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Genetic-Algorithm-Optimization-Based Predictive Functional Control for Chemical Industry Processes Against Partial Actuator Faults

YI XIANG[1], ZHUOLONG LIU[1], AND LIMIN WANG[1,2]
[1]School of Mathematics and Statistics, Hainan Normal University, Haikou 571158, China
[2]Key Laboratory of Computational Science and Application of Hainan Province, Haikou 571158, China

Corresponding author: Limin Wang (wanglimin0817@163.com)

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ABSTRACT Actuator faults, which are common in industrial processes, can make the controller fail to achieve the desired control objectives, which may lead to the degradation of control performance. In order to solve this problem, this paper proposes a predictive functional control based on genetic algorithm optimization. Firstly, an extended dimension discrete switched model is constructed, which consists of a state difference variable, tracking error and a new state variable including tracking error. In this model, the performance index function based on a genetic optimization algorithm is selected, and its parameters are adjusted and the controller is designed. Then, under the obtained control law, the switching signal is designed and the range of uncertainty caused by the actuator fault is given to realize the robustness of the system. At the same time, the corresponding robustly sufficient conditions are presented. The advantage of this design is to avoid the disadvantages of manually adjusting the performance parameters, and the system has good tracking performance. Finally, taking the typical injection molding process of chemical production process as an example, the speed and pressure parameters are controlled, and compared with the traditional control method, the effectiveness and feasibility of the proposed method are verified.

INDEX TERMS Chemical industry processes, partial actuator faults, genetic-algorithm-optimization design, predictive functional control.

I. INTRODUCTION

Chemical process control plays an important role in the manufacturing of industrial products. It has made great progress in control theory and application [1]. At the same time, people put forward higher and higher requirements for high-quality automation level. However, the existence of disturbances may make the tracking performance of the system worse [2], [3]. In addition, if the production is carried out under more complicated conditions, the possibility that the system occurs faults will increase correspondingly.

In the current process, if the system fault has been unable to be effectively corrected, the control performance will generally become poor, which will affect product quality, and even leading to serious safety problems. Therefore, it is urgent to find a useful method to solve this problem. In this respect, the research of fault tolerant control (FTC) has been widely concerned since FTC can keep the closed-loop control performance in case of faults. Some representative results are available [4]–[10]. They can be roughly divided into two types: active and passive. Passive fault-tolerant control is to control the faulty system with the same design controller, while active fault-tolerant control is to design the corresponding controller according to different faults, including control reconfiguration [5]–[7], fault compensation [8], [9] and fault hiding [10]. In industrial processes, the model based on data may not be consistent with the actual one. The controller we constructed is designed for the established model instead of the actual one. In production, this controller is used to control the actual system. The control in this case can be regarded as the fault-tolerant control of industrial process. After all, the actual model mismatch may be caused by actuator faults or system internal faults. Therefore, this kind of fault-tolerant control is also passive fault-tolerant control [11], [12]. Zhang *et al.* proposed a new constrained MPC control [11] and applied it to the injection molding machine. Industrial processes are considered to be time and batch dependent, i.e. two-dimensional. Fault-tolerant control has also been studied in

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two dimensions [13]–[17]: in [14], the author transformed the industrial process with unknown disturbances and actuator faults into two-dimensional Fornasini-Marchesini (2D-FM) model. A controller is designed to ensure the closed-loop convergence of the system along the time and batch directions. Wang *et al.* proposed a control law, which can guarantee the closed-loop convergence in time and period direction to satisfy H_∞ performance even in the case of unknown disturbances and actuator faults [15]. For uncertainty, state delay and actuator faults, Wang *et al.* [16] proposed H-infinity learning fault-tolerant guaranteed cost control, which is based on the equivalent 2D system description of these processes. At present, FTC has been extended to multi-phase or even optimal guaranteed cost fault-tolerant control [17].

Iterative learning control (ILC) has good robustness, especially for repetitive processes [18]–[24]. It includes single-phase chemical process [23] and multi-phase chemical process [24]. However, in fact, many industrial processes have non repetitive dynamic characteristics and unknown disturbances, which may lead to ILC losing effectiveness [25], [26] and closed-loop robust stability [27]. This brings great challenges and difficulties to iterative learning control. In this complex situation, it is necessary to seek new control methods.

As a current control algorithm, model predictive control (MPC) is widely used because of its ability to improve control performance [28]–[35]. Especially for a class of systems whose process is nonlinear and its exact model is difficult to obtain or whose process time delay is large, this method is more popular. In order to solve the problem of disturbances and faults, a model predictive fault-tolerant control (MPFTC) strategy based on genetic algorithm (GA) is proposed [33]. The nonlinear model predictive control (NMPC) method is constructed in [34], which solves the constraints and nonlinear problems. Considering the uncertainty and disturbance of the model, a multi-phase NMPC method is proposed in [35]. Predictive functional control (PFC) is the third generation of the model predictive control algorithm, which not only keeps the advantages of model predictive control, but also makes the generated control input more regular, and can effectively reduce the calculation amount of the algorithm, so it can meet the fast requirements of a class of fast-responding controlled objects for the control algorithm. PFC regards the structure of control input as a key problem, which can overcome the control input problem with unknown laws in model predictive control, and has the advantages of simple algorithm, small calculation, good tracking ability and strong robustness. At present, there are also some studies on batch processes [36]. Obviously, the research results are based on a single model. In addition, the optimal control method mentioned above belongs to an analytical method, which is based on the deviation between model predicted value and actual value. At present, another commonly used optimization control method is numerical solution method, which is a kind of intelligent algorithm. As an intelligent search algorithm, the genetic algorithm has a strong advantage in batch process optimization problem. In the description of the optimization problem, it only needs to express the target simply, and the operation object is the population individual after coding, and the target has no continuous and differentiable constraints, which reduces the difficulty of solving the problem. In the process of solving the optimization problem, only the value information is needed, and no additional external information is required, which reduces the excessive requirements for the accuracy and prior knowledge of the mathematical model. At the same time, the implicit parallel search method is used to search every point in the whole population area, which has a wide coverage and is conducive to obtain the global optimal solution. In the research of industrial process control methods, it is found that combining analytical methods and numerical methods to control some parameters of industrial process may have better optimization effect, and the corresponding results are embodied in the paper [37]. However, there are still few research achievements in the multi-phase industrial process. Some chemical industry processes have multi-phase characteristics, and the parameters represented by their models have different meanings in different phases, which lead to different control objectives in each phase. In addition, when to switch from one phase to another and how long each phase runs will affect the quality of the products produced. Therefore, it is very important to seek new control methods and switching strategies to achieve multi-phase chemical process control optimization and robustness.

