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FAULT-TOLERANT CONTROL FOR CONSTRAINED LINEAR SYSTEMS BASED ON MPC AND FDI

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Abstract. This paper considers fault-tolerant control (FTC) for constrained linear systems subject to partial actuator failures. An active fault-tolerant control scheme based on model predictive control (MPC) and fault detection and isolation (FDI) is proposed. The FDI module using a two-stage Kalman filtering algorithm provides simultaneous control parameter and state estimation, which are used to modify the MPC formulation such as internal model to accommodate partial actuator failures. The most important advantage of the scheme is that partial actuator failures and input constraints can be dealt with simultaneously. Simulation results show the effectiveness of the proposed method.

Key Words. Fault-tolerant control, model predictive control, fault detection and isolation.

1. Introduction

Modern control systems are becoming more and more complex due to high performance requirements of modern industries. At the same time, component failures such as actuator failure, sensor failure and controller failure are inevitable. Faults may change dynamics, lead to performance degradation, and even result in instability. So it is not trivial to consider fault tolerance in control system design. A fault-tolerant control system is a control system that possesses the ability to accommodate for system failures automatically and to maintain overall system stability and acceptable performance in the event of component failures [19].

Faut-tolerant design approaches can be broadly classified into two types: the passive approach such as robust fault accommodation approach [1][2] etc., and the active approach such as eigenstructure assignment [3]; multiple model [4][5]; adaptive approach [6][7]; pseudo-inverse [8]; and model following [9] etc. In the passive approach, the same controller is used throughout normal and fault cases, and several performance indexes such as H_∞, H_2 and cost functions mainly based on algebraic Riccati equation (ARE) or linear matrix inequality (LMI) methods can be used to describe the performances of closed-loop systems with fixed controller gains. On the other hand, a fault-tolerant control system based on active approach can compensate for faults either by selecting a pre-computed control law or by synthesizing a new control strategy on-line. A typical approach for fault compensations is based on fault detection and isolation subsystems [8][9]. This paper only considers an active fault-tolerant control design.

It is readily appreciated that almost all real world control systems have an associated set of constraints; for example, inputs always have maximum and minimum

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values and states are usually required to lie within certain ranges [15]. In addition, when some actuators fail, to achieve the control objectives such as tracking, more demands are placed on other healthy actuators, which can lead to actuator saturations and state limit violations. Therefore, it is of great interest to take into account constraints such as input constraints in fault-tolerant control design. However, there are few results in the open literature, to the authors' knowledge. In this paper, we present some initial results on the fault-tolerant control for constrained linear systems against partial actuator failures.

There are two popular approaches for designing non-linear controllers for linear systems with constraints: anti-windup and MPC. Here, we use the MPC technique as the basic control strategy to deal with constraints. It is well known that, MPC is a form of control in which the current control action is obtained by solving on-line, at each sampling instant, a finite horizon open-loop optimal control problem, using the current state of the plant as the initial state; the optimization yields an optimal control sequence and the first control in this sequence is applied to the plant [14]. An important advantage of MPC is its ability to handle hard constraints on controls and states. In addition, MPC has a degree of implicit fault-tolerance capability.

In this paper, an active fault-tolerant control scheme based on combining MPC with FDI is designed to accommodate partial actuator failures of constrained linear systems. The FDI module based on the two-stage Kalman filtering algorithm in [17]-[19] is used to estimate the reduction of control effectiveness and the state. The fault information provided by FDI module is then used to modify the MPC formulation such as internal model to enhance the fault tolerance capability. And the state estimation can also be used by the MPC formulation if the state is unmeasurable. The proposed FTC scheme can apply to industrial processes, especially chemical processes, where constraints are inevitable. An example is given to illustrate the effectiveness of the proposed approach.

The main contributions of this paper are: 1) constraints and actuator failures are dealt with simultaneously in the fault-tolerant control design; 2) an FDI scheme based the two-stage Kalman filtering algorithm is explicitly given to provide MPC formulation with fault information.

