Multiple Model Predictive Control for MIMO Systems[1)]

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Abstract A multi-model-based predictive control (MMPC) strategy dealing with nonlinear model-based predictive control (NMPC) for MIMO systems is developed in this paper. Firstly a multi-model identification method is given. Using fuzzy satisfactory clustering algorithm presented in this paper, the complex nonlinear system can be quickly divided into multiple fuzzy parts. A global model can be obtained by some transformation of the obtained multiple linear models. An MMPC algorithm is therefore designed for the global MIMO systems with system performance analysis. Taking a pH neutralization control system as simulation example, the simulation results verify the effectiveness of MMPC on complex nonlinear systems.

Key words MIMO systems, multi-model, model-based predictive control (MPC), fuzzy satisfactory clustering, pH neutralization process

1 Introduction

Recently Model Predictive Control (MPC) has become an attractive research field in automatic control for its advantages over conventional techniques and successful applications in industry. MPC algorithms were originally developed for linear processes, but the basic idea can be transferred to nonlinear systems [1,2]. Unfortunately, two major issues limit its possible application to nonlinear systems. The first is their assumption of a model that has to be quite accurate; however, the modeling of industrial systems often presents problems of nonlinearity, strong coupling, uncertainty, and even wide operating range, a satisfied model is always difficult to obtain. The second is that a nonlinear non-convex optimization problem must be solved for each sampling period with algorithms which are usually too slow for real-time control due to a large amount of computation. The facts have forced the control community to study simplifications of this general approach in order to remove these drawbacks. Usually, the nonlinear model is linearized iteratively in each control interval to solve the above problems. This paper will present a new solution based on multi-model approach.

Multi-model approaches are very proper to control industrial processes, especially chemical processes for their inherently nonlinearity and large set point changes or load disturbances. Based on divide-and-conquer strategy, multi-model approaches develop local linear models or controllers corresponding to typical operating regimes, then fit the global system through certain integration of local models or controllers. Actually, applying multi-model control to nonlinear or time-varying systems has a long history. However, multi-model approach for MIMO systems seldom appears in literatures.

In this paper, a Multi-Model Predictive Control (MMPC) is presented to deal with NMPC problem of MIMO systems. Firstly, a multi-model modeling method using T-S structure model is introduced. Using fuzzy satisfactory clustering algorithm given in this paper, a complex nonlinear system can be quickly divided into local systems, and the global system can be described by integration of the local linear models. Secondly, merging the obtained multiple linear models with MIMO Generalized Predictive Control (GPC), a no-

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vel MMPC algorithm is designed for the global system. As a major benefit of the multi-model strategy, linear predictive controllers can be used. Then, the paper tries to use MMPC to regulate a typical complex nonlinear process: an MIMO pH neutralization system.

2 Multi-model identification based fuzzy satisfactory clustering

It is well known that clustering algorithms aim to divide a data set into several subsets. Therefore, they can be naturally used for system division in multi-model approach. It is thought that cluster number c in the clustering algorithm corresponds to the number of local models in the multi-model approach. Therefore, to divide a global system in a satisfactory way equals to look for a proper cluster number. However, for many kinds of clustering methods, including GK algorithm[3], clustering number c is always needed in advance, which hampers clustering algorithms to be used. This paper aims to solve complex system control problem. It is known that, for control problems, the modeling precision is the contrary of model numbers. To give attention to them, here we present a satisfactory clustering algorithm based on GK. Simply speaking, let the clustering method start with $c=2$ ($c\in[2,c^*]$), where c^* is the satisfactory cluster number. Then determine whether a new cluster center should be increased or not. If the clustering result is not satisfied yet, from the given data set, find out a sample most different from the existing cluster centers $\boldsymbol{v}_1\sim\boldsymbol{v}_c$ as new center $\boldsymbol{v}_{c+1}$. Start with $\boldsymbol{v}_1\sim\boldsymbol{v}_{c+1}$ as initial cluster centers, and compute the new NOT-random partition matrix U. Then repeat GK algorithm to divide the set into $c+1$ parts. Do the above steps again until the result is satisfactory.

Consider a MISO system, whose data set Z is composed of system input-output data. Define a data pair as $z_j=[\boldsymbol{\varphi}_j, y_j]^{\mathrm{T}}\in R^{d+1}$, $j=1,\cdots,N$, where $\boldsymbol{\varphi}_j$ is called as regression vector or generalized input vector, y_j is system output. Suppose Z is divided into c clusters. That is, the system can be composed of c local models. The global model is constructed by fuzzy interpolation of these local models. Multi-model identification based on satisfactory clustering (Algorithm I) can be described as follows:

Step 1. Set initial cluster number $c=2$.

