in the performance index, additional degrees of freedom can be offered for the controller design. The effectiveness of the proposed 2-D method is tested on the injection velocity regulation in an injection molding process.**

***Index Terms*—Batch processes, error compensation, predictive functional control (PFC), state-space model, two-dimensional (2-D) control.**

I. Introduction

LOW-VOLUME and high-value products are widely used in practice, and their quality and yield are determined by the control of relevant batch processes [1]. With the rapid development of economy and the increasing demand, control requirements are stricter and there may be challenges for batch process control, although there have been great developments on the corresponding technologies [2], [3].

Repetitive characteristics are typical in batch processes because the same manufacturing process will continue until the specified product is enough [4]. Based on such backgrounds, there has been a lot of progress on the development of iterative learning control (ILC) strategies in which the repetitive nature is used to obtain better control performance and there are many representative results [5]. In [6], the improved ILC scheme in which a run-to-run model is employed was developed to handle the control problem of product quality in batch processes. Hao *et al.* [7] proposed a robust ILC approach for batch processes in which the input delay is time-varying. A new hierarchical ILC strategy in which the operating trajectories are updated by the repetitive nature was presented for the batch cooling crystallizers by Sanzida and Nagy [8]. For the control issue of batch processes with sensor faults and disturbances, an iterative learning reliable control approach was put forward by Wang *et al.* [9]. Based on the T–S model, a fuzzy delay-range-dependent ILC strategy was proposed to cope with the control of highly nonlinear batch processes with time-varying delays in [10]. By employing the repetitive process setting, a fault-tolerant ILC approach was developed for a class of batch processes with differential time delay and actuator faults by Tao *et al.* [11].

It is known that various uncertain factors exist in practice inevitably, which indicates that the characteristics between cycles in the batch processes are hard to be completely repetitive. It is a fact that the control law of pure ILC strategies is acquired beforehand such that the desired control performance cannot be guaranteed under uncertainty [12]. In order to cope with such situations, the feedback control is introduced to combine with ILC to compensate for the effects caused by uncertainty. There are many feedback control strategies that have been employed. In [13], the internal model control and ILC scheme were combined to handle the model uncertainty. A robust feedback control was used to unite ILC for batch processes with time-varying delay and uncertain perturbations by Wang *et al.* [14]. Jia *et al.* [15] developed a novel scheme with dynamic R-parameter in which the model predictive control (MPC) and ILC are integrated. On the basis of time-varying linear models, the MPC technique and ILC were combined for temperature tracking of a batch reactor in [16]. In [17], a robust ILC strategy was proposed based on the proportional–integral–derivative control structure.

In terms of these integrated strategies, both the process information of the time index and the cycle index are considered. In other words, the batch process can be viewed as a two-dimensional (2-D) system. Based on such concept, the 2-D framework in which the dynamics of both timewise and cyclewise are included has been put forward and there are many significant fruits [18]. Based on a 2-D model, the ILC strategy and the MPC were combined for batch processes by Li *et al.* [19]. In [20], the design of the feedback feedforward

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ILC approach was converted into a 2-D system based control problem. Based on 2-D system design, a robust ILC method was presented by Liu and Gao [21]. The idea of the two-stage optimization was used to enhance the control performance of the integrated strategy in which the 2-D model is employed by Lu *et al.* [22]. In [23], a 2-D model based indirect ILC system in which the ILC and the MPC are in the outer loop and the inner loop, respectively, was put forward. Other researchers have also contributed to the development of 2-D framework based strategies for batch processes under uncertainty [24], [25].

It is a fact that not all key quality variables are available for online control. Based on such backgrounds, many important approaches that enable quality control issues are developed and improved [26]. The quality control and data-driven modeling for batch processes were discussed by Corbett and Mhaskar [27]. In [28], the quality control of the injection molding process was completed by employing a multivariate sensor. The self-tuning final product quality control based on a midcourse correction approach was developed for batch processes by Jia *et al.* [29]. In [30], the subspace identification strategy was introduced for the quality modeling and control of batch processes.

As stated above, there have been many strategies for batch processes with uncertainty. To meet the stricter control requirements, there is still room for the improvement of relevant control schemes. In this paper, the predictive functional control (PFC) algorithm and the ILC are united in the 2-D framework. A 2-D extended model development will first be developed based on 1-D extended state-space model formulation strategy and a novel error compensation method will be employed to enhance the control performance [31]–[34]. By using the extended state-space model, more degrees of freedom are obtained by the separate tuning of the state variables and the tracking error. Meanwhile, the effects caused by uncertainty can be compensated gradually from cycle to cycle through the new error compensation approach. Case study on the injection velocity regulation in an injection molding batch process demonstrates the effectiveness of the proposed strategy.

The structure of this paper is as follows. The conventional two-dimensional predictive functional iterative learning control (2D-PFILC) is discussed in Section II. In Section III, the proposed scheme in which the extended state-space model and new error compensation method are introduced is described. Case studies on the injection velocity regulation are illustrated in Section IV, and the conclusion is given in Section V.