In view of this, this paper proposes a predictive function control based on genetic algorithm for multi-phase chemical industry process, and designs the corresponding switching signal to ensure that the chemical process can still run smoothly and maintain its optimal performance under the influence of faults. Different from the traditional method, this paper introduces a new state variable related to tracking error, which is combined with a state difference variable along time direction and tracking error to form an extended state variable. Under this variable, the new extended state space model is praised, and then the performance index function is constructed and the predictive function control law is designed. In order to make the chemical industry process have better control optimization performance, some parameters in the performance index function are optimized by a genetic algorithm, and the optimal control law is obtained. Then, considering the mismatch of system parameters caused by uncertain factors such as actuator faults, the range of uncertain parameters that can be resisted under this control law and the conditions that the switching law needs to meet are given. The advantages of this design are as follows: Search some parameter variables in the function index by the genetic algorithm, which avoids the disadvantages of artificial adjustment; According to the newly formed extended state space model, the control law designed by the genetic algorithm combined with predictive function control method has the advantages of simple design and good tracking performance. Finally, taking the injection molding process as an example, compared with the traditional method, the case analysis results show that the proposed method is feasible and effective.

II. PROBLEM DESCRIPTION

For complex chemical processes, it may be necessary to control multiple models to complete the control task, or it may be necessary to approximate multiple models due to the complexity of the models. For the ith model which is assumed to be single-input single-output (SISO), the following system model with disturbances can be constructed:

$$\begin{cases} x^i(k+1) = \tilde{A}^i x^i(k) + Bu^i(k) \\ y^i(k) = C^i x^i(k) \end{cases} \tag{1}$$

where, k represents the current time, $x^i(k) \in R^n$, $y^i(k) \in R$ and $u^i(k) \in R$ represent the state, output and input of the process at time k, respectively, A^i, B^i, C^i are process matrices with appropriate dimensions and $\tilde{A}^i = A^i + \Delta A^i$, ΔA^i means the system disturbance, which is caused by system actuator faults here.

In the actual production process, the design of the controller is mostly not for the system with disturbances, but for the nominal system, and the designed controller has a certain anti-interference ability. Therefore, the following controller design is for the nominal system, that is, the case of $\Delta A^i = 0$. The nominal system model is as follows:

$$\begin{cases} x^i(k+1) = A^i x^i(k) + Bu^i(k) \\ y^i(k) = C^i x^i(k) \end{cases} \tag{2}$$

For the above-mentioned systems, especially in the case of a single model, in order to meet the needs of industrial processes, model predictive control came into being. The most commonly used design method is to directly use the system state to design the controller, namely $u(k+j|k) = K_i x^i(k+j|k)$, where j is the prediction step size. In order to improve its control performance and make the system tracking control show better control results, different model predictive control algorithms have been proposed, such as the extended state control model based on output, as in [38], the control law is designed as follows:

$$\Delta u(k) = K \begin{bmatrix} \Delta x(k) \\ y(k) \end{bmatrix},$$

where $\Delta x(k)$ is the state difference variable along the time direction. Here we call it state difference variable. Recently, based on the extended model related to tracking error, [37] proposed such a design method of the control law

$$\Delta u(k) = K \begin{bmatrix} \Delta x(k) \\ e(k) \end{bmatrix},$$

where $e(k)$ is the following formula (4). It can be seen from the case in the article that the control method proposed above can indeed improve the control effect of the system. So, in addition to the above methods, is there a better control scheme that makes the control effect better? The next thing to do is to achieve the above goals: design a new controller to achieve the actual output better track the given output.

III. A NEW PREDICTIVE FUNCTION CONTROL BASED ON GENETIC ALGORITHM OPTIMIZATION

A. THE ESTABLISHMENT OF NEW STATE SPACE MODEL

Introducing the difference operator Δ and defining

$$\Delta x^i(k+1) = x^i(k+1) - x^i(k), \tag{3a}$$

We can get

$$\Delta x^i(k+1) = A^i \Delta x^i(k) + B\Delta u^i(k) \tag{3b}$$

In order to have better tracking performance and keep the system running in a more stable state, the output tracking error is defined as:

$$e^i(k) = y^i(k) - r^i(k) \tag{4}$$

And then it has:

$$e^i(k+1) = e^i(k) + C^i A^i \Delta x^i(k) + C^i B^i \Delta u^i(k) - \Delta r^i(k+1) \tag{5}$$

where $y^i(k)$ and $y^i_r(k)$ are respectively the actual output value and tracking set point of the i model at time k, $e^i(k)$ is the output error of the i model at time k; $\Delta r^i(k+1)$ is the difference between the set value of the ith model of the chemical process at time $k+1$.

Introduce a new state variable:

$$\hat{x}^i(k+1) = \hat{x}^i(k) + e^i(k) \tag{6}$$

where the selection of $\hat{x}^i(k)$ is determined by the output error $e^i(k)$.

Define a new state variable $z^i(k)$ as the following form

$$z^i(k) = \begin{bmatrix} \Delta x^{iT}(k) & \hat{x}^{iT}(k) & e^{iT}(k) \end{bmatrix}^T \tag{7}$$

A new type of equivalent model can be obtained from (3-7)

$$z^i(k+1) = \bar{A}^i(k)\bar{x}^i(k) + \bar{B}^i \Delta u^i(k) + \bar{C}^i \Delta r^i(k+1) \tag{8}$$

where

$$\bar{A}^i = \begin{bmatrix} A^i & 0 & 0 \\ 0 & I & I \\ C^i A^i & 0 & I \end{bmatrix}, \quad \bar{B}^i = \begin{bmatrix} B^i \\ 0 \\ C^i B^i \end{bmatrix}, \quad \bar{C}^i = \begin{bmatrix} 0 \\ 0 \\ -I \end{bmatrix}^T,$$

I represents the unit matrix, and 0 represents the zero matrix.

The above system is represented by a switched system model, and its form is as follows:

$$z(k+1) = A^{\sigma(t)} z(k) + B^{\sigma(t)} \Delta u(k) + C^{\sigma(t)} \Delta r(k+1) \tag{9}$$

where, $\sigma(k) : Z^+ \to \underline{N} := \{1, 2, \cdots, N\}$ represents the switching signal, which may be related to time or system state, N is the model of the subsystem, and $A^{\sigma(t)}$, $B^{\sigma(t)}$, $C^{\sigma(t)}$ represent the model (9).

