Received July 2, 2018, accepted August 15, 2018, date of publication September 5, 2018, date of current version September 28, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2868777

A Framework for Adaptive Predictive Control System Based on Zone Control

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This work was supported in part by the National Key Research and Development Program of China under Grant 2017YFB0603703 and in part by the National Natural Science Foundation of China under Grant 61773366.

ABSTRACT In view of the degradation of predictive control performance caused by model mismatch, a multi-variable adaptive predictive control system framework which is composed of zone model predictive control (MPC), identification module and performance monitoring module, is presented. The proposed framework synthesizes the traditional control mode and the test mode to construct a unified form, which is convenient to implement with the MPC software packages. Traditional setpoint control is switched to zone control to ensure that the process constraints remain satisfied in testing, while multi-variable test signals are introduced to guarantee the sufficient excitation of the plant. In addition, in order to maximize the signal-to-noise ratio, an adaptive method of determining the amplitude of test signals is proposed. All the online open-loop identification methods are suitable for this framework, as the testing is treated as ''open-loop,'' which solves the problem of the correlation between input signals and noises in the closed-loop identification. These characteristics of the proposed framework are illustrated via a simulation.

INDEX TERMS Adaptive control, predictive control, system identification, parameter estimation.

I. INTRODUCTION

Model predictive control (MPC) is a class of computer control algorithms which can deal with multivariable systems with interactions and constraints, and has been widely used in various fields of industry arears including chemicals, powers, automotive, and aerospace applications. The predictive control algorithm predicts the future responses by a process model and obtains a sequence of future manipulated variable adjustments through a performance index at each control interval. An accurate process model is one of the key factors for the successful implementation of MPC [1].

The implementation of MPC project mainly has the following steps [2], [3]:

1) Preliminary design and benefit analysis.
2) Pre-test.
3) Dynamic response test and model identification.
4) Off-line simulation and parameter tuning.
5) Controller commissioning online.
6) Training and controller maintenance

Usually, the process model is identified by open-loop step tests which takes up more than 50% of the time of a whole project implementation [4]. After the commissioning of a MPC controller, the variations of plant dynamic characteristics caused by the factors, such as time variable characteristics of equipment life cycle (wear, tear, erosion, congestion, etc.) and operating conditions change, will degrade the MPC controller performance over time. In order to obtain a satisfactory control performance, it is essential to update the model by re-identification when the plant/model error is large. However, disconnecting the MPC controller in the process of re-identification, the products quality will not be guaranteed well, neither production safety, so the idea of off-line re-identification cannot meet the enterprise requirement. An adaptive mechanism with online closed-loop re-identification is an effective method to solve the above problems [5], [6]. Closed-loop identification method is classified into direct identification and indirect identification. For indirect identification method, a prior knowledge of the controller is required. MPC does not have a certain expression, so the indirect identification method is not suitable for MPC applications.

Online identification based on MPC has received extensive attention in the last decade. In the closed-loop re-identification of MPC, a persistent excitation is needed, while MPC is used to control the plant at a steady-state target. MPC and Identification (MPCI) [7] solves an optimization problem on-line with all conventional MPC constraints and additional input constraints which assure persistent excitation of the process. The resulting problem is that the convex optimization problem of the original MPC is converted to a non-convex optimization problem. A two stages approach is presented in [8], in the first stage, a typical optimization task of MPC is solved, and the cost function value is utilized as a threshold for the second stage. In the second stage, the persistent excitation condition is included, and the optimal inputs are obtained by solving a maximization of the minimal eigenvalue of the information matrix increase problem. Similarly to the methods in [7] and [8], another simple modification of MPC formulation called persistently exciting MPC (PE-MPC) [9] is given, with the difference that the persistent excitation constraints are imposed only on the first adjustments of MPC manipulated variables. A MPC relevant identification (MRI) method [10] minimizing a multistep ahead prediction error cost function is proposed based on a high order finite impulse response (FIR) model of the plant, and the cost function is highly nonlinear in the model parameters. Considering the main advantage of MRI method, a more robust MRI method named enhanced multistep prediction error method (EMPEM) [11] is presented by replacing the high order FIR model by an ARX structure and introducing the multistep prediction error method (MPEM) proposed by Huang and Wang [12]. Considering the main problem that the dynamic control and identification objectives are conflicting in closed-loop identification, an invariant target set is included extending the equilibrium-point-stability to the invariant-set-stability in [13], which ensures the system's closed-loop stability, and at the same time a persistent excitation is generated. This method is explored later in [14], the concept of probabilistic invariant sets is introduced, instead of invariant target sets, which stretches the methodology's range. Almost all the MPC products adopt two-layer structure consisting of steady-state target calculation (SSTC) in upper layer and dynamic optimization (DO) in lower layer, where SSTC computes steady-state input, state and output targets, and DO drives the process to the desired steady-state operating points form SSTC without violating constraints. Considering the two-layer structure MPC, Sotomayor *et al.* [15] propose a methodology where generalized binary noise (GBN) test signals are adopted. A diagonal matrix consisting of binary values (1 or −1) as tuning parameter is introduced in the target calculation problem of SSTC, and the tuning parameters of weighting matrix of input deviations in DO are set large enough to accomplish fast input targets tracking. Zhu *et al.* [16] develop a semi-automatic MPC system which consists of three modules: an MPC module, an online identification module and a control monitor module, for the sake of reducing the cost of MPC commissioning and maintenance. In the online identification module, the so-called asymptotic (ASYM) identification method is used to improve control performance.

In real industrial application, especially for thin processes with more outputs than inputs, zone control whose objective is to control some outputs within a specified range, rather than at fixed set-points, is often required. Based on the characteristic increasing the degree of freedom of the process for zone control, a framework for adaptive MPC is proposed to solve the problem of MPC performance degradation caused by plant/model mismatch, under the premise of maintaining production safety. The scope of the paper is limited to linear time-invariant (LTI) model-based considerations with quadratic cost and penalty terms, and this general framework allows a kind of simplicity in the applicable excitations to be used for system identification. These approximations and limitations are quite reasonable and justified in a wide set of chemical reactor models that are frequently applied in the practice. When the MPC performance cannot be accepted, it transforms the traditional control mode to comprehensive test mode, where orthogonal test signals with maximal amplitudes are introduced to excite all inputs of the process simultaneously, and zone control is used to satisfy the constraints on process inputs and/or outputs. Compared with [15] and [16], on the account that test signals effect on the plant directly, the proposed method in this paper is identical to an online open-loop identification which avoids the fundamental problem of closed-loop identification: (1) conflicting between the dynamic control and identification objectives. (2) correlation between the input and the unmeasured noise [17]. In addition, not only the method does not need additional computation, but also it can be implemented with commercial MPC software packages conveniently, without modifying the original form of optimization problem.