The rest of the paper is organized as follows. Section 2 gives an introduction of the MPC scheme. Section 3 shows the fault-tolerance capability of the MPC formulation and the necessity of an FDI module to diagnose the faults. Section 4 is the main result of this paper, which gives an FDI scheme based on the two-stage Kalman filtering algorithm and the fault-tolerant control scheme based on MPC and FDI. Section 5 gives an example to illustrate the effectiveness of the proposed method. Finally, conclusions are given in Section 6.

2. Model Predictive Control

Model predictive control has become the accepted standard for complex constrained multivariable control problems in the process industries. At each sample time, starting at the current state, an open-loop optimal control problem is solved over a finite horizon. At the next time step, the computation is repeated starting from the new state and over a shifted horizon, leading to a moving horizon policy. The solution relies on a linear dynamic model, respects all input and output constrains, and optimizes a quadratic performance index [12]. MPC is able to handle control problems where off-line computation of a control law is difficult or impossible, such as multivariable plants. It is also one of the few control methods to handle constraints including input constraint, state constraint and output constraint which often occur in the process industries.

Consider the problem of regulating to the origin the discrete-time linear time invariant system

$$\left\{ \begin{array}{l} x_{k+1} = Ax_k + Bu_k \\ y_k = Cx_k \end{array} \right. \tag{1}$$

while fulfilling the constraints

$$y_{\min} \leq y_k \leq y_{\max},\ u_{\min} \leq u_k \leq u_{\max} \tag{2}$$

at all time instants $k \geq 0$, where $x_k \in R^n, u_k \in R^m$, and $y_k \in R^p$ are the state, input and output vectors, respectively, $y_{\min} \leq y_{\max}(u_{\min} \leq u_{\max})$ are $p(m)$-dimensional vectors, and the pair (A, B) is stabilizable.

Model predictive control solves such a constrained regulation problem in the following way [12]. The optimization problem

$$\min_{u_0,\cdots,u_{N_u-1}} \sum_{k=0}^{N_y-1} [x_k^T Q x_k + u_k^T R u_k] + x_{N_y}^T P x_{N_y} \tag{3}$$

subject to :

$$y_{\min} \leq y_k \leq y_{\max},\ k = 1, \ldots, N_c, \tag{4}$$

$$u_{\min} \leq u_k \leq u_{\max},\ k = 1, \ldots, N_c, \tag{5}$$

$$x_{k+1} = Ax_k + Bu_k,\ k \geq 0, \tag{6}$$

$$y_k = Cx_k,\ k \geq 0, \tag{7}$$

$$u_k = Kx_k,\ N_u \leq k < N_y, \tag{8}$$

is solved at each time, where we assume that $Q = Q' \succeq 0, R = R' \succ 0, (Q^{1/2}, A)$ detectable, K is some feedback gain, N_y, N_u, N_c are the output, input, and constraint horizons, respectively, with $N_u \leq N_y$ and $N_c \geq N_y - 1$.

Remark 1: MPC has made a significant impact on control engineering and is being increasingly in process control. It has several advantages [16]: constraint handling capability; good tracking performance; adaptation to changing parameters; broad industrial applications. In addition, MPC has a degree of fault-tolerance capability, which will be discussed in the next section.

3. Fault-tolerance capability of MPC

Model predictive controllers have the fault-tolerance capability to a certain extent. When a sensor of controlled output fails, it is possible to abandon control of that output by removing the corresponding output from the cost function. When an actuator has stuck failure, it is then represented by changing the constraints $|\Delta u_j| = 0$. If a failure affects the capabilities of the plant, then it is possible to change the objectives or (and) the constraints. MPC's fault-tolerance properties are due to the fact that the control signal is recomputed at each sample time by solving an optimization problem, so that it is easy to make changes in the problem formulation [20].

In addition, [22] shows that constrained predictive controllers have a considerable degree of implicit fault-tolerance capability. For set-point tracking problem, if an actuator failure occurs which is compatible with the set-point specification, then a constrained predictive controller with a model of the actuator saturation characteristics, and a disturbance model which gives rise to integral action, will reconfigure the actuators so as to track the set-point without error. This can be achieved without special-purpose devices or algorithms, and can offer protection even against unanticipated failures.

