IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received August 4, 2021, accepted August 19, 2021, date of publication August 24, 2021, date of current version September 1, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3107282

A New Active Fault Tolerant Control System: Predictive Online Fault Estimation

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ABSTRACT This study presents a new approach for active fault-tolerant controller (FTC) design for constrained nonlinear multi-variable systems. The proposed approach utilize the nonlinear model predictive controller (NMPC) and fault estimation method which is on basis of extended kalman filters (EKFs). The deficiency of actuators and sensors and also the plant states measurement errors are estimated by the suggested approach. A supervisor unit using the fault information and fault modeling per sampling time, corrects the predictor model of the controller and compensates actuator and sensor faults in control system. Furthermore, by the presented feedback compensation, the robustness of the designed method against plant faults and uncertainties is ensured. The important advantages of the proposed method are: (1) The suggested FTC scheme based on NMPC leads to calculate more accurate control action than MPC in nonlinear processes, (2) it is comprehensive in fault accommodation point of view because it is able to compensate all types of faults in control systems simultaneously, (3) it has low computational cost because of using NMPC by analytical solution, (4) it can handle control and states constraints to prevent of actuator saturations and unsafe situations, (5) the simplicity and effectiveness of the designed FTC scheme for real applications is more significant. Simulation results on continuous stirred tank reactor process verifies the superiority and capability of the designed approach.

INDEX TERMS Fault-tolerant controller, fault modeling, uncertainty, predictive control method, robustness.

I. INTRODUCTION

In recent decades, many efforts has been made to design FTC systems to guarantee the desirable performance for the process in the presence of components malfunction and dynamic perturbations. A FTC system is designed to automatically compensate the system faults and, to ensure the stability and satisfactory level of overall performance in both fault free and faulty condition [1]–[3]. The design techniques of FTC systems can be classified in two cases: passive approach (PFTC) and active approach (AFTC). In the first PFTC case, the controller is constant and system can accommodate only a confined number of known faults. On the other hand, AFTC can accommodate faults by restructuring or reconfiguration the controller structure using the fault information [4]–[6].

The MPC scheme has been known as a mature practical control technique for constrained multi-variable control system design problem. In this control scheme, the optimization techniques and plant model are used to generate the suitable control signals based on the predicted information of plant state changes. At each sampling time, by solving a constrained problem the optimal input sequence is computed. Then, considering the prediction horizon, the suitable item of generated sequence is employed [7]–[9].

The associate editor coordinating the review of this manuscript and approving it for publication was Qiuye Sun.

The main advantage of MPC in process control problem can be mentioned as its well ability to handle the complicated control and states constraints [10]–[13]. The idea of FTC design using MPC was first presented in [14], and applied on a simulated air craft system in [15]. These studies have been shown that MPC results in most desirable implementation structure for FTC. The FTC based MPC system design methods are similarly categorized in two cases: passive and active types. In passive cases [16], the faults that are known, are compensated by coping the extra constraints in MPC design. On the other hand, in active approaches, MPC can be reconfigured by using the received fault information [17]. These schemes can be categorized in two types: multiple MPCs methods such as [18], [19] that in majority are based on fuzzy models, and adaptive methods such as [20], [21]. In adaptive methods, faults can be compensated by correction the internal model [20], [22], or by correction the constraints in MPC problem [23], [24], or fault correction in measured outputs [25].

Most of the above reviewed papers, consider a linear model of the system and design the controller based on it. While, in practice we encounter with nonlinear processes and the use of their linear model in the design of the controller, is not efficient. To achieve higher performance, in this paper, the nonlinear system model is used in the design of the controller. Also, in fault accommodation point of view, most of the reviewed methods are not comprehensive and often consider only one type of actuator or sensor fault.

The main core of this paper is based on [20], that presents an active FTC for compensation of all types of fault in linear systems; in this study, a similar architecture is used for nonlinear systems. In this paper, an AFTC scheme based on combination the nonlinear MPC (NMPC) with fault estimation is presented to accommodate actuator and sensor faults of affine nonlinear systems with some constraints on control and states. The architecture of the designed FTC approach is depicted in Fig. 1, where controller consist of NMPC, fault/state estimator and supervisor unit. The fault/state estimator is based on the EKFs that estimates both the loss of effectiveness of actuators and sensors $(\hat{\gamma}_a, \hat{\gamma}_s)$ and the states of plant $\hat{\chi}\ (\kappa)$. The fault information provided by fault estimator is then used in supervisor that modifies the internal model in NMPC. Thus, the proposed controller can compensate actuator and sensor faults. Also by feedback compensation (FC) in NMPC, the proposed controller is robust against plant faults and uncertainties.

