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Improved Robust Constrained Model Predictive Control Design for Industrial Processes Under Partial Actuator Faults

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ABSTRACT Focusing on industrial processes under uncertainties and partial actuator faults, a new robust constrained model predictive control (MPC) strategy is developed. To enhance the corresponding control performance, a new state-space model in which an extended state vector is constructed by combining the state variables and the tracking error is introduced for the proposed MPC algorithm. As a consequence, there are extra degrees of freedom for the subsequent controller design by adjusting the output tracking error and the state variables separately, and the enhanced control performance is anticipated. Note that the state variables cannot be tuned in the robust MPC design that utilizes the traditional state space model so that its control performance may be limited because of the restricted degrees of freedom. Finally, the validity of the proposed robust MPC strategy is evaluated on the injection velocity control under uncertainties and partial actuator failures.

INDEX TERMS Industrial process, partial actuator fault, robust MPC, extended state space model.

I. INTRODUCTION

As a vital role in manufacturing various high-value products, industrial chemical processes exist widely in industries. In order to meet the increasing demands, both the control theory and applications of such processes have gained lots of progresses in the past decades [1], [2]. It is known that the system performance may be deteriorated greatly under all kinds of disadvantages in practice, such as model/plant mismatches, disturbances, actuator faults, etc [3]. Moreover, the existing approaches may hardly satisfy higher control demands [4]. Based on such backgrounds, it is of necessity to research improved control approaches for industrial processes further.

Actuators are the essential part in control systems, and they implement the control signals calculated by controllers and ensure the normal operation of industrial processes [5]. However, actuator failures are common in industrial processes, which are caused by some physical damages. Under such situations, the system performance will be affected significantly because the controller output cannot be implemented accurately by the actuator [6]. Generally speaking, there are three common actuator failures, that is, actuator outage, actuator stuck and partial actuator fault [7]. It is worth mentioning that the industrial chemical process systems under actuator outage and actuator stuck is uncontrollable, so that the relevant studies may be meaningless [8]. In this paper, we focus on industrial processes in which partial actuator failures occur.

To cope with the module fault in controlled processes, fault-tolerant control (FTC) approaches, whose goal is to maintain the system performance against module failures, have been studied to a great extent, and there are many representative results for industrial processes under partial actuator failures [9]. On the basis of fuzzy iterative learning control strategy, a fault-tolerant guaranteed cost controller was investigated for nonlinear batch processes with disturbances and actuator faults in [10]. Concentrating on the regulation of a value-actuated quadruple-tank process with actuator failures, Arici and Kara [11] developed a modified adaptive fault compensation controller. In [12], the problem of fault compensation and diagnosis was studied for a discrete time systems that have time-varying state delays. Focusing on actuator faults and inevitable time delays in the batch process, an improved robust iterative learning FTC method was proposed by Shen *et al*. [13]. By using the repetitive process setting, an improved fault-tolerant iterative learning control approach was presented in [14].

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As another important branch for dealing with industrial processes with actuator faults and various uncertainties, the developments of iterative learning control (ILC) algorithm are also great [15]. It is the fact that repetitive characteristics exist in the operation of chemical batch processes, which facilitates the progress of ILC strategies. Note that pure ILC scheme is feedforward control that is unable to handle the unknown disturbance and other uncertainties, so that feedback control approaches are employed to combine with ILC normally [16]. Many researchers have addressed their significant fruits about the control of such processes in which uncertainties and partial actuator faults exist utilizing ILC methods [17]. In [18], the nonlinear constrained system under actuator failures was controlled by an improved ILC scheme. For the uncertain discrete linear processes with polytopic uncertainties and actuator failures, a novel ILC approach was designed in [19]. To handle the non-linearly parameterized systems which have actuator failures and time-varying state delays, Ji *et al.* [20] developed an adaptive iterative learning reliable control scheme. In [21], an modified iterative learning FTC strategy was put forward for networked batch processes under external disturbances and actuator failures. A fuzzy delay-range dependent ILC approach was presented for nonlinear batch processes in which time-varying delays exist by adopting T-S model in [22].

Besides these aforementioned results, many other control algorithms have also been studied [23]–[27]. As a valid control approach in dealing with systems with uncertainties, MPC with robustness has drawn much attention, and there are also lots of crucial viewpoints about the application of robust MPC schemes in industrial processes under uncertainties and partial actuator failures [28]. As to the constrained batch processes with model uncertainty, an enhanced robust MPC approach was developed based on the reverse-time reachability region in [29]. Zhang *et al.* [30] presented a systematic min-max MPC method to control the batch processes under unknown disturbances and partial actuator uncertainty. On the basis of the multi-stage economic nonlinear MPC method, a modified robust control method was put forward for constrained batch processes under parametric uncertainties in [31]. In [32], a robust MPC method was addressed for process supply chains.

In this paper, we concentrate on the robust MPC design for constrained industrial processes in which partial actuator failures and uncertainties exist. To the author's knowledge, most state space models adopted in robust MPC are conventional, that is, the adjustable factors in the relevant performance index are insufficient, which implies that the corresponding controller design may be restricted on the degree of freedom. In order to solve this situation, an improved state space model is formed by uniting the tracking error and the state variables for the robust MPC approach. By utilizing the improved state space model, there are extra degrees of freedom for the relevant controller design through regulating tracking error and state variables independently, so that the modified control performance is expected. Finally, the validity of the modified model based robust MPC strategy is verified on the constrained injection velocity regulation process with model uncertainty and partial actuator faults.

II. PROBLEM FORMULATION

We consider the following singe-input single-output (SISO) time-varying industrial system.

$$\begin{aligned} x(k+1) &= A(k)x(k) + B(k)u(k) \\ y(k+1) &= Cx(k+1) \end{aligned} \tag{1}$$

where $x(k), u(k), y(k)$ are process state, input and output. $A(k), B(k), C$ are the corresponding parameter matrices. Suppose that $[A(k)\,|B(k)] \in \Omega$, Ω is the polytope $Co\{[A_1\,|B_1], \cdots, [A_L\,|B_L]\}$ and Co represents collection. In other words, there are L nonnegative factors $\upsilon_l(k)(l = 1, 2, \cdots, L)$ which satisfy the following equations

$$\sum_{l=1}^{L} \upsilon_l(k) = 1, \quad [A(k)\,|B(k)] = \sum_{l=1}^{L} \upsilon_l(k)[A_l\,|B_l] \tag{2}$$

Under partial actuator fault, the details are described as follows.

$$u_F(k) = \alpha u(k) \tag{3}$$

where $u_F(k)$ is the practical actuator movement. α denotes the degree of the actuator failure. Note that

$$0 < \alpha \leq 1 \tag{4}$$

Remark 1: From (4), we can easily see that $\alpha = 1$ represents the normal case in which no actuator failures occur. $0 < \alpha < 1$ corresponds to cases with partial actuator fault.