The rest of this paper is structured as follows: the zone MPC and the framework of adaptive MPC system are illustrated in Section 2 and 3, respectively; In Section 4, a formulation of comprehensive test mode based on zone MPC is given; In Section 5, an example of the Shell heavy oil fractionators benchmark problem is presented. Finally, in Section 6, some conclusions are discussed.

II. ZONE MPC

A. THE PLANT MODEL

For a linear, time-invariant system with m inputs, n outputs and q measured disturbances, the step responses of output variable y_i for input variable u_j and measurable disturbances v_l are $\boldsymbol{g}_{ij} = \left[g_{ij}(1), \cdots, g_{ij}(N)\right]^T$ and $\boldsymbol{h}_{il} = \left[h_{il}(1), \cdots, h_{il}(N)\right]^T$ respectively, where $i = 1, \cdots, n$, $j = 1, \cdots, m$, $l = 1, \cdots, q$ and N is the model length. For a stable plant the sequences will asymptotically reach constant values, i.e. $g_{ij}(N) \approx g_{ij}(N+1)$, $h_{ij}(N) \approx h_{ij}(N+1)$. Then after adding M control movements $\Delta u_j(k), \cdots, \Delta u_j(k+M-1)$ for each input u_j, the output prediction value with a finite horizon [2] can be as

$$\tilde{\boldsymbol{y}}_{PM}(k) = \tilde{\boldsymbol{y}}_{P0}(k) + \boldsymbol{G}\Delta\boldsymbol{u}_M(k) + \boldsymbol{H}\Delta\boldsymbol{v}(k) \tag{1}$$

where P and M denote prediction horizon and control horizon, respectively. $\tilde{\boldsymbol{y}}_{PM}(k) = \left[\tilde{\boldsymbol{y}}_{1,PM}(k) \cdots \tilde{\boldsymbol{y}}_{n,PM}(k)\right]^T$

and $\tilde{\boldsymbol{y}}_{P0}(k) = \left[\tilde{y}_{1,P0}(k) \cdots \tilde{y}_{n,P0}(k)\right]^T$ are the future and initial output prediction values at time k, respectively; and $\Delta \boldsymbol{u}_M(k) = \left[\Delta \boldsymbol{u}_{1,M}(k) \cdots \Delta \boldsymbol{u}_{m,M}(k)\right]^T$, $\Delta \boldsymbol{u}_{i,M}(k) = \left[\Delta u_i(k) \cdots \Delta u_i(k) \cdots\right]^T \quad (i = 1, \cdots, m)$; $\Delta \boldsymbol{v}(k) = \left[\Delta v_1(k) \cdots \Delta v_q(k) \cdots\right]^T$; as disturbances are unpredictable, it is usually assumed $\Delta v_i(k) = v_i(k) - v_i(k-1)\,(i = 1, \cdots, q)$;

$$\boldsymbol{G} = \begin{bmatrix} \boldsymbol{G}_{11} & \boldsymbol{G}_{12} & \cdots & \boldsymbol{G}_{1m} \\ \boldsymbol{G}_{21} & \boldsymbol{G}_{22} & \cdots & \boldsymbol{G}_{2m} \\ \vdots & \vdots & & \vdots \\ \boldsymbol{G}_{n1} & \boldsymbol{G}_{n2} & \cdots & \boldsymbol{G}_{nm} \end{bmatrix},$$

$$\boldsymbol{G}_{ij} = \begin{bmatrix} g_{ij}(1) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ g_{ij}(M) & \cdots & g_{ij}(1) \\ \vdots & \vdots & \vdots \\ g_{ij}(P) & \cdots & g_{ij}(P-M+1) \end{bmatrix},$$

$$\boldsymbol{H} = \begin{bmatrix} \boldsymbol{H}_{11} & \boldsymbol{H}_{12} & \cdots & \boldsymbol{H}_{1q} \\ \boldsymbol{H}_{21} & \boldsymbol{H}_{22} & \cdots & \boldsymbol{H}_{2q} \\ \vdots & \vdots & & \vdots \\ \boldsymbol{H}_{n1} & \boldsymbol{H}_{n2} & \cdots & \boldsymbol{H}_{nq} \end{bmatrix}, \quad \text{and } \boldsymbol{H}_{il} = \begin{bmatrix} h_{il}(1) \\ \vdots \\ h_{il}(M) \\ \vdots \\ h_{il}(P) \end{bmatrix}.$$

B. RECEDING OPTIMIZATION

MPC employs the receding horizon strategy. At each time step, a sequence of future manipulated variable adjustments is calculated by solving an open-loop optimization problem with constraints, and the first one is injected to the plant. At the next time, a new open-loop optimization is performed, while the initial states are updated by means of an output feedback. Based on the operational requirements, the aim of outputs for industrial MPC controller is divided into setpoints and zones [18], as shown in Figure 1.

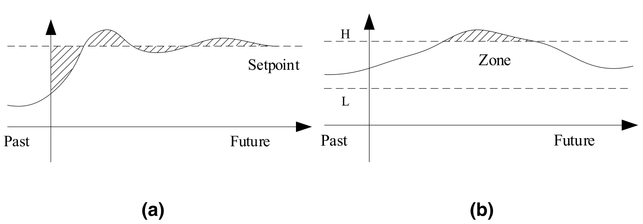

FIGURE 1. Industrial MPC. (a) setpoint control. (b) zone control.

The shaded areas present the deviations between the objective values of controlled variables and their prediction values. For MPC with a fixed setpoint objective, the deviations penalized in the objective function are on both sides of "the line". For MPC with a zone objective, the deviations are outside of "the zone".

A fixed setpoint MPC typically solves the following optimization problem:

$$\begin{aligned} &\min_{\Delta \boldsymbol{u}_M} \left\| \boldsymbol{y}_{\text{sp}}(k) - \tilde{\boldsymbol{y}}_{PM}(k) \right\|_{\boldsymbol{Q}}^2 + \left\| \Delta \boldsymbol{u}_M(k) \right\|_{\boldsymbol{R}}^2 \\ &\text{s.t. } \tilde{\boldsymbol{y}}_{PM}(k) = \tilde{\boldsymbol{y}}_{P0}(k) + \boldsymbol{G}\Delta \boldsymbol{u}_M(k) + \boldsymbol{H}\Delta \boldsymbol{v}(k) \\ &\quad \boldsymbol{y}_{\text{LL}} \leq \tilde{\boldsymbol{y}}_{PM}(k) \leq \boldsymbol{y}_{\text{HL}} \\ &\quad \boldsymbol{u}_{\text{LL}} \leq \boldsymbol{u}_M(k) + \Delta \boldsymbol{u}_M(k) \leq \boldsymbol{u}_{\text{HL}} \\ &\quad \Delta \boldsymbol{u}_{\text{LL}} \leq \Delta \boldsymbol{u}_M(k) \leq \Delta \boldsymbol{u}_{\text{HL}} \end{aligned} \tag{2}$$

where $\boldsymbol{y}_{\text{sp}}(k)$ denotes the setpoints of controlled variables with appropriate dimension; LL and HL respectively represent the upper and lower limits, and $\boldsymbol{y}_{\text{LL}}$ represents the lower limit of outputs, and so on; $\boldsymbol{Q}$ is positive semidefinite matrix and $\boldsymbol{R}$ is positive definite.

