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An Active Fault-Tolerant MPC for Systems with Partial Actuator Failures*

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Abstract— **An active fault-tolerant model predictive control (FTMPC) scheme for systems with partial actuator failures is presented. The faulty system is first transformed into a linear system with input uncertainties, and then a minimum variance unbiased (MVU) filter is introduced to estimate both the state and the input uncertainties. To obtain a reliable fault information, a closed loop identification based fault detection and isolation approach is proposed. Offset-free control can be achieved by using the proposed FTMPC in the presence of partial actuator faults and/or unmeasured disturbances. Several example are given to demonstrate the effectiveness of the proposed approach.**

I. INTRODUCTION

Practical systems are invariably subject to faults [1]. Actuator faults are ubiquitous in process industries, and may arise from damages of bearings, defects in gears, corroded plug or seat, ruptured diaphragm, ageing effects, etc. The effects of the actuator faults can easily propagate to other control loops and degrade the overall closed loop performance of the process, and in some cases drive the system to instability. It is therefore of practical interest to design control systems which can tolerate some actuator failures.

In the past two decades, remarkable progress have been made in fault tolerant control (FTC). We can broadly classify the FTC methods into two categories [2]: the passive approaches and the active approaches. In the passive approaches, the control algorithms (e.g. robust control) are designed to be able to ensure desired system stability and asymptotic tracking properties, despite the presence of uncertain failures. However, as the number of possible faults and the degree of system redundancy increases, the conservativeness and the online computational costs need to be carefully considered with respect to practical implementations. In active approaches, faults detection and isolation can be achieved by the fault diagnosis techniques, and the control law is then adaptively changed along with faults. Therefore, compared with the passive approaches, active approaches are more attractive in practice.

Fault detection and isolation (FDI) plays an important role in the design of an active FTC system. Reliable fault information provided by the FDI detector can be directly used by the decision makers to achieve fault accommodation or reconfigurable control. A great deal of theoretical work is therefore devoted to the design of FDI schemes, and this can be found in several review papers [3], [4], [5], [6] and references therein. Among the active approaches, data driven and observer based approaches are two important research areas. Data driven based approaches diagnose the possible faults by using principal component analysis (PCA), Fisher discriminant analysis, partial least squares analysis, canonical correlation analysis, and so on [7]. Observers are adopted to estimate system faults by using residuals in the design of observer based FTC systems [4], [8], [9]. By treating faults as the unknown inputs, unknown input observers are suitable for FDI, especially for detecting actuator faults.

Fault-tolerant model predictive control (FTMPC) has drawn considerable attention with the development of both MPC and FDI techniques. To the best of our knowledge, Maciejowski first studied the FTC problems in the MPC framework [10]. Data driven based FDI approaches are naturally integrated into the design of FTMPC. Pranatyasto et al. proposed a PCA based approach to detect, identify, and reconstruct faulty sensors in a simulated fluid catalytic cracking unit [11]. Chilin et al. focused on the design of a model based FDI method, and then FTC switching rules are proposed based on the backup control configuration to handle actuator faults of the distributed MPC system [12]. Prakash et al. studied an active on-line FTMPC scheme by integrating state space formulation of MPC with the FDI method based on generalized likelihood ratios. Deshpande et al. proposed a nonlinear version of the generalized likelihood ratio based FDI scheme [13] , and an active FTMPC (AFTMPC) scheme is developed that makes use of the fault/failure location and magnitude estimates generated by the FDI [14]. Zhang et al. presented a non-minimal state space model based predictive fault-tolerant control scheme for batch processes with partial actuator faults [15]. Bavili et al. studied a two optimal observers based FDI approach to estimate the plant states and loss of effectiveness factor of actuators and sensors [16]. Chilin et al. proposed a residual based FDI approach in a distributed MPC system, and then optimal operation point is recalculated according to the detected faults [17]. Prakash et al. proposed a residual based FDI approach to detect the actuator faults, and then a compensation strategy (supervisory system) which uses the information provided by the FDI to appropriately modify the controller as well as the model used in FDI [18].