In Comparison with existing works, the main features of proposed method are:

- Unlike to the previous studies, It is a nonlinear FTC based on predictive control scheme.
- Actuator, sensor and plant faults as well as constraints can be compensated simultaneously in the suggested FTC approach.
- The proposed approach has low computational cost, because of using NMPC with analytical solution and dealing with actuator and sensor faults by correction of internal model instead of changing constraints.
- An fault estimator is explicitly designed to provide fault information for NMPC.
- Simplicity and superiority of the designed FTC in practical cases is significant.

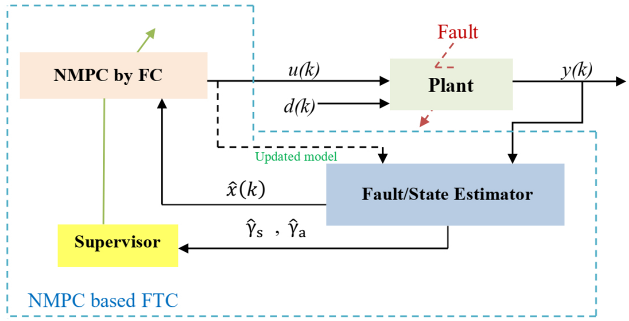

FIGURE 1. Block diagram of the proposed FTC scheme.

The following, Section II, illustrates the general NMPC formulation. Section III, explains the proposed FTC based on NMPC. Section IV, illustrates the simulations and, conclusions are given in Section V.

II. NONLINEAR MODEL PREDICTIVE CONTROL

The reason of MPC popularity in industrial process is mostly due to its basic effectiveness in handling the constraints on inputs and states, and process with complex dynamics such as multi-variable, nonlinear, time delayed and so on. In MPC at each sample time, the future plant outputs on the prediction horizon, N_P, are predicted based on available information and the optimal future input trajectory is proposed using the process model. These inputs are computed by solving a constrained optimization problem which yields an optimal input trajectory. Then only the first element of this trajectory is injected to the system and the other elements are removed. In the next sample instant by using the updated measurements, the all calculation is repeated. This policy is called the receding horizon control principle (RHC) [26]. MPC has been widely used for control of industrial processes, but for highly nonlinear process is mostly inefficient. To tackle this problem, NMPC has received a lot of attention over the last decade [27], [28]. Although the various characteristic of NMPC have been studied in literature, however its computational complexity is neglected in most cases. In general, for design the NMPC systems, the numerical techniques such as deep learning and sequential quadratic programming (SQP) have been suggested [29]. The complexity of NMPC by these methods is much heavy than can be implemented in practice. This paper uses a NMPC with little computational load and analytical solution which is recently presented in [30]. Its formulation is corrected to compensate disturbance and to be robust against uncertainties.

A. THE NMPC FORMULATION

Consider the affine model of time-invariant discrete system as:

$$\chi(\kappa+1) = f(\chi(\kappa)) + g(\chi(\kappa))\,u(\kappa) + g_d(\chi(\kappa))\,d(\kappa) \tag{1}$$

$$y(\kappa) = C\chi(\kappa) \tag{2}$$

where, $\chi(\kappa) \in X \subseteq R^n, u(\kappa) \in U \subseteq R^m$ and $y(\kappa)$ are the state vector, input and output respectively. Also $d(\kappa)$ is the known disturbance and f, g and g_d denote nonlinear functions. The one-step prediction of states could be obtained directly as

$$\hat{\chi}(\kappa+1|\kappa) = f(\chi(\kappa)) + g(\chi(\kappa))\,.u(\kappa) + g_d(\chi(\kappa))\,d(\kappa) \tag{3}$$

$$\begin{aligned}\hat{\chi}(\kappa+\iota|\kappa) = f&\left(\hat{\chi}(\kappa+\iota-1|\kappa)\right)\\ &+ g\left(\hat{\chi}(\kappa+\iota-1|\kappa)\right).u(\kappa+\iota-1|\kappa)\\ &+ g_d\left(\hat{\chi}(\kappa+\iota-1|\kappa)\right)d(\kappa+\iota-1|\kappa)\\ &\iota = 2, 3, \ldots, N_p\end{aligned} \tag{4}$$