Further, the process in which partial actuator faults exist can be expressed as follows.

$$\begin{aligned} x(k+1) &= A(k)x(k) + B(k)u_F(k) \\ y(k+1) &= Cx(k+1) \end{aligned} \tag{5}$$

For the industrial system shown in (5), the goal of the relevant robust MPC design is tracking the reference value as close as possible, meanwhile, maintaining the desired system performance under uncertainties and partial actuator faults.

III. CONVENTIONAL ROBUST MPC

As to the model shown in (1), it can be rewritten as the following equation using the difference operator Δ

$$\begin{aligned} \Delta x(k+1) &= A(k)\Delta x(k) + B(k)\Delta u(k) \\ \Delta y(k+1) &= C\Delta x(k+1) \end{aligned} \tag{6}$$

where $\Delta x(k) = x(k) - x(k-1)$, and the similar formulas can be obtained for $\Delta u(k)$ and $\Delta y(k)$.

By constructing a new state as $x_m(k) = [\Delta x(k), y(k)]^T$, the model in (6) can be converted into

$$\begin{aligned} x_m(k+1) &= A_m(k)x_m(k) + B_m(k)\Delta u(k) \\ y(k+1) &= C_m x_m(k+1) \end{aligned} \tag{7}$$

where

$$A_m(k) = \begin{bmatrix} A(k) & 0 \\ CA(k) & 1 \end{bmatrix}; \quad B_m(k) = \begin{bmatrix} B(k) \\ CB(k) \end{bmatrix};$$
$$C_m = \begin{bmatrix} 0 & 1 \end{bmatrix}$$

In $A_m(k)$ and C_m, 0 is the appropriate zero vector.

The following objective function aiming at tracking the reference trajectory is selected for the traditional approach.

$$\min_{\Delta u(k+i|k)} \max_{[A(k+i)|B(k+i)]\in\Omega} J_\infty(k)$$
$$= \sum_{i=0}^{\infty} [(y(k+i|k) - y_r(k+i))^T Q(y(k+i|k) - y_r(k+i))$$
$$+ \Delta u(k+i|k)^T R \Delta u(k+i|k)] \tag{8}$$

subject to

$$\begin{cases} |\Delta u(k+i|k)| \le \Delta u_{\max} \\ |\Delta y(k+i|k)| \le \Delta y_{\max} \end{cases}$$

where $y_r(k+i)$ is the reference trajectory. Q is the weighting matrix for the output tracking error, and R is the weighting matrix for the control input increment. Here, $Q > 0$ and $R > 0$. $y(k+i|k)$, $\Delta u(k+i|k)$ are the output prediction and the input increment prediction, respectively. $\Delta u_{\max}$ and $\Delta y_{\max}$ are upper limits for input increments and output increments.

To obtain the optimal control law, some transformations are needed to be done for the cost function in (8). Note that $C_m T = I$ is satisfiable for a given matrix C_m with full rank, where I is a proper unit matrix. By letting $T = C_m^T(C_m C_m^T)^{-1}$ and $x_r(k) = Ty_r(k)$, the performance index in (8) is transformed as

$$\min_{\Delta u(k+i)} \max_{[A(k+i)|B(k+i)]\in\Omega} J_\infty(k)$$
$$= \sum_{i=0}^{\infty} [(x_m(k+i|k) - x_r(k+i))^T Q'(x_m(k+i|k)$$
$$-x_r(k+i)) + \Delta u(k+i|k)^T R \Delta u(k+i|k)] \tag{9}$$

subject to

$$\begin{cases} |\Delta u(k+i|k)| \le \Delta u_{\max} \\ |\Delta y(k+i|k)| \le \Delta y_{\max} \end{cases}$$

where $Q' = C_m^T Q C_m$. $x_m(k+i|k)$ is the state prediction for time instant $k+i$ made at time instant k.

By solving the optimization problem in (9), the relevant optimal control law is derived, and the related details can be referred in [33].

IV. PROPOSED ROBUST MPC

A. EXTENDED STATE SPACE MODEL

Here, the formula in (6) can be acquired from the model in (1) via combining the difference operator Δ at first.

Denote $y_r(k)$ as the reference value, we can obtain the tracking error as

$$e(k) = y(k) - y_r(k) \tag{10}$$

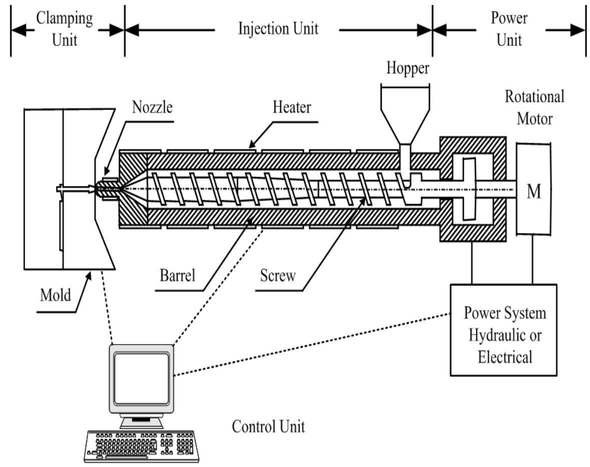

FIGURE 1. Sketch map of the injection molding machine.

