Integrating Fault Diagnosis with Nonlinear Model Predictive Control

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1 Introduction

The abundance of batch processes and continuous processes with wide operating ranges has motivated the development of nonlinear MPC (NMPC) techniques, which employ nonlinear models for prediction. The prediction model is typically developed once in the beginning of implementation of an NMPC scheme. However, as time progresses, slow drifts in unmeasured disturbances and changes in process parameters can lead to significant mismatch in plant and model behavior. Also, NMPC schemes are typically developed under the assumption that sensors and actuators are free from faults. However, *soft faults*, such as biases in sensors or actuators, are frequently encountered in the process industry. In addition to this, some actuator(s) may fail during operation, which results in loss of degrees of freedom for control. Occurrences of such faults and failures can lead to a significant degradation in the closed loop performance of the NMPC.

The conventional approach to deal with the plant model mismatch in the NMPC formulations is through the introduction of additional artificial states in the state observer. The main limitation of this approach is that number of extra states introduced cannot exceed the number of measurements. This implies that it is necessary to have a priori knowledge of which subset of faults are most likely to occur or which parameters are most likely to drift. In such a formulation, the state estimates can become biased when un-anticipated faults occur. Moreover, the permanent state augmentation approach cannot systematically deal with the difficulties arising out of sensor biases or actuator failures.

Attempts to develop fault-tolerant MPC schemes have mainly focused on dealing sensor or actuator failures [1]. Recently, Prakash et al. [2] have proposed an active fault tolerant linear MPC (FTMPC) scheme, which can systematically

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deal with soft faults in a unified framework. The main limitation of this approach arises from the use of linear perturbation model for performing control and diagnosis tasks. The use of linear models not only restricts its applicability to a narrow operating range but also limits the diagnostic abilities of fault detection and identification (FDI) components to only linear additive type faults. As a consequence, many faults that nonlinearly affect the system dynamics, such as abrupt changes in model parameters or unmeasured disturbances, have to be approximated as linear additive faults. Moreover, the FTMPC scheme doesn't deal with failures of sensors or actuators.

In the present work, we propose a fault tolerant NMPC (FTNMPC) formulation with an intelligent nonlinear state estimator, Extended Kalman Filter (EKF), which can diagnose the root cause of model plant mismatch and correct itself. The whiteness of innovation sequence generated by the state estimator is taken as an indicator of good health of the model. A significant and sustained departure from this behavior is assumed to result from model plant mismatch and a nonlinear version of generalized likelihood ratio (GLR) based FDI scheme is used to analyze the root cause of model plant mismatch. The proposed FDI method also generates an estimate of the magnitude of the fault, which is used to compute an online bias correction to the model at the location isolated by the FDI scheme. The model correction strategy overcomes the limitation on the number of extra states that can be added to the state space model in NMPC for offset removal and allows bias compensation for more variables than the number of measured outputs. The proposed FTNMPC eliminates offset between the true values and set points of controlled variables in presence of variety of faults while conventional NMPC does not. Also, the true values of state variables, manipulated inputs and measured variables are maintained within their imposed bounds in FTNMPC while in conventional NMPC these may be violated when soft faults occur. When an actuator fails, the proposed FTNMPC formulation is able to make modifications in the controller objective function and constraint set to account for the loss of a degree of freedom. These advantages of the proposed scheme are demonstrated using simulation studies on a benchmark continuous stirred tank reactor (CSTR) control problem, which exhibits strongly nonlinear dynamics.