For the ith model at time k, if the switching condition is true for model $i+1$, the system will switch to model $i+1$ at time $k+1$. The switching time can be defined as:

$$T^i_s = \min\left\{k > T^{i-1}_s | L^i(x(k)) < 0\right\}, \quad T^0_s = 0 \tag{10a}$$

The above process has n models, and $\left[T_s^{i-1}, T_s^i\right]$ is called the time interval when the $i(i = 1, 2, \ldots n)$ model is switched at time T_s^{i-1}. Therefore, the switching sequence of the entire chemical process can be described as

$$\Sigma = \begin{Bmatrix} T_1^1, \sigma\left(T_1^1\right), T_1^2, \sigma\left(T_1^2\right), \ldots, T_1^p, \sigma\left(T_1^p\right), \\ T_2^1, \sigma\left(T_2^1\right), \ldots T_2^p, \sigma\left(T_2^p\right), \ldots, T_s^i, \sigma\left(T_s^i\right), \ldots \end{Bmatrix} \tag{10b}$$

where $\left[(T_i^n), \sigma(T_i^n)\right]$ connects the connection point at the end of the previous handover and the start of the next handover.

In addition, in the industrial production process, if the parameters that need to be controlled by different models are different, their dimensions may be different, the following formula is used to express the state relationship between the two models at the time of switching

$$x^{i+1}(T_k^i) = L^i x^i(T_k^i) \tag{10c}$$

where, L^i is called the state transition matrix. If the system state has the same physical meaning in adjacent models, then $L^i = I^i$.

B. CONTROLLER DESIGN OF A NEW PREDICTIVE FUNCTION BASED ON GENETIC ALGORITHM OPTIMIZATION

Aiming at system (9), the controller (optimal controller) based on a new predictive function optimized by a genetic algorithm is design. The idea is as follows:

Select the corresponding performance index form as follows:

$$J^i = \sum_{j=1}^{p} z^{i\mathrm{T}}(k+j) Q_j^i z^i(k+j) \tag{11}$$

where, p is the prediction layer, and Q_j^i is the symmetric weighting matrix of the i$^{\text{th}}$ model, with an appropriate power, which can be expressed as:

$$Q_j^i = diag\left\{q_{jx1}, q_{jx2}, \cdots, q_{jxn}, q_{j\hat{x}}, q_{je}\right\} \quad 1 \le j \le p \tag{12}$$

Formula (11) includes output tracking error and process state variable, as well as newly introduced state variable, which are considered together in controller design.

Select the input signal as follows:

$$u^i(k+t) = \sum_{j=1}^{N} \mu_j^i f_j^i(t) \tag{13}$$

where $u^i(k+t)$ is the industrial process input signal of the i$^{\text{th}}$ model at time $k+t$, u_j^i is the weight coefficient, $f_j^i(t)$ is the basis function sampled at time $k+t$, and N is the number of basis functions.

Define the following two variables

$$\begin{aligned} T_t^i &= [f_1(t), f_2(t), \cdots, f_N(t)], \quad (t = 0, 1, \cdots, p-1) \\ \gamma^i &= \begin{bmatrix} \mu_1^i & \mu_2^i & \cdots & \mu_N^i \end{bmatrix}^{\mathrm{T}} \end{aligned} \tag{14}$$

The formula (13) can be further expressed as:

$$u^i(k+t) = T_t^i \gamma^i \tag{15}$$

Based on equation (8), the state predictor variable from sampling time k is expressed as:

$$Z^i = \begin{bmatrix} z^i(k+1) \\ z^i(k+2) \\ \vdots \\ z^i(k+p) \end{bmatrix}, \quad \Delta R^i = \begin{bmatrix} \Delta r^i(k+1) \\ \Delta r^i(k+2) \\ \vdots \\ \Delta r^i(k+p) \end{bmatrix} \tag{16}$$

The future state vector Z^i is related to the current state $z^i(k)$ and the future control vector γ^i by the following equation:

$$Z^i = F^i z^i(k) - G^i u^i(k-1) + \phi^i \gamma^i + S^i \Delta R^i \tag{17}$$

And

$$F^i = \begin{bmatrix} \bar{A}^i \\ \bar{A}^{2i} \\ \vdots \\ \bar{A}^{pi} \end{bmatrix}, \quad G^i = \begin{bmatrix} \bar{B}^i \\ \bar{A}^i \bar{B}^i \\ \bar{A}^{2i} \bar{B}^i \\ \vdots \\ \bar{A}^{pi} \bar{B}^i \end{bmatrix} \tag{18a}$$

$$S^i = \begin{bmatrix} \bar{C}^i & 0 & 0 & 0 & 0 \\ \bar{A}^i \bar{C}^i & \bar{C}^i & 0 & 0 & 0 \\ \bar{A}^{2i} \bar{C}^i & \bar{A}^i \bar{C}^i & \bar{C}^i & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \bar{A}^{(p-1)i} \bar{C}^i & \bar{A}^{(p-2)i} \bar{C}^i & \bar{A}^{(p-3)i} \bar{C}^i & \cdots & \bar{C}^i \end{bmatrix} \tag{18b}$$

$$\phi^i = \begin{bmatrix} \bar{B}^i T_0^i \\ (\bar{A}^i \bar{B}^i - \bar{B}^i) T_0^i + \bar{B}^i T_1^i \\ (\bar{A}^{2i} \bar{B}^i - \bar{A}^i \bar{B}^i) T_0^i + (\bar{A}^i \bar{B}^i - \bar{B}^i) T_1^i + \bar{B}^i T_2^i \\ \vdots \\ \sum_{k=1}^{p-1} (\bar{A}^{ik} \bar{B}^i - \bar{A}^{(k-1)i} \bar{B}^i) T_{p-1-k}^i + \bar{B}^i T_{p-1}^i \end{bmatrix} \tag{18c}$$

The performance index (11) can be expressed in vector form as:

$$J^i = \left(Z^T\right)^i Q^i Z^i \tag{19}$$

where, $Q^i = diag\left\{Q_1^i, Q_2^i, \cdots, Q_P^i\right\}$

Substituting formula (17) into (19), the control law can be derived as:

$$\gamma^i = -(\phi^{i\mathrm{T}} Q^i \phi^i)^{-1} \phi^{i\mathrm{T}} Q^i (F^i z^i(k) - G^i u^i(k-1) + S^i \Delta R^i) \tag{20}$$