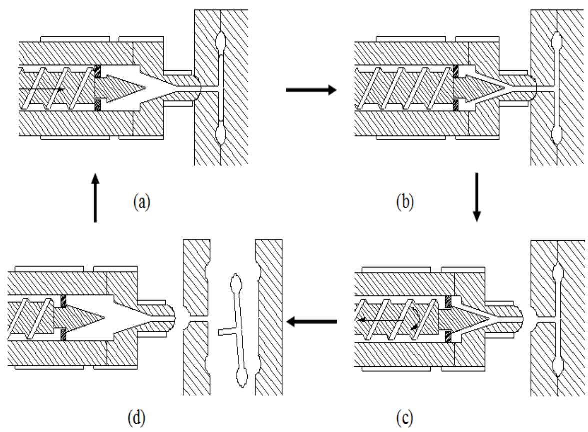

FIGURE 2. The corresponding workflow. (a) Filling stage. (b) Packing/holding stage. (c) Cooling stage. (d) Plastication stage.

On the basis of the difference model in (6) and (10), we can derive the following prediction for tracking error further.

$$e(k+1) = e(k) + CA(k)\Delta x(k) + CB(k)\Delta u(k) \tag{11}$$

To gain the improved state space model, the following extended state vector is chosen.

$$z(k) = \begin{bmatrix} \Delta x(k) \\ e(k) \end{bmatrix} \tag{12}$$

then we can acquire the corresponding extended state space model as

$$z(k+1) = A_z(k)z(k) + B_z(k)\Delta u(k)$$
$$\Delta y(k+1) = C_z z(k+1) \tag{13}$$

where

$$A_z(k) = \begin{bmatrix} A(k) & 0 \\ CA(k) & 1 \end{bmatrix}; \quad B_z(k) = \begin{bmatrix} B(k) \\ CB(k) \end{bmatrix};$$
$$C_z = \begin{bmatrix} C & 0 \end{bmatrix}$$

0 in $A_z(k)$ is an appropriate zero vector.

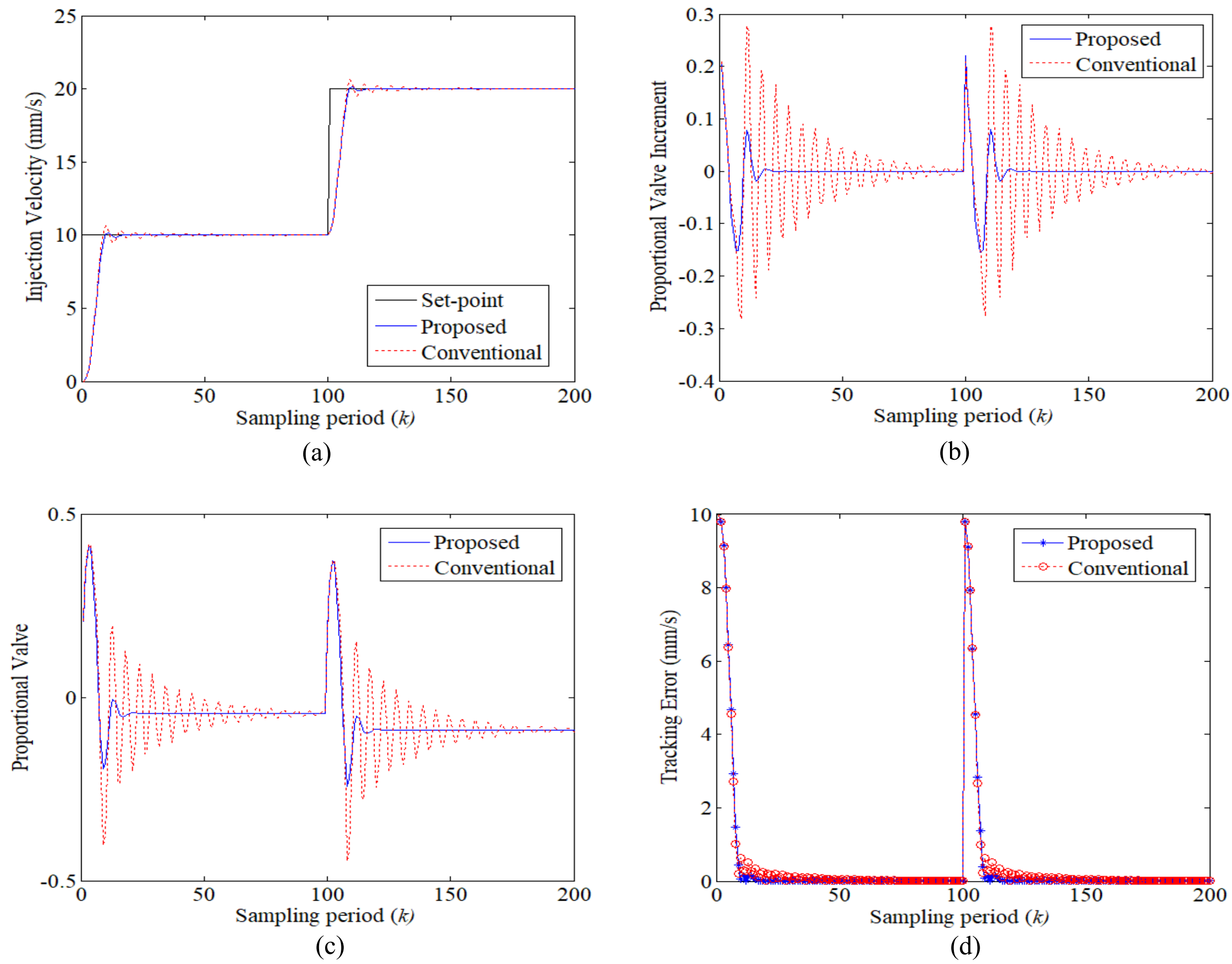

FIGURE 3. Responses under case 1. (a) Injection velocity. (b) Proportional valve increment. (c) Proportional valve. (d) Tracking error.