II. Conventional 2D-PFILC Strategy

For the batch process that is operated repetitively based on the same manufacturing procedure, the following state-space model is introduced:

$$\begin{aligned} x_m(t+1,k) &= Ax_m(t,k) + Bu(t,k) \\ y_m(t+1,k) &= Cx_m(t+1,k) \end{aligned} \tag{1}$$

where $x_m(t,k), u(t,k), y_m(t,k)$ are the state, input and output of the model at time instant t in the kth cycle, respectively. A, B, C are the corresponding coefficient matrices.

Based on (1), the output prediction can be acquired. Here, we define the output prediction as $y_m(t+i,k)$, where i is the prediction step.

Due to model/plant mismatches, disturbance, etc., we need to correct the output prediction to compensate for the influence caused by uncertainty. If we only consider the timewise error between the actual process output and model output, the following error compensation method is employed:

$$y_{mc}(t+i,k) = y_m(t+i,k) + e(t,k) \tag{2}$$

$$e(t,k) = y(t,k) - y_m(t,k) \tag{3}$$

where $y_{mc}(t+i,k)$ is the corrected output prediction at time instant $t+i$ in the $k\text{th}$ cycle. $y(t,k)$ is the actual process output, and $e(t,k)$ is the error between the actual process output and the model output at time instant t in the $k\text{th}$ cycle.

It is worth noting that the process information between cycles can also be considered to enhance the control performance, i.e., the error compensation method in (2) can be replaced by

$$\begin{aligned} y_{mc}(t+i,k) = y_m(t+i,k) + e(t,k) + e(t+i,k-1) \\ - e(t,k-1). \end{aligned} \tag{4}$$

Remark 1: It is clear that both timewise error and cyclewise error are considered in the error compensation method in (4). To some extent, it also indicates that such error compensation approach based strategy is in the 2-D framework.

The following cost function is selected for the conventional 2D-PFILC scheme:

$$\begin{aligned} \min J = \sum_{i=1}^{P} \{&\gamma(i)(y_{mc}(t+i,k) - y_r(t+i,k))^2 \\ &+ \lambda(i)(\Delta_t u(t+i-1,k))^2 \\ &+ \beta(i)(\Delta_k u(t+i-1,k))^2)\} \end{aligned} \tag{5}$$

where P is the prediction horizon and y_r is the reference trajectory. $\gamma(i), \lambda(i), \beta(i)$ are the relevant weighting coefficients. Δ_t, Δ_k are the timewise backward difference operator and cyclewise backward difference operator, respectively, i.e.,

$$\begin{aligned} \Delta_t u(t,k) &= u(t,k) - u(t-1,k) \\ \Delta_k u(t,k) &= u(t,k) - u(t,k-1). \end{aligned} \tag{6}$$

Remark 2: From the objective function in (5), we can see that the input increment of both timewise and cyclewise indexes is restrained. As to $\Delta_t u(t,k)$, it is helpful for restraining the divergent problem along cycle index when encountering the unstable inverse dynamics. For $\Delta_k u(t,k)$, it affects the robustness of the convergence for the controlled system along cycle index.

By choosing appropriate base functions and minimizing the objective function in (5), the optimal control law can be obtained finally.

III. Proposed 2D-PFILC Strategy

In this section, the new extended state-space model, the error compensation strategy, the new structure construction of the basis functions, and the new cost function are formulated to form the new 2D-PFILC framework.

A. New Extended State-Space Model

Considering (1), the following model can be obtained easily by adding Δ_t:

$$\begin{aligned}\Delta_t x_m(t+1,k) &= A\Delta_t x_m(t,k) + B\Delta_t u(t,k)\\ \Delta_t y_m(t+1,k) &= C\Delta_t x_m(t+1,k).\end{aligned} \tag{7}$$

Define the reference trajectory y_r as

$$y_r(t+i,k) = w^i y(t,k) + (1-w^i)c(t) \tag{8}$$

where $y(t,k)$ is the actual process output, $c(t)$ is the setpoint at time instant t, and w is the smoothing factor for the reference trajectory.

Based on (8), the uncorrected tracking error $e_t(t,k)$ can be calculated as

$$e_t(t,k) = y_m(t,k) - y_r(t,k). \tag{9}$$

Further, the formula of $e_t(t+1,k)$ can be derived

$$\begin{aligned}e_t(t+1,k) &= e_t(t,k) + \Delta_t y_m(t+1,k) - \Delta_t y_r(t+1,k)\\ &= e_t(t,k) + CA\Delta_t x_m(t,k) + CB\Delta_t u(t,k)\\ &\quad - \Delta_t y_r(t+1,k).\end{aligned} \tag{10}$$

Select the extended state vector as

$$z(t,k) = \begin{bmatrix}\Delta_t x_m(t,k)\\ e_t(t,k)\end{bmatrix} \tag{11}$$

then the relevant extended state-space model is

$$z(t+1,k) = A_e z(t,k) + B_e\Delta_t u(t,k) + C_e\Delta_t y_r(t+1,k) \tag{12}$$

where

$$A_e = \begin{bmatrix}A & 0\\ CA & 1\end{bmatrix};\ B_e = \begin{bmatrix}B\\ CB\end{bmatrix};\ C_e = \begin{bmatrix}0\\ -1\end{bmatrix}.$$

Here, 0 in A_e, C_e are zero vectors with appropriate dimensions.