An example is given to illustrate the implicit fault-tolerance of MPC. Consider a continuous linear system

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx \end{aligned} \tag{9}$$

where

$$A = \begin{bmatrix} -0.0151 & -60.5651 & 0 & -0.32174 \\ -0.0001 & -1.3411 & 0.9929 & 0 \\ -0.00018 & 42.2541 & -0.86939 & 0 \\ -0.4 & 0 & 1 & 0.5 \end{bmatrix},$$

$$B = \begin{bmatrix} -2.516 & -13.136 & -3.136 \\ -0.1689 & -0.2514 & -1.004 \\ -17.251 & -1.5766 & -0.7822 \\ 0 & 2 & 0 \end{bmatrix}, C = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

The inputs are subject to hard constraints $|u_i| \leq 25, i = 1, 2, 3$. The continuous-time model is sampled every $T_s = 0.05s$ and a zero-hold is used at the input. The task is to track the reference inputs ($y_1^* = 2, y_2^* = 10$). Here, we consider the following actuator failure: u_3 is outage at $5s$. The simulation results are shown in Fig.1 and Fig.2. From the simulation results, we know that MPC can accommodate

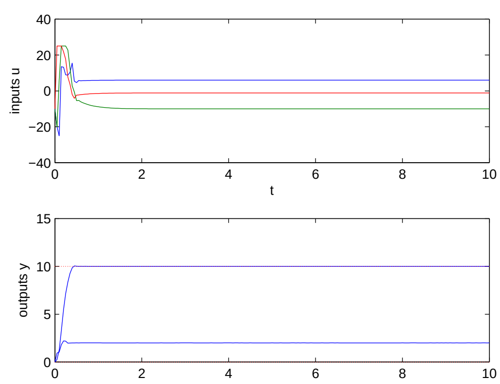

FIGURE 1. No actuators fail

this actuator failure automatically.

However, the implicit fault-tolerance capability of MPC is limited because it is blind to actuator failures and cannot take measures immediately to commodate them. For redundantly-actuated systems, where there are more degrees of control freedom than control objectives, MPC can automatically redistribute the control effort among actuators to accommodate one or more actuator failures. But when there are no redundant actuators (i.e., the number of actuators is no more than that of outputs) and partial actuator failures occur, MPC often can't obtain the

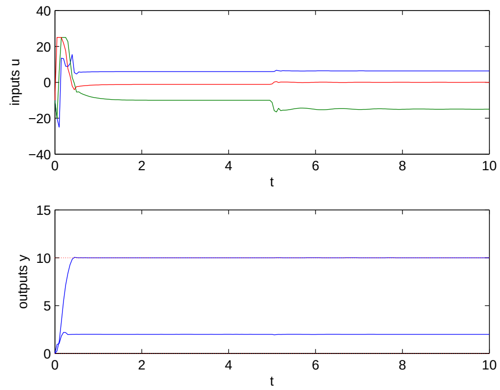

FIGURE 2. u_3 is outage at $5s$

objective or even becomes unstable (see example 1). This is because actuator failures lead to mismatching between plant and internal model. In this situation, it can't only rely on MPC for fault accommodation.

Then it is necessary to design an FDI scheme to diagnose actuator faults and modify the MPC formulation according to the fault information. Here we will design a fault-tolerant control scheme based on MPC and FDI to accommodate partial actuator failures. The FDI module based on a two-stage Kalman filtering algorithm detects and isolates actuator faults and provides the fault information to modify the MPC formulation, such as internal model. We'll discuss it in details in the following section.

4. Fault-tolerant Control Scheme

4.1. Fault detection and isolation scheme. Consider a linear discrete model of the form

$$\begin{aligned} x_{k+1} &= A_k x_k + B_k u_k + w_k^x \\ y_{k+1} &= C_k x_{k+1} + v_{k+1} \end{aligned} \tag{10}$$

with constraints

$$y_{\min} \le y_k \le y_{\max}, \tag{11}$$

$$u_{\min} \le u_k \le u_{\max}, \tag{12}$$

where $x_k \in R^n, u_k \in R^m$ and $y_{k+1} \in R^p$ are the state, control input and output variables, respectively. w_k^x and v_{k+1} denote the white noise sequences of uncorrelated Gaussian random vectors with zero means and covariance matrices Q_k^x and R_{k+1}, respectively. The initial state X_0 is specified as a random Gaussian vector with mean $\tilde{x}_0$ and covariance $\tilde{P}_0$. And $y_{\min} \le y_{\max} (u_{\min} \le u_{\max})$ are $p(m)$-dimensional vectors.