Refer to (2), $[A_z(k)\,|B_z(k)\,]$ also can be cast into the following polytopic description. Here Ω_z is the relevant polytope and Co denotes the collection.

$$[A_z(k)\,|B_z(k)\,] \in \Omega_z = Co\{[A_{z1}\,|B_{z1}\,], \cdots, [A_{zL}\,|B_{zL}\,]\} \tag{14}$$

$$[A_z(k)\,|B_z(k)\,] = \sum_{l=1}^{L} \vartheta_l(k)[A_{zl}\,|B_{zl}\,], \quad \sum_{l=1}^{L} \vartheta_l(k) = 1$$
$$\vartheta_l(k) \geq 0 \tag{15}$$

B. CONTROLLER DESIGN

The following objective function is adopted for the proposed robust MPC method to track the reference value.

$$\min_{\Delta u(k+i|k)} \max_{[A_z(k+i)|B_z(k+i)]\in\Omega_z} J_\infty(k)$$
$$= \sum_{i=0}^{\infty} [z(k+i\,|k\,)^T Qz(k+i\,|k\,)$$
$$+\Delta u(k+i\,|k\,)^T R\Delta u(k+i\,|k\,)] \tag{16}$$

subject to

$$\begin{cases} |\Delta u(k+i\,|k\,)| \leq \Delta u_{\max} \\ |\Delta y(k+i\,|k\,)| \leq \Delta y_{\max} \end{cases}$$

where Q, R are the weighting matrices for the extended state variables and the control input increment. $z(k+i\,|k\,)$ is the state prediction, and $\Delta u(k+i\,|k\,)$ is input increment prediction. $\Delta u_{\max}$, $\Delta y_{\max}$ are upper limits for input increments and output increments.

Remark 2: By utilizing the improved model in (13), both the output tracking error and the state variables can be tuned in (16) separately because the state contains such variables, so that extra degrees of freedom are acquired for the proposed robust MPC design.

Remark 3: Note that the additional state variables are adjustable in (16), as a consequence, the dynamics changes are considered in the proposed robust MPC strategy and the modified control performance is expected.

To minimize the performance index in (16), we employ the following state feedback law

$$\Delta u(k+i\,|k\,) = F(k)z(k+i\,|k\,) \tag{17}$$

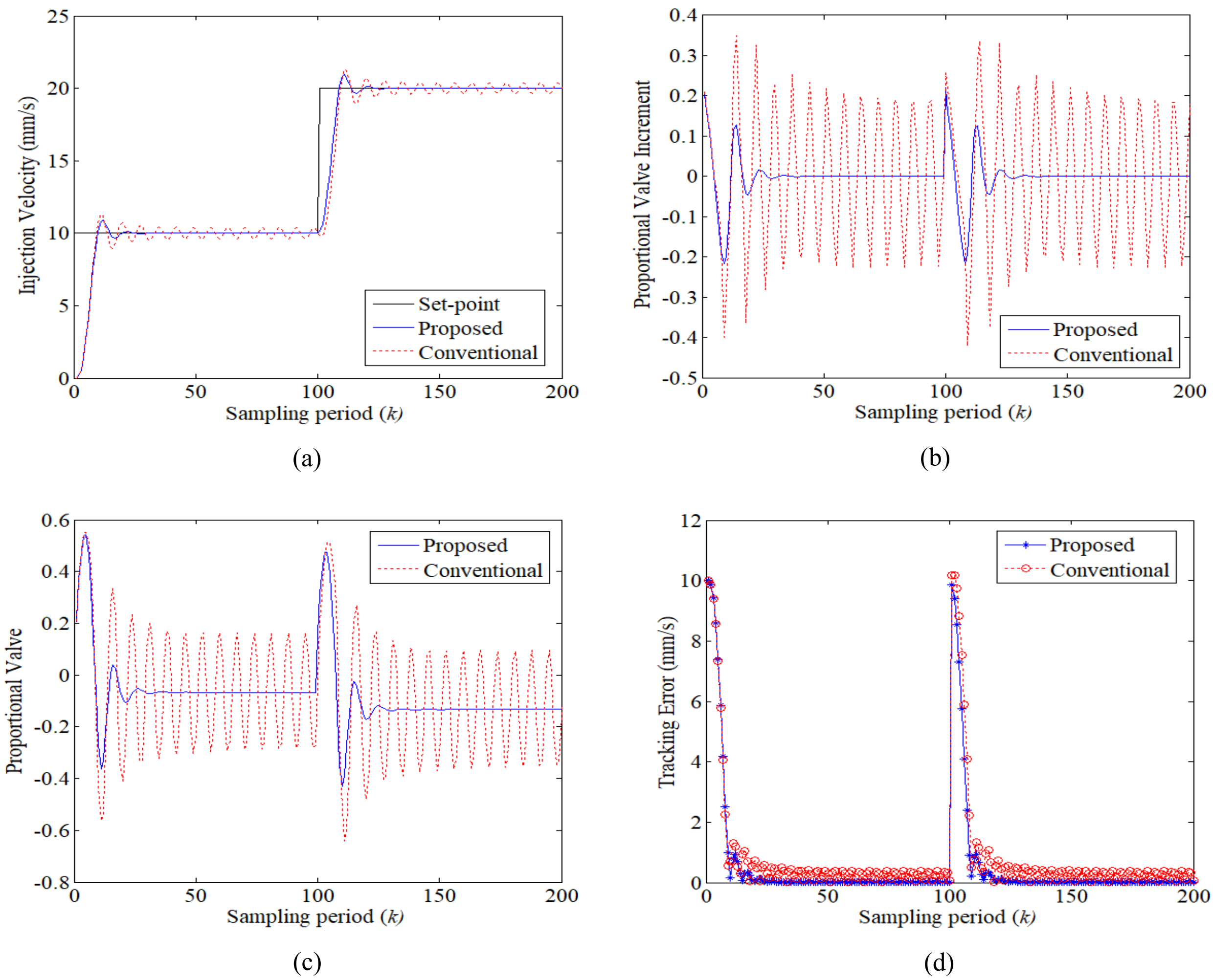

FIGURE 4. Responses under case 2. (a) Injection velocity. (b) Proportional valve increment. (c) Proportional valve. (d) Tracking error.

Define $V(z) = z^T P(k)z$, $P(k) > 0$. And assume that the following robust stability constraint is satisfied for arbitrary $[A_z(k+i)\,|B_z(k+i)] \in \Omega_z$.

$$\begin{aligned} V(z(k+i+1\,|k)) - V(z(k+i\,|k)) \\ \leq -[z(k+i\,|k)^T Qz(k+i\,|k) \\ + \Delta u(k+i\,|k)^T R\Delta u(k+i\,|k)] \end{aligned} \tag{18}$$

Through summing (18) from $i = 0$ to ∞, we can derive the following formula by demanding $z(\infty\,|k) = 0$ or $V(z(\infty\,|k)) = 0$.

$$\max_{[A_z(k+i)|B_z(k+i)]\in\Omega_z} J_\infty(k) \leq V(z(k)) \leq \gamma \tag{19}$$

where γ is the upper limit of $J_\infty(k)$.