2 Fault Diagnosis Using Nonlinear GLR Method

In this section, we first describe the FDI method as applied once when a fault is detected for the first time. Consider a continuous time nonlinear stochastic system described by the following set of equations

$$\mathbf{x}(k+1) = \mathbf{x}(k) + \int_{kT}^{(k+1)T} \mathbf{F}\left[\mathbf{x}(t), \mathbf{u}(k), \mathbf{p}, \mathbf{d}(k)\right] dt \tag{1}$$

$$\mathbf{y}(k) = \mathbf{H}\left[\mathbf{x}(k)\right] + \mathbf{v}(k) \quad ; \quad \mathbf{d}(k) = \overline{\mathbf{d}} + \mathbf{w}(k) \tag{2}$$

where $\mathbf{x} \in R^n, \mathbf{y} \in R^r$ and $\mathbf{u} \in R^m$ represent the state variables, measured outputs and manipulated inputs, respectively. The variables $\mathbf{p} \in R^p$ and $\mathbf{d} \in R^d$ represent the vector of parameters and unmeasured disturbance variables, respectively, which are likely to undergo deterministic changes. The unmeasured disturbances are also assumed to undergo random fluctuations. For mathematical tractability, these are simulated as piecewise constant between each sampling period and changing randomly from their nominal value at each sampling instant. Here, $\mathbf{v}(k)$ and $\mathbf{w}(k)$ are zero mean Gaussian white noise sequences with known covariance matrices. Equations 1 and 2 represent the normal or fault free behavior of the process and are used to develop the standard linearized EKF [3]. In remainder of the text, we refer to this EKF as *normal EKF*.

In order to isolate faults and estimate their magnitudes, it is necessary to develop a model for each hypothesized fault that describes its effect on the evolution of the process variables. The models that are used to describe some of the faults are as follows:

- **Bias in j^{th} sensor :** Subsequent to occurrence of bias in the sensor at instant t, the behavior of measured outputs is modeled as

$$\mathbf{y}_{y_j}(k) = \mathbf{H}\left[\mathbf{x}(k)\right] + b_{y_j}\mathbf{e}_{y_j}\sigma(k-t) + \mathbf{v}(k)$$

  Here, b_{y_j} represents sensor bias magnitude, $\mathbf{e}_{y_j}$ represents sensor fault vector with j^{th} element equal to unity and all other elements equal to zero and $\sigma(k-t)$ represents a unit step function defined as

$$\sigma(k-t) = 0 \text{ if } k \prec t \quad ; \quad \sigma(k-t) = 1 \text{ if } k \succeq t$$

- **Abrupt change in j^{th} unmeasured disturbance variable:**

$$\mathbf{d}_{d_j}(k) = \overline{\mathbf{d}} + \mathbf{w}(k) + b_{d_j}\mathbf{e}_{d_j}\sigma(k-t)$$

- **Failure of j^{th}Actuator / Sensor:**

$$\mathbf{u}_{m_j}(k) = \mathbf{m}(k) + \left[b_{m_j} - \mathbf{e}_{m_j}^T\mathbf{m}(k)\right]\mathbf{e}_{m_j}\sigma(k-t) \tag{3}$$

$$\mathbf{y}_{s_j}(k) = \mathbf{H}\left[\mathbf{x}(k)\right] + \left[b_{s_j} - \mathbf{e}_{s_j}^T\mathbf{H}\left[\mathbf{x}(k)\right]\right]\mathbf{e}_{s_j}\sigma(k-t) + \mathbf{v}(k) \tag{4}$$

  where b_{m_j}/b_{s_j} represents constant value at which the j^{th}actuator/sensor is stuck. Note that we differentiate the controller output $\mathbf{m}$ and manipulated input $\mathbf{u}$ entering the process. The controller output equals the manipulated input under the fault free conditions. Similar fault models can be formulated for other faults.