In the existing observer based AFTMPC approaches, FDI is usually achieved by analyzing the residuals of process outputs to eliminates the effects of control signals and also the the effects of disturbances and/or model uncertainties on the residuals generated [9]. In certain cases faults might be

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detected from residuals as shown in the above mentioned approaches. However, residuals are the results of a variety of factors, e.g. actuator faults, external disturbances, and/or model-plant mismatch. It is therefore difficult to identify the possible faults just from the online residuals. On the other hand, the residuals are usually obtained from steady-state operation data, which contains very limited dynamic information of the process. It is thus difficult to achieve FDI just from steady-state operation data, and wrong fault information may be obtained by the decision makers. Therefore, false alarms and/or improper control laws caused by the wrong fault information will degrade the control performance and/or economic performance.

In this paper, a closed loop fault identification based FTMPC for systems with partial actuator faults is proposed. First, the faulty system is transformed into a time-varying linear system with input uncertainties, and then a minimum-variance unbiased (MVU) filter [19] is introduced to estimate both the state and the input uncertainties. To obtain a reliable estimate of the actuator faults, a closed loop fault identification based FDI approach is proposed. This enables us to tackle the problems of controlling systems disturbed simultaneously by actuator faults and unmeasured disturbances. Prior knowledge of the actuator faults is not required because the faults are treated as input uncertainties, which can be detected online by the MVU filter. The proposed approach is therefore applicable for simultaneously handling unmeasured disturbances and actuator faults. We show that offset-free control can be achieved in the presence of partial actuator faults and unmeasured disturbances by using the proposed approach.

The rest of this paper is organized as follows. In Section 2, the fault tolerant control problem is presented. In Section 3, we first show that a faulty nonlinear system can be transformed into a time-varying linear system with input uncertainties, and then an MVU filter is introduced to estimate both the state and the input uncertainties. Section 4 addresses the design of the AFTMPC, and offset-free tracking performance of the proposed scheme is analyzed. An illustrative example is provided in Section 5 to demonstrate effectiveness of the proposed method. At last, a brief conclusion is given in Section 6.

II. Problem Formulation

A typical MPC system is shown in Fig.1, in which $r \in \mathbb{R}^{n_y}$, $u \in \mathbb{R}^{n_u}$, $n \in \mathbb{R}^{n_u}$, and $y \in \mathbb{R}^{n_y}$ are the reference, the control input, the actuator output, and the measured output vector, respectively. In the absence of actuator failures the

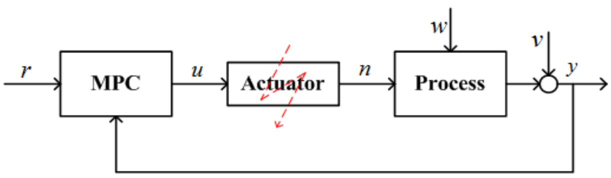

Fig. 1. MPC system configuration.

outputs of the actuator should be equal to the inputs, $n = u$. In this paper we use the following linear discrete-time model to describe local or global dynamics of the process:

$$\begin{cases} x_{k+1} = Ax_k + Bu_k + w_k \\ y_k = Cx_k + v_k \end{cases} \tag{1}$$

where x_k is the state variable, w_k and v_k are process noise and measurement noise with known covariances $Q_k = \mathbb{E}(w_k w_k^T)$ and $R_k = \mathbb{E}(v_k v_k^T)$. Typically, the measurement noise covariance R_k can be derived from the properties of the sensors used.

As mentioned in Section 1, there are errors caused by defects in actuators in practice. Therefore, practical systems are invariably subject to actuator faults. There are three main cases of actuator faults considered in practice, i.e., partial actuator failure, the actuator outage and the actuator stuck. Reconfigurable control strategy is required in the presence of the first two failures, since the output of an actuator stay at a constant value. Therefore, partial actuator failure is widely considered both in academic research and in practice. In this paper, the following partial actuator failure model is used:

$$n_k = \begin{bmatrix} f_{1,k} & 0 & \cdots & 0 \\ 0 & f_{2,k} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & f_{n_u,k} \end{bmatrix} u_k = F_k u_k, \tag{2}$$

where F_k is a diagonal matrix, and $0 < f_{i,k} \leq 1, (i = 1, 2, \cdots, n_u)$. Considering actuator faults are often uncertain in time, value, and pattern, here we assume that F_k is not known.