Step 2. Using GK algorithm, by initial partition matrix U_0, divide Z into c parts $\{Z_1, Z_2,\cdots,Z_c\}$ and obtain fuzzy partition matrix $U=[\mu_{i,j}]_{c\times N}$.

Step 3. For each subset, identify its consequent parameters using stable-state Kalman filter method[4]. The local model is then described as

$$R_i \text{ if } (\boldsymbol{\varphi}_j, y_j)\in Z_i \quad \text{then} \quad y^i = p_0^i + p_1^i\boldsymbol{\varphi}_j(1)+\cdots+p_d^i\boldsymbol{\varphi}_j(d) \quad i=1,\cdots,c \tag{1}$$

Step 4. Compute the system output $\hat{y}$ corresponding to input z_j

$$\hat{y} = \sum_{i=1}^{c}\mu_{ij}y_i \Big/ \sum_{i=1}^{c}\mu_{ij} \tag{2}$$

To predict the output $\tilde{y}$ of a new input $\tilde{\boldsymbol{\varphi}}$, return GK algorithm and use the following equation to calculate $\tilde{\mu}_i$ corresponding to ith rule[5],

$$\tilde{\mu}_i(\tilde{\boldsymbol{\varphi}}) = \frac{1}{\sum_{j=1}^{c}\left(D_{A_i^x}(\tilde{\boldsymbol{\varphi}},\boldsymbol{v}_i^x)/D_{A_i^x}(\tilde{\boldsymbol{\varphi}},\boldsymbol{v}_j^x)\right)^{2/(m-1)}} \tag{3}$$

where $\boldsymbol{v}_i^x$ denotes the projection of the ith cluster center $\boldsymbol{v}_i$ onto the generalized input space; $D_{A_i^x}(\tilde{\varphi},\boldsymbol{v}_i^x)$ measures the distance of the new input vector from the projection of the cluster center $\boldsymbol{v}_i^x$; $m>1$ is a parameter that controls fuzziness of clusters. Then the predicted output $\tilde{y}$ can be calculated by (2).

Step 5. Use $S=RMSE$ to evaluate modeling results. If $S\leqslant S_{TH}$ is satisfied, where S_{TH} is given threshold, modeling is over. Otherwise, go to Step 6.

Step 6. From data set, find out a sample z_n different from each cluster center. The dissimilarity can be calculated by

$$n = \arg\min_{n} \sum_{\substack{1\leqslant i,j\leqslant c \\ i\neq j}} (\mu_{ni} - \mu_{nj}) \tag{4}$$

Step 7. Using new cluster centers $v_1, \cdots, v_c, v_{c+1}$, compute a new one, the initial partition matrix U_0, which is not the random partition matrix.

Step 8. Let $c=c+1$, $U=U_0$, and go to Step2.

With the satisfactory clustering algorithm, a complex nonlinear modeling problem is decomposed into a set of simple linear models valid within certain operating regimes defined by fuzzy boundaries. Fuzzy inference is then used to interpolate the outputs of the local models in a smooth fashion to get a global model. This also makes it possible to transform an NMPC problem to an LMPC one.

3 Multiple model predictive control

In this section, we will introduce a multivariable GPC algorithm, then merge it with multiple linear models to design MMPC. We will also extend it to the constrained case, and its stability robustness will be analyzed in next section.

3.1 Multivariable GPC algorithm

Assume that a multivariable CARIMA model can be written as

$$A(z^{-1})\Delta \boldsymbol{y}(t) = B(z^{-1})\Delta \boldsymbol{u}(t-1) + \boldsymbol{\xi}(t) \tag{5}$$

where $\Delta = 1 - z^{-1}$, z^{-1} is difference operator or backward shift operator. $\boldsymbol{y}(t)$, $\boldsymbol{u}(t)$ and $\boldsymbol{\xi}(t)$ are, respectively, M-output, R-input and R_d noise vectors, $A(z^{-1})$, $B(z^{-1})$ are polynomial matrices of z^{-1}. Without constraints, [6] presented the control law for (5) as

$$\Delta \boldsymbol{u}(t) = R(z)\boldsymbol{y}_r(t) - R_y(z^{-1})\boldsymbol{y}(t) - R_u(z^{-1})\Delta \boldsymbol{u}(t-1) \tag{6}$$