To detect occurrence of a fault, it is assumed that the sequence of innovations $\gamma(k)$ generated by the *normal EKF* is a zero mean Gaussian white noise process with covariance matrix $\mathbf{V}(k)$. A sustained departure from this behavior is assumed to result from a fault. Simple statistical tests, namely, fault detection test (FDT) and fault confirmation test (FCT) as given in [4] are modified based on innovations obtained from EKF and used for estimating time of occurrence of fault. Taking motivation from *nonlinear GLR* method proposed for gross error detection under steady-state conditions [5], we propose a version of *nonlinear GLR* method under dynamic operating conditions. By this approach, once the FCT confirms the occurrence of a fault at instant t, we formulate a separate EKF over a time window $[t, t+N]$ for each hypothesized fault. For example, assuming that actuator j has failed at instant t, the process behavior over window $[t, t+N]$ can be described as follows

$$\mathbf{x}_{m_j}(i+1) = \mathbf{x}_{m_j}(i) + \int_{iT}^{(i+1)T} \mathbf{F}\left[\mathbf{x}_{m_j}(t), \mathbf{u}_{m_j}(i), \overline{\mathbf{p}}, \overline{\mathbf{d}}\right] dt \tag{5}$$

$$\mathbf{y}_{m_j}(i) = \mathbf{H}\left[\mathbf{x}_{m_j}(i)\right] + \mathbf{v}(k) \tag{6}$$

where $\mathbf{u}_{m_j}(i)$ is given by equation 3. The magnitude estimation problem can now be formulated as a nonlinear optimization problem as follows

$$\min_{b_{m_j}} (\Psi_{m_j}) = \sum_{i=t}^{t+N} \gamma_{m_j}^T(i) \mathbf{V}_{m_j}(i)^{-1} \gamma_{m_j}(i) \tag{7}$$

where $\gamma_{m_j}(i)$ and $\mathbf{V}_{m_j}(i)$ are the innovations and the innovations covariance matrices, respectively, generated by the EKF constructed using equations 5 and 6 with initial state $\widehat{\mathbf{x}}(t|t)$. The estimates of fault magnitude can be generated for each hypothesized fault in this manner. The fault isolation is viewed as a problem of finding the observer that best explains the output behavior observed over the window. Thus, the fault that corresponds to minimum value of the objective function, Ψ_{f_j}, with respect to f_j, where $f \in (p, d, y, u, m, s)$ represents the fault type, is taken as the fault that has occurred at instant t. Since the above method is computationally expensive, we use a simplified version of nonlinear GLR proposed by Vijaybaskar, [6] for fault isolation. This method makes use of the recurrence relationships for *signature matrices* derived under linear GLR framework [4], which capture the effect of faults on state estimation error and innovation sequence. If a fault of magnitude b_{f_j} occurs at time t, the expected values of the innovations generated by the *normal EKF* at any subsequent time are approximated as

$$E\left[\gamma(i)\right] = b_{f_j} \mathbf{G}_f(i;t) \mathbf{e}_{f_j} + \mathbf{g}_{f_i} \quad \forall i \succeq t \tag{8}$$

Here, $\mathbf{G}_f(i;t)$ and $\mathbf{g}_{f_j}(i;t)$ represent fault signature matrix and fault signature vector, respectively, which depend on type, location and time of occurrence of a fault. For example, if j^{th} actuator fails, then the corresponding signature matrices and the signature vectors can be computed using the following recurrence relations for $i \in [t, t+N]$:

$$\mathbf{G}_m(i;t) = \mathbf{C}(i)\mathbf{\Gamma}_u(i) - \mathbf{C}(i)\mathbf{\Phi}(i)\mathbf{J}_m(i-1;t) \tag{9}$$

$$\mathbf{g}_{m_j}(i;t) = \mathbf{C}(i)\mathbf{\Gamma}_u(i)\left[\mathbf{e}_{m_j}^T \mathbf{m}(i)\right]\mathbf{e}_{m_j} - \mathbf{C}(i)\mathbf{\Phi}(i)\mathbf{j}_{m_j}(i-1;t) \tag{10}$$

$$\mathbf{J}_m(i;t) = \mathbf{\Phi}(i)\mathbf{J}_m(i-1;t) + \mathbf{L}(i)\mathbf{G}_m(i-1;t) - \mathbf{\Gamma}_u(i) \tag{11}$$

$$\mathbf{j}_{m_j}(i;t) = \mathbf{\Phi}(i)\mathbf{j}_{m_j}(i-1;t) + \mathbf{L}(i)\mathbf{g}_{m_j}(i-1;t) - \mathbf{\Gamma}_u(i)\left[\mathbf{e}_{m_j}^T \mathbf{m}(i)\right]\mathbf{e}_{m_j} \tag{12}$$