And make the following definition:

$$\begin{aligned} \mu_1^i &= -(1, 0, \cdots, 0)(\phi^{i\mathrm{T}} Q^i \phi^i)^{-1} \phi^{i\mathrm{T}} Q^i \\ &\quad \times (F^i z^i(k) - G^i u^i(k-1) + S^i \Delta R^i) \\ &= -h_1^i z^i(k) + h_{u_1}^i u^i(k-1) - m_1^i \Delta R^i \\ &\ \ \vdots \\ \mu_N^i &= -(0, 0, \cdots, 1)(\phi^{i\mathrm{T}} Q^i \phi^i)^{-1} \phi^{i\mathrm{T}} Q^i \end{aligned}$$

$$\times(F^i z^i(k) - G^i u^i(k-1) + S^i \Delta R^i) = -h_N^i z^i(k) + h_{u_N}^i u^i(k-1) - m_N^i \Delta R^i \tag{21}$$

Then the control signal is:

$$u^i(k) = \sum_{j=1}^{N} \mu_j^i f_j^i(0) = -H^i z^i(k) + H_u^i u^i(k-1) - M^i \Delta R^i \tag{22}$$

where, $H^i = \sum_{j=1}^{N} f_j^i(0) h_j^i$, $H_u^i = \sum_{j=1}^{N} f_j^i(0) h_{u_j}^i$, $M^i = \sum_{j=1}^{N} f_j^i(0) m_j^i$

C. Q_j^i SELECTION BASED ON GENETIC ALGORITHM

Usually, the process response is related to the elements in Q_j^i. It is often the weighting factor of the performance index. It is necessary to achieve some compromise between the output tracking error and the control input. In the result [42], the weighting factor of the process output tracking error q_{je} can be set to a fixed value and q_{je} is selected as 1. Now what we have to do is all elements in Q_j^i participate in the design.

This paper takes the sum

$$J = \sum_{i=1}^{n} J^i = \sum_{i=1}^{n} \sum_{j=1}^{p} z^{i\mathrm{T}}(k+j) Q_j^i z^i(k+j) \tag{23}$$

of all model performance indicators as the objective function, the initial population size of decision variables Q_j^i is set to 20, the crossover rate is set to 0.8, the mutation rate is set to 0.05, and the elite strategy is adopted in the genetic algorithm (Reserve in each generation and the best two solutions are retained for the next generation), and the termination criterion is that 50 consecutive iterations no longer produce better solutions.

The controller obtained above is designed under the nominal system. The real industrial process is influenced by the factors such as actuator faults, internal disturbances, and so on, and these factors are the main reason that the system performance is degenerative and even instable.

Below what we mainly do is to analyze the robustness of the uncertain system caused by actuator faults and design the switching law in different phase.

The actuator fault we consider here is a partial actuator fault, and the control input under the fault can be expressed as

$$u^{iF}(k) = \alpha^i u^i(k) \tag{24}$$

where $0 < \underline{\alpha}^i \leq \alpha^i \leq \bar{\alpha}^i$ with $\underline{\alpha}^i \leq 1, \bar{\alpha}^i \geq 1$, $u^i(k)$ is the calculated input for the actuator, and $u^{iF}(k)$ is the actual physical actuator action. Equation (24) is widely used to describe the partial actuator faults. $\alpha^i = 0$ denotes the actuator is completely invalid. At this time, the controller is no longer functioning, so it will not be considered here. $\alpha^i = 1$ denotes the healthy situation.

Theorem 1: For chemical industry processes with partial actuator faults that is described by Eq. (24), if the predictive function controller is designed through the nominal process model described by Eq. (1) such that the following conditions holds:

$$\sigma_{\max}(\Delta\bar{A}^i) < -\sigma_{\max}(\bar{A}^i - \bar{B}^i K_s^i) + \sqrt{\sigma_{\max}^2(\bar{A}^i - \bar{B}^i K_s^i) + \frac{\lambda_{\min}(W^i)}{\lambda_{\max}(P^i)}} \tag{25a}$$

and the switching signal satisfies:

$$\tau_i^a \geq (\tau_i^a)^* = -\frac{\ln \mu_i}{\ln \beta_i} \tag{25b}$$

$\sigma_{\max}(\xi^i)$, $\lambda_{\min}(\xi^i)$, $\lambda_{\max}(\xi^i)$ are the maximum singular value, minimum eigenvalue and maximum eigenvalue of matrix ξ, the matrix P^i, W^i are positive definite symmetric matrices and defined as

$$(\bar{A}^i - \bar{B}^i K_s^i)^T P^i (\bar{A}^i - \bar{B}^i K_s^i) - \beta_i P^i = -W^i \tag{25c}$$

the matrices $\Delta\bar{A}^i$, K_s^i are given as

$$\Delta\bar{A}^i = \begin{bmatrix} \Delta A^i & 0 & 0 \\ 0 & 0 & 0 \\ C^i \Delta A^i & 0 & 0 \end{bmatrix} \tag{26}$$

$$K_s^i = (1, 0, \ldots, 0)(\psi^{iT} \phi^i \phi^{iT} Q^i \psi^i)^{-1} \psi^{iT} \phi^i \phi^{iT} Q^i F^i \tag{27}$$

$$\psi^i = \begin{bmatrix} \bar{B}^i & 0 & 0 & \cdots & 0 \\ \bar{A}^i \bar{B}^i & \bar{B}^i & 0 & \cdots & 0 \\ \bar{A}^{2i} \bar{B}^i & \bar{A}^i \bar{B}^i & \bar{B}^i & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \bar{A}^{(p-1)i} \bar{B}^i & \bar{A}^{(p-2)i} \bar{B}^i & \bar{A}^{(p-3)i} \bar{B}^i & \cdots & \bar{B}^i \end{bmatrix} \tag{28}$$

then the proposed predictive function control holds robust stability for the chemical industry process.