where $R(z)$, $R_y(z^{-1})$, $R_u(z^{-1})$ are regression matrices defined in [6], $\boldsymbol{y}_r = [y_r^{\tau}(t+1), \cdots, y_r^{\tau}(t+N)]^{\tau}$ is the MN dimensional reference vector. If we consider the cost function of multivariable GPC as

$$\min J = \min\Big\{ \sum_{j=1}^{N} [\boldsymbol{y}(t+j) - \boldsymbol{y}_r(t+j)]^{\mathrm{T}} P(j) [\boldsymbol{y}(t+j) - \boldsymbol{y}_r(t+j)] + \sum_{j=1}^{N_u} \Delta \boldsymbol{u}(t+j-1)^{\mathrm{T}} Q(j) \Delta \boldsymbol{u}(t+j-1) \Big\} \tag{7a}$$

and constraints

$$\begin{cases} \boldsymbol{u}_{\min} \leqslant \boldsymbol{u}(t+j-1) \leqslant \boldsymbol{u}_{\max}, & j = 1, \cdots N_u \\ \boldsymbol{y}_{\min} \leqslant \boldsymbol{y}(t+j) \leqslant \boldsymbol{y}_{\max}, & j = 1, \cdots N \\ \Delta \boldsymbol{u}_{\min} \leqslant \boldsymbol{u}(t+j-1) - \boldsymbol{u}(t+j-2) \leqslant \Delta \boldsymbol{u}_{\max}, & j = 1, \cdots N_u \\ \Delta \boldsymbol{y}_{\min} \leqslant \boldsymbol{y}(t+j) - \boldsymbol{y}(t+j-1) \leqslant \Delta \boldsymbol{y}_{\max}, & j = 1, \cdots N \end{cases} \tag{7b}$$

where P, Q are the weighting matrices that penalize the output error and control increment, respectively, then the above problem becomes a constrained multivariable GPC one. As in [6], predicted outputs $\hat{\boldsymbol{y}}(t+k)$ can be formulated by

$$\hat{\boldsymbol{y}} = \boldsymbol{s} + H\Delta \boldsymbol{U} \tag{8}$$

where $\hat{\boldsymbol{y}} = [\hat{\boldsymbol{y}}(t+1), \cdots, \hat{\boldsymbol{y}}(t+N)]$, $\Delta \boldsymbol{U} = [\Delta \boldsymbol{u}(t+1), \Delta \boldsymbol{u}(t+2), \cdots, \Delta \boldsymbol{u}(t+N_u-1)]^{\mathrm{T}}$, $\boldsymbol{s}$ and H are vector and matrix defined in [6]. After removing the constant terms, the complete optimization problem can be written in the following quadratic form:

$$\min_{\Delta U} J = \min_{\Delta U}\left\{ \frac{1}{2}(\Delta \boldsymbol{U})^{\mathrm{T}}(H^{\mathrm{T}}PH + Q)(\Delta \boldsymbol{U}) - \boldsymbol{E}^{\mathrm{T}}PH(\Delta \boldsymbol{U}) \right\} \tag{9}$$

subject to

$$C\Delta \boldsymbol{U} \leqslant \boldsymbol{l} \tag{9a}$$

where $\boldsymbol{E} = \boldsymbol{y}_r - \boldsymbol{s}$, C, $\boldsymbol{l}$ are constant matrix and vector using (7a) and (8). With constraints, the former problem can be easily solved by Quadratic Programming algorithm (QP) available in MATLAB Toolbox.

3.2 Multiple Model transformation

Consider an R-input M-output system. Divide it into M MISO systems. The global system can be described by M local models as in (1). Obviously, the obtained multiple linear models (1) can not be used as CARIMA structure model directly. However, by simple transformation, (1) can be reformulated into the required structure. Take the ith sub-model/rule of one MISO system as example,

$$R_i \text{ if } \boldsymbol{\varphi} \in v_i^T \text{ then } \Delta y^i = p_1^i \Delta\boldsymbol{\varphi}(1) + \cdots + p_d^i \Delta\boldsymbol{\varphi}(d) \tag{10}$$

where $i=1,2,\cdots,c$. An advantage of such an incremental form is that the identification of the offset term p_0^i is no longer necessary, which makes it easy to format (1) to CARIMA structure. At every instant, compute membership degree of each sub-model by (3), and integrate MISO systems to describe the global system as

$$\text{if } \boldsymbol{\varphi}^k \text{ then } \Delta y_k = \left(\sum_{i=1}^{c_k} \mu_i^k\, p_{k,1}^i\right)\Delta\boldsymbol{\varphi}^k(1) + \cdots + \left(\sum_{i=1}^{c_k} \mu_i^k p_{k,d_k}^i\right)\Delta\boldsymbol{\varphi}^k(d_k) \tag{11}$$