In this paper, we consider partial actuator failures, that is, reduction of control effectiveness. When ith actuator fails,

$$u_i^F = u_i(1 + \gamma_k^i) \tag{13}$$

where $-1 \le \gamma_k^i \le 0,\ i = 1, \cdots, m$ are control effectiveness factors. If $\gamma_k^i = 0$, u_i is normal; if $\gamma_k^i = -1$, u_i is outage.

Then, the state equation with partial actuator failures is

$$x_{k+1} = A_k x_k + B_k u_k + [b_1\gamma_k^1 \; b_2\gamma_k^2 \cdots b_m\gamma_k^m] \begin{bmatrix} u_k^1 \\ u_k^2 \\ \vdots \\ u_k^m \end{bmatrix} + w_k^x \tag{14}$$

or, in a compact form,

$$x_{k+1} = A_k x_k + B_k u_k + E_k \gamma_k + w_k^x \tag{15}$$

where E_k is defined by

$$E_k = B_k U_k \tag{16}$$

and

$$U_k = \begin{bmatrix} u_k^1 & 0 & \cdots & 0 \\ 0 & u_k^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & u_k^m \end{bmatrix}, \quad \gamma_k = \begin{bmatrix} \gamma_k^1 \\ \gamma_k^2 \\ \vdots \\ \gamma_k^m \end{bmatrix} \tag{17}$$

In the absence of the knowledge on the evolution of the effectiveness factors, the control effectiveness factors can be modeled as a random bias vector

$$\gamma_{k+1} = \gamma_k + w_k^\gamma \tag{18}$$

The bias augmented model has the following form:

$$x_{k+1} = A_k x_k + B_k u_k + E_k \gamma_k + w_k^x \tag{19}$$

$$\gamma_{k+1} = \gamma_k + w_k^\gamma \tag{20}$$

$$y_{k+1} = C_{k+1} x_{k+1} + v_{k+1} \tag{21}$$

where the noise sequences w_k^x, w_k^x, and v_k are assumed to be zero mean uncorrelated white Gaussian noise sequences with

$$E = \left\{ \begin{bmatrix} w_k^x \\ w_k^\gamma \\ v_k \end{bmatrix} \begin{bmatrix} w_j & w_j^\gamma & v_j \end{bmatrix} \right\} = \begin{bmatrix} Q^x & 0 & 0 \\ 0 & Q^\gamma & 0 \\ 0 & 0 & R \end{bmatrix} \delta_{kj} \tag{22}$$

where $Q^x > 0, Q^\gamma > 0, R > 0$ and δ_{kj} are the Kronecker delta. The initial states x_0 and γ_0 are assumed to be uncorrelated with the white noise processes w_k^x, w_k^γ, and v_k.

The modified two-stage adaptive Kalman filtering algorithm to estimate control effectiveness factors and states is as follows [18]:
Control effectiveness factor estimator

$$\hat{\gamma}_{k+1|k} = \hat{\gamma}_{k|k} \tag{23}$$

$$P_{k+1|k}^\gamma = \sum_{i=1}^{l} \frac{\alpha_{k|k}^i}{\lambda_k^i} e_k^i (e_k^i)^T + Q_k^\gamma, \quad 0 < \lambda_k^i \le 1 \tag{24}$$

$$\hat{\gamma}_{k+1|k+1} = \hat{\gamma}_{k+1|k} + K_{k+1}^\gamma (\tilde{r}_{k+1} - H_{k+1|k} \hat{\gamma}_{k|k}) \tag{25}$$

$$K_{k+1}^\gamma = P_{k+1|k}^\gamma H_{k+1|k}^T (H_{k+1|k} P_{k+1|k}^\gamma H_{k+1|k}^T + \tilde{S}_{k+1})^{-1} \tag{26}$$

$$P_{k+1|k+1}^\gamma = (I - K_{k+1}^\gamma H_{k+1|k}) P_{k+1|k}^\gamma \tag{27}$$