Proof: The robust stability criterion follows the general idea of Lyapunov theory. Now we prove it as follows. Firstly, the incremental control input is shown as below. Equation (21) can be rewritten as

$$\phi^{i\mathrm{T}} Q^i [\phi^i \gamma^i - G^i u^i(k-1)] = -\phi^{i\mathrm{T}} Q^i (F^i z^i(k) + S^i \Delta R^i) \tag{29}$$

According to formula (14) and (15), formula (18a-18c) can be rewritten as

$$\begin{aligned} \phi^i \gamma^i - G^i u^i(k-1) &= \begin{bmatrix} \bar{B}^i T_0^i \\ (\bar{A}^i \bar{B}^i - \bar{B}^i) T_0^i + \bar{B}^i T_1^i \\ (\bar{A}^{2i} \bar{B}^i - \bar{A}^i \bar{B}^i) T_0^i + (\bar{A}^i \bar{B}^i - \bar{B}^i) T_1^i + \bar{B}^i T_2^i \\ \vdots \\ \sum_{k=1}^{p-1} (\bar{A}^{ik} \bar{B}^i - \bar{A}^{(k-1)i} \bar{B}^i) T_{p-1-k}^i + \bar{B}^i T_{p-1}^i \end{bmatrix} \gamma^i \\ &\quad - \begin{bmatrix} \bar{B}^i \\ \bar{A}^i \bar{B}^i \\ \bar{A}^{2i} \bar{B}^i \\ \vdots \\ \bar{A}^{pi} \bar{B}^i \end{bmatrix} u^i(k-1) \qquad (30) \\ &= \Psi^i \Delta U^i \qquad (31) \end{aligned}$$

That means the following is true

$$\phi^{i\mathrm{T}} Q^i \Psi^i \Delta U^i = -\phi^{i\mathrm{T}} Q^i (F^i z^i(k) + S^i \Delta R^i) \tag{32}$$

Multiply both sides of equation (14) by $\Psi^i \phi^{iT}$ at the same time to get

$$\Delta U^i = -(\Psi^{iT} \phi^i \phi^{iT} Q^i \Psi^i)^{-1} \Psi^{iT} \phi^i \phi^{iT} Q^i (F^i z^i(k) + S^i \Delta R^i) \tag{33}$$

let

$$K_s^i = (1, 0, \ldots, 0)(\Psi^{iT} \phi^{iT} \phi^i Q^i \Psi^i)^{-1} \Psi^{iT} \phi^i \phi^{iT} Q^i F^i \tag{34a}$$

$$K_R^i = (1, 0, \ldots, 0)(\Psi^{iT} \phi^{iT} \phi^i Q^i \Psi^i)^{-1} \Psi^{iT} \phi^i \phi^{iT} Q^i S^i \tag{34b}$$

Then the incremental control vector at time k is

$$\Delta u^i(t) = -K_s^i z^i(t) - K_R^i \Delta R^i \tag{35}$$

When considering closed-loop stability, the set point can be selected as $\Delta R^i = 0$ without loss of generality. This shows that the control law of the proposed method is

$$\Delta u^i(t) = -K_s^i z^i(t) \tag{36}$$

Using the same idea shown in Section III (A), it is easy to conclude that $\Delta \bar{A}^i$ and the uncertain system (1) are related to the nominal system (2) in the following form:

$$\begin{aligned} z^i(k+1) &= \overline{A}^i z^i(k) + \overline{B}^i \alpha^i \Delta u^i(k) \\ z^i(k+1) &= \overline{A}^i z^i(k) + \overline{B}^i \Delta u^i(k) - \overline{B}^i \Delta u^i(k) + \overline{B}^i \alpha^i \Delta u^i(k) \end{aligned} \tag{37}$$

Substitute (36) into (37), it has

$$z^i(k+1) = (\bar{A}^i - \overline{B}^i K_s^i) z^i(k) + \overline{B}^i (I^i - \alpha^i) K_s^i z^i(k)$$

Here $\overline{B}^i (I^i - \alpha^i) K_s^i$ is represented by $\Delta \bar{A}^i$, that is, it is an internal disturbance. Then check the stability of the following closed-loop uncertain system:

$$z^i(k+1) = (\bar{A}^i - \bar{B}^i K_s^i) z^i(k) + \Delta \bar{A}^i z^i(k) \tag{38}$$

Define the stability function V^i, and obtain its increment ΔV^i in the following form:

$$\begin{aligned} &\Delta V^i(z^i(k)) \\ &= V^i(z^i(k+1)) - V^i(z^i(k)) \le V^i(z^i(k+1)) - \beta_i V^i(z^i(k)) \\ &= z^{i\mathrm{T}}(k)(\bar{A}^i - \bar{B}^i K_s^i)^{\mathrm{T}} P^i (\bar{A}^i - \bar{B}^i K_s^i) z(k) + z^{i\mathrm{T}}(k) \\ &\quad \times (\bar{A}^i - \bar{B}^i K_s^i)^{\mathrm{T}} P^i (\Delta \bar{A}^i) z(k) + z^{i\mathrm{T}}(k)(\Delta \bar{A}^{i\mathrm{T}}) P^i (\bar{A}^i - \bar{B}^i K_s^i)^{\mathrm{T}} \\ &\quad \times z(k) + z^{i\mathrm{T}}(k)(\Delta \bar{A}^{i\mathrm{T}}) P^i \Delta \bar{A}^i z^i(k) - z^{i\mathrm{T}}(k) \beta_i P^i z^i(k) \end{aligned} \tag{39}$$

where $i \in N, N := \{1, 2, \cdots, N\}$.

According to equation (26), the first and last terms on the right side of equation (39) represent

$$\begin{aligned} z^{i\mathrm{T}}(k) &\left[(\bar{A}^i - \bar{B}^i K_s^i)^T P^i (\bar{A}^i - \bar{B}^i K_s^i) - \beta_i P^i \right] z^i(k) \\ &\le -\lambda_{\min}(W^i) \left\| z^i(k) \right\|^2 \end{aligned} \tag{40}$$

The second and third terms indicate

$$\begin{aligned} &z^{i\mathrm{T}}(k)(\bar{A}^i - \bar{B}^i K_s^i)^{\mathrm{T}} P^i (\Delta \bar{A}^i) z^i(k) + z^{i\mathrm{T}}(k)(\Delta \bar{A}^i)^{\mathrm{T}} \\ &\quad \times P^i (\bar{A}^i - \bar{B}^i K_s^i) z^i(k) \\ &\quad \le 2\sigma_{\max}(\bar{A}^i - \bar{B}^i K_s^i) \lambda_{\max}(P^i) \left\| \Delta \bar{A}^i \right\| \left\| z^i(k) \right\|^2 \end{aligned} \tag{41}$$

The fourth item means

$$\begin{aligned} &z^{i\mathrm{T}}(k)(\Delta \bar{A}^i)^{\mathrm{T}} P^i (\Delta \bar{A}^i) z^i(k) + z^{i\mathrm{T}}(k)(\Delta \bar{A}^i)^{\mathrm{T}} \\ &\quad \times P^i (\Delta \bar{A}^i) z^i(k) \\ &\quad \le \lambda_{\max}(P^i) \left\| \Delta \bar{A}^i \right\|^2 \left\| z^i(k) \right\|^2 \end{aligned} \tag{42}$$