where $\boldsymbol{\varphi}^k(k=1,\cdots,M)$ represent generalized input vectors corresponding to M MISO system, y_k are M system outputs, c_k represents the number of sub-model/rules for M MISO systems, d_k are the dimension of each generalized input vector, μ_i^j represents the membership degree of the ith sub-model belonging to the jth MISO system$(j=1,\cdots,M)$, $\sum_{i=1}^{c_j}\mu_i^j = 1$, and p_{j,d_j}^i represents the d_ith parameter of the ith sub-model consequent belonging to the jth MISO system. Obviously, after the system model transformation, it is easy to convert (11) to (5) as

$$A(z^{-1})\Delta\boldsymbol{y}(t) = B(z^{-1})\Delta\boldsymbol{u}(t-1) \tag{12}$$

3.3 MMPC algorithm

After integrating multiple sub-models multiple sub-systems into a global system, we get a CARIMA structure LPV model, whose $A(z^{-1}), B(z^{-1})$ are dynamically obtained by fuzzy clustering method. For the above type system model, we can therefore use multivariable GPC algorithm presented in Section 3.1 to design the system multiple model predictive controller. That is, at each instant, combine the given multiple local models of each MISO through membership degrees, and calculate control increments using multivariable GPC algorithm based on the obtained CARIMA global model. The MMPC (Algorithm Ⅱ), shown in Fig. 1, can be organized as the following steps.

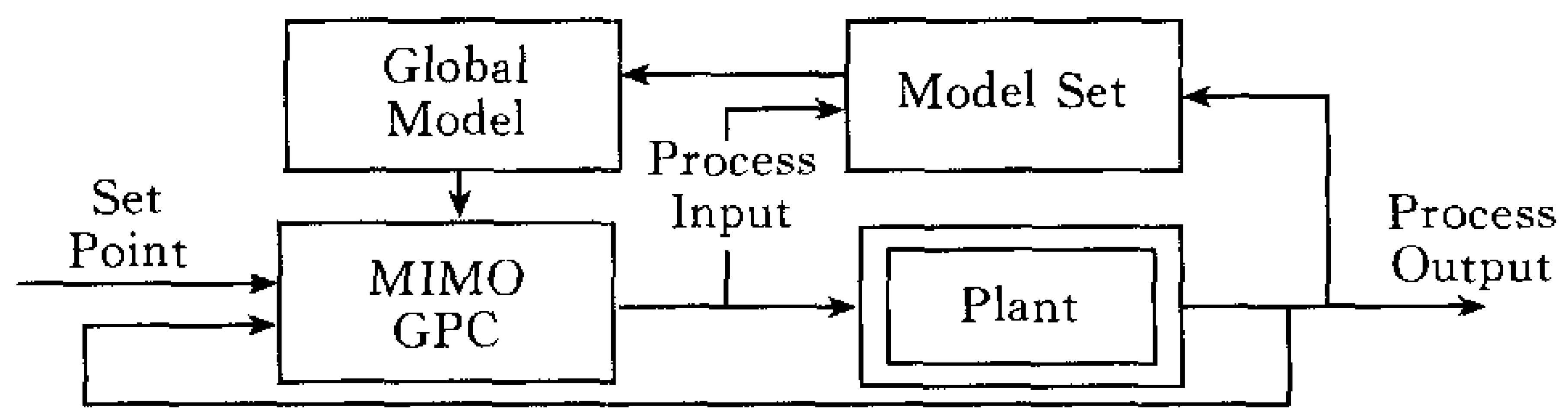

Fig. 1 Structure of MMPC

Step 1. Develop data set, and off-line design sub-models of each MISO system using Algorithm Ⅰ.

Step 2. Measure actual output $\boldsymbol{y}$, and compute membership degree of each sub-model belonging to each MISO system using $\boldsymbol{\varphi}^1 \sim \boldsymbol{\varphi}^M$ and equation (3).

Step 3. Design MIMO system global model using (11).

Step 4. Compute control increment $\Delta\boldsymbol{u}$ using multivariable generalized predictive control algorithm.

Step 5. Calculate system control output $\boldsymbol{u}=\boldsymbol{u}+\Delta\boldsymbol{u}$, and go to Step 2.

4 Performance analysis

4.1 Closed-loop steady-state analysis

From (6), the closed-loop feedback structure of multivariable GPC can be described as Fig. 2. [6] proved that the closed-loop system has zero steady-error for a given reference trajectory. And in static mode, the system is completely decoupled. These conclusions also hold for MMPC system. This section will consider its robustness stability with unmodeled uncertainty.