B. Novel Error Compensation Approach

If we only consider the timewise error, the uncorrected tracking error prediction needs to be modified as

$$e_{tc}(t+i,k) = e_t(t+i,k) + e(t,k) \tag{13}$$

$$e(t,k) = y(t,k) - y_m(t,k) \tag{14}$$

where $e_{tc}(t+i,k)$ is the corrected error prediction, and $e(t,k)$ is the error between the actual process output and the model output at time instant t in the kth cycle.

On the basis of the extended state-space model in (12), the state prediction can be obtained

$$Z(k) = \theta z(t,k) + \psi\Delta_t U(k) + \xi\Delta_t Y_r(k) \tag{15}$$

where

$$Z(k) = \begin{bmatrix}z(t+1,k)\\ z(t+2,k)\\ \vdots\\ z(t+P,k)\end{bmatrix};\quad \Delta_t U(k) = \begin{bmatrix}\Delta_t u(t,k)\\ \Delta_t u(t+1,k)\\ \vdots\\ \Delta_t u(t+P-1,k)\end{bmatrix}$$

$$\Delta_t Y_r(k) = \begin{bmatrix}\Delta_t y_r(t+1,k)\\ \Delta_t y_r(t+2,k)\\ \vdots\\ \Delta_t y_r(t+P,k)\end{bmatrix};\quad \theta = \begin{bmatrix}A_e\\ {A_e}^2\\ \vdots\\ {A_e}^P\end{bmatrix}$$

$$\psi = \begin{bmatrix}B_e & 0 & 0 & \cdots & 0\\ A_eB_e & B_e & 0 & \cdots & 0\\ {A_e}^2B_e & A_eB_e & B_e & \cdots & 0\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ {A_e}^{P-1}B_e & {A_e}^{P-2}B_e & {A_e}^{P-3}B_e & \cdots & B_e\end{bmatrix}$$

$$\xi = \begin{bmatrix}C_e & 0 & 0 & \cdots & 0\\ A_eC_e & C_e & 0 & \cdots & 0\\ {A_e}^2C_e & A_eC_e & C_e & \cdots & 0\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ {A_e}^{P-1}C_e & {A_e}^{P-2}C_e & {A_e}^{P-3}C_e & \cdots & C_e\end{bmatrix}.$$

Here, P is the prediction horizon.

Referring to (13), the state prediction is corrected as

$$Z_c(k) = Z(k) + E(k) \tag{16}$$

where

$$Z_c(k) = \begin{bmatrix}z_c(t+1,k)\\ z_c(t+2,k)\\ \vdots\\ z_c(t+P,k)\end{bmatrix};\ E(k) = \begin{bmatrix}e_v(t,k)\\ e_v(t,k)\\ \vdots\\ e_v(t,k)\end{bmatrix};$$

$$e_v(t,k) = \begin{bmatrix}0\\ e(t,k)\end{bmatrix}.$$

Here, 0 in $e_v(t,k)$ is a zero vector with appropriate dimensions.

In order to improve the control performance, here the cyclewise tracking errors are also taken into account, and the following error compensation method is introduced:

$$Z_c(k) = Z(k) + E(k) + \tau E_c(k-1) \tag{17}$$

where

$$E_c(k-1) = \begin{bmatrix} e_c(t+1,k-1) \\ e_c(t+2,k-1) \\ \vdots \\ e_c(t+P,k-1) \end{bmatrix},$$

$$e_c(t+i,k-1) = \begin{bmatrix} 0 \\ \sum_{j=1}^{k-1} e_r(t+i,j) \end{bmatrix}$$

$$e_r(t+i,j) = y(t+i,j) - y_r(t+i,j).$$

Here, 0 in $e_c(t+i,k-1)$ is a zero vector with appropriate dimensions. τ is the weighting coefficient of the cyclewise accumulated tracking error.

Remark 3: It is obvious that the control strategy in which the improved error compensation approach in (17) is employed is in the 2-D framework. The error of both timewise and cyclewise indexes is considered.

Remark 4: For τ, its value needs to be appropriately chosen. A bigger τ helps to compensate for the cyclewise effects caused by uncertainty more quickly, but may result in divergence of the system.

C. New Structure Construction of Base Functions

For the PFC algorithm, its control law is the linear combination of typical basis functions, the choice of which is determined by the actual situations.

Generally, the control law of PFC schemes can be described as

$$u(t+i) = \sum_{n=1}^{N} \mu_n f_n(i), \quad i = 0, \ldots, P-1 \tag{18}$$

where N is the number of the basis functions, μ_n is the linear coefficient, and $f_n(i)$ is the value of the basis function at time instant iT_s (here T_s is the sampling period).

In this paper, the new structure is chosen as follows:

$$u(t+i,k) = \mu_1 + \mu_2 i + \mu_3 i^2 + \mu_4 i^3 + \cdots \mu_N i^{N-1}. \tag{19}$$

Remark 5: It is clear that the basis functions in (19) are $1, i, i^2, \ldots, i^{N-1}$.

Combining (15) with (19), the state prediction is rewritten as follows:

$$Z(k) = \theta z(t,k) + \chi W(k) + \xi \Delta_t Y_r(k) - \theta_u u(t-1,k) \tag{20}$$

where unnumbered equations are shown at the bottom of this page.