We can get:

$$\begin{aligned} \Delta V^i(z^i(k)) \le \left\| z^i(k) \right\|^2 &(-\lambda_{\min}(W^i) + 2\sigma_{\max}(\bar{A}^i - \bar{B}^i K_s^i) \lambda_{\max} \\ &\times (P^i) \left\| \Delta \bar{A}^i \right\| + \lambda_{\max}(P^i) \left\| \Delta \bar{A}^i \right\|^2) \end{aligned} \tag{43}$$

Obviously the following conditions are met

$$\begin{aligned} &-\sigma_{\max}(\bar{A}^i - \bar{B}^i K_s^i) - \sqrt{\sigma_{\max}^2(\bar{A}^i - \bar{B}^i K_s^i) + \frac{\lambda_{\min}(W^i)}{\lambda_{\max}(P^i)}} \\ &< \left\| \Delta \bar{A}^i \right\| < -\sigma_{\max}(\bar{A}^i - \bar{B}^i K_s^i) \\ &\quad + \sqrt{\sigma_{\max}^2(\bar{A}^i - \bar{B}^i K_s^i) + \frac{\lambda_{\min}(W^i)}{\lambda_{\max}(P^i)}} \end{aligned} \tag{44}$$

Therefore,

$$\begin{aligned} \sigma_{\max}(\Delta \bar{A}^i) &< -\sigma_{\max}(\bar{A}^i - \bar{B}^i K_s^i) \\ &\quad + \sqrt{\sigma_{\max}^2(\bar{A}^i - \bar{B}^i K_s^i) + \frac{\lambda_{\min}(W^i)}{\lambda_{\max}(P^i)}} \end{aligned} \tag{45}$$

That is, the controller designed in this paper still has robust stability when the above equation is satisfied within the interference range.

Then for the switching system model, we find the system stability conditions and design the switching signal.

If the switching system is stable, there must be $\Delta V^i(z^i(k)) < 0$, which is equivalent to

$$(\bar{A}^i - \bar{B}^i K_s^i)^T P^i (\bar{A}^i - \bar{B}^i K_s^i) - \beta_i P^i = -W^i < 0 \tag{46}$$

And under the constraint condition of (45), we can get

$$(\bar{A}^i - \bar{B}^i K_s^i + \Delta \bar{A}^i)^{\mathrm{T}} P^i (\bar{A}^i - \bar{B}^i K_s^i + \Delta \bar{A}^i) - \beta_i P^i < 0 \tag{47}$$

From the formula (39) we can know $\Delta V^i < 0$, that is $V^i(k+1) \le \beta_i V^i(k)$, then

$$V^i(k+1) \le \beta_i V^i(k) \le \beta^{t - T_s^{i-1}} V^i\left(T_s^{i-1}\right) \tag{48}$$

where T_s^{i-1} is the switching time of the i$^{\text{th}}$ model.

From $V^i < \mu_i V^{i-1}$, we can know

$$\begin{aligned} V^{\sigma(k)}(k) &\le \alpha_i^{k - T_s^{i-1}} \mu_i V^{i-1}\left(T_s^{i-1}\right) \\ &\vdots \\ &\le \prod_{i=1}^{p} (\beta_i)^{\widetilde{T}(k_0,k)} \prod_{i=1}^{p} (u_i)^{\frac{\widetilde{T}(k_0,k)}{\tau_i}} V^{\sigma k_0}(k_0) \end{aligned}$$

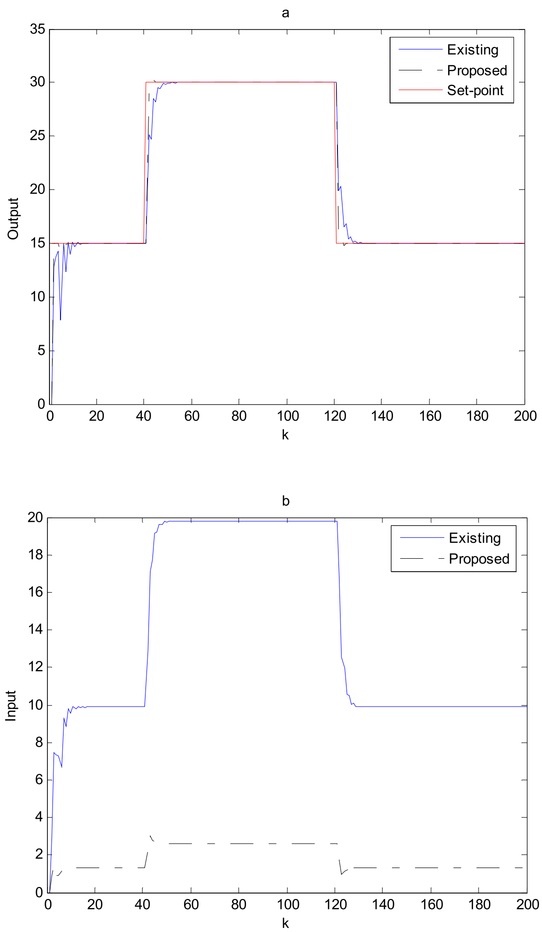

FIGURE 1. Comparison under constant fault: a output comparison, b input comparison.

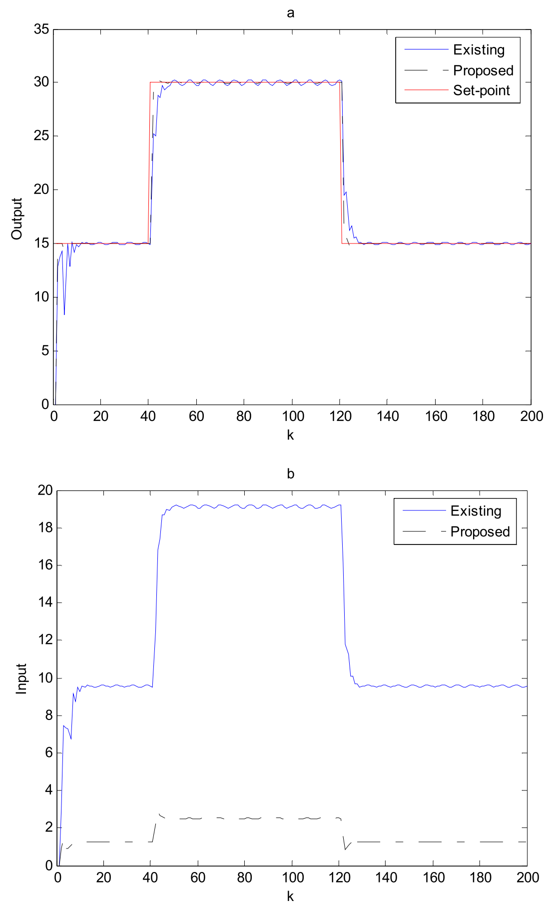

FIGURE 2. Comparison under time-varying fault: a output comparison, b input comparison.