From Fig. 2, the transfer function from $\boldsymbol{y}_r(t)$ to $\boldsymbol{y}(t)$ can be written as

$$\boldsymbol{y}(t)=\frac{R(z)(Iz+R_u(z^{-1}))^{-1}\Delta^{-1}B(z^{-1})A^{-1}(z^{-1})}{I+(Iz+R_u(z^{-1}))^{-1}\Delta^{-1}B(z^{-1})A^{-1}(z^{-1})R_y(z^{-1})}\boldsymbol{y}_r(t)=\frac{FH_L}{I+H_L}\boldsymbol{y}_r(t)$$

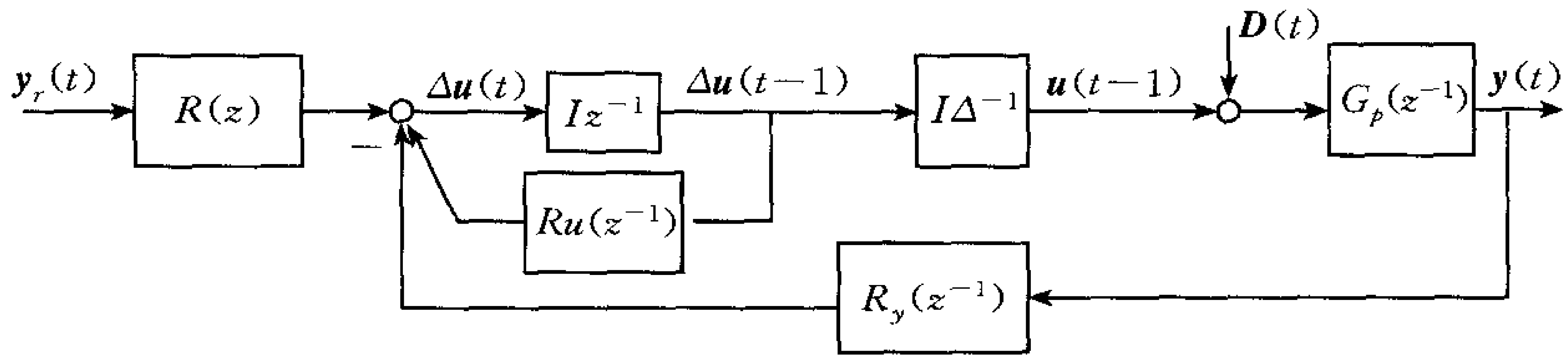

Fig. 2 Block diagram of the closed-loop system

where $H_L=\dfrac{B(z^{-1})R_y(z^{-1})}{\Delta(Iz+R_u(z^{-1}))A(z^{-1})}$, $F=\dfrac{R(z)}{R_y(z^{-1})}$. H_L is called the loop transfer function. Note that FH_L denotes the open-loop transfer function.

Lemma[7]. If the loop transfer function of the nominal system (i. e., the closed-loop system based on the model) and the true system are given by $\hat{H}_L(j\omega)$ and $H_L(j\omega)$, respectively, then stability of the closed-loop system is guaranteed if the nominal system and the process are stable and if the following condition is satisfied:

$$|H_L(j\omega)-\hat{H}_L(j\omega)|<|1+\hat{H}_L(j\omega)| \quad \forall\omega\geqslant 0 \tag{13}$$

For MMPC system, let the frequency type of $X(z^{-1})$ be $X(e^{-j\omega T})$. For simplicity, $X(e^{-j\omega T})$ as X, $e^{-j\omega T}$ as $\bar{\omega}$, where ω is angular frequency and T is the sampling period. Hence,

$$H_L=\frac{BR_y}{\Delta(I\bar{\omega}^{-1}+R_u)A}=H\frac{R_y}{\Delta(I\bar{\omega}^{-1}+R_u)} \tag{14}$$

$$\hat{H}_L=\frac{\hat{B}R_y}{\Delta(I\bar{\omega}^{-1}+R_u)\hat{A}}=\hat{H}\frac{R_y}{\Delta(I\bar{\omega}^{-1}+R_u)} \tag{15}$$

where H and $\hat{H}$ are the transfer functions of the process and model, respectively.