Here,

$$\mathbf{\Gamma}_u(i) = \int_0^T \exp\left(\mathbf{A}(i)q\right)\mathbf{B}_u(i)dq \quad ; \quad \mathbf{B}_u(i) = \left[\frac{\partial \mathbf{F}(\mathbf{x},\mathbf{m},\mathbf{p},\mathbf{d})}{\partial \mathbf{m}}\right]_{(\widehat{\mathbf{x}}(i|i),\mathbf{m}(i),\overline{\mathbf{p}},\overline{\mathbf{d}})}$$

$$\mathbf{\Phi}(i) = \exp\left[\mathbf{A}(i)T\right] \;\; ; \;\; \mathbf{A}(i) = \left[\frac{\partial \mathbf{F}}{\partial \mathbf{x}}\right]_{(\widehat{\mathbf{x}}(i|i),\mathbf{m}(i),\overline{p},\overline{\mathbf{d}})} \quad ; \quad \mathbf{C}(i) = \left[\frac{\partial \mathbf{H}(\mathbf{x})}{\partial \mathbf{x}}\right]_{(\widehat{\mathbf{x}}(i|i)}$$

are the linearized discrete time varying system matrices and $\mathbf{L}(i)$ is the Kalman gain computed using the *normal EKF*. Similar recurrence relations can be constructed for other types of faults. For each hypothesized fault, the log likelihood ratio, T_{f_j}, is computed as follows

$$T_{f_j} = \left[d_{f_j}^2/c_{f_j}\right] + \sum_{i=t}^{t+N} \mathbf{g}_{f_j}^T(i;t)\mathbf{V}(i)^{-1}\left[2\gamma(i) - \mathbf{g}_{f_j}(i;t)\right] \tag{13}$$

$$d_{f_j} = \mathbf{e}_{f_j}\sum_{i=t}^{t+N} \mathbf{G}_f^T(i;t)\mathbf{V}(i)^{-1}\left[\gamma(i) - \mathbf{g}_{f_j}(i;t)\right] \tag{14}$$

$$c_{f_j} = \mathbf{e}_{f_j}^T\sum_{i=t}^{t+L} \mathbf{G}_f^T(i;t)\mathbf{V}(i)^{-1}\mathbf{G}_f(i;t)\mathbf{e}_{f_j} \tag{15}$$

where $\gamma(i)$ and $\mathbf{V}(i)$ are obtained using *normal EKF*. The fault location can be obtained from the maximum value of the test statistic T_{f_j}. An estimate of the bias magnitude is generated as $b_{f_j}^{(0)} = d_{f_j}/c_{f_j}$. Once a fault f_j is isolated, a refined estimate of the fault magnitude is generated by formulating a nonlinear optimization problem as described above, starting from the initial guess of $b_{f_j}^{(0)}$.

3 Fault Tolerant NMPC (FTNMPC) Formulation

To begin with, let us consider conventional NMPC formulation. Let us assume that at any instant k, we are given p future manipulated input moves

$$\{\mathbf{m}(k|k), \mathbf{m}(k+1|k)........\mathbf{m}(k+p-1|k)\}$$

The future (predicted) estimates of the state variables and outputs, which have been compensated for plant model mismatch, are given as follows

$$\widetilde{\mathbf{x}}(k+j+1|k) = \widehat{\mathbf{x}}(k+j|k) + \int_{(k+1)T}^{(k+l+1)T} \mathbf{F}\left[\widehat{\mathbf{x}}(\tau), \mathbf{m}(k+j|k), \overline{\mathbf{p}}, \overline{\mathbf{d}}\right] d\tau \tag{16}$$

$$\widehat{\mathbf{x}}(k+j+1|k) = \widetilde{\mathbf{x}}(k+j+1|k) + \mathbf{L}(k)\gamma(k); \;\; \varepsilon(k) = \mathbf{y}(k) - \widehat{\mathbf{y}}(k|k) \tag{17}$$

$$\widehat{\mathbf{y}}(k+j|k) = \mathbf{G}\left[\widehat{\mathbf{x}}(k+j|k)\right] + \varepsilon(k) \;;\; j \in [0,\; p] \tag{18}$$