However, instead of a fixed setpoint, the optimization of zone MPC aims to keep or move outputs into a zone defined by upper and lower boundaries. The cost function of a zone MPC application used in [19] belongs to mixed integer programming, which increases the computational complexity. Here, based on (2), another way to implement zone control is introduced, which maintains the original optimization problem as a QP (quadratic programming) problem. The optimization problem is defined as follows:

$$\begin{aligned} &\min_{\Delta \boldsymbol{u}_M} \left\| \Delta \boldsymbol{u}_M(k) \right\|_{\boldsymbol{R}}^2 \\ &\text{s.t. } \tilde{\boldsymbol{y}}_{PM}(k) = \tilde{\boldsymbol{y}}_{P0}(k) + \boldsymbol{G}\Delta \boldsymbol{u}_M(k) + \boldsymbol{H}\Delta \boldsymbol{v}(k) \\ &\quad \boldsymbol{y}_{\text{Lb}} \leq \tilde{\boldsymbol{y}}_{PM}(k) \leq \boldsymbol{y}_{\text{Hb}} \\ &\quad \boldsymbol{u}_{\text{LL}} \leq \boldsymbol{u}_M(k) + \Delta \boldsymbol{u}_M(k) \leq \boldsymbol{u}_{\text{HL}} \\ &\quad \Delta \boldsymbol{u}_{\text{LL}} \leq \Delta \boldsymbol{u}_M(k) \leq \Delta \boldsymbol{u}_{\text{HL}} \end{aligned} \tag{3}$$

where the penalty term on the deviations between the setpoints and outputs predicted values in the cost function of (2) is ignored. The control objective of zone is only considered in the constraint conditions. $\boldsymbol{y}_{\text{Lb}}$ and $\boldsymbol{y}_{\text{Hb}}$ represent the lower and upper boundaries for the zone respectively.

III. THE FRAMEWORK FOR AN ADAPTIVE PREDICTIVE CONTROL SYSTEM

Figure 2 shows the framework for an adaptive predictive control system based on zone control, composed of several modules: zone MPC, identification and performance monitoring. The performance monitoring module detects the performance of MPC controller through a performance evaluation criterion periodically. Traditional control mode is transformed to comprehensive test mode, when the MPC performance is detected below the desired value. In the comprehensive test mode, multivariable test signals are introduced to guarantee the sufficient excitation of the plant. The zone MPC module ensures that the process constraints are satisfied to realize production safety and persistence of process. The identification module is used to identify the plant model online with the test data. Then the model of MPC is re-identified and updated. At this moment, if the MPC performance meets the requirements, turn comprehensive test mode to traditional control mode.

Otherwise, continue the comprehensive test mode until the MPC performance meets the requirements after updating the model.

A. PERFORMANCE MONITORING MODULE

The performance of a controller refers to its ability to adjust the deviation between the controlled variables and the control targets. The MPC performance is related to tuning parameters, the degree of model mismatch, and so on. In this paper, a method based on non-disturbing small sinusoidal test signals [3] is introduced to judge whether the controller's performance is deteriorated by model mismatch. The procedure of model error detection is illustrated as follow:

1) Choose three different frequency points, construct small sinusoidal test signals.
2) Perform tests and estimate frequency responses at the three frequencies.
3) Calculate the 85.7% upper error bounds, If the error bounds are less than the setting bound value, go to (4); Otherwise, go to (2).
4) Calculate the model error index matrix $\boldsymbol{ERR}$.
5) The quality of the model is not qualified, if the element in $\boldsymbol{ERR}$ is greater than the desired value.

B. IDENTIFICATION MODULE

The goal of this paper is an online correction of model parameters when the original MPC model is not accurate enough, at the same time keeping the continuity and stability of production. Therefore, an initial model (also known as a "seed model") is required. In later stage of controller maintenance, the initial model can be continuously improved through online identification. Equation (1) is an expression of parameter model, and identification methods of a parameter model include: parameter estimation method, iterative optimization, subspace, neural network, etc. A recursive least squares identification method with forgetting factor is adopted in this paper, but the framework mentioned in this paper is not limited to this identification method.

IV. COMPREHENSIVE TEST MODE BASED ON ZONE MPC

A. TEST SIGNALS

For the case in which the model structure is correct, the accuracy of unknown parameters will depend directly on the test signals [20]. It is very important to persistently excite the process while constraints are satisfied. The condition for persistent excitation is introduced as following definition:

Definition 1: The input signal $u(k)$ is termed persistently exciting of order r, if the matrix $\overline{R_r}$ is positive definite [21].

$$\overline{R_r} = \begin{bmatrix} R_u(0) & R_u(1) & \cdots & R_u(r-1) \\ R_u(1) & R_u(0) & \cdots & R_u(r-2) \\ \vdots & \vdots & & \vdots \\ R_u(r-1) & R_u(r-2) & \cdots & R_u(0) \end{bmatrix} \tag{4}$$

where $R_u(\tau) = \lim_{N\to\infty} \frac{1}{N} \sum_{k=1}^{N} u(k+\tau)u^T(k)$.

For a MIMO system, it will save a lot of time to excite all inputs simultaneously, if the input signals are uncorrelated. Since Pseudo Random Binary Sequence (PRBS) signals used in SISO systems case do not meet this requirement, an amplitude modulated PRBS (APRBS) signal comprised of two binary periodic signals [22] is introduced as

$$u_i(k) = h_i(k)\, p(k) \tag{5}$$

where $p(k)$ is a PRBS signal with period length N_p and amplitudes $[a, -a \times \mathrm{P}]$, $\mathrm{P} = \frac{\sqrt{N_p+1}-2}{\sqrt{N_p+1}}$. The signal $h_i(k)$ with the period length N_h is chosen from the i-th line of a Hadamard matrix of the order $N_h = 2^{m-1}$.

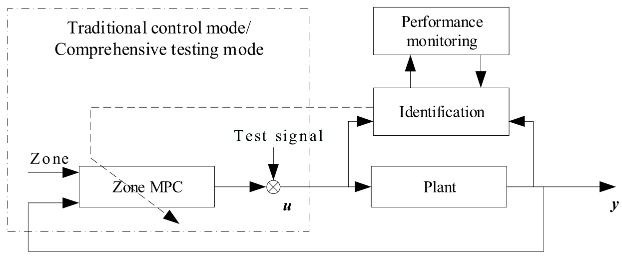

FIGURE 2. The framework for the adaptive predictive control system.