where

$$P^{\gamma}_{k|k} \triangleq \sum_{i=1}^{m} e^i_k \alpha^i_{k|k} (e^i_k)^T \tag{28}$$

$$\lambda^i_k = \begin{cases} 1, & \alpha^i_{k|k} > \alpha_{\max} \\ \alpha^i_{k|k}[\alpha_{\min} + \frac{\alpha_{\max}-\alpha_{\min}}{\alpha_{\max}}\alpha^i_{k|k}]^{-1}, & \alpha^i_{k|k} \le \alpha_{\max} \end{cases} \tag{29}$$

The state estimator

$$\tilde{x}_{k+1|k} = A_k \tilde{x}_{k|k} + B_k u_k + W_k \hat{\gamma}_{k|k} - V_{k+1|k}\hat{\gamma}_{k|k} \tag{30}$$

$$\tilde{P}^x_{k+1|k} = A_k \tilde{P}^x_{k|k} A^T_k + Q^x_k + W_k P^{\gamma}_{k|k} W^T_k - V_{k+1|k} P^{\gamma}_{k+1|k} V^T_{k+1|k} \tag{31}$$

$$\tilde{x}_{k+1|k+1} = \tilde{x}_{k+1|k} + \tilde{K}^x_{k+1}(y_{k+1} - C_{k+1}\tilde{x}_{k+1|k}) \tag{32}$$

$$\tilde{K}^x_{k+1} = \tilde{P}^x_{k+1|k} C^T_{k+1}(C_{k+1}\tilde{P}^x_{k+1|k} C^T_{k+1} + R_{k+1})^{-1} \tag{33}$$

$$\tilde{P}^x_{k+1|k+1} = (I - \tilde{K}^x_{k+1} C_{k+1})\tilde{P}^x_{k+1|k} \tag{34}$$

where the filter residual and its covariance are given as

$$\tilde{r}_{k+1} = y_{k+1} - C_{k+1}\tilde{x}_{k+1|k} \tag{35}$$

$$\tilde{S}_{k+1} = C_{k+1}\tilde{P}^x_{k+1|k} C^T_{k+1} + R_{k+1} \tag{36}$$

Coupling equations

$$W_k = A_k V_{k|k} + E_k \tag{37}$$

$$V_{k+1|k} = W_k P^{\gamma}_{k|k} (P^{\gamma}_{k+1|k})^{-1} \tag{38}$$

$$H_{k+1|k} = C_{k+1} V_{k+1|k} \tag{39}$$

$$V_{k+1|k+1} = V_{k+1|k} - \tilde{K}^x_{k+1} H_{k+1|k} \tag{40}$$

Compensated state and error covariance estimates

$$\hat{x}_{k+1|k+1} = \tilde{x}_{k+1|k+1} + V_{k+1|k+1}\hat{\gamma}_{k+1|k+1} \tag{41}$$

$$P_{k+1|k+1} = \tilde{P}^x_{k+1|k+1} + V_{k+1|k+1} P^{\gamma}_{k+1|k+1} + V^T_{k+1|k+1} \tag{42}$$

Remark 2: The two-stage Kalman filtering algorithm was developed in [17] and modified in [18][19] to estimate the control effectiveness factors. See [17]-[19] for details. Here, we use the modified two-stage Kalman filtering algorithm in [18] to provide the estimation of control effectiveness factors, which are used to modify the internal model of the MPC formulation. And the algorithm also provides state estimation to be used in the MPC formulation when the states are unmeasurable.

Based on the control effectiveness factor estimates, statistical variables can be constructed for hypothesis tests [18]. Under the normal condition, the ith component $\hat{\gamma}^i_{k|k}$ of the bias estimate $\gamma^i_{k|k}$ is a zero mean Gaussian variable. Define the weighted sum-squared bias estimate as

$$d^i_k = \frac{1}{L}\sum_{j=k-L+1}^{k} (\hat{\gamma}^i_{j|j})^2 / P^{\gamma^i}_{j|j} \tag{43}$$

where $P^{\gamma^i}_{j|j}$ is the ith diagonal element of $P^{\gamma}_{j|j}$. d^i_k is small until there is a reduction of effectiveness in the ith control input channel. Hence the following hypothesis test can be used:

(44) $$d_k^i \overset{H_0}{<} \varepsilon_i, \quad i = 1, \cdots, l$$

where H_0={no significant reduction of effectiveness in ith control input};

(45) $$d_k^i \overset{H_i}{\geq} \varepsilon_i, \quad i = 1, \cdots, l$$

where H_i={ith control input has significant reduction of effectiveness}. The thresholds $\varepsilon_i, i = 1, \ldots, l$ are design parameters.