To robustness analysis, two types of modeling errors are often considered: additive and multiplicative modeling errors. By definition, the following relation between process and model transfer function exists:

$$H=\hat{H}+\varepsilon_a=\hat{H}(1+\varepsilon_m) \tag{16}$$

where ε_a and ε_m are transfer functions that represent the additive and multiplicative modeling errors, respectively. Rewriting (13) using (14) and (15) yields:

$$|H-\hat{H}|<|1+\hat{H}_L|\cdot\left|\frac{\Delta(I\bar{\omega}^{-1}+R_u)}{R_y}\right| \quad \forall\omega\geqslant 0 \tag{17}$$

By using (16) and (17), then

$$|\varepsilon_a| < |\bar{\varepsilon}_a| < \left|\frac{\Delta(I\tilde{\omega}^{-1} + R_u)\hat{A} + \hat{B}R_y}{\hat{A}R_y}\right| \quad \forall \omega \geqslant 0 \tag{18}$$

Similarly, we have

$$|\varepsilon_m| < |\bar{\varepsilon}_m| < \left|1 + \frac{\Delta(I\tilde{\omega}^{-1} + R_u)\hat{A}}{\hat{B}R_y}\right| \quad \forall \omega \geqslant 0 \tag{19}$$

where $|\bar{\varepsilon}_a|$ and $|\bar{\varepsilon}_m|$ are the upper bounds on $|\varepsilon_a|$ and $|\varepsilon_m|$, respectively. Hence, if the nominal system is stable and the process is stable, then the closed-loop system is stable if the additive /multiplicative modeling errors satisfy (18) /(19). Obviously, the right-hand sides of the above two relations are determined by the model and the design parameters of the MMPC controller. Hence, in order to guarantee stability of the closed-loop system, the MMPC controller design parameters must be chosen to satisfy the above conditions. Since the relation between R_u, R_y and the MMPC design parameters is quite complicated, it is hardly possible to explicitly present their relation to satisfy (18) or (19). However if we properly select design parameters, they can be satisfied. Therefore we have the following conclusion.

Theorem. If the nominal system and the process are stable and if modeling errors satisfy (18) or (19), then stability of the closed-loop MMPC system is guaranteed.

5 Simulation example

5.1 System description

Consider a pH process with three reaction streams: HNO_3, NaOH, $NaHCO_3$ and two output variables: liquid level h and pH[8]. Let F_a, F_b, F_{bf} correspond to three streams flow rates, respectively. The process can be regarded as a two-input(F_a, F_b) two output (h, pH) system, and the buffer stream NaHCO3 is considered to be a disturbance. Define the following input-output relations:

$$\hat{y}_h(t) = \Psi_h(F_a(t-1), F_b(t-1), F_{bf}(t-1), y_h(t-2), y_h(t-1)) \tag{20}$$

$$\hat{y}_{pH}(t) = \Psi_{pH}(F_a(t-1), F_b(t-1), F_{bf}(t-1), y_{pH}(t-2), y_{pH}(t-1)) \tag{21}$$

5.2 Multiple model description

Identify the above pH process using Algorithm I. Give the simulation conditions as $F_a(t)=16+4\sin(2\pi t/15)$, $F_b(t)=16+4\cos(2\pi t/25)$, $F_{bf}(t)=0.55+0.055\sin(2\pi t/10)$ The satisfactory clustering $c=6$. The model gives a good fit for pH and h, RMSEs of pH and h channels are 0.2161 and 0.0439, respectively, which are superior to those of SSOCPN method[8]. The model parameters and figure of modeling results are omitted due to the lack of space, see [9] for details.

5.3 MMPC for MIMO system

Corresponding to two MISO sub-systems, design proper GPC controller using Algorithm Ⅱ. The tuning parameters for MMPC controller were as follows:

$$N = 5,\ N_u = 2,\ P = \mathrm{diag}(0.1, 0.1),\ Q = \mathrm{diag}(0.01, 0.01).$$

Fig. 3 shows the good performance of unconstrained MMPC in response to set point changes in pH (9→5→6→7) and h (18→15→17→16) with different invariant disturbance $F_{bf}=0.055$ml/s and $F_{bf}=0.55$ml/s. The tests further demonstrate that the MMPC has zero steady-error for constant disturbance input, which was proved in Section 4.