D. New Cost Function and Control Law

The following cost function is introduced for the proposed 2D-PFILC strategy:

$$\begin{aligned} \min J = \sum_{i=1}^{P} \{ & \gamma(i)(z_c(t+i,k))^2 + \lambda(i)(\Delta_t u(t+i-1,k))^2 \\ & + \beta(i)(\Delta_k u(t+i-1,k))^2)\} \end{aligned} \tag{21}$$

where $\gamma(i), \lambda(i), \beta(i)$ are the corresponding weighting matrices or coefficients, and P is the prediction horizon.

Remark 5: By introducing the extended state vector, it is easily seen that the state variables and the tracking error can be regulated separately, and there will be more degrees of freedom for the subsequent controller design.

Synthesizing (19) into (21), we obtain

$$\min J = \gamma Z_c(k)^2 + \lambda (GW(k))^2 + \beta (HW(k) - U(k-1))^2 \tag{22}$$

where unnumbered equations are shown at the bottom of next page.

Finally, the optimal linear coefficients of the basis functions can be obtained by minimizing the objective function in (22). The details are as follows:

$$\begin{aligned} W(k) = & -(\chi^T \gamma \chi + G^T \lambda G + H^T \beta H)^{-1} (\chi^T \gamma (\theta z(t,k) \\ & + \xi \Delta_t Y_r(k) - \theta_u u(t-1,k) + E(k) + \tau E_c(k-1)) \\ & - H^T \beta U(k-1)) \end{aligned} \tag{23}$$

$$\chi = \begin{bmatrix} B_e & 0 & 0 & \cdots & 0 \\ A_e B_e & B_e & B_e & \cdots & B_e \\ {A_e}^2 B_e & F(1,1) & F(1,2) & \cdots & F(1,N-1) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ {A_e}^{P-1} B_e & F(P-2,1) & F(P-2,2) & \cdots & F(P-2,N-1) \end{bmatrix}$$

$$W(k) = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_N \end{bmatrix}; \theta_u = \begin{bmatrix} B_e \\ A_e B_e \\ \vdots \\ {A_e}^{P-1} B_e \end{bmatrix}$$

$$F(i,t) = {A_e}^i B_e + \sum_{j=1}^{i} ((j+1)^t - j^t) {A_e}^{i-j} B_e.$$

then we can obtain the following control law:

$$u(t,k) = \mu_1. \tag{24}$$

Remark 6: Note that there is no history data in the first cycle, so the relevant optimal linear coefficients can be derived by the normal PFC strategy, i.e.,

$$\begin{aligned} W(k) = &-(\chi^T\gamma\chi + G^T\lambda G)^{-1}(\chi^T\gamma(\theta z(t,k) + \xi\Delta_t Y_r(k) \\ &+ E(k) - \theta_u u(t-1,k))). \end{aligned} \tag{25}$$

Remark 7: Similar to MPC framework, the tuning for PFC is not clearly defined since the tradeoff between the parameters and closed-loop performance or stability is generally not clear. However, some general guidelines can be referred to. For example, the control horizon should be smaller than the prediction horizon, i.e., P should be at least equal to the number of basis functions. Under model/plant mismatch cases, larger elements in $\gamma(i)$ will result in more stable closed-loop system since the process input and output will behave steadier.

The procedure of the proposed 2D-PFILC scheme is as follows.

1) Formulate the state-space model using (1).
2) Choose the smoothing factor of the reference trajectory w and obtain the extended state-space model in (12).
3) Select the proper basis functions for the control law using (19).
4) Specify the control parameters for the proposed PFC approach including the prediction horizon P and the weighting coefficients $\gamma, \lambda, \beta, \tau$.
5) Compute the known parts in (23) offline.
6) Execute initialization: $t \leftarrow 0$ and $k \leftarrow 1$.
7) Calculate the optimal control law using (25).
8) Let $t \leftarrow t+1$, and calculate the manipulated variable in (25).
9) If the end of the batch k is achieved, then go to step 12; otherwise, proceed to step 8.
10) Let $t \leftarrow t+1$ and compute the control law in (23).
11) If the end of the batch k is arrived, then proceed to step 12; otherwise, proceed to step 10.
12) Let $t \leftarrow 0$ and $k \leftarrow k+1$ and continue with step 10.

IV. Case Studies

A. Injection Molding Process

The goal of the process is to convert plastic granules into the desired products [see Fig. 1(a) and (b)]. There are three main stages for the whole process, i.e., the filling, the packing/holding, and the cooling [35]. During the filling stage, the plastic is melted under the high pressure from the injection screw and sent to the mold cavity. When the mold cavity is almost full [see Fig. 1(b)(i)], the filling stage will be finished and the next stage starts, where extra material will be added into the mold cavity to make up for the shrinkage [see Fig. 1(b)(ii)]. It will finish until the material in the mold cavity is frozen and its volume is no longer changed. During the third stage, the material will be cooled and ejected. The polymer is melted under the screw rotation [see Fig. 1(b)(iii)]. Finally, the mold will be opened and

$$\gamma = \begin{bmatrix} \gamma(1) & 0 & \cdots & 0 \\ 0 & \gamma(2) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \gamma(P) \end{bmatrix}; \quad \lambda = \begin{bmatrix} \lambda(1) & 0 & \cdots & 0 \\ 0 & \lambda(2) & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & \lambda(P) \end{bmatrix}$$