Since $\hat{\chi}(\kappa+\iota-1|\kappa)$ is related to the previous data, then the equation (4) cannot be solved for one more prediction horizon. So, by the use of reference system, for $\iota \geq 2$, we can write:

$$\begin{aligned}\hat{\chi}(\kappa+\iota|\kappa) = f&\left(w_\chi(\kappa+\iota-1|\kappa)\right)\\ &+ g\left(w_\chi(\kappa+\iota-1|\kappa)\right).u(\kappa+\iota-1|\kappa)\\ &+ g_d\left(w_\chi(\kappa+\iota-1|\kappa)\right)d(\kappa+\iota-1|\kappa)\end{aligned} \tag{5}$$

where,

$$\begin{aligned}w_\chi(\kappa+\iota|\kappa) &= \alpha w_\chi(\kappa+\iota-1|\kappa)\\ &\quad + (1-\alpha)\,\chi_{sp}; \quad \iota = 1, 2, \ldots, N_P-1\end{aligned} \tag{6}$$

where, $\alpha \in [0, 1)$ is the soften factor, x_{sp} is the desired plant states and we can write $w_\chi(\kappa|\kappa) = \chi(\kappa)$. A stair-like control method is employed to reduce the computational burden of nonlinear optimization problem. Define, $\Delta u(\kappa) = u(\kappa) - u(\kappa-1) := \Delta$, then, $\Delta u(\kappa+\iota)$ is expressed as bellow:

$$\begin{aligned}\Delta u(\kappa+\iota) &= \beta\Delta u(\kappa+\iota-1)\\ &= \beta^\iota\Delta u(\kappa) = \beta^\iota\Delta; \quad \iota = 1, 2, \ldots, N_P-1\end{aligned} \tag{7}$$

where, β is positive number. Then, only the computation of $\Delta u(\kappa)$ is required, instead of computing $[\Delta u(\kappa)\,\Delta u(\kappa+1|\kappa)\ldots\Delta u(\kappa+N_P-1|\kappa)]$ which has N_P elements. Thus, the computation load in NMPC become independent to the prediction horizon. This property make it possible to use long N_P to achieve a better performance. By attention to (7) and

$$u(\kappa+\iota-1|\kappa) = u(\kappa-1) + \sum_{i=0}^{\iota-1}\Delta u(\kappa+i|\kappa) \tag{8}$$

The equation (6) can be expressed as

$$\begin{aligned}&\hat{\chi}(\kappa+\iota|\kappa)\\ &= f\left(w_\chi(\kappa+\iota-1|\kappa)\right)\\ &\quad + g\left(w_\chi(\kappa+\iota-1|\kappa)\right).\left(u(\kappa-1) + \sum_{i=0}^{\iota-1}\beta^i\Delta\right)\\ &\quad + g_d\left(w_\chi(\kappa+\iota-1|\kappa)\right)d(\kappa+\iota-1|\kappa)\\ &= f\left(w_\chi(\kappa+\iota-1|\kappa)\right)\\ &\quad + g\left(w_\chi(\kappa+\iota-1|\kappa)\right).u(\kappa-1)\\ &\quad + g_d\left(w_\chi(\kappa+\iota-1|\kappa)\right)d(\kappa+\iota-1|\kappa)\\ &\quad + g\left(w_\chi(\kappa+\iota-1|\kappa)\right).\sum_{i=0}^{\iota-1}\beta^i\Delta\\ &= \hat{\chi}^1(\kappa+\iota|\kappa)\\ &\quad + g\left(w_\chi(\kappa+\iota-1|\kappa)\right).\sum_{i=0}^{\iota-1}\beta^i\Delta\end{aligned} \tag{9}$$

where $\hat{\chi}^1(\kappa+\iota|\kappa)$ is defined as

$$\begin{aligned}\hat{\chi}^1(\kappa+\iota|\kappa) = f&\left(w_\chi(\kappa+\iota-1|\kappa)\right)\\ &+ g\left(w_\chi(\kappa+\iota-1|\kappa)\right).u(\kappa-1)\\ &+ g_d\left(w_\chi(\kappa+\iota-1|\kappa)\right)d(\kappa+\iota-1|\kappa)\end{aligned} \tag{10}$$