B. THE PROPOSED FRAMEWORK OF COMPREHENSIVE TEST MODE

As described in Figure 2, comprehensive test mode is launched, while the performance monitoring module detects that the MPC performance cannot be accepted for large plant/model error. To complete the automatic test, and to ensure the economic benefit and production safety simultaneously, the zone MPC described in (3) is adopted in comprehensive test mode. According to (3), it can be seen that input movement $\Delta u_j(k)$ is equal to zero ($j = 1, \cdots, m$), when output predictive values are all in the zone. This means that there is no relation between the MPC controller and the plant unless some of the output prediction values get outside of the zone. Therefore, the comprehensive test mode in which test signals with appropriate amplitudes are used to excite all the outputs simultaneously under the premise of satisfaction of zone constraints, can be regarded as "open-loop test". The structure of the comprehensive test mode is shown in Figure 3.

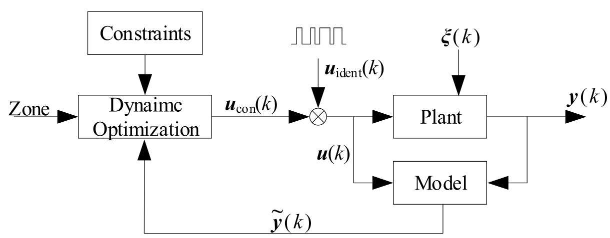

FIGURE 3. The structure of the comprehensive test mode.

Where the manipulated variable adjustments $\boldsymbol{u}(k) = \boldsymbol{u}_{con}(k) + \boldsymbol{u}_{ident}(k)$. $\boldsymbol{u}_{ident}(k)$ denotes the test signals which could be look upon as measured disturbances. $\boldsymbol{u}_{con}(k)$ is used to adjust the output prediction values within the zone. Equation (1) can be expressed as

$$\begin{aligned}\tilde{\boldsymbol{y}}_{PM}(k) &= \tilde{\boldsymbol{y}}_{P0}(k) + \boldsymbol{G}\boldsymbol{\Delta u}_{M}(k) + \boldsymbol{H}\boldsymbol{\Delta v}(k) \\ &= \tilde{\boldsymbol{y}}_{P0}(k) + \boldsymbol{G}(\boldsymbol{\Delta u}_{con,M}(k) + \boldsymbol{\Delta u}_{ident,M}(k))\end{aligned} \tag{6}$$

Where $\boldsymbol{\Delta u}_{con,M}(k)$ and $\boldsymbol{\Delta u}_{ident,M}(k)$ present the increment of future behavior of MPC adjustments and test signals over the prediction horizon of length M. In order to construct a unified form of comprehensive test mode and traditional control mode, a parameter λ called amplitude intensity is introduced in this paper. Therefore, the output prediction values

$$\tilde{\boldsymbol{y}}_{PM}(k) = \tilde{\boldsymbol{y}}_{P0}(k) + \boldsymbol{G}(\Delta\boldsymbol{u}_{con,M}(k) + \lambda\Delta\boldsymbol{u}_{ident,M}(k)) \tag{7}$$

Then (3) can be written as

$$\begin{aligned}&\min_{\Delta\boldsymbol{u}_M} \ \|\Delta\boldsymbol{u}_{con,M}(k)\|_{\boldsymbol{R}}^2 \\ &\text{s.t. } \boldsymbol{\Delta u}_{M}(k) = \Delta\boldsymbol{u}_{con,M}(k) + \lambda\Delta\boldsymbol{u}_{ident,M}(k) \\ &\quad \tilde{\boldsymbol{y}}_{PM}(k) = \tilde{\boldsymbol{y}}_{P0}(k) + \boldsymbol{G}\boldsymbol{\Delta u}_{M}(k) \\ &\quad \boldsymbol{y}_{\text{Lb}} \le \tilde{\boldsymbol{y}}_{PM}(k) \le \boldsymbol{y}_{\text{Hb}} \\ &\quad \boldsymbol{u}_{\text{LL}} \le \boldsymbol{u}_{M}(k) + \boldsymbol{\Delta u}_{M}(k) \le \boldsymbol{u}_{\text{HL}} \\ &\quad \boldsymbol{\Delta u}_{\text{LL}} \le \boldsymbol{\Delta u}_{M}(k) \le \boldsymbol{\Delta u}_{\text{HL}}\end{aligned} \tag{8}$$

To integrate setpoint control and zone control problem (traditional control mode and comprehensive test mode), a unified form is given by:

$$\begin{aligned}&\min_{\Delta\boldsymbol{u}_M} \ \|\boldsymbol{y}_{\text{sp}}(k) - \tilde{\boldsymbol{y}}_{PM}(k)\|_{\boldsymbol{Q}}^2 + \|\Delta\boldsymbol{u}_{M}(k)\|_{\boldsymbol{R}}^2 \\ &\qquad + \|\boldsymbol{\epsilon}_{\text{L}}\|_{\boldsymbol{E}_{\text{Lb}}}^2 + \|\boldsymbol{\epsilon}_{\text{H}}\|_{\boldsymbol{E}_{\text{Hb}}}^2 \\ &\text{s.t. } \boldsymbol{\Delta u}_{M}(k) = \Delta\boldsymbol{u}_{con,M}(k) + \lambda\Delta\boldsymbol{u}_{ident,M}(k) \\ &\quad \tilde{\boldsymbol{y}}_{PM}(k) = \tilde{\boldsymbol{y}}_{P0}(k) + \boldsymbol{G}\boldsymbol{\Delta u}_{M}(k) \\ &\quad \boldsymbol{y}_{\text{Lb}} - \boldsymbol{\epsilon}_{\text{L}} \le \tilde{\boldsymbol{y}}_{PM}(k) \le \boldsymbol{y}_{\text{Hb}} + \boldsymbol{\epsilon}_{\text{H}} \\ &\quad \boldsymbol{u}_{\text{LL}} \le \boldsymbol{u}_{M}(k) + \boldsymbol{\Delta u}_{M}(k) \le \boldsymbol{u}_{\text{HL}} \\ &\quad \boldsymbol{\Delta u}_{\text{LL}} \le \boldsymbol{\Delta u}_{M}(k) \le \boldsymbol{\Delta u}_{\text{HL}} \\ &\quad 0 \le \boldsymbol{\epsilon}_{\text{H}} \le \boldsymbol{y}_{\text{HL}} - \boldsymbol{y}_{\text{Hb}} \\ &\quad 0 \le \boldsymbol{\epsilon}_{\text{L}} \le \boldsymbol{y}_{\text{Lb}} - \boldsymbol{y}_{\text{LL}}\end{aligned} \tag{9}$$

where the third and fourth items in the objective function of (9) respectively represent the penalty for the outputs prediction values lower than the lower boundaries and upper than the upper boundaries. $\boldsymbol{\epsilon}_{\text{L}}$ and $\boldsymbol{\epsilon}_{\text{H}}$ are defined as output constraint slack variables, which guarantee the optimization problem feasible. $\boldsymbol{E}_{\text{Lb}}$ and $\boldsymbol{E}_{\text{Hb}}$ are the corresponding weighting matrices. By comparing (9) to (3) and (2), (9) is equivalent to the dynamic objective function of zone MPC, when $\boldsymbol{Q} = 0$. Equation (9) is equivalent to the dynamic objective function of setpoint MPC, when $\boldsymbol{Q} \neq 0$;

For the amplitude intensity λ, one may in general discern the following two cases.