$$\beta = \begin{bmatrix} \beta(1) & 0 & \cdots & 0 \\ 0 & \beta(2) & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & \beta(P) \end{bmatrix}; \quad U(k-1) = \begin{bmatrix} u(t,k-1) \\ u(t+1,k-1) \\ \vdots \\ u(t+P-1,k-1) \end{bmatrix}$$

$$G = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 1 & \cdots & 1 \\ 0 & 2-1 & 2^2-1^2 & \cdots & 2^{N-1}-1^{N-1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & (P-1)-(P-2) & (P-1)^2-(P-2)^2 & \cdots & (P-1)^{N-1}-(P-2)^{N-1} \end{bmatrix}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 1 & 1 & 1 & \cdots & 1 \\ 1 & 2 & 2^2 & \cdots & 2^{N-1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & (P-1) & (P-1)^2 & \cdots & (P-1)^{N-1} \end{bmatrix}.$$

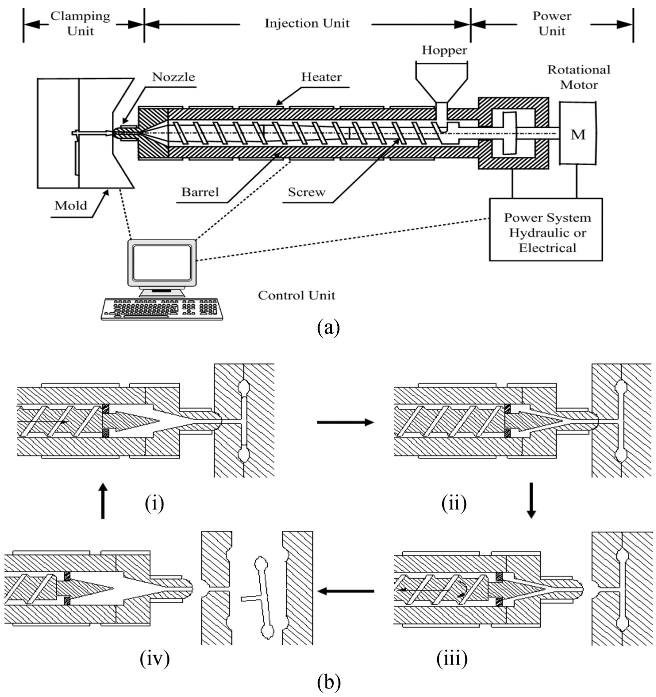

Fig. 1. (a) Injection molding machine. (b) Injection molding process: (i) filling, (ii) packing-holding, (iii) cooling, and (iv) mold open and part ejection.

the material will be ejected [see Fig. 1(b)(iv)]. Now, the current cycle is completed and the next one is prepared.

B. Simulation Results

The injection velocity during the process should be maintained at the desired value for product quality and safe operation. Referring to [4], the state-space representation of the model from the proportional value to the injection velocity is

$$\begin{cases} x(t+1,k) = \begin{bmatrix} 1.582 & -0.5916 \\ 1 & 0 \end{bmatrix} x(t,k) + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u(t,k) \\ y(t,k) = \begin{bmatrix} 1.69 & 1.419 \end{bmatrix} x(t,k) + w(t,k), \quad 0 \le t \le 100, \\ \quad k = 1,2,\ldots \end{cases} \tag{26}$$

where $w(t,k)$ is the unknown disturbance.

In this paper, the setpoint is chosen as

$$\begin{cases} c(t) = 15, & 1 \le t < 50 \\ c(t) = 30, & 50 \le t \le 100 \end{cases}. \tag{27}$$

And the following disturbances are considered.

Case 1: $w(t,k) = 0$.

Case 2: $w(t,k) = \sin(0.04\pi t)$.

Here, the evaluation is made in simulation on a laptop. The details of the laptop are: CPU: Inter(R) Core(TM) i5-2410M @2.30 GHz; RAM: 2 GB; Operation System: 32 b Windows 7.

In order to mimic the real conditions, the injection molding process shown in (26) will be approximated as a first-order process model for controller design. Note that the equivalent autoregressive model for (26) is a second-order model

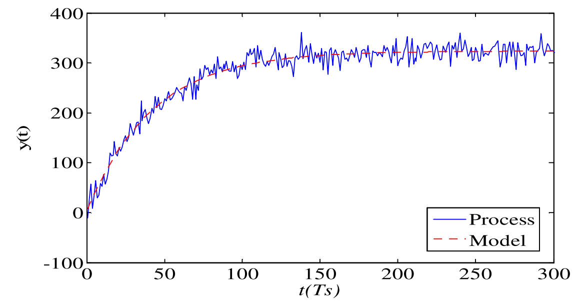

Fig. 2. Step responses of the process and model.

as follows:

$$P(z) = \frac{1.69z + 1.419}{z^2 - 1.582z + 0.5916}. \tag{28}$$

Here, a first-order model will be built for the real process shown in (28) and the subsequent controller design will base on this first-order model for performance evaluation.