Further, the corresponding linear matrix inequalities (LMIs) can be obtained for the inequalities in (19).

$$\begin{bmatrix} 1 & z(k)^T \\ z(k) & S \end{bmatrix} \geq 0, \quad S > 0 \tag{20}$$

where $S = \gamma P(k)^{-1}$.

Based on (13), (17) and the form of $V(z)$, the inequality in (18) can be converted into

$$\begin{aligned} z(k+i\,|k)^T [(A_z(k) + B_z(k)F(k))^T P(k)(A_z(k) + B_z(k)F(k)) \\ - P(k) + F(k)^T RF(k) + Q]z(k+i\,|k) \leq 0 \end{aligned} \tag{21}$$

It is obvious that (21) will be satisfied if the following inequality is tenable for any $[A_z(k+i)\,|B_z(k+i)] \in \Omega_z$.

$$\begin{aligned} [(A_z(k) + B_z(k)F(k))^T P(k)(A_z(k) + B_z(k)F(k)) \\ - P(k) + F(k)^T RF(k) + Q] \leq 0 \end{aligned} \tag{22}$$

Denote $Y = F(k)S$ and note $P(k) = \gamma S^{-1}$, then the formula in (22) is equivalent to the following LMI

$$\begin{bmatrix} S & SA_{zl}^T + Y^T B_{zl}^T & SQ^{1/2} & Y^T R^{1/2} \\ A_{zl}S + B_{zl}Y & S & 0 & 0 \\ Q^{1/2}S & 0 & \gamma I & 0 \\ R^{1/2}Y & 0 & 0 & \gamma I \end{bmatrix} \geq 0$$
$$l = 1, 2, \cdots, L \tag{23}$$

where I is the appropriate unit matrix.

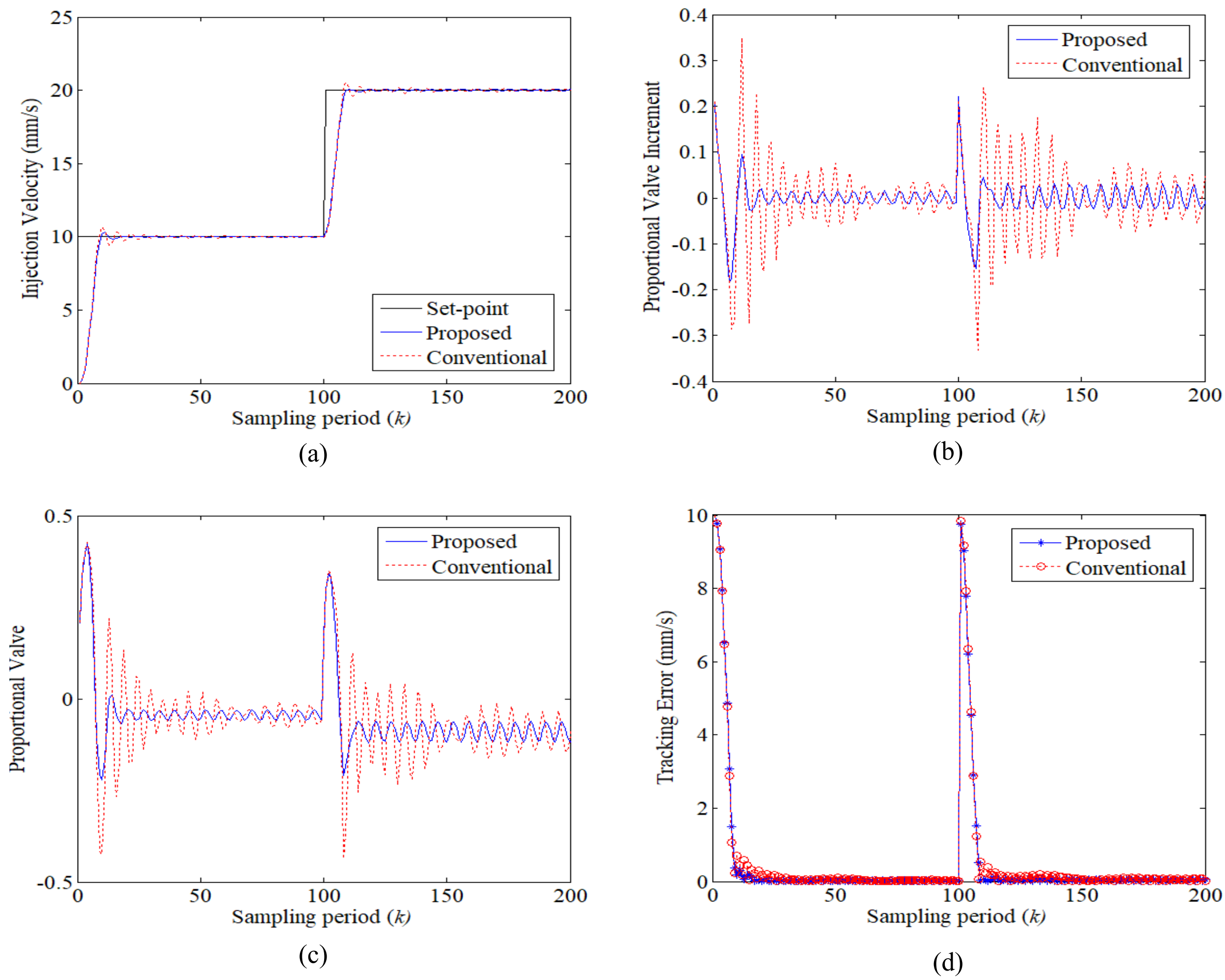

FIGURE 5. **Responses under case 3. (a) Injection velocity. (b) Proportional valve increment. (c) Proportional valve. (d) Tracking error.**

As to the constraints in (16), they will be satisfied if symmetric matrices X and Z are existing to meet the following LMIs.

$$\begin{bmatrix} X & Y \\ Y^T & S \end{bmatrix} \geq 0, \quad X \leq \Delta u_{\max}^2 \tag{24}$$

$$\begin{bmatrix} Z & C_z(A_{zl}S + B_{zl}Y) \\ (A_{zl}S + B_{zl}Y)^T C_z^T & S \end{bmatrix} \geq 0$$
$$Z \leq \Delta y_{\max}^2, \quad l = 1, 2, \cdots, L \tag{25}$$

Here, the details for the derivation of (24) and (25) can be seen in [34], so that the relevant contents are omitted for brevity.