It should be noted that the information about future of disturbance mainly is unknown, and only in instant κ and before, it is known. By zero order extrapolation, $d(\kappa+\iota-1|\kappa)$ is approximated by $d(\kappa-1)$. Furthermore, the term $\hat{\chi}^1(\kappa+\iota|\kappa)$ in (9), includes only the available data at instant κ, while the next term includes the increment of future input. Then the unavailable data are divided linearly by (9), to find a analytic solution. By writing the predictions in the matrix form for $\iota = 1, 2, \ldots, N_P$,, we have

$$\hat{X}_\kappa = \begin{bmatrix}\hat{\chi}(\kappa+1|\kappa)\\ \hat{\chi}(\kappa+2|\kappa)\\ \vdots\\ \hat{\chi}(\kappa+N_P|\kappa)\end{bmatrix}; \quad X_\kappa^1 = \begin{bmatrix}\hat{\chi}^1(\kappa+1|\kappa)\\ \hat{\chi}^1(\kappa+2|\kappa)\\ \vdots\\ \hat{\chi}^1(\kappa+N_P|\kappa)\end{bmatrix}$$

$$W_{yk} = \begin{bmatrix}w_y(\kappa+1|\kappa)\\ w_y(\kappa+2|\kappa)\\ \vdots\\ w_y(\kappa+N_P|\kappa)\end{bmatrix}$$

$$\Delta U_\kappa = \begin{bmatrix}\Delta u(\kappa)\\ \Delta u(\kappa+1|\kappa)\\ \vdots\\ \Delta u(\kappa+N_P-1|\kappa)\end{bmatrix} = \begin{bmatrix}\Delta\\ \beta\Delta\\ \vdots\\ \beta^{N_P-1}\Delta\end{bmatrix}$$

$$s_\iota = g\left(w_\chi(\kappa+\iota-1|\kappa)\right),$$

$$S_\kappa = \begin{bmatrix}s_1 & 0 & \ldots & 0\\ s_2 & s_2 & \ldots & 0\\ \vdots & \vdots & \ddots & \vdots\\ s_p & s_p & \ldots & s_p\end{bmatrix}$$

$$S_\kappa.\Delta U_\kappa = \begin{bmatrix}s_1\\ s_2(1+\beta)\\ \vdots\\ s_p(1+\beta+\ldots+\beta^{N_P-1})\end{bmatrix}\Delta = \bar{S}_\kappa.\Delta \tag{11}$$

where, $w_{(}y)$ is the reference trajectory of output. The states and outputs predictions can be expressed as

$$\hat{X}_\kappa = X_\kappa^1 + S_\kappa.\Delta U_\kappa = X_\kappa^1 + \bar{S}_\kappa.\Delta \quad (12)$$

$$\hat{Y}_\kappa = C\hat{X}_\kappa = C\left(X_\kappa^1 + \bar{S}_\kappa.\Delta\right) \quad (13)$$

With objective function

$$J_\kappa = \left(\hat{Y}_\kappa - W_{yk}\right)^T Q\left(\hat{Y}_\kappa - W_{yk}\right) + \Delta U_\kappa{}^T R\Delta U_\kappa \quad (14)$$

where, Q and R are weight matrices, by $\frac{\partial J_\kappa}{\partial\Delta} = 0$ and $\frac{\partial^2 J_\kappa}{\partial\Delta^2} > 0$, for single and unconstrained input, $\Delta u(\kappa)$ is obtained as

$$\Delta u(\kappa) = \frac{\bar{S}_\kappa^T C^T Q\left(W_{yk} - CX_\kappa^1\right)}{\bar{S}_\kappa^T C^T QC\bar{S}_\kappa + 0.5R\left(1 + \beta^2 + \ldots + \beta^{2(N_P-1)}\right)} \quad (15)$$

To satisfy the constraints, the lagrange method can be used. It is supposed that every constraint on control or states can be rewritten as $a_i^T \Delta u(\kappa) \le b_i;\ i = 1, 2, \ldots, p$, so all constraints can be expressed as bellow matrix form

$$A\Delta u(\kappa) \le B \quad (16)$$

where, $B = \left[b_1 b_2 \ldots b_q\right]^T, A = \left[a_1^T a_2^T \ldots a_p^T\right]^T$. By choose the lagrange function as

$$L_\kappa(\lambda_i) = J_\kappa + \lambda_i^T\left(a_i^T \Delta u(\kappa) - b_i\right); \quad i = 1, 2, \ldots, p \quad (17)$$

and $\frac{\partial L}{\partial\Delta u(\kappa)} = 0$ and $\frac{\partial L}{\partial\lambda_i} = 0$, then