With the performance of MMPC controller shown to be good for the unconstrained case, we wish to examine its effect with constraints. Given the expected operating condition of the process:

Output: $pH=7.0$, $h=14$cm

Constraints: $-1 \leqslant \Delta \boldsymbol{u}_i \leqslant 1$, $0 \leqslant \boldsymbol{u}_i \leqslant 15.8$ for $i=1,2$

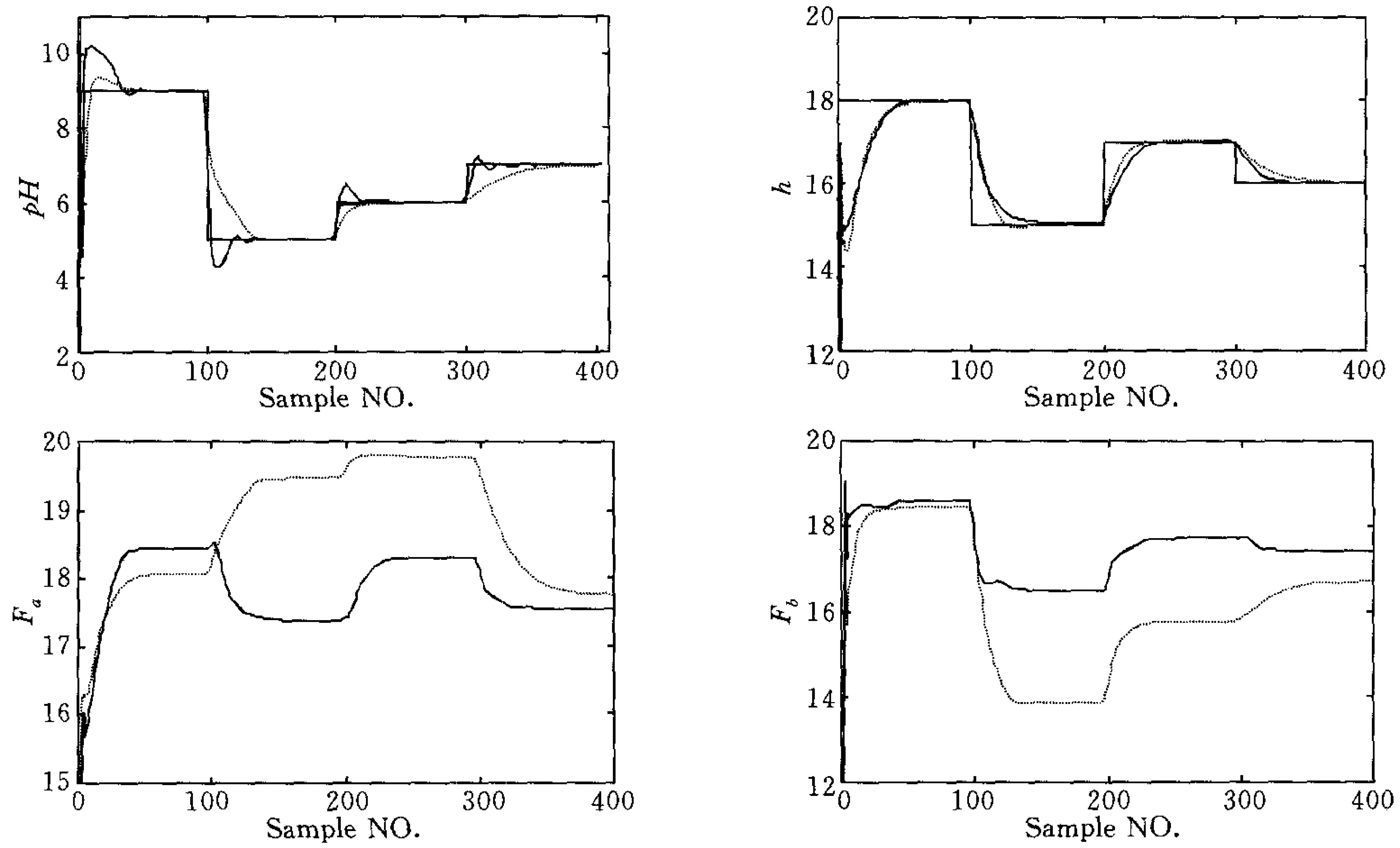

Fig. 3 MMPC control results of MIMO pH system (solid: $F_{bf}=0.055$ml/s; dotted: $F_{bf}=0.55$ml/s)

the results are shown as Fig. 4, where it is observed that the MMPC still have good performance within the constraints. It also shows that the constraints are satisfied in the given constraint domain.