This paper aims to design an active fault-tolerant MPC for system (1) with unknown actuator faults (2) to track a specified piece-wised reference r without steady-state tracking error (offset-free control).

III. Model Transformation and Fault Detection

A. Model transformation

Substituting (2) into the linear model (1), we can obtain the following linear model with unknown input:

$$\begin{cases} x_{k+1} = Ax_k + BF_k u_k + w_k \\ y_k = Cx_k + v_k \end{cases}. \tag{3}$$

Since F_k is unknown, it is difficult to design a controller directly according to model (3). If we define a new variable d_k as

$$d_k = (F_k - I)u_k \tag{4}$$

Model (3) can then be expressed as

$$\begin{cases} x_{k+1} = Ax_k + Bu_k + Bd_k + w_k \\ y_k = Cx_k + v_k \end{cases} \tag{5}$$

It is clear that the unknown actuator faults are transformed into input uncertainties d_k. From (2), and considering F_k is a diagonal matrix, we know that there is a one-to-one relationship between u_k and n_k. This means that there exists a unique d_k for any given F_k. After the transformation, we'll seek for a proper filter for system (5) to estimate both x_k and d_k, and this will be discussed as follows.

B. MVU filter design for fault detection

As previously mentioned, actuator faults are often uncertain in time, value, and pattern, that is, it is unknown when, how much, and which actuators fail. It is thus difficult to specify a model for d_k or F_k. Therefore, optimal filtering cannot be guaranteed when using traditional Kalman filters. In this section, linear MVU filtering techniques [19] will be introduced to estimate system state and the input uncertainties. A complete treatise on the MVU filter is beyond the scope of this study. Here the main results are briefly recounted.

Throughout the study, we assume that (C, A) is observable, $(A, Q_k^{1/2})$ is stabilizable, the initial state x_0 is of mean $\hat{x}_0$ and covariance P_0, and is independent of v_k for all k. The following recursive filter is given for system (5):

$$\begin{cases} \hat{x}_{k|k-1} = A\hat{x}_{k-1} + Bu_{k-1} \\ \hat{d}_{k-1} = L_d(y_k - C\hat{x}_{k|k-1}) \\ \hat{x}_k^* = \hat{x}_{k|k-1} + B\hat{d}_{k-1} \\ \hat{x}_k = \hat{x}_k^* + L_x(y_k - C\hat{x}_k^*) \end{cases}. \tag{6}$$

To obtain an unbiased estimate of d_{k-1}, the condition

$$L_dCB = I \tag{7}$$

must be satisfied[19], which is equivalent to $\mathrm{rank}(CB) = n_u$.

C. Closed loop fault identification

As mentioned before, FDI is often achieved by analyzing residuals of process outputs online in the existing observer based FTMPCs. There are two facts that may hamper the effectiveness of the residual based approaches. The first is that the residual is a compound information related to faults, disturbances, and/or model-plant mismatch. And the second is that only steady-state data is obtained if the process operates in the steady-state, which contains very limited dynamic information of the process. It is therefore difficult to identify the possible faults just from the online residuals.

To obtain a reliable fault information, a closed loop identification based approach is proposed in this part, and the basic idea is shown in Fig. 2. Here, closed-loop identification means that the identification data are collected from a closed-loop test where the underlying process is fully under feedback control.

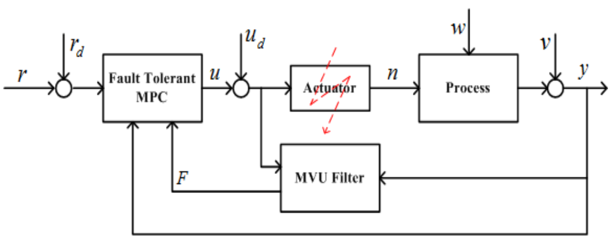

Fig. 2. Closed loop fault detection and identification.