At any sampling instant k, the nonlinear model predictive control problem is defined as a constrained optimization problem whereby the future manipulated input moves are determined by minimizing an objective function

$$\min_{\mathbf{m}(k|k),\mathbf{m}(k+1|k)........\mathbf{m}(k+q-1|k)} \begin{Bmatrix} \sum_{j=1}^{p} \mathbf{e}_f(k+j|k)^T W_E \mathbf{e}_f(k+j|k) + \\ \sum_{j=0}^{q-1} \Delta\mathbf{m}(k+j|k)^T W_u \Delta\mathbf{m}(k+j|k) \end{Bmatrix}$$

subject to following constraints

$$\begin{aligned} \mathbf{m}(k+q|k) &= \mathbf{m}(k+q+1|k) = ...\mathbf{m}(k+p-1|k) = \mathbf{m}(k+q-1|k) \\ \mathbf{m}^L &\leq \mathbf{m}(k+j|k) \leq \mathbf{m}^U \text{ (for } j=0..q-1) \\ \Delta\mathbf{m}^L &\leq \Delta\mathbf{m}(k+j|k) \leq \Delta\mathbf{m}^U \text{ (for } j=0..q-1) \\ \mathbf{e}_f(k+j|k) &= \mathbf{y}_r(k+j|k) - \widehat{\mathbf{y}}(k+j|k) \\ \Delta\mathbf{m}(k+j|k) &= \mathbf{m}(k+j|k) - \mathbf{m}(k+j-1|k) \end{aligned}$$

Here, $\mathbf{y}_r(k+j|k)$ represents the future setpoint trajectory.

We now present the modifications necessary in the NMPC formulation when a fault is detected for the first time by FDI component. Consider a situation where FDT has been rejected at time instant t and subsequently FCT has been rejected at time $t+N$ for the first time. Further assume that at instant $t+N$ we have isolated a fault f using modified GLR method and estimated the fault magnitude using data collected in the interval $[t, t+N]$. During the interval $[t, t+N]$, the NMPC formulation is based on the prediction model given by equations 16 to 18. However after the identification of the fault at instant $t+N$, we modify the model for $k \geq t+N$ as follows:

- **Sensor faults:** If sensor bias is isolated, the measured output is compensated as $\mathbf{y}_c(k) = \mathbf{y}(k) - \widehat{b}_{y_j}\mathbf{e}_{y_j}$ and used in FDI as well as MPC formulation for computing innovation sequence. If a sensor failure is diagnosed, the measurements coming from a failed sensor are replaced by corresponding estimates in the FTNMPC formulation.
- **Step jump in unmeasured disturbance:** The prediction equation in the state estimator and future predictions in NMPC are modified as follows

$$\begin{aligned} \widehat{\mathbf{x}}(k+1|k) &= \widehat{\mathbf{x}}(k|k) + \int_{kT}^{(k+1)T} \mathbf{F}\left[\widehat{\mathbf{x}}(t), \mathbf{m}(k), \overline{\mathbf{p}}, \overline{\mathbf{d}} + \widehat{b}_{d_j}\mathbf{e}_{d_j}\right] dt \\ \widehat{\mathbf{x}}(k+l+1|k) &= \widehat{\mathbf{x}}(k+l|k) \\ &\quad + \int_{(k+l)T}^{(k+l+1)T} \mathbf{F}\left[\widehat{\mathbf{x}}(\tau), \mathbf{m}(k+l|k), \overline{\mathbf{p}}, \overline{\mathbf{d}} + \widehat{b}_{d_j}\mathbf{e}_{d_j}\right] d\tau + \mathbf{L}(k)\gamma(k) \end{aligned}$$