By solving LMIs in (20), (23), (24) and (25), we can obtain S, Y, then $F(k) = YS^{-1}$ is gained. Finally, the optimal control input increment is gained by (17).

V. CASE STUDIES

A. THE INJECTION MOLDING PROCESS

The schematic diagram and the workflow of the injection molding machine are given in Figure 1a and Figure 2. For the injection molding process, it is aimed at getting the needed products by processing the plastic granules under batch mode. Generally speaking, there are four stages in the injection molding process: filling, packing/holding, cooling, and plastication. When the process flow starts, the injection screw generates high pressure in the filling stage, which will result in the melt of the plastic. Then the melted plastic will be sent to the mold cavity. Note that the cavity pressure is increased gradually among this stage (see Figure 2(a)). when the mold cavity is topful with the melted plastic, the packing-holding stage will begin, then the cavity pressure will increase fast. Meanwhile, in order to make up for the plastic shrinkage, extra material will be added into the cavity until the gate freezes off (see Figure 2(b)). After this, cooling and ejection are happened for the material in cavity, which is known as the cooling stage. Along with the material solidification, the plastication stage also happens at the same time in the barrel. The polymer is melted by the rotating of the screw until enough melted polymers are obtained (see Figure 2(c)). When the relevant material is hard enough, it will be ejected finally (see Figure 2(d)). Then a completed work procedure is over.

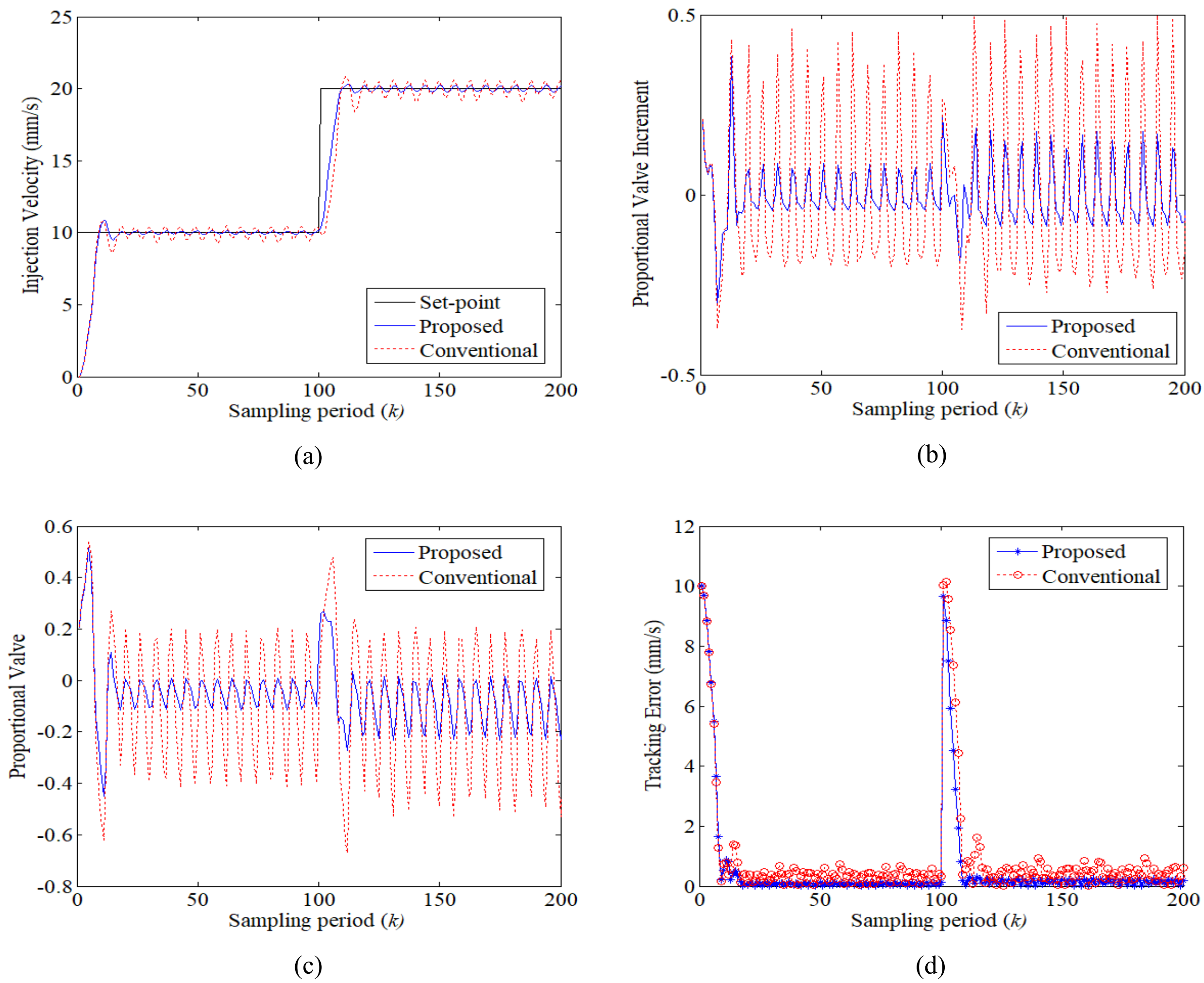

FIGURE 6. **Responses under case 4. (a) Injection velocity. (b) Proportional valve increment. (c) Proportional valve. (d) Tracking error.**

As to this process, the injection velocity affects the quality of the products greatly, and it should be regulated to track the reference value in the filling stage.