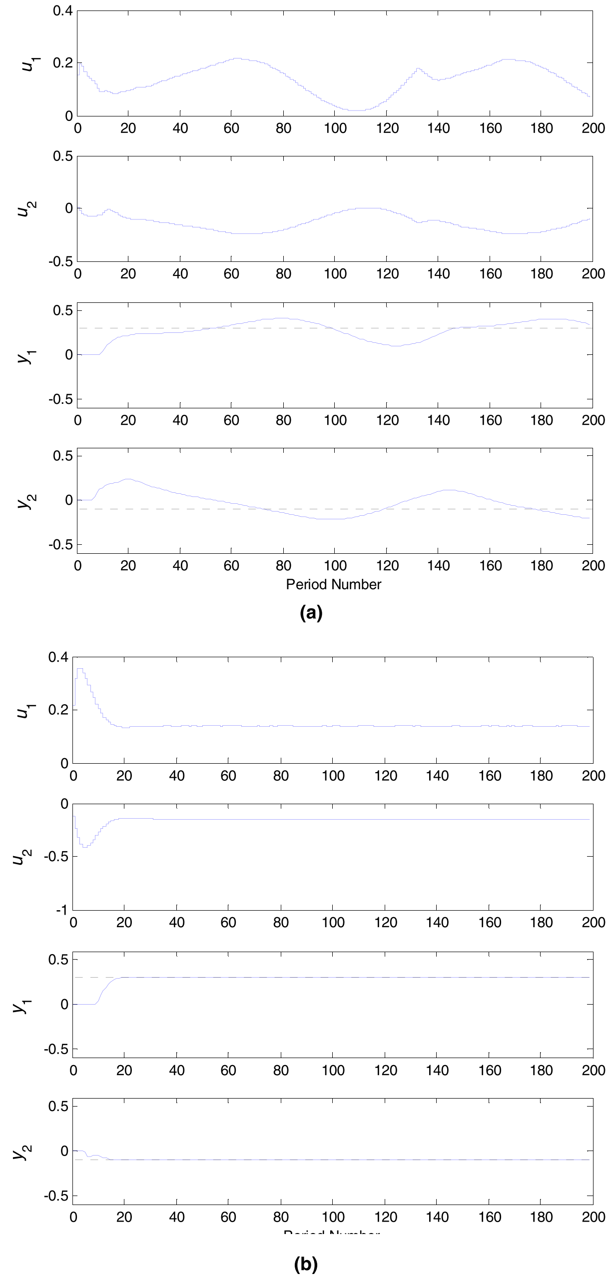

FIGURE 4. **Closed-loop response for the plant. (a) with the initial model. (b) with the re-identified model.**

1) $\lambda = 0$: It is in traditional control mode. Furthermore, the control objectives of outputs are setpoints, and (9) is equivalent to (2), when $\boldsymbol{y}_{\text{Lb}} = \boldsymbol{y}_{\text{LL}}, \boldsymbol{y}_{\text{Hb}} = \boldsymbol{y}_{\text{HL}}$ and $\boldsymbol{Q} \neq 0$.
2) $\lambda \neq 0$: It is in comprehensive test mode. In order to drive the inputs as close as possible to the orthogonal persistently excitation signals, the numerical value of $\boldsymbol{R}$ should be large enough to reduce the affection caused by $\Delta\boldsymbol{u}_{con,M}$.

With the increase of amplitude intensity λ, the input adjustments $\boldsymbol{u}(k)$ also will increase correspondingly, which will lead to higher signal to noise ratio and better test result. However, the possibility of constraint violation will be greater. To settle this problem, consider the following optimization problem:

$$\min_{\Delta \boldsymbol{u}_M} \left\|\boldsymbol{y}_{\mathrm{sp}}(k)-\tilde{\boldsymbol{y}}_{PM}(k)\right\|_{\boldsymbol{Q}}^2+\left\|\Delta \boldsymbol{u}_{con,M}(k)\right\|_{\boldsymbol{R}}^2 + \|\boldsymbol{\epsilon}_{\mathrm{L}}\|_{\boldsymbol{E}_{\mathrm{Lb}}}^2+\|\boldsymbol{\epsilon}_{\mathrm{H}}\|_{\boldsymbol{E}_{\mathrm{Hb}}}^2-\|\lambda\|_S^2 \tag{10}$$

the constraints are the same as these of (9). where S is a weighting coefficient. The target is to seek a large λ and small $\Delta \boldsymbol{u}_{con,M}(k)$ while satisfying the constraints.

Remark:

1) The proposed framework synthesizes traditional control mode and test mode to construct a unified form. The steps of pre-test and dynamic response test in the implementation of MPC project can be omitted. Therefore, this proposed framework can effectively improve the efficiency of the implementation of MPC project, especially the maintenance of MPC controller.
2) In contrast to the "Set-point Control", in the proposed framework the application of the "Zone Control" makes the identification process similar to the "open loop identification" because within the zone no "error feedback" is required. Almost all of the MPC products (RMPCT, Aspen DMC3, Pavilion8, Taiji, *et al.*) have "Zone Control" option. Therefore, the proposed framework in this paper can be easily applied in these products.
3) The performance monitoring module and the identification module can be implemented by the way of offline computing to reduce the online computing complexity. In (9), since the amplitude coefficient is known, the comprehensive test module based on zone MPC is still a QP problem, without adding computational complexity. In (10), as the amplitude coefficient is unknown, the computational complexity of the comprehensive test module based on zone MPC is increased, and the standard QP optimization methods are no longer applicable.

V. SIMULATION

Consider the MIMO plant for the Shell heavy oil fractionator [23]

$$\boldsymbol{G}(s)=\begin{bmatrix} \dfrac{4.05e^{-27s}}{50s+1} & \dfrac{1.77e^{-28s}}{60s+1} \\ \dfrac{5.39e^{-18s}}{50s+1} & \dfrac{5.72e^{-14s}}{60s+1} \end{bmatrix},$$

TABLE 1. Estimated errors of the initial MPC model (%).