$$\Delta u(\kappa) = \frac{\bar{S}_\kappa^T C^T Q\left(W_{yk} - CX_\kappa^1\right) - 0.5\lambda_i^T a_i^T}{\bar{S}_\kappa^T C^T QC\bar{S}_\kappa + 0.5R\left(1 + \beta^2 + \ldots + \beta^{2(N_P-1)}\right)} \quad (18)$$

$$\lambda_i^T = \left[a_i^T \bar{S}_\kappa^T C^T Q\left(W_{yk} - CX_\kappa^1\right) - b_i\begin{pmatrix}\bar{S}_\kappa^T C^T QC\bar{S}_\kappa \\ +0.5R\left(1 + \beta^2 + \ldots + \beta^{2(N_P-1)}\right)\end{pmatrix}\right] / 0.5a_i^T a_i \quad (19)$$

If $\lambda_i \le 0$ in (19), it denotes that the corresponding constraint do not change $\Delta u(\kappa)$. Then it can be chosen $\bar{\lambda}_i = 0$, however, if $\lambda_i > 0$, the corresponding constraint can change $\Delta u(\kappa)$, so $\bar{\lambda}_i = \lambda_i$. Then, the constrained NMPC control action could be computed as

$$\Delta u(\kappa) = \frac{\bar{S}_\kappa^T C^T Q\left(W_{yk} - CX_\kappa^1\right) - 0.5A^T\bar{\Lambda}}{\bar{S}_\kappa^T C^T QC\bar{S}_\kappa + 0.5R\left(1 + \beta^2 + \ldots + \beta^{2(N_P-1)}\right)} \quad (20)$$

where, $\bar{\Lambda} = \left[\bar{\lambda}_1\bar{\lambda}_2 \ldots \bar{\lambda}_q\right]^T$. It should be noted that the effect of $d(k)$ is taken in to account in (20) by the term X_k^1, defined in (11), which its components are calculated from (10).

Remark 1: The NMPC formulation presented above can be extended to MIMO systems easily.

Remark 2: The term $w_a(k)$, which denotes the zero-mean white Gaussian noise with covariance matrices q_a, in (34) represents the possibility of rapid changes in the case that the effectiveness factor of actuators $\gamma_a(k)$ is lost. The sensitivity of the suggested method to these changes is low. However, to reduce the sensitivity of the method to the loss of effectiveness factor when it has rapid changes in the time domain, the dynamics can be considered as:

$$\gamma_a(k+1) = A\gamma_a(k) + w_a((k) \quad (21)$$

where, matrix A needs to be known.

B. FEEDBACK COMPENSATION

In the most cases, there are not explicit model of the process and there are some uncertainties in process model. In these cases, model of process is achieved by model mismatch. When MPC uses this model, it cannot achieve control objectives. For this purpose, feedback compensation (FC) could be used to solve this problem by marking $e(\kappa)$ at time κ as follows

$$e(\kappa) = \chi(\kappa) - \hat{\chi}(\kappa|\kappa-1) \quad (22)$$

where $\chi(\kappa)$ can be achieved by system feedback or state observer at sample instant κ, and $\hat{\chi}(\kappa|\kappa-1)$ is the predicted amount of $\chi(\kappa)$ at instant $\kappa - 1$. Similarly,

$$e(\kappa+\iota|\kappa) = \chi(\kappa+\iota) - \hat{\chi}(\kappa+\iota|\kappa+\iota-1) \quad (23)$$

By adding error in NMPC formulation, equation (10) is rewritten as follows

$$\begin{aligned}\hat{\chi}^1(\kappa+\iota|\kappa) = &f\left(w_\chi(\kappa+\iota-1|\kappa)\right) \\ &+ g\left(w_\chi(\kappa+\iota-1|\kappa)\right).u(\kappa-1) \\ &+ g_d\left(w_\chi(\kappa+\iota-1|\kappa)\right)d(\kappa+\iota-1|\kappa) \\ &+ e(\kappa+\iota|\kappa)\end{aligned} \quad (24)$$

where, by zero order extrapolation, $d(\kappa+\iota-1|\kappa) = d(\kappa-1)$ and $e(\kappa+\iota|\kappa) = e(\kappa)$. Thus, by using FC, NMPC is robust against uncertainties.

Remark 3: When the fault occurs in plant, it can be modeled as model mismatch; then by using FC in NMPC formulation, the control system can accommodates the fault in plant.