B. SIMULATIONS

Here the proportional valve is the manipulated variable and the injection velocity is the controlled variable, and the model is obtained from the relevant responses [35].

$$\begin{cases} x(k+1) = \begin{bmatrix} 1.582 & -0.5916 \\ 1 & 0 \end{bmatrix} x(k) + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u(k) \\ y(k+1) = \begin{bmatrix} 1.69 & 1.419 \end{bmatrix} x(k+1) \end{cases} \quad (26)$$

In this chapter, the conventional robust MPC approach is adopted as the comparison to evaluate the control performance of the proposed robust MPC method. Meanwhile, model/plant mismatched case is generated by Monte Carlo simulation to value the ensemble control performance further.

Here, the corresponding mismatched case is

$$\begin{cases} x(k+1) = \begin{bmatrix} 1.693 & -0.6341 \\ 1.08 & 0 \end{bmatrix} x(k) + \begin{bmatrix} 0.95 \\ 0 \end{bmatrix} u(k) \\ y(k+1) = \begin{bmatrix} 1.69 & 1.419 \end{bmatrix} x(k+1) \end{cases} \quad (27)$$

Note that the proposed robust MPC strategy will be designed on the basis of the model in (26), and the obtained control law will be implemented into the process in (27).

Moreover, the partial actuator faults and constraints are considered for the simulations. Here, the constraints are selected as

$$\begin{cases} |\Delta u(k+i\,|k)| \leq 0.5 \\ |\Delta y(k+i\,|k)| \leq 2 \end{cases} \quad (28)$$

and two types of partial actuator faults are adopted, i.e., constant fault and time-varying fault. The details of the cases are

Case 1: $\alpha = 0.6$

Case 2: $\alpha = 0.4$

Case 3: $\alpha = 0.6 + 0.1\sin(k)$
Case 4: $\alpha = 0.6 + 0.4\sin(k)$
The corresponding form of the set-point is taken as

$$\begin{cases} y_r(k) = 10, & 1 \le k \le 100 \\ y_r(k) = 20, & 101 \le k \le 200 \end{cases} \tag{29}$$

and two robust MPC schemes utilize the control parameters which are shown in Table 1.

TABLE 1. The detailed control parameters.

Control Parameters	Proposed	Conventional
Q	$diag(50,30,1)$	1
R	0.1	0.1

Figures 3∼6 show entire responses for all cases. On the whole, the proposed robust MPC method shows more superior ensemble control performance. From Figure 3, we can readily see that the overshoot and oscillations in the conventional approach are bigger than those of the proposed strategy. The proposed method provides smoother responses, and the tracking errors are smaller, which proves that the proposed robust MPC offers modified control performance farther. In Figures 4∼6, the conditions are analogous to those of case 1. The responses of the proposed strategy are smoother with smaller overshoot and oscillations, which implies that the extra weightings on the state variables restrict the drastic change of system dynamics. Meanwhile, smaller tracking errors are also obtained for the proposed method under cases 2∼4, which also verifies the validity of the proposed approach further.

VI. CONCLUSION

An extended state space model based robust constrained MPC approach is presented for industrial processes under uncertainties and partial actuator failures in this article. By adopting such improved state space model, additional degrees of freedom are acquired in the design of corresponding MPC method, and modified control performance is divinable. The validity of the proposed robust MPC scheme is verified on the injection molding system with uncertainties and partial actuator failures.