By adopting the simple "two-point method" that can be referred to [32], two points are selected as follows:

$$\begin{cases} y(t_1) = 0.39K \\ y(t_2) = 0.63K \end{cases} \tag{29}$$

where K is the gain of the first-order model and t_1, t_2 are chosen as $t_1 = 21, t_2 = 42$.

The nominal first-order model is then obtained as

$$P_m(z) = \frac{7.623}{z - 0.9765}. \tag{30}$$

Fig. 2 shows the process response based on (28) and the model output using (30). Note that in order to simulate the real conditions, white noise is added to the real process output. It shows that the model maps the process dynamics well.

Note that various uncertainties exist in practice inevitably; here, additional mismatch is added to the original model to simulate the real conditions further, and the final model used for controller design is

$$P_m(z) = \frac{7.31}{z - 0.92}. \tag{31}$$

In other words, the controller will be designed based on the model in (31), whose dynamics deviate more from the real process shown in (28), to control the real process in (28).

Here, the conventional 2D-PFILC approach [35] is employed as the comparison and the random white noise with standard derivation 0.5 is considered to test the control performance of both methods. The control parameters for the two strategies are listed in Table I. Note that the control horizon is chosen as 2 to simplify the real-time controller design.

The responses for both schemes under case 1 are shown in Fig. 3(a)–(d). From an overall perspective, the proposed approach provides improved control performance since there are smaller overshoot and oscillations in the responses. Figs. 4–6 show the responses of the two schemes under specified cycles. We can easily find that their responses are improved cycle by cycle. In cycle 1, it is obvious that the responses of the proposed

TABLE I
CONTROL PARAMETERS FOR TWO METHODS

Parameters	Proposed	Conventional
P	3	3
N	2	2
$\gamma(i)$	diag(2,1)	1
$\lambda(i)$	5	5
$\beta(i)$	0.01	0.01
w	0.8	0.8
τ	1	\

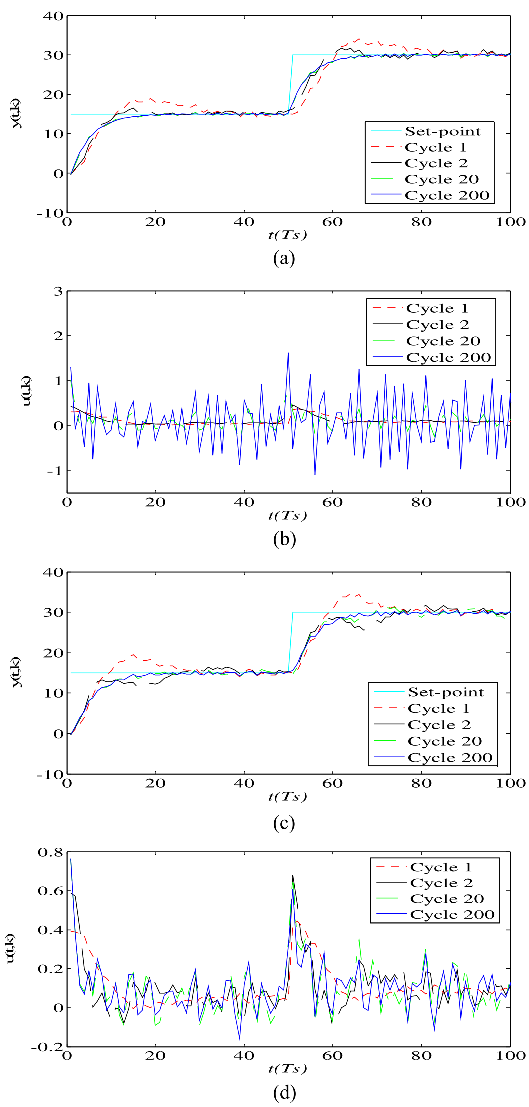

Fig. 3. (a) Output responses of case 1 for the proposed strategy. (b) Input signals of case 1 for the proposed strategy. (c) Output responses of case 1 for the conventional strategy. (d) Input signals of case 1 for the conventional strategy.

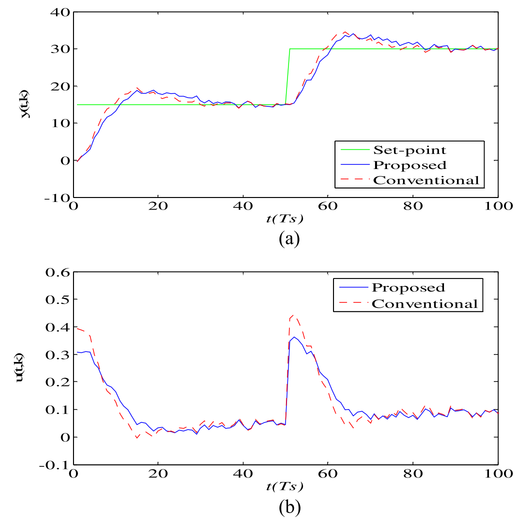

Fig. 4. (a) Output responses of case 1 for cycle 1. (b) Input signals of case 1 for cycle 1.