III. FTC BASED ON NMPC

In this section, the proposed FTC approach is discussed. The fault description in control system components is introduced in subsection 3.1, and the proposed fault estimator and supervisory schemes are presented in subsection 3.2 and 3.3 respectively, and the architecture of proposed FTC scheme is shown in 3.4.

A. FAULT DESCRIPTION IN CONTROL SYSTEM COMPONENTS

During the operation of a control system, failures or faults may be occurred in the components of control system such as actuators, sensors and plant. These type of faults can be modeled as multiplicative/additive faults. The fault which

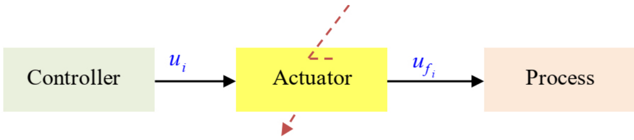

FIGURE 2. Actuator fault.

changes the dynamics of the plant is named as plant fault. This type of fault in affine systems is written as bellow

$$f(\chi(\kappa))_f = f(\chi(\kappa)) + \delta f(\chi(\kappa)) \tag{25}$$

For example, the tank system that is pierced and its flow rate is changed, has the plant fault. The fault that may be occurred in actuators can be bias or partial failure, that is reduction of control effectiveness. From Fig. 2, the control action of $i-th$ faulty actuator can be expressed as follow [20]:

$$u_{fi} = (1+\gamma_{ai})\,u_i + u_{f0_i}; \quad i = 1, 2, \ldots, m, \quad -1 \le \gamma_{ai} \le 0 \tag{26}$$

where, m is the actuators number, and γ_{ai} is the loss of control effectiveness factor and u_{f0_i} is the bias of $i-th$ actuator. All types of actuator faults in literature are shown in Table 1.

The actuator fault can also be represented in a control system by the following compact form

$$u_f = (I+\gamma_a)u + u_{f0} \tag{27}$$

where, $\gamma_a = diag\,(\gamma_{a1}, \gamma_{a2}, \ldots, \gamma_{am})$, I is the identity matrix and $u_{f0} = \left[u_{f01} u_{f02} \ldots u_{f0_m}\right]^T$. In a similar way, sensor faults can be represented as bellow

$$y_f = (I+\gamma_s)\,y + y_{f0} \tag{28}$$

where, $\gamma_s = diag\left(\gamma_{s1}, \gamma_{s2}, \ldots, \gamma_{sq}\right)$ *and* $y_{f0} = \left[y_{f01} y_{f02} \ldots y_{f0_q}\right]^T$.

B. FAULT/STATE ESTIMATOR SCHEME

We design a new fault/state estimator based on EKF that estimates the control and output effectiveness factors γ_a, γ_s and states of the plant (χ) used in NMPC. Consider the fault free, affine nonlinear system

$$\chi(\kappa+1) = f(\chi(\kappa)) + g(\chi(\kappa))\,u(\kappa) + g_d(\chi(\kappa))\,d(\kappa) \tag{29}$$

$$y(\kappa) = C\chi(\kappa) \tag{30}$$

Regarding (27), the state equation with actuator fault is as follow

$$\begin{aligned}\chi(\kappa+1) = f(\chi(\kappa)) &+ g(\chi(\kappa))\,u(\kappa) + E(\kappa)\,\gamma_a(\kappa) \\ &+ g_d(\chi(\kappa))\,d(\kappa)\end{aligned} \tag{31}$$

where

$$E(\kappa) = g(\chi(\kappa))\,U(\kappa),$$
$$\gamma_a(\kappa) = \begin{bmatrix}\gamma_{a1}(\kappa) \\ \gamma_{a2}(\kappa) \\ \vdots \\ \gamma_{am}(\kappa)\end{bmatrix},$$
$$U(\kappa) = \begin{bmatrix} u_1(\kappa) & 0 & \cdots & 0 \\ 0 & u_2(\kappa) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & u_m(\kappa)\end{bmatrix} \tag{32}$$