REFERENCES

[1] A. Garg and P. Mhaskar, "Utilizing big data for batch process modeling and control," *Comput. Chem. Eng.*, vol. 119, pp. 228–236, Nov. 2018.
[2] R. Zhang and J. Tao, "A nonlinear fuzzy neural network modeling approach using improved genetic algorithm," *IEEE Trans. Ind. Electron.*, vol. 65, no. 7, pp. 5882–5892, Jul. 2018.
[3] H. Habibi, H. R. Nohooji, and I. Howard, "Adaptive PID control of wind turbines for power regulation with unknown control direction and actuator faults," *IEEE Access*, vol. 6, pp. 37464–37479, Jul. 2018.
[4] J. Zhang, G. Frey, A. Al-Ahmari, T. Qu, N. Wu, and Z. Li, "Analysis and control of dynamic reconfiguration processes of manufacturing systems," *IEEE Access*, vol. 6, pp. 28028–28040, Oct. 2017.
[5] T. Wu, W. Gui, D. Hu, and C. Du, "Adaptive fuzzy sliding mode control for translational oscillator with rotating actuator: A fuzzy model," *IEEE Access*, vol. 6, pp. 55861–55869, Sep. 2018.
[6] J. Cai, J. Wan, H. Que, Q. Zhou, and L. Shen, "Adaptive actuator failure compensation control of second-order nonlinear systems with unknown time delay," *IEEE Access*, vol. 6, pp. 15170–15177, Jan. 2018.
[7] L. Wang, X. Chen, and F. Gao, "An LMI method to robust iterative learning fault-tolerant guaranteed cost control for batch processes," *Chin. J. Chem. Eng.*, vol. 21, no. 4, pp. 401–411, Apr. 2013.
[8] L. Wang, S. Mo, D. Zhou, F. Gao, and X. Chen, "Robust delay dependent iterative learning fault-tolerant control for batch processes with state delay and actuator failures," *J. Process Control*, vol. 22, no. 7, pp. 1273–1286, Aug. 2012.
[9] R. Zhang, R. Lu, A. Xue, and F. Gao, "New minmax linear quadratic fault-tolerant tracking control for batch processes," *IEEE Trans. Autom. Control*, vol. 61, no. 10, pp. 3045–3051, Oct. 2016.
[10] J. Yu, H. Dang, and L. Wang, "Fuzzy iterative learning control-based design of fault tolerant guaranteed cost controller for nonlinear batch processes," *Int. J. Control Autom. Syst.*, vol. 16, no. 5, pp. 2518–2527, Oct. 2018.
[11] M. Arici and T. Kara, "Improved adaptive fault-tolerant control for a quadruple-tank process with actuator faults," *Ind. Eng. Chem. Res.*, vol. 57, no. 29, pp. 9537–9553, Jul. 2018.
[12] D. Zhao, D. Shen, and Y. Wang, "Fault diagnosis and compensation for two-dimensional discrete time systems with sensor faults and time-varying delays," *Int. J. Robust Nonlinear Control*, vol. 27, no. 16, pp. 3296–3320, Jan. 2017.
[13] Y. Shen, L. Wang, J. Yu, R. Zhang, and F. Gao, "A hybrid 2D fault-tolerant controller design for multi-phase batch processes with time delay," *J. Process Control*, vol. 69, pp. 138–157, Sep. 2018.
[14] H. F. Tao, W. Paszke, E. Rogers, H. Z. Yang, and K. Galkowski, "Iterative learning fault-tolerant control for differential time-delay batch processes in finite frequency domains," *J. Process Control*, vol. 56, pp. 112–128, Aug. 2017.
[15] J. Lu, Z. Cao, R. Zhang, and F. Gao, "Nonlinear monotonically convergent iterative learning control for batch processes," *IEEE Trans. Ind. Electron.*, vol. 65, no. 7, pp. 5826–5836, Jul. 2018.
[16] Q. Yan, J. Cai, L. Wu, and Q. Zhou, "Error-tracking iterative learning control for nonlinearly parametric time-delay systems with initial state errors," *IEEE Access*, vol. 6, pp. 12167–12174, Jan. 2018.
[17] L. Wang, B. Liu, J. Yu, P. Li, R. Zhang, and F. Gao, "Delay-range-dependent-based hybrid iterative learning fault-tolerant guaranteed cost control for multiphase batch processes," *Ind. Eng. Chem. Res.*, vol. 57, no. 8, pp. 2932–2944, Feb. 2018.
[18] X. Jin, "Iterative learning control for output-constrained nonlinear systems with input quantization and actuator faults," *Int. J. Robust Nonlinear Control*, vol. 28, no. 2, pp. 729–741, Jan. 2018.
[19] J. Ding, B. Cichy, K. Galkowski, E. Rogers, and H. Z. Yang, "Parameter-dependent Lyapunov function-based robust iterative learning control for discrete systems with actuator faults," *Int. J. Adapt. Control Signal Process.*, vol. 30, no. 12, pp. 1714–1732, Dec. 2016.
[20] H. Ji, Z. Hou, L. Fan, and F. L. Lewis, "Adaptive iterative learning reliable control for a class of non-linearly parameterised systems with unknown state delays and input saturation," *IET Control Theory Appl.*, vol. 10, no. 17, pp. 2160–2174, Nov. 2016.
[21] M. Gao, L. Sheng, D. Zhou, and F. Gao, "Iterative learning fault-tolerant control for networked batch processes with multirate sampling and quantization effects," *Ind. Eng. Chem. Res.*, vol. 56, no. 9, pp. 2515–2525, Mar. 2017.
[22] L. Wang, C. Zhu, J. Yu, L. Ping, R. Zhang, and F. Gao, "Fuzzy iterative learning control for batch processes with interval time-varying delays," *Ind. Eng. Chem. Res.*, vol. 56, no. 14, pp. 3993–4001, Apr. 2017.
[23] W. Kahm and V. S. Vassiliadis, "Stability criterion for the intensification of batch processes with model predictive control," *Chem. Eng. Res. Des.*, vol. 138, pp. 292–313, Oct. 2018.
[24] L. Mears, S. M. Stocks, G. Sin, and K. V. Gernaey, "A review of control strategies for manipulating the feed rate in fed-batch fermentation processes," *J. Biotechnol.*, vol. 245, pp. 34–46, Mar. 2017.
[25] R. D. Zhang, S. Wu, and J. L. Tao, "A new design of predictive functional control strategy for batch processes in the two-dimensional framework," *IEEE Trans. Ind. Informat.*, Oct. 2018. doi: 10.1109/TII.2018.2874711.
[26] H. Y. Guo, C. Shen, H. Zhang, H. Chen, and R. Jia, "Simultaneous trajectory planning and tracking using an MPC method for cyber-physical systems: A case study of obstacle avoidance for an intelligent vehicle," *IEEE Trans. Ind. Informat.*, vol. 14, no. 9, pp. 4273–4283, Mar. 2018.
[27] M. S. Darup and M. Monnigmann, "Optimization-free robust MPC around the terminal region," *Automatica*, vol. 95, pp. 229–235, Sep. 2018.

[28] R. D. Zhang, A. K. Xue, S. Q. Wang, and Z. Y. Ren, "An improved model predictive control approach based on extended non-minimal state space formulation," *J. Process Control*, vol. 21, no. 8, pp. 1183–1192, Sep. 2011.
[29] S. Aumi and P. Mhaskar, "Robust model predictive control and fault handling of batch processes," *AICHE J.*, vol. 57, no. 7, pp. 1796–1808, Jul. 2011.
[30] R. Zhang, S. Wu, Z. Cao, J. Lu, and F. Gao, "A systematic min–max optimization design of constrained model predictive tracking control for industrial processes against uncertainty," *IEEE Trans. Control Syst. Technol.*, vol. 26, no. 6, pp. 2157–2164, Nov. 2018.
[31] J. Puschke and A. Mitsos, "Robust feasible control based on multi-stage eNMPC considering worst-case scenarios," *J. Process Control*, vol. 69, pp. 8–15, Sep. 2018.
[32] R. Mastragostino, S. Patel, and C. L. E. Swartz, "Robust decision making for hybrid process supply chain systems via model predictive control," *Comput. Chem. Eng.*, vol. 62, pp. 37–55, Mar. 2014.
[33] Z. Y. Wan and M. V. Kothare, "An efficient off-line formulation of robust model predictive control using linear matrix inequalities," *Automatica*, vol. 39, no. 5, pp. 837–846, May 2003.
[34] M. V. Kothare, V. Balakrishnan, and M. Morari, "Robust constrained model predictive control using linear matrix inequalities," *Automatica*, vol. 32, no. 10, pp. 1361–1379, 1996.
[35] R. Zhang and Q. Jin, "Design and implementation of hybrid modeling and PFC for oxygen content regulation in a coke furnace," *IEEE Trans. Ind. Informat.*, vol. 14, no. 6, pp. 2335–2342, Jun. 2018.

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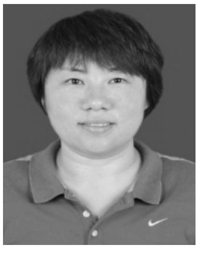

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