$\begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix}$	$f=0.015\mathrm{Hz}$	$f=0.067\mathrm{Hz}$	$f=0.13\mathrm{Hz}$
Estimated errors (%)	$\begin{bmatrix} 116.3 & 99.1 \\ 89.5 & 66.7 \end{bmatrix}$	$\begin{bmatrix} 70.5 & 108.3 \\ 96.0 & 98.9 \end{bmatrix}$	$\begin{bmatrix} 92.1 & 97.4 \\ 98.6 & 98.0 \end{bmatrix}$

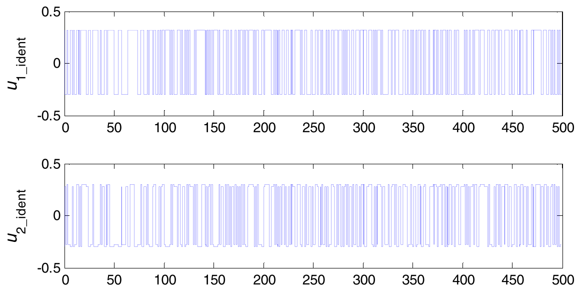

FIGURE 5. Portion of the uncorrelated APRBS signals.

discretized as $\boldsymbol{G}(z)$, as shown at the bottom of this page, where the input variables u_1 and u_2 represent the product draw rate from the top and the side of the column, respectively. The output variables y_1 and y_2 represent the draw composition from the top and the side of the column, respectively. The constraints of the input variables are set with $\boldsymbol{u}_{\mathrm{LL}}=\left[-0.5\ -0.5\right]$, $\boldsymbol{u}_{\mathrm{HL}}=\left[0.5\ 0.5\right]$, and that of the output variables are $\boldsymbol{y}_{\mathrm{LL}}=\left[-0.5\ -0.5\right]$, $\boldsymbol{y}_{\mathrm{HL}}=\left[0.5\ 0.5\right]$. The setpoints of the output variables are $\boldsymbol{y}_{\mathrm{SP}}=\left[0.3\ -0.1\right]$.

The unmeasured disturbance ξ_1 and ξ_2 are respectively generated by filtering a white noise $e(k)$. The variance of $e(k)$ is 0.1.

$$\xi_1=\frac{1}{1-0.95z^{-1}}e(k), \quad \xi_2=\frac{1+0.5z^{-1}}{1-1.5z^{-1}+0.7z^{-2}}e(k)$$

The model used in the MPC is

$$\boldsymbol{G}_{\mathrm{MPC}}(s)=\begin{bmatrix} \dfrac{2.52e^{-27s}}{15s+1} & \dfrac{3.8e^{-28s}}{45s+1} \\ \dfrac{2.17e^{-18s}}{45s+1} & \dfrac{2.15e^{-14s}}{15s+1} \end{bmatrix}$$

In this paper, a quadratic dynamic matrix control (QDMC) algorithm is adopted for the simulation, where the main tuning parameters are: $P=50$, $M=20$, $\boldsymbol{Q}_1=\boldsymbol{Q}_2=\boldsymbol{I}_{P\times P}$, $\boldsymbol{R}_1=\boldsymbol{R}_2=\boldsymbol{I}_{M\times M}$. The simulation result of closed-loop responses is shown in Figure 4(a). It can be observed that the output variables are in the limits, however, they are fluctuating up and down near the setpoints all the time due to the model deviation.

$$\boldsymbol{G}(z)=\begin{bmatrix} \dfrac{0.2359z^{-1}-0.2244z^{-2}}{1-1.8930z^{-1}+0.8958z^{-2}}z^{-9} & \dfrac{0.058-0.0264z^{-1}-0.0266z^{-1}}{1-1.8930z^{-1}+0.8958z^{-2}}z^{-10} \\ \dfrac{0.3139-0.2986z^{-1}}{1-1.8930z^{-1}+0.8958z^{-2}}z^{-6} & \dfrac{0.0945+0.0954z^{-1}-0.1737z^{-2}}{1-1.8930z^{-1}+0.8958z^{-2}}z^{-5} \end{bmatrix}$$