When we have no infirmation about the changes of the loss of effectiveness factors, we can model the control loss of effectiveness factors by a random bias vector as bellow

$$\gamma_a(\kappa+1) = \gamma_a(\kappa) + w_a(\kappa) \tag{33}$$

where, $w_a(\kappa)$ denote the zero mean white Gaussian noise and covariance matrices q_a. Defining the new state such as $z_a(\kappa) = [\chi(\kappa)\ \ \gamma_a(\kappa)]^T$, we have

$$\begin{aligned} z_a(\kappa+1) = \tilde{f}(z_a(\kappa)) &+ \tilde{g}(z_a(\kappa))\,u(\kappa) \\ &+ \tilde{g}_d(z_a(\kappa))\,d(\kappa) \\ &+ g_{wa} w_a(\kappa)\end{aligned} \tag{34}$$

$$y(\kappa) = \tilde{C}_a z_a(\kappa) \tag{35}$$

where,

$$\tilde{f}(z_a(\kappa)) = \begin{bmatrix} f(\chi(\kappa)) + E(\kappa)\,\gamma_a(\kappa) \\ \gamma_a(\kappa)\end{bmatrix},$$
$$\tilde{g}(z_a(\kappa)) = \begin{bmatrix} g(\chi(\kappa)) \\ 0 \end{bmatrix},$$
$$\tilde{g}_d(z_a(\kappa)) = \begin{bmatrix} g_d(\chi(\kappa)) \\ 0 \end{bmatrix},$$
$$g_{wa} = \begin{bmatrix} 0 \\ I \end{bmatrix}; \quad \tilde{C}_a = [C \quad 0] \tag{36}$$

By an estimator both state vector of plant and control effectiveness factors can be approximated. Similarly, the output equation with sensor faults is as follow

$$y(\kappa) = C\chi(\kappa) + F(\kappa)\,\gamma_s(\kappa) \tag{37}$$

where

$$F(\kappa) = -Y(\kappa),$$
$$Y(\kappa) = \begin{bmatrix} y_1(\kappa) & 0 & \cdots & 0 \\ 0 & y_2(\kappa) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & y_q(\kappa)\end{bmatrix},$$
$$\gamma_s(\kappa) = \begin{bmatrix}\gamma_{s1}(\kappa) \\ \gamma_{s2}(\kappa) \\ \vdots \\ \gamma_{sq}(\kappa)\end{bmatrix} \tag{38}$$

TABLE 1. Actuator faults type.

Fault free	$\gamma_{ai} = 0, u_{foi} = 0$
Bias	$u_{foi} \neq 0$
Partial failure	$-1 < \gamma_{\text{ai}} < 0$
Failure	$\gamma_{\text{ai}} = -1$
Stuck	$\gamma_{\text{ai}} = -1,\ u_{foi} \neq 0$

In similar way, the sensor loss of effectiveness factors can be modeled as

$$\gamma_s(\kappa+1) = \gamma_s(\kappa) + w_s(\kappa) \tag{39}$$

where, $w_s(\kappa)$ denotes zero mean white Gaussian noise and covariance matrices q_s. By defining the new state $z_s(\kappa) = [\chi(\kappa)\,\gamma_s(\kappa)]^T$, the augmented model is

$$\begin{aligned} z_s(\kappa+1) = &\tilde{f}(z_s(\kappa)) \\ &+ \tilde{g}(z_s(\kappa))\,u(\kappa) \\ &+ \tilde{g}_d(z_s(\kappa))\,d(\kappa) \\ &+ g_{\text{ws}} w_s(\kappa) \end{aligned} \tag{40}$$

$$y(\kappa) = \tilde{C}_s z_s(\kappa) \tag{41}$$

where,

$$\tilde{f}(z_s(\kappa)) = \begin{bmatrix} f(\chi(\kappa)) \\ \gamma_s(\kappa) \end{bmatrix}, \quad \tilde{g}(z_s(\kappa)) = \begin{bmatrix} g(\chi(\kappa)) \\ 0 \end{bmatrix}, \quad \tilde{g}_d(z_s(\kappa)) = \begin{bmatrix} g_d(\chi(\kappa)) \\ 0 \end{bmatrix},$$

$$g_{\text{ws}} = \begin{bmatrix} 0 \\ I \end{bmatrix}; \quad \tilde{C}_s = [C \quad F \quad (\kappa)] \tag{42}$$

For state estimation of the augmented models aforementioned above, nonlinear observers can be used. The EKF is a natural observer for nonlinear systems. The general formulation of EKF is as following. Consider the nonlinear discrete- time system as:

$$z_i(k+1) = L_i(z_i(k), u(k), d(k)) + \text{G}_i w_i(k) \tag{43}$$

$$y(k) = C_i z_i(k) + v_i(k) \tag{44}$$

where, $w_i(k)$ and $v_i(k)$ are the zero-mean white Gaussian noise sequence with covariance matrices q_i and r_i, respectively and