Remark 3: The FDI module makes sure that partial actuator failures occur by hypothesis tests. Only when a fault is declared to occur by hypothesis tests, will the estimation of control effectiveness factor be used to modify the internal model of MPC formulation.

4.2. Fault-tolerant Control Architecture. The architecture of the fault-tolerant control scheme based on integrating MPC and FDI is shown in Fig. 3. There are two control loops in the FTC architecture: MPC control loop and FDI control loop. The two control loops operate in parallel. The former deals with constraints including input constraint, output constraint and state constraint using the MPC technique. The latter copes with actuator failures. The two-stage adaptive Kalman filter estimates the control effectiveness factors at all times. Only when the FDI module, by hypothesis tests, makes sure that actuator failures occur, estimation of control effectiveness factors passes to supervisor and new faulty model will take the place of the old fault-free model in the MPC formulation by the supervisor. In addition, the Kalman filter provides state estimation, which is also used in MPC formulation when the states are unmeasurable. If the states are measurable, only estimation of control effective factors are used in the MPC. In this case, the fault-tolerant architecture is shown in Fig. 4.

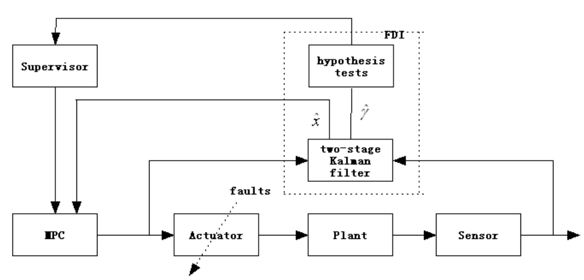

FIGURE 3. The fault-tolerant architecture (state unmeasurable)

When partial actuator failures occur and the FDI module detects and isolates them, estimation of control effective factors γ_k passes to supervisor, then new model

(46) $$x_{k+1} = A_k x_k + B_k u_k + E_k \gamma_k$$

will replace the old fault-free model

(47) $$x_{k+1} = A_k x_k + B_k u_k$$

in the MPC formulation so that the internal model matches the plant. MPC will use the new model to predict the future trajectory. Due to the fault information provided by the FDI module, MPC is no longer blind to actuator failures. Prompt measures are taken by MPC to accommodate actuator faults. If the plant state lies in the attractive domain of the new MPC when faults are detected and isolated by FDI module, the system can still be stabilized.

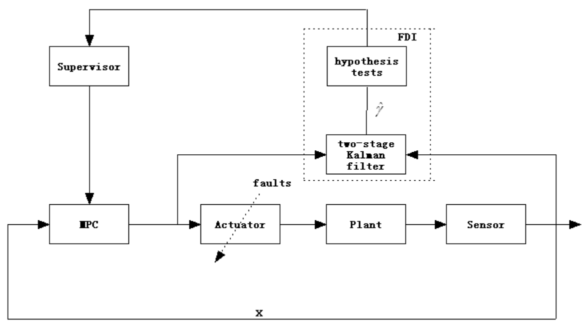

FIGURE 4. The fault-tolerant architecture (state measurable)

Remark 4: For tracking control problem, at most $m-p$ actuators are permitted to lose effectiveness completely, where m, p are the number of actuators and outputs respectively.

Remark 5: Severe actuator failures can render the constrained optimization of the MPC formulation infeasible. This is a practical problem in using the fault-tolerant control scheme based on MPC and FDI. Infeasibility can occur because of unachievable targets due to restrictions on control inputs and outputs, limited control moves due to short horizons, and uncontrollable disturbances etc. Hence, it is necessary to take measures to avoid infeasibility problem.