1) Experiment Design: There are two common ways to design a closed loop experiment. The first one is to add excitation signals to the control inputs, and the second one is to add excitation signals to the references. As shown in Fig. 2, r_d and u_d are pseudo random binary (PRBS) or generalized binary noise (GBN) signals [20] which are used as excitation signals for fault identification. For convenience of implementation, only one excitation signal is used (r_d or u_d) in practice. And the two approaches are routine procedures in system identification area [21].

2) Fault Identification: Both of the above mentioned approaches estimate the potential faults from u and y directly or indirectly. We need find a trade-off between achieve good nominal transient performance as well as accurate estimates of the faults. We are in some ?dual control dilemma? where the two goals conflict with each other. The problem can be solved in the dual control framework (see [22], [23] and references therein). However, the computational burden should be carefully considered. To reduce the computational burden, here we propose a heuristic approach to solve the above problem.Frank1997

Considering equation (4), the ith actuator fault at time instant k can be calculated as $\hat{f}_{i,k} = \hat{d}_{i,k}u_{i,k}^T(u_{i,k}u_{i,k}^T)^{-1}+1$, where $i = 1, \cdots, n_u$. In fact, the estimated value of $\hat{f}_i$ will potentially affected by external disturbances and/or model uncertainties. To overcome the above problems, a estimated disturbance sequence $\mathbb{D}_{i,N} = [\hat{d}_{i,k-1}, \cdots, \hat{d}_{i,k-N}]$ and a control sequence $\mathbb{U}_{i,N} = [u_{i,k-1}, \cdots, u_{i,k+N}]$ are used to estimate the actuator faults in the least-squares sense:

$$\hat{f}_i = \mathbb{D}_{i,N}\mathbb{U}_{i,N}^T(\mathbb{U}_{i,N}\mathbb{U}_{i,N}^T)^{-1} + 1 \tag{8}$$

where N is the length of the data.

IV. Active Fault-Tolerant MPC Design

There are three main parts in current formulations of an MPC: a state estimator, a dynamic constrained regulator, and a target calculator. A basic block diagram for a linear MPC scheme is shown in Fig. 3.

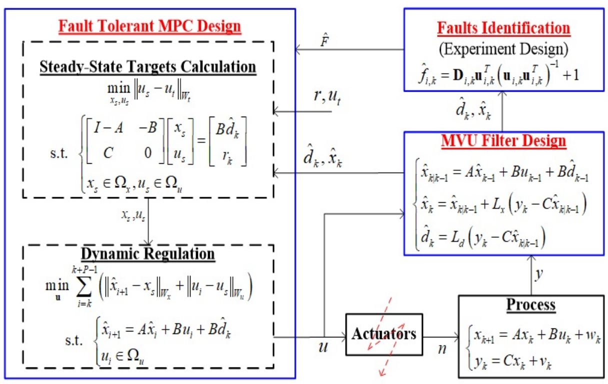

Fig. 3. Configuration of the proposed AFTMPC

r and u_t are the set-points for the output and the input, x_s and u_s are the calculated state and input, $\hat{x}$ and $\hat{d}$ are the estimated state and input uncertainties, Ω_x, Ω_u, and Ω_y

are the constraints of the state, the input, and the output, respectively.

A. Target calculation

To guarantee zero offset steady-state, a target calculator is used to calculate the steady-state targets x_s and u_s for the regulator. x_s and u_s can be determined from the following quadratic program:

$$\begin{aligned} &\min_{x_s,u_s} \quad (u_s-u_t)^T R_s (u_s-u_t) \\ &\text{s.t.} \begin{cases} \begin{bmatrix} I-A & -B \\ C & 0 \end{bmatrix} \begin{bmatrix} x_s \\ u_s \end{bmatrix} = \begin{bmatrix} B\hat{d}_k \\ r_k \end{bmatrix}, \\ x_s \in \Omega_x, \\ u_s \in \Omega_u. \end{cases} \end{aligned} \tag{9}$$

where $r \in \Omega_y$, u_t is the desired value of the input at steady state provided by the real-time optimization (RTO) layer, and R_s is a positive definite weighting matrix for the deviation of the input vector from the target input u_t.