- **Failed actuator:** In state estimation the failed actuator is treated as constant $\mathbf{m}_j(k) = \widehat{b}_{m_j}$, where $\widehat{b}_{m_j}$ is the estimate of stuck actuator signal for j^{th} actuator. Also, in the NMPC formulation, we introduce additional constraints as $\mathbf{m}_j(k+l|k) = \widehat{b}_{m_j}$ for $l = 0....q-1$. If number of setpoints specified in the NMPC formulation equals the number of manipulated inputs, then we modify the NMPC objective function by relaxing setpoint on one of the controlled outputs.

The main concern with the above approach is that the magnitude and the position of the fault may not be accurately estimated. Thus, there is a need to introduce integral action in such a way that the errors in estimation of fault magnitude or position can be corrected in the course of time. Furthermore, other faults may occur at subsequent time instants. Thus, in the on-line implementation of FTNMPC, we resume application of FDI method starting at $t + N + 1$. The FDI method may identify a fault in the previously identified location or a new fault may be identified. In either case, we modify the above equations with cumulative estimate of the bias as described in Prakash et al. [2]. These are computed as $\widetilde{b}_{f_j} = \sum_{l=1}^{n_{f_j}} \widehat{b}_{f_j}(l)$ with initial value $\widehat{b}_{f_j}(0) = 0$, where n_{f_j} represents the number of times a fault of type f was isolated in the j^{th} position. The use of cumulative bias estimates can be looked upon as a method of introducing integral action to account for plant model mismatch, in which some of the states (cumulative bias estimates) are integrated at much slower rate and at regular sampling intervals.

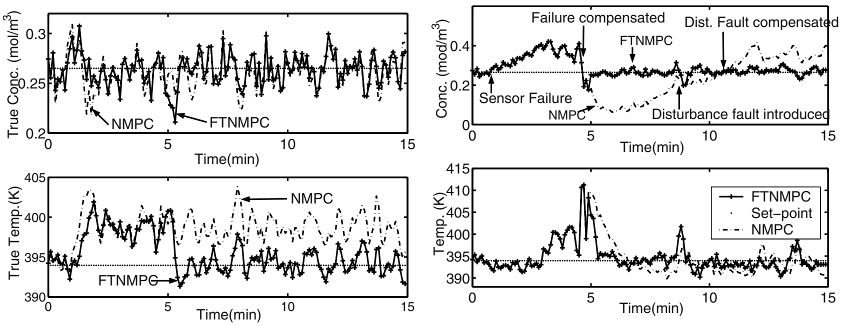
4 Simulation Case Study

Simulation studies are carried out to evaluate the proposed FTNMPC scheme on non-isothermal CSTR system. The reactor system has two state variables, the reactor concentration (C_A) and the reactor temperature(T), both of which are measured and controlled. The coolant flow rate F_c and feed flow rate F are the manipulated inputs while the feed concentration(C_{AO}) is treated as a disturbance variable. Model equations are given in Marlin. ([7]) and nominal parameters, simulation conditions and tuning parameters used for controller tuning are described in Prakash et al. [4] and [2] . The bounds imposed on the inputs are as follows