$$\le \prod_{i=1}^{p}\left(\beta_i \mu_i^{\frac{1}{\tau_i}}\right)^{\widetilde{T}(k_0,k)} V^{\sigma(k_0)}\left(k_0\right) \tag{49}$$

Assuming that $\nu = \max\left(\beta_i \mu_i^{\frac{1}{\tau_i}}\right)$, it has

$$V^{\sigma(k)}(k) \le \nu^{k-k_0} V^{\sigma k_0}\left(k_0\right) \tag{50}$$

It can be seen from the above that when the switching signal is satisfied to be $\tau_i^a \ge -\frac{\ln \mu_i}{\ln \beta_i}$, $V^{\sigma(k)}(k)$ is convergent, that is, the system is asymptotically stable.

This method designs a corresponding simple, real-time and flexible controller based on different models and interferences. The controller has a certain degree of robustness, thereby improving its control quality and solving the disadvantage of the existing method that the controller gain cannot be adjusted in the whole process. And use the average dwell time method to design the switching signal, we can find the minimum running time. The biggest advantage of this method is: the traditional method is to obtain Q^i through debugging. This method uses the genetic algorithm and uses the concept of population to select the optimal Q^i to achieve better control effects, so as to achieve the goals of energy saving and consumption reduction.

IV. SIMULATION CASE

The injection molding process is a typical chemical industry production process based on multi-phase production. Each product produced mainly includes five steps, namely, clamping section → injection section → pressure holding section → cooling section → mold opening section. Parameters such as the injection speed of the injection section and the holding pressure of the holding pressure section require high-precision control to achieve an increase in the yield of the final product. Here we take the single-phase and multi-phase as examples to consider its control effect.

A. SINGLE PHASE SITUATION

Take the control speed parameter as the research object. First, the response to the injection speed (process output) of the proportional valve (process input) is determined as the autoregressive model, and the mathematical model of the injection section is established as follows:

$$P(z) = \frac{1.69z + 1.419}{z^2 - 1.582z + 0.5916} \tag{51}$$

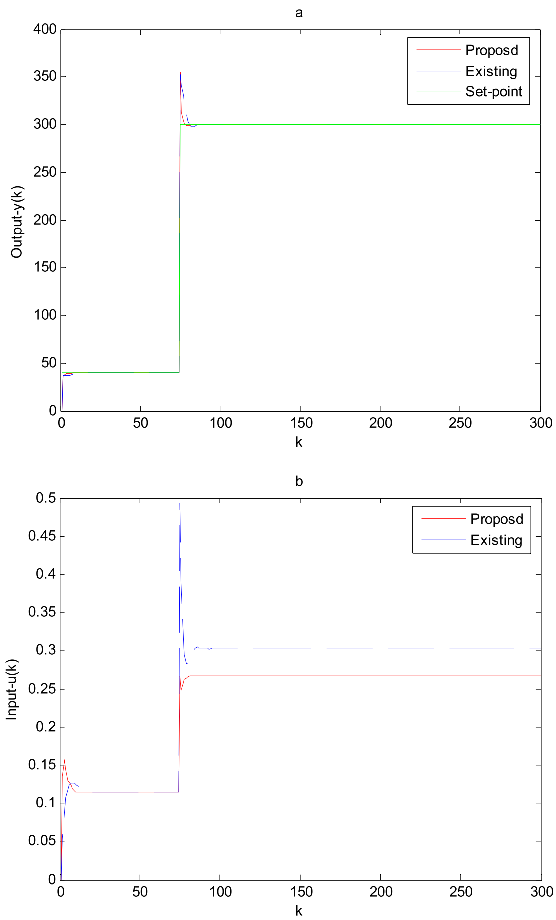

FIGURE 3. Comparison under constant faults: a output comparison, b input comparison.

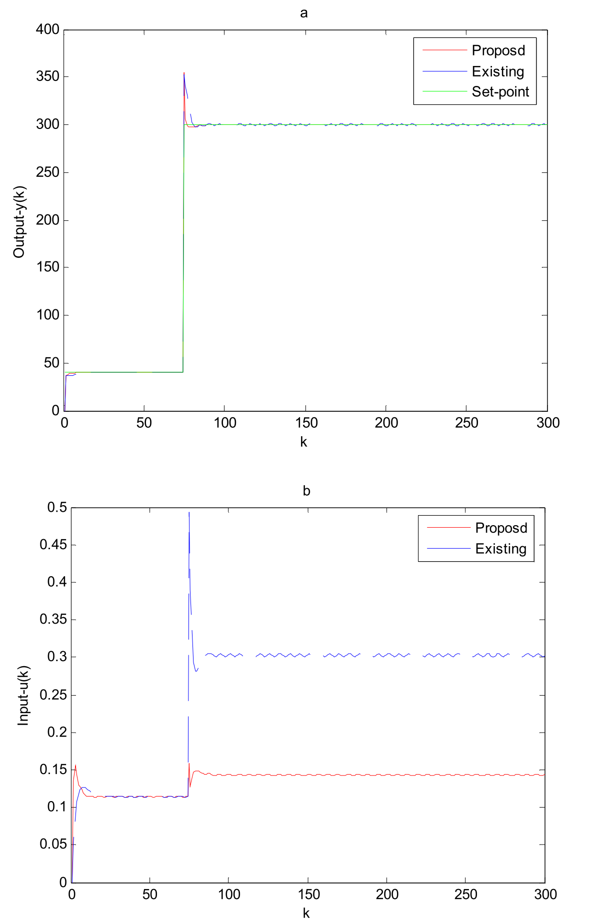

FIGURE 4. Comparison under time-varying faults: a output comparison, b input comparison.

For the above model, the set point takes the following form:

$$\begin{cases} r(k) = 15 & (1 \leq k \leq 40) \\ r(k) = 20 & (41 \leq k \leq 120) \\ r(k) = 15 & (121 \leq k \leq 200) \end{cases} \tag{52}$$

In the nominal traditional controller design, its control law is designed as follows

$$u(k) = u(k-1) + \Delta u(k) = u(k-1) + K \begin{bmatrix} \Delta x(k) \\ e(k) \end{bmatrix}.$$

Table 1 lists the performance function parameter comparison of these two methods. Here the final parameters are optimized by the genetic algorithm, and then the controller is designed. It can be seen that the proposed method will have more degrees of freedom to adjust the control performance due to the newly introduced state variables.