If there are insufficient degrees of freedom, the following quadratic program can be used to track the output target in a least squares sense:

$$\begin{aligned} &\min_{x_s,u_s} \quad (r_k - Cx_s)^T Q_s (r_k - Cx_s) \\ &\text{s.t.} \begin{cases} \begin{bmatrix} I-A & -B \end{bmatrix} \begin{bmatrix} x_s \\ u_s \end{bmatrix} = B\hat{d}_k, \\ x_s \in \Omega_x, \\ u_s \in \Omega_u. \end{cases} \end{aligned} \tag{10}$$

where r_k is the set-points for the output, $y_{min} \le r_k \le y_{max}$, $\hat{d}_i = \hat{d}_{k-1}$ $(i = k, k+1, ..., k+N-1)$, and Q_s is a positive definite weighting matrix for the output tracking error.

Here, only partial actuator faults are considered. When other fault patterns occur (e.g., actuator outage and actuator stuck), there may be no extra freedom to obtain a unique target. One possible remedy for this problem is to use the reconfigurable control schemes [1], [24].

B. Dynamic regulation

The regulation problem can be formulated by the following quadratic programming with constraints and penalties ($W_x > 0$ and $W_u > 0$):

$$\begin{aligned} &\min_{\boldsymbol{U}_P} \sum_{i=k}^{k+P-1} (\|\hat{x}_{i+1} - x_s\|^2_{W_x} + \|u_i - u_s\|^2_{W_u}) \\ &\text{s.t.} \begin{cases} \hat{x}_{i+1} = A_k \hat{x}_i + B_k u_i + B_k \hat{d}_i \\ u_i \in \Omega_u \end{cases} \end{aligned} \tag{11}$$

where $\boldsymbol{U}_P = [u_k, \cdots, u_{k+P-1}]$, and the estimated input $\hat{d}_i$ is assumed to be a constant in the prediction horizon $\hat{d}_i = \hat{d}_{k-1}$ $(i = k, k+1, ..., k+P-1)$. Here, the control horizon and the prediction horizon are assumed to be the same number P.

C. Offset-free tracking

First, we define the estimated output $\hat{y}_k = C\hat{x}_k$ and tracking error $e_k = y_k - \hat{y}_k = C(I - L_x C)(A\tilde{x}_{k-1} + B\tilde{d}_{k-1} + w_{k-1}) - (I - CL_x)v_k$, where $\tilde{d}_{k-1} = d_{k-1} - \hat{d}_{k-1}$. Since $\hat{x}_{k-1}$ and $\hat{d}_{k-1}$ are unbiased estimates of x_{k-1} and d_{k-1}, we can obtain

$$\begin{aligned} \mathbb{E}(e_k) =& C(I - L_x C)(A\mathbb{E}(\tilde{x}_{k-1}) + B\mathbb{E}(\tilde{d}_{k-1}) \\ &+ \mathbb{E}(w_{k-1})) - (I - CL_x)\mathbb{E}(v_k) = 0 \end{aligned} \tag{12}$$

where $\mathbb{E}(*)$ is the expectation value of $(*)$. This means a zero offset output estimation can be obtained for every sample time.

The offset-free tracking problem will be addressed in the proposed framework. Before the discussion, three more assumptions are required.

Assumption 1. The target problem (9) has a unique feasible solution, and the regulation problem (11) is feasible for all k.

The target problem (9) has a unique solution means that the target tracking goal can be achieved under the fault situations. Once the target is not achievable, (10) can be used to calculate the output target in a least squares sense.

Assumption 2. The reference and actuator fault are asymptotically constants ($r_k \to r_\infty$ and $F_k \to F_\infty$), and the closed-loop system reaches a steady state ($x_k \to x_\infty$, $u_k \to u_\infty$ and $y_k \to y_\infty$).