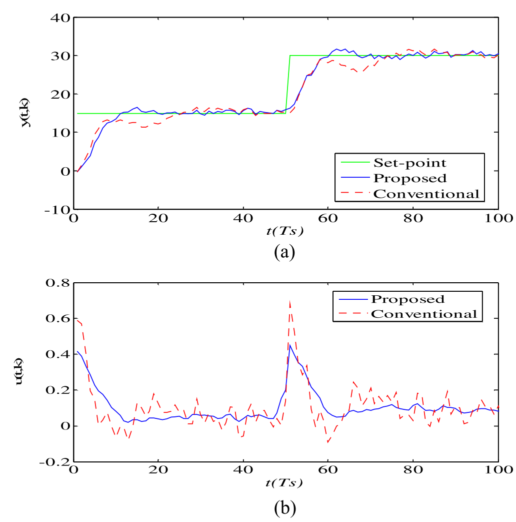

Fig. 5. (a) Output responses of case 1 for cycle 2. (b) Input signals of case 1 for cycle 2.

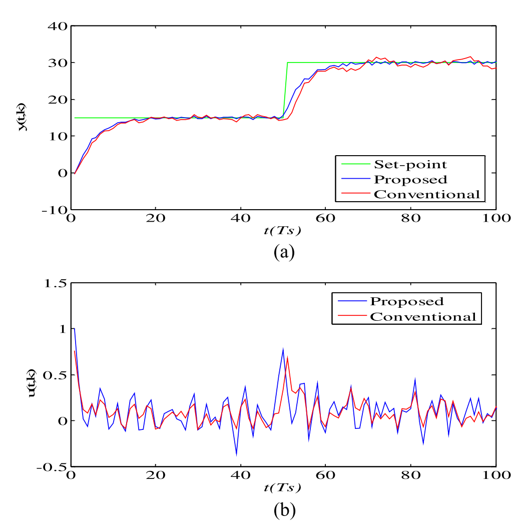

Fig. 6. (a) Output responses of case 1 for cycle 20. (b) Input signals of case 1 for cycle 20.

strategy are smoother. From cycle 2 on, responses of both schemes are improved, but the ensemble control performance of the proposed method is better because oscillations of the responses for the conventional scheme are more drastic. The statistical results for the integral of absolute error (IAE) value and the integral of absolute control signal (IACS) value in

TABLE II
STATISTICAL RESULTS FOR CASE 1

Item	IAE		IACS	
	Proposed	Conventional	Proposed	Conventional
Cycle1	285.5548	243.6908	10.7231	10.7442
Cycle2	177.8777	232.9662	10.5973	11.3244
Cycle20	152.7029	208.9010	16.4660	12.5085
Cycle200	144.4787	186.2655	50.8028	12.0996

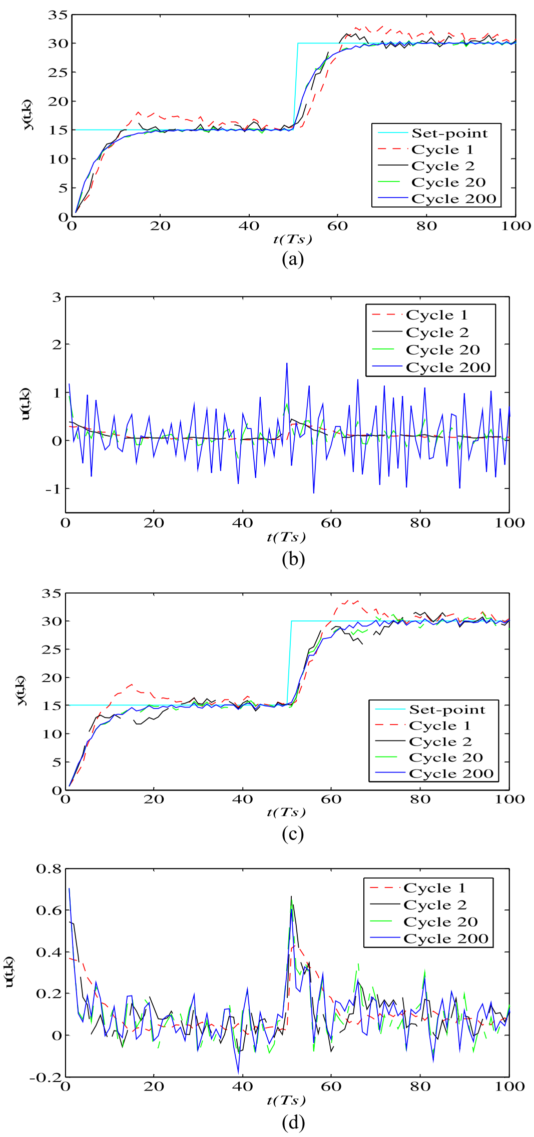

Fig. 7. (a) Output responses of case 2 for the proposed strategy. (b) Input signals of case 2 for the proposed strategy. (c) Output responses of case 2 for the conventional strategy. (d) Input signals of case 2 for the conventional strategy.

Table II indicate the aforementioned viewpoints further due to the fact that the IAE value of the proposed approach is smaller than that of the traditional method after several cycles.