1) CONSTANT FAULTS

Figure 1 is a comparison diagram of output and input in case of a constant fault. The actuator fault is $\alpha = 0.45$. From the output comparison Figure 1a, it can be seen that the output is obviously worse under the traditional method, while it has only a small fluctuation with the method in this paper. Moreover, it is obvious that a smaller input is required, as shown in Figure 1b.

TABLE 1. Comparison of performance index function parameters.

parameter	GA algorithm (new type)	GA algorithm (traditional)
k_f	20	20
Q	$diag([15,15,1,10^6])$	$diag([5,5,1])$
Q_f	$diag([15,15,1,10^6])$	$diag([5,5,1])$
R	0.01	0.01
γ	1.5	1.5

2) TIME VARYING FAULT

A time varying fault is selected as $\alpha = 0.5 + 0.01\sin(k)$. It can be seen from Figure 2 that although all kinds of curves fluctuate under the influence of such faults, it is obvious that the curve fluctuation is smaller and smoother under the proposed method, and the control performance is obviously better.

B. MULTI -PHASE SITUATION

In this example, take injection processes as an example, and define injection section as the first phase and pressure maintaining section as the second phase.

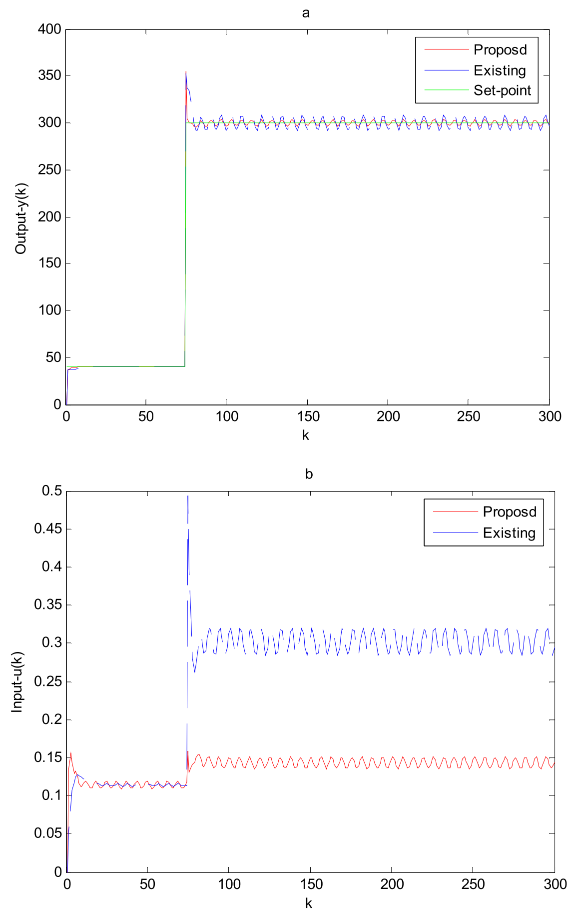

FIGURE 5. **Comparison under time-varying faults: a output comparison, b input comparison.**

In the injection section, the injection velocity (IV) model corresponding to the valve opening (VO) can be described as follows:

$$\left(1-0.9291z^{-1}-0.03191z^{-2}\right) IV = \left(8.687z^{-1}-5.617z^{-2}\right) VO + z^{-1}w(z) \quad (53)$$

The model of nozzle pressure (NP) corresponding to injection velocity is as follows:

$$\left(1-z^{-1}\right) NP = 0.1054IV \quad (54)$$

Similarly, in the pressure maintaining section, the nozzle pressure model corresponding to the valve opening is as follows:

$$\left(1-1.317z^{-1}+0.3259z^{-2}\right) NP = \left(171.8z^{-1}-156.8z^{-2}\right) VO + z^{-1}w(z) \quad (55)$$

(53) and (54) constitute the state space model according to the former form. The state of the first phase is considered as $x^1(k)$, and the switching condition between phases is $G^1(x(k)) = 350 - \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} x^1(k) < 0$, that is, when the nozzle pressure is greater than 350 Pa, the switching occurs.

TABLE 2. **Performance index function parameters.**

Parameter	Phase one	Phase two
k_f	20	20
Q	$diag([1,10^8,0.1,0.01,0.1])$	$diag([10^6,1,0.07,0.105])$
Q_f	$diag([10^4,10^9,10,0.01,30])$	$diag([10^7,10^9,10^7,10^6])$
R	0.41	0.34

In case 2, the control effect is analyzed in two cases. In Figure 3, the constant fault is chosen as $\alpha = 0.8$; and in Figure 4 and Figure 5, the time-varying faults are considered, which are $\alpha = 0.8 + 0.01\sin(k)$ and $\alpha = 0.8 + 0.1\sin(k)$. The occurrence time is the starting time.

In this case, the selection of multi-phase parameters is as follows:

Figure 3a, Figure 4a and Figure 5a represent the output curve, Figure 3b, Figure 4b and Figure 5b are the input curve. It can be seen that they are relatively smooth by using the new control method. Figure 3 is various curves of the system under constant faults. It can be seen that when the fault occurs, no matter what kind of curve has a certain mutation and is of different degrees, the control effect of the system will become worse. Under the control algorithm proposed in this paper, there is not much change. Figure 4 and Figure 5 are all kinds of curve tracing diagram of the system under time-varying fault. It can be seen from the diagram that the time-varying fault has a great impact on the control performance of the system, but within the allowable range, it is obviously better than the existing control methods.

V. CASE STUDIES

For chemical production processes, considering actuator faults, a new predictive functional control method based on genetic algorithm optimization has been constructed and realized the output tracking performance improvement of the system in case of faults. The advantage of the proposed strategy is that the controller is designed by adjusting the performance index parameters of the genetic algorithm, which can achieve better control effect of the system. Compared with the existing results, the proposed method is more effective.

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YI XIANG is currently pursuing the bachelor's degree with Hainan Normal University. Her research interest includes automation control.

ZHUOLONG LIU is currently pursuing the bachelor's degree with Hainan Normal University. His research interest includes automation control.

LIMIN WANG received the Ph.D. degree in operations research and cybernetics from the Dalian University of Technology, in 2009. She is currently an Associate Professor with the School of Mathematics and Statistics, Hainan Normal University. Her current research interests include batch process control, fault tolerant control, and fault diagnosis.