It is well known that offset-free control cannot be achieved in the stochastic framework. Here only the deterministic case ($Q_k \approx 0$ and $R_k \approx 0$) is considered. A very simple proof for offset-free control for system (5) is given in the following theorem.

Theorem 1. Consider system (**??**) with unknown actuator faults F_k described by (2), the MVU filter (6), and MPC (9) and (11), if assumptions 1-3 are satisfied and the unbiasedness condition (7) holds, then offset-free nominal tracking ($y_\infty \to r_\infty$) can be achieved.

Proof. Because the closed-loop system reaches steady state and the unbiasedness condition holds, unbiased estimation of x_k and d_k can be obtained from the MVU filter (6). From equation (4), there is a one-to-one relationship between d and F, and this means that $\hat{d}_k \to d_\infty$ along with $F_k \to F_\infty$. Therefore, we have $\hat{x}_\infty = x_\infty$ and $\hat{F}_\infty = F_\infty$. The target problem (9) has a unique feasible solution implies $C_k x_s = r_\infty$ and $x_s = x_\infty$. On the other hand, from (12) we can obtain $y_\infty = \hat{y}_\infty = C_k \hat{x}_\infty$. This means the predicted output $\hat{y}_\infty$ is equal to the real output y_∞ at the steady state, i.e. $y_\infty = \hat{y}_\infty = r_\infty$. Therefore, at steady-state we get the offset-free stabilization, which completes the proof. □

It should be noted that unmeasured disturbances and unmodeled dynamics can also be lumped into the term d_k in the above discussions. If $d_k \to d_\infty$, offset-free control can also be achieved, and the proof is similar to that of Theorem 1.

V. Illustrative Examples

A two-input-two-output linear time-invariant model is given by the following equations:

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \frac{1}{5s+1} & \frac{2}{6s+1} \\ 0 & \frac{2s+1}{(3s+1)(s+2)} \end{bmatrix} \begin{bmatrix} n_1 \\ n_2 \end{bmatrix}$$

where the fault matrix F is given as $[0.4, 0; 0, 0.8]$. A minimal state-space realization of the linear dynamic model (discrete time with a sampling time of 1 second) is obtained in the following tests. MPC parameters are chosen as: $W_x = I$ and $W_u = I$, and the prediction horizon and the control horizon are assumed to be the same number 20. The filter is initialized as: $Q_k \approx 0$, $R_k \approx 0$, and $P_0 = 0$.

A. *Offset-free tracking*

Here we consider the unconstraint case. As shown in Theorem 1, offset-free control can be achieved if assumptions 1-3 are satisfied in the presence of partial actuator faults. Two independent GBN signals are applied at the reference simultaneously. The average switch times of GBN signals are set about 10 of the settling time of the plant which is 50s in our case. The amplitudes are chosen as 0.5 and 0.2. The test results are shown in Fig. 4. It is clear that system outputs can track the reference without offsets in the presence of actuator faults.

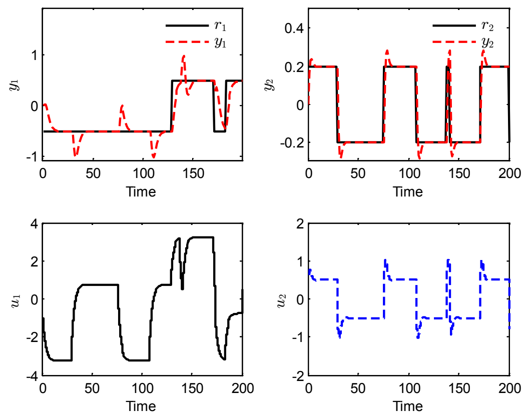

Fig. 4. Offset-free tracking performance.

B. *Online faults identification*

Although offset-free control can be achieved in the presence of partial actuator faults, it is of practical interest to identify which actuator is fault, and how serious is the problem. In this part, we first examine the proposed closed loop FDI approach under the nominal case, and then we check the model plant mismatch case.

1) Nominal case: Similar to the above test, two independent GBN signals with amplitudes 0.2 and 0.1 are applied at the reference simultaneously. After 200 seconds, the two actuator faults can be calculated from (8). The estimated value of both f_1 and f_2 are 0.4110 and 0.6244, which are very closed to the real faults (0.4 and 0.6).