Remark 6: Constraint softening [21] is a common approach to avoid infeasibility. Slack variables, which are non-zero only if the corresponding constraints are violated, are introduced to handle any infeasibility. In the soft-constrained MPC, violations of the output constraints are usually allowed. Additional terms penalizing these violations are introduced into the objective function.

Remark 7: Another method to avoid infeasibility is to change the objective of MPC. For most constrained systems, perfect tracking is usually unachievable. When actuator failures occur, it is usually impossible for perfect tracking. Hence, such unachievable targets must be adjusted at every time step before the MPC optimization.

5. Numerical Example

Consider a continuous linear system

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) + Du(t) \end{aligned} \tag{48}$$

where

$$A = \begin{bmatrix} -0.0151 & -60.5651 & 0 & -0.32174 \\ -0.0001 & -1.3411 & 0.9929 & 0 \\ -0.00018 & 42.2541 & -0.86939 & 0 \\ -0.4 & 0 & 1 & 0.5 \end{bmatrix},$$

$$B = \begin{bmatrix} -2.516 & -13.136 \\ -0.1689 & -0.2514 \\ -17.251 & -1.5766 \\ 0 & 2 \end{bmatrix},$$

$$C = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \; D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}.$$

The inputs are subject to hard constraints $|u_i| \leq 25$. The open-loop response of the system is unstable. The task is to stabilize the system, while avoiding instability due to input saturation. The continuous-time model is sampled every $T_s = 0.05s$ and a zero-hold is used at the input.

We consider the following partial actuator failure: u_1 is 50% of control effectiveness at $t = 5s$.

Without the FDI scheme, MPC cannot accommodate this actuator failure and the system becomes unstable. The simulation results are shown in Fig. However,

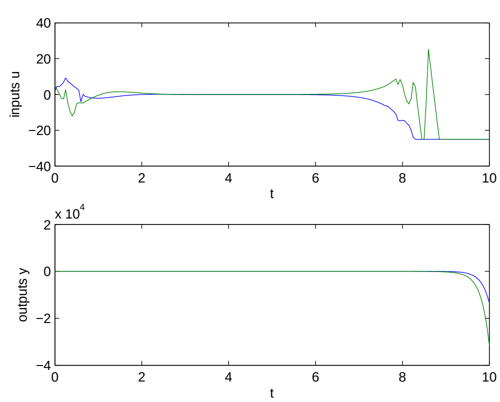

FIGURE 5. MPC without FDI

using our fault-tolerant control scheme based on MPC and FDI, the system is stabilized even though partial actuator failure occur. The simultaneous results are shown in Fig.

6. Conclusions

This paper presents an active fault-tolerant control for constrained linear systems based on MPC and FDI. A two-stage Kalman filtering algorithm is used in FDI module for simultaneous fault parameter and state estimation. The fault parameter estimation is then used to modify the internal model of the MPC formulation to accommodate partial actuator faults.

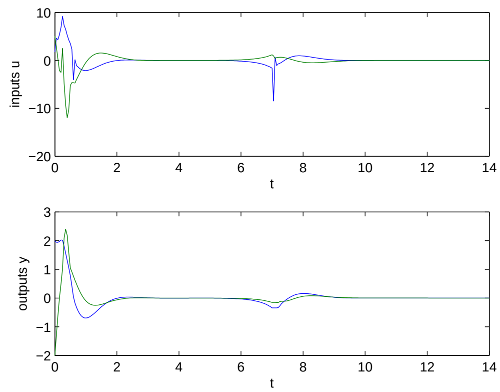

FIGURE 6. MPC with FDI

Advantages of this fault-tolerant control scheme are: 1) it is able to deal with input constraints and partial actuator failures simultaneously; 2) certain performances such as quadratic performances are assured even if partial actuator failures occur; 3) it has robustness property if min-max performance index instead of quadratic performance index is used in MPC formulation. The disadvantage is complex calculation, which is the common problem of MPC technique. However, due to development of modern microprocessors, it becomes less and less important. As constraints often occur in industrial control, especially in chemical control, and MPC is now used widely, fault-tolerant control design based on MPC and FDI will have a promising application.

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