In Fig. 7(a)–(d), the responses of both strategies under case 2 are shown. It is clear that the ensemble control performance of the proposed scheme is better because its responses are smoother with smaller oscillations. The responses of specified cycles for

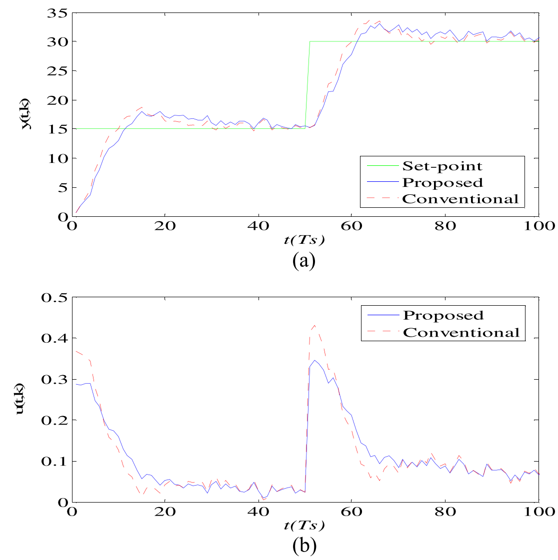

Fig. 8. (a) Output responses of case 2 for cycle 1. (b) Input signals of case 2 for cycle 1.

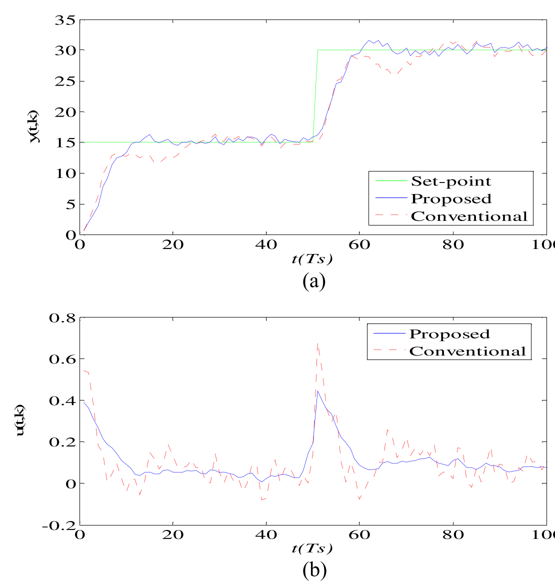

Fig. 9. (a) Output responses of case 2 for cycle 2. (b) Input signals of case 2 for cycle 2.

the two methods are shown in Figs. 8–10, and the situations are similar to those in case 1. Although improved responses are obtained from cycle to cycle for both schemes, the proposed scheme provides better ensemble control performance since the oscillations of the conventional method are bigger. The statistical results listed in Table III verify the enhanced control performance of the proposed approach further. The IAE value of the proposed scheme is improved faster and smaller than that of the traditional method after several cycles.

Remark 8: It is seen from the responses that the proposed method can achieve the steady output (or the control goal) earlier than the traditional method. This shows that the proposed method increases the treatment efficiency of the raw materials, which will be good for increasing the yield of the product, etc.,

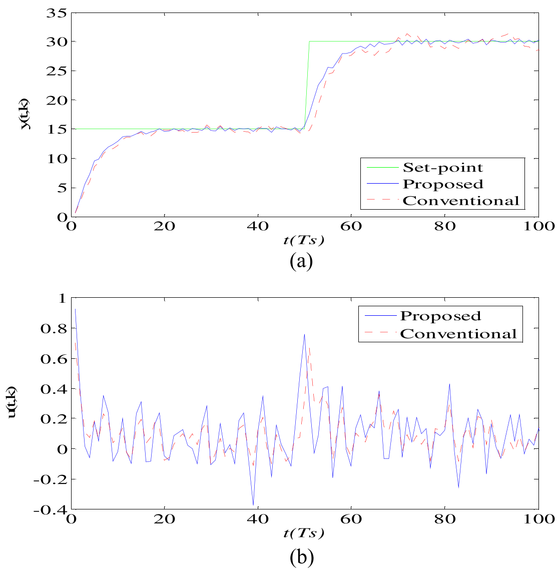

Fig. 10. (a) Output responses of case 2 for cycle 20. (b) Input signals of case 2 for cycle 20.

TABLE III
STATISTICAL RESULTS FOR CASE 2

Item	IAE		IACS	
	Proposed	Conventional	Proposed	Conventional
Cycle1	273.7404	230.4121	10.6302	10.6161
Cycle2	173.7867	214.9103	10.4640	11.1358
Cycle20	147.7319	200.6600	16.3037	12.4219
Cycle200	139.7127	180.8182	50.5572	12.0129

because the proposed method can reach the production goal through smaller number of batches.

V. CONCLUSION

In this paper, an improved 2D-PFILC strategy using the extended state-space model and a new error compensation method is introduced for batch processes under uncertainty. By employing the new extended state-space model and novel error compensation approach, there are additional tuning degrees for the controller design; meanwhile, the effects caused by uncertainty can be compensated gradually between cycles. Case studies on the injection velocity regulation under uncertainty demonstrate the effectiveness of the proposed strategy. The results show that better ensemble control performance is provided by the proposed 2D-PFILC scheme compared with the typical conventional 2D-PFILC approach.

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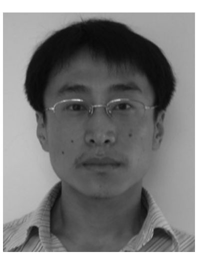

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