$$0 \leq F_c \leq 30m^3/\min$$
$$0 \leq F \leq 2m^3/\min$$

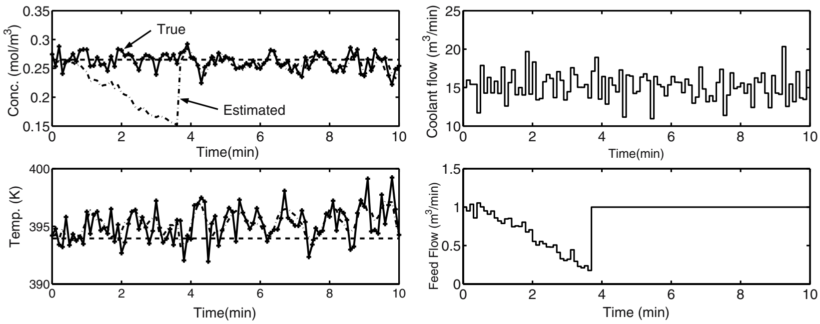
Ten different faults consisting of biases in two measurements, biases in two actuators, failures of the two actuators, failures of two sensors, step change in inlet concentration and change in the frequency factor were hypothesized for this process.

In the conventional NMPC and FTNMPC the control objective is to maintain the temperature close to 393.95^oK, while ensuring that the temperature does not exceed the set-point by more than 1.5^oK, i.e. $T \leq 395.45^oK$ A comparison of performances of conventional NMPC and FTNMPC, when a bias of magnitude -5^oK occurs in the measured temperature at sampling instant $k = 11$, is given in Figure 1(a). In case of NMPC, the true temperature exceeds the constraint limit when the bias occurs. Thus, the conventional NMPC leads to an offset between the true temperature and the set-point as well as violation of constraint. The FTNMPC scheme on the other hand, correctly isolates the fault, compensates for the bias in temperature measurement (estimated magnitude -4.75^oK)



(a) Sensor Bias (b) Inferential control

Fig. 1. Comparison of Closed Loop Responses of NMPC and FTNMPC



(a) True and estimated outputs (b) Manipulated inputs

Fig. 2. FTNMPC behavior for Actuator Failure

and thereby maintains the true temperature within the constraint limit. Thus FTNMPC also eliminates the offset between true temperature and the set-point, as illustrated in Figure 1(a).

It may be expected that the advantages of FTNMPC will become visible in case of inferential control where estimated states are used for control. In order to verify this we simulate failure of sensor for concentration. After the failure is detected and diagnosed, FTNMPC switches over to inferential control using concentration estimates generated using temperature measurements. The comparison of performances of conventional NMPC and FTNMPC, when sensor 1 fails at k =6 and a step jump of 0.5 kmol/m^3 is introduced at k =86 in the inlet concentration (estimated magnitude 0.5233 kmol/m^3) are shown in Figure 1(b). It can be seen that the conventional NMPC results in offset between true concentration and the setpoint. The FTNMPC formulation on the other hand is able to maintain it at the desired setpoint even after the sensor failure and the step change in the disturbance. This can be attributed to the fact that unbiased state estimates are obtained once the faults are correctly identified by the FDI component and model is corrected subsequently to accommodate the faults.

Figure 2(a) shows response of FTNMPC when the actuator for coolant flow is stuck at 1.04 $m^3/\min$ subsequent to $k = 6$. The corresponding manipulated input variation is shown in Figure 2(b). As evident from Figure 2(a), the state estimation deteriorates subsequent to the failure of the actuator. There is an offset in the true values and the setpoints during the time window used for fault isolation. However, the FDI component correctly isolates the actuator failure and estimates the constant value as 1.037 $m^3/\min$. Subsequent to on-line correction of the model, the state estimate improves and concentration is again controlled close to the setpoint using the remaining degree of freedom.

5 Conclusions

In this work, a fault tolerant NMPC scheme, equipped with an intelligent state estimator has been proposed. In FTNMPC formulation, to account for plant model mismatch, the corrections to the model are made as and when necessary and at the qualified locations identified by the nonlinear FDI component. The proposed fault accommodation strategy overcomes the limitation on the number of extra states that can be augmented to the state space model in NMPC and FDI formulations and allows bias compensation for more variables than the number of measured outputs. The proposed FTNMPC has significant advantages over the conventional NMPC while dealing with soft faults such as actuator and sensor biases and step jumps in unmeasured disturbances or model parameters. When sensor or actuator failure is isolated, the proposed FTNMPC formulation redefines the controller objectives to accommodate the fault.

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