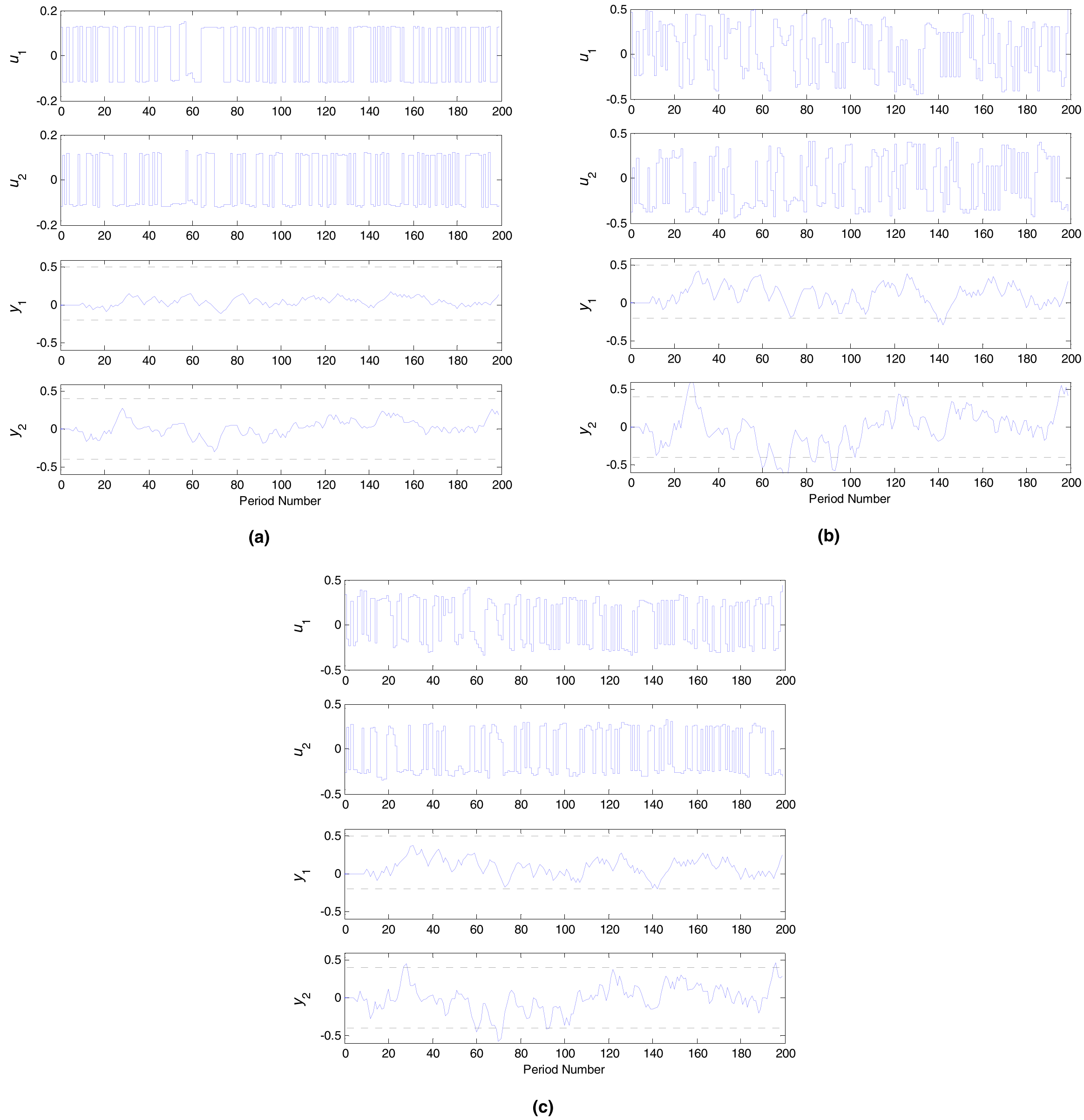

FIGURE 6. Closed-loop response for the online comprehensive test mode: (a) $\lambda = 0.4$. (b) $\lambda = 1.4$. (c) adaptive λ.

In performance monitoring module, the two small sinusoidal test signals used are

$$\begin{aligned} r_{t1} &= 0.13 \sin(0.015 \times 2\pi t) \\ &\quad + 0.054 \sin(0.067 \times 2\pi t - \pi) \\ &\quad + 0.11 \sin(0.13 \times 2\pi t - 1.5\pi) \\ r_{t2} &= 0.092 \sin(0.015 \times 2\pi t) \\ &\quad + 0.052 \sin(0.067 \times 2\pi t - \pi) \\ &\quad + 0.078 \sin(0.13 \times 2\pi t - 1.5\pi) \end{aligned}$$

where three frequency points: 0.015, 0.067, 0.13 are chosen.

Perform tests and estimate the frequency responses at the three frequencies, the results of estimated errors are shown in Table 1.

Then the model error index matrix $\boldsymbol{ERR}$ can be determined as

$$\begin{aligned} \boldsymbol{ERR} &= 0.4 \times \begin{bmatrix} 116.3 & 99.1 \\ 89.5 & 66.7 \end{bmatrix} + 0.4 \times \begin{bmatrix} 70.5 & 108.3 \\ 96.0 & 98.9 \end{bmatrix} \\ &\quad + 0.2 \times \begin{bmatrix} 92.1 & 97.4 \\ 98.6 & 98.0 \end{bmatrix} \\ &= \begin{bmatrix} 93.2 & 102.4 \\ 93.9 & 85.8 \end{bmatrix} \end{aligned}$$

The values of all the elements in $\boldsymbol{ERR}$ are quite big (more than 50%), and one can conclude that the model error is large. Therefore, it is necessary to perform re-identification. Then control mode is switched to

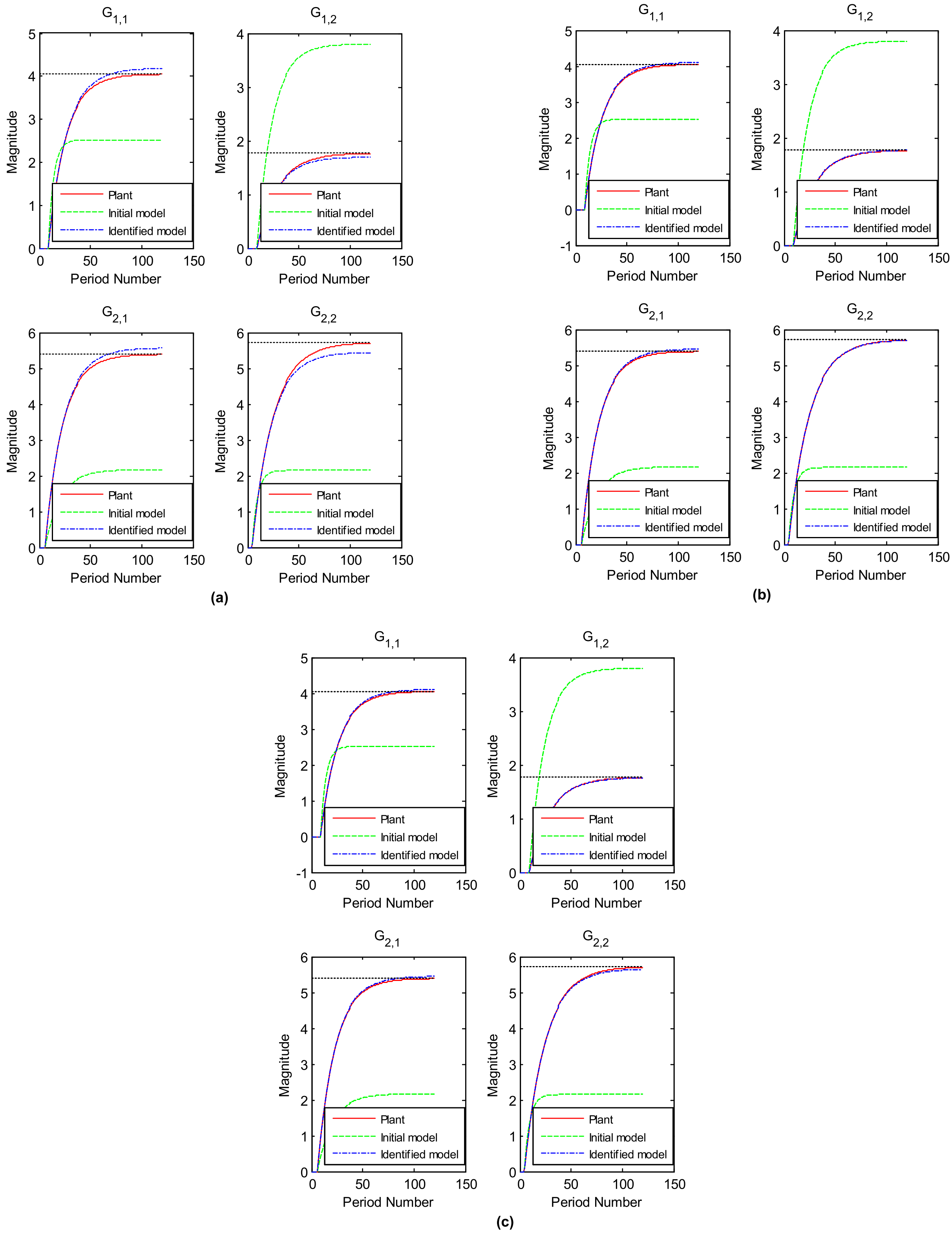

FIGURE 7. Step response for the plant, initial model, re-identified model. (a) $\lambda = 0.4$. (b) $\lambda = 1.4$. (c) adaptive λ.

comprehensive test mode, in which the uncorrelated APRBS signals are introduced, and portion of the signals are shown in Figure 5.