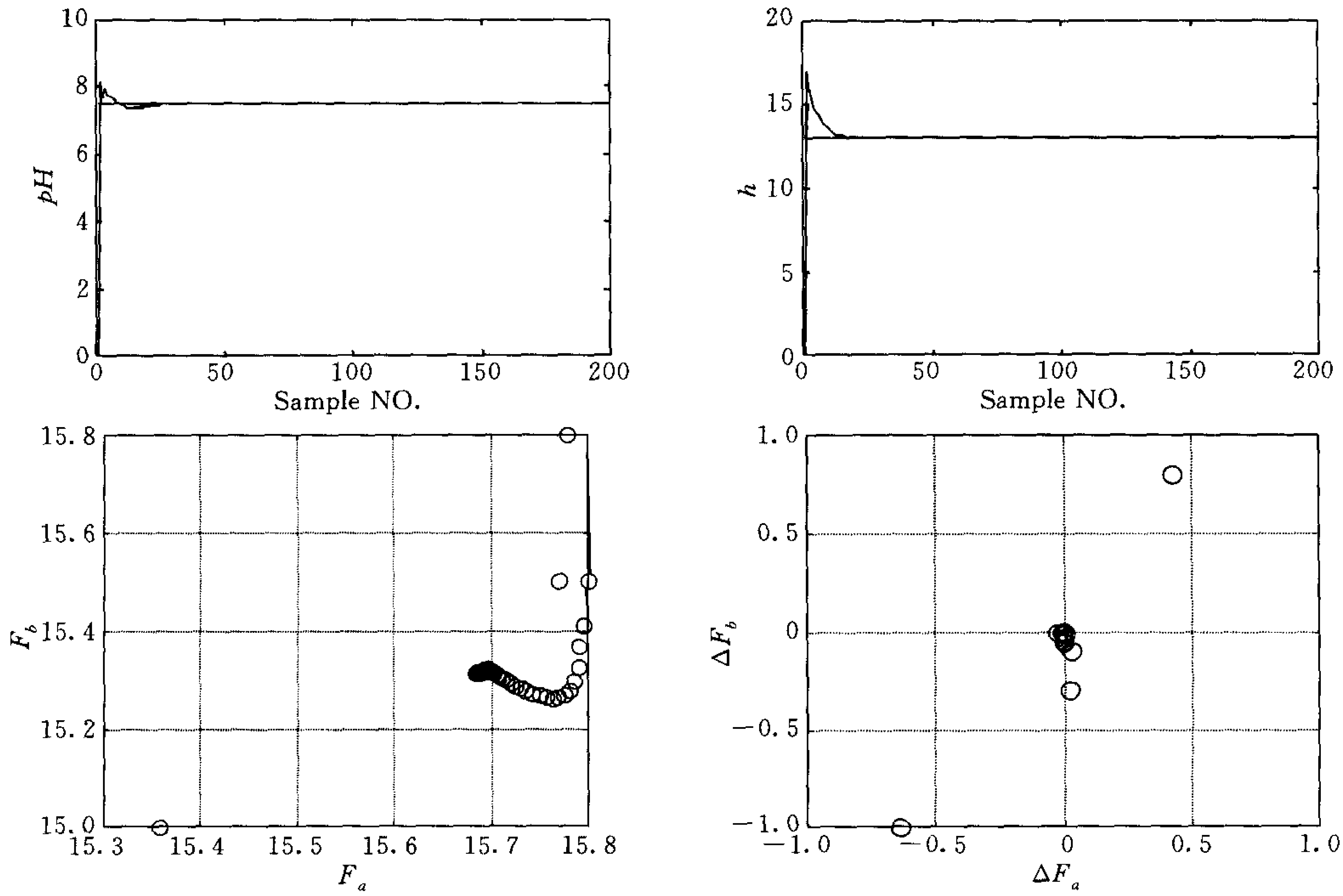

Fig. 4 Constrained MMPC control results

6 Conclusion

This paper gives a technique to use multi-model structure for modeling nonlinear systems with an effective way to determine satisfactory number of models. It also presents unconstrained and constrained MMPC of nonlinear MIMO processes using these models, and analyzes the robust stability conditions. MMPC is a novel strategy to solve NMPC problems using multiple models for a class of industrial processes with wide operating regimes. It is worth attention that the structure of multiple model control does not limit to generalized predictive control only, and with proper modification, other linear control algorithms can also be adapted to multiple model control framework. The feasibility of the proposed approach is demonstrated by simulation case study of an MIMO neutralization system involving pH and level control.

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MIMO 系统的多模型预测控制

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摘 要 针对非线性多变量系统提出一种多模型预测控制（MMPC）策略. 首先给出一种多模型辨识方法，利用模糊满意聚类算法将复杂非线性系统划分为若干子系统，并获得多个线性模型，通过模型变换得出全局系统模型，接着对全局 MIMO 系统设计 MMPC，并进行了系统的性能分析，最后以 pH 中和过程为例，通过仿真研究验证了辨识和控制算法的有效性.

关键词 MIMO 系统，多模型，模型预测控制（MPC），模糊满意聚类，pH 中和过程

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