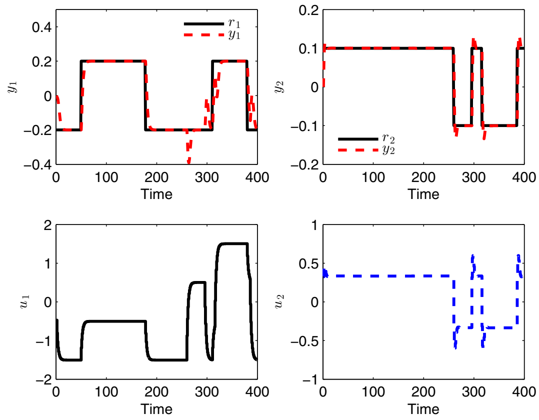

Fig. 5. Closed loop FDI under the nominal case.

2) Model mismatch case: In this part, we examine the proposed closed loop FDI approach in the presence of model mismatch which is inevitably encountered in practical applications. We assume that the process model is changed as follows.

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \frac{1.5}{s+1} & \frac{1.5}{3s+1} \\ 0 & \frac{0.5}{2s+1} \end{bmatrix} \begin{bmatrix} n_1 \\ n_2 \end{bmatrix}$$

Note that the new model is very different from the original one, the comparison of the two models is shown in Fig. 6. The test procedure is the same as the nominal case, and the results are shown in Fig. 7. And the estimated value of the actuator faults are 0.4222 (real value is 0.4) and 0.6348 (real value is 0.6).

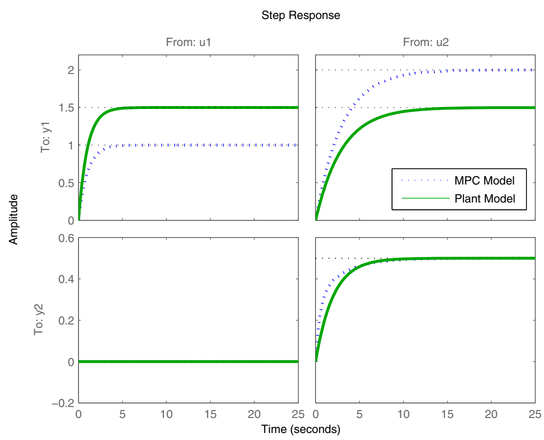

Fig. 6. Comparison of the internal model of MPC and the process model.

From the above tests, it is shown that the proposed FDI approach can provide a reliable fault information, and this is helpful to the design of the FTMPC.

VI. Conclusions

The design of an offset-free MPC for systems with partial actuator failures is discussed in this paper. The faulty

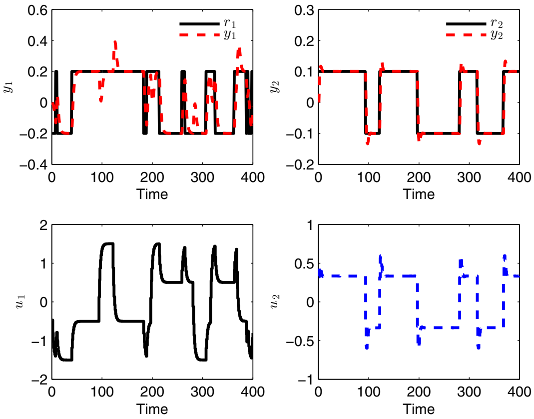

Fig. 7. Closed loop FDI under the model mismatch case.

system is first transformed into a linear model with input uncertainties. Using this transformation, prior knowledge of the actuator faults is not required. An MVU filter is then introduced to estimate both the states and the input uncertainties. And the actuator faults can be identified from the estimated input uncertainties. We have shown that offset-free control can be achieved in the presence of actuator faults and unmeasured disturbances. Tracking performance using this approach is often comparable with traditional approaches, and the proposed approach performs better in accommodating faults and in rejecting unmeasured disturbances.

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