For the desired range of zone MPC, the upper boundary $\boldsymbol{y}_{\mathrm{Hb}} = [0.5; 0.4]$, the lower boundary $\boldsymbol{y}_{\mathrm{Lb}} = [-0.2; -0.4]$. the closed-loop responses of comprehensive test are

TABLE 2. Results corresponding comprehensive test.

Parameter	Actual value	$\lambda = 0.4$	$\lambda = 1.4$	Adaptive λ
$a(1)$	-1.8930	-1.8331	-1.8875	-1.8818
$a(2)$	0.8958	0.8393	0.8906	0.8852
$b_{11}(0)$	0.0000	0.0000	0.0000	0.0000
$b_{11}(1)$	0.2359	0.2359	0.2359	0.2358
$b_{11}(2)$	-0.2244	-0.2103	-0.2231	-0.2217
$b_{12}(0)$	0.0580	0.0580	0.0580	0.0580
$b_{12}(1)$	-0.0264	-0.0229	-0.0261	-0.0257
$b_{12}(2)$	-0.0266	-0.0248	-0.0264	-0.0263
$b_{21}(0)$	0.0000	0.0000	0.0000	0.0000
$b_{21}(1)$	0.3139	0.3138	0.3139	0.3139
$b_{21}(2)$	-0.2986	-0.2799	-0.2969	-0.2951
$b_{22}(0)$	0.0945	0.0945	0.0945	0.0945
$b_{22}(1)$	0.0954	0.1010	0.0959	0.0965
$b_{22}(2)$	-0.1737	-0.1625	-0.1727	-0.1716
$Total\_e^2$	0.0000	0.0075	0.0001	0.0003

presented respectively in Figure 6(a) for $\lambda = 1.4$, in Figure 6(b) for $\lambda = 0.4$ and in Figure 6(c) for adaptive λ which is calculated by (10).

As shown in Figure 6(a) and Figure 6(b), a greater value of λ means greater amplitudes of test signals treated as measured disturbances, which deteriorate the output constrains (the outputs fluctuate seriously in Figure 6(b), for instance, y_1 is beyond the objective zone at the sampling time $k = 140 - 144$, and y_2 is beyond the objective zone at the sampling time $k = 27 - 30, 60 - 62, 67 - 73, 84, 85, 93-95, 123, 124, 126, 196-200$). On the contrary, a smaller value of λ means smaller amplitudes of test signals, which results in better control result. The adaptive method, in which persistently excitation and process constraints are considered comprehensively, is presented as Figure 6(c). However, the magnitude of constraint violation in Figure 6(c) is significantly less than that in Figure 6(b), there are some constraint violation (y_1 is beyond the objective zone at the sampling time $k = 73, 74, 141$ and y_1 is beyond the objective zone at the sampling time $k = 27 - 30, 67 - 73, 199$).

An online identification method of recursive least squares with forgetting factor is adopted, the result is shown in Table 2, where $Total\_e^2$ represents the sum of squares of deviations between the result identified and the actual values. The step responses of plant, model used in MPC and the re-identified model for adaptive λ are presented as Figure (7). The following conclusions can be drawn from the graph: with larger value of λ, the greater signal-to-noise ratio, the better identification result. Otherwise the opposite result instead.

Then, switch MPC with the re-identified model for adaptive λ, and turn comprehensive test mode to traditional control mode. As in the previous model error detection procedure with the same two small sinusoidal test signals, the estimated errors of the new model are shown in Table 3.

TABLE 3. Estimated errors of the identified model for adaptive λ (%).

$\begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix}$	$f = 0.015\text{Hz}$	$f = 0.067\text{Hz}$	$f = 0.13\text{Hz}$
Estimated errors (%)	$\begin{bmatrix} 32.0 & 54.8 \\ 27.1 & 36.5 \end{bmatrix}$	$\begin{bmatrix} 40.8 & 31.4 \\ 38.2 & 46.2 \end{bmatrix}$	$\begin{bmatrix} 25.7 & 48.6 \\ 55.6 & 54.8 \end{bmatrix}$

The model error index matrix $\boldsymbol{ERR}$ can be calculated as

$$\begin{aligned} \boldsymbol{ERR} &= 0.4 \times \begin{bmatrix} 32.0 & 54.8 \\ 27.1 & 36.5 \end{bmatrix} + 0.4 \times \begin{bmatrix} 40.8 & 31.4 \\ 38.2 & 46.2 \end{bmatrix} \\ &\quad + 0.2 \times \begin{bmatrix} 25.7 & 48.6 \\ 55.6 & 54.8 \end{bmatrix} \\ &= \begin{bmatrix} 34.3 & 44.2 \\ 37.2 & 44.0 \end{bmatrix} \end{aligned}$$

where the values of all the elements of the matrix are less than 50%. As already mentioned, the same parameters of QDMC are used. The result of closed-loop responses for the re-identified model is shown in Figure 4(b). As can be seen in the figure, the outputs are all within the upper and lower limits, and they are quickly stabilized at the setpoint. It can be concluded that the performance of the MPC with the identified model for adaptive λ can meet the requirements well, however, $Total\_e^2$ for adaptive λ is larger than that for $\lambda = 1.4$ as shown in Table 2.

VI. CONCLUSION

In this work, a framework for adaptive MPC which is composed of zone MPC, identification module and performance monitoring module is proposed to compensate MPC performance deterioration caused by large plant/model error. The traditional control mode of setpoint MPC is switched to comprehensive test mode of zone MPC, when performance monitoring module detects that the controller performance cannot be accepted. In the proposed comprehensive test mode, uncorrelated test signals are introduced to excite the process simultaneously, while zone MPC is used to guarantee the production safety in test. In order to construct a unified form of comprehensive test mode and traditional control mode for MPC in industrial applications, a parameter called amplitude intensity λ is introduced. The main feature of the proposed method is that 1) the test data can be treated as open-loop, therefor all the proved technology of open-loop identification can be adopted. 2) the method synthesizes control mode and test mode. It can be developed to implement with the MPC software packages. Finally, the proposed approach is tested by a simulation with a MIMO plant of a Shell heavy oil fractionator. The result shows that the proposed method is promising in terms of future application.

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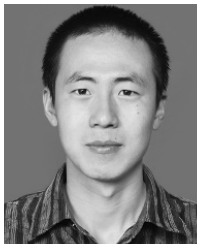

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