$$\begin{aligned} &L_i(z_i(k), \xi_i(k)) \\ &\quad = \tilde{f}(z_i(k)) + \tilde{g}(z_i(k))\; u(k) + \tilde{g}_d(z_i(k))\,d(k) \end{aligned} \tag{45}$$

where, $G_i \triangleq g_{wi}$ and $C_i = \tilde{C}_i$ for $i = a, s$. For above system, following equations are the standard EKF representation:
Prediction phase:

$$\hat{z}_i(k)^- = L_i\left(\hat{z}_i(k-1)^+, u(k-1), d(k-1)\right) \tag{46}$$

$$A_{i_{k-1}} = \left.\frac{\partial L_{i_{k-1}}}{\partial z}\right|_{\hat{z}_i(k-1)^+} \tag{47}$$

Update phase:

$$K_k = P_k^- {C_{i_k}}^T \left(C_{i_k} P_k^- {C_{i_k}}^T + r_{i_k}\right)^{-1} \tag{48}$$

$$\hat{z}_i(k)^+ = \hat{z}_i(k)^- + K_k\left(y(k) - C_{i_k}\hat{z}_i(k)^-\right) \tag{49}$$

$$P_k^+ = P_k^- - K_k C_{i_k} P_k^- \tag{50}$$

where, $\hat{z}_i(k)^-$ is a priori estimation, P_k^- is a priori covariance, $\hat{z}_i(k)^+$ is a posteriori estimation, P_k^+ is a posteriori covariance and K_k in the above equations is determined from the Riccati equation and called the EKF gain. It should be noted that in practice we do not know the process noise covariance matrix (q_i) and the measurement noise matrix (r_i), that affect the system. But, during filter design, they are adjusted by trial and error approach to achieve better EKF filter performance.

By the use of EKFs, the states of the augmented systems (43-44), (i.e., $z_i(k) = [x(k)\,\gamma_i(k)]^T$, *for* $i = a, s$, which include the variables of the plant state and the loss of effectiveness factor of actuator or sensors, are estimated at each sampling time and are passed to the supervisor unit.

Remark 4: If the bias in actuators is unknown, it can be estimated in similar way by above method. For state estimation of the augmented models aforementioned above, nonlinear observers can be used. The EKF is a natural observer for nonlinear systems. The general formulation of EKF can be found in [31]. Thus by using two EKFs for augmented systems the states of process and $\gamma_s(\kappa)$ and $\gamma_a(\kappa)$ can be estimated.

C. SUPERVISORY SCHEME

The supervisor is unit that gives the fault information from fault/state estimator, then modifies the internal model of process in NMPC. The technique of modeling the all types of faults in actuators and sensors is presented in the following. Consider the fault-free model of process described by (29), (30). When actuator fault occurs, by replacing $u(\kappa)$ with $u_f(\kappa)$, presented in (27), the state equation (29) is changed by equation bellow

$$\begin{aligned} \chi(\kappa+1) = &f(\chi(\kappa)) \\ &+ g(\chi(\kappa))(I+\gamma_a)u(\kappa) \\ &+ g(\chi(\kappa))\,u_{f0} \\ &+ g_d(\chi(\kappa))\,d(\kappa) \end{aligned} \tag{51}$$

By definition of $g(\chi(\kappa))_{new} = g(\chi(\kappa))(I+\gamma_a)$, the equation (38) become

$$\begin{aligned} \chi(\kappa+1) = &f(\chi(\kappa)) \\ &+ g(\chi(\kappa))_{new} u(\kappa) \\ &+ g(\chi(\kappa))\,u_{f0} \\ &+ g_d(\chi(\kappa))\,d(\kappa) \end{aligned} \tag{52}$$

For compensating the actuators partial failure, by using the information about γ_a, $g(\chi(\kappa))_{new}$ is constructed, and NMPC is then redesigned. Also for accommodate the bias fault the term $g(\chi(\kappa))u_{f0}$ can be treated as disturbance in NMPC formulation; in compact form the NMPC can be designed for

$$\chi(\kappa+1) = f(\chi(\kappa)) + g(\chi(\kappa))u(\kappa) + \bar{g}_d(\chi(\kappa))\bar{d}(\kappa) \quad (53)$$

$$y(\kappa) = C\chi(\kappa) \quad (54)$$

where, $\bar{g}_d(\chi(\kappa)) = [g_d(\chi(\kappa)) \quad g(\chi(\kappa))]$ and $\bar{d}(\kappa) = \left[d(\kappa) \quad u_{f0}(\kappa)\right]^T$. In a similar way, when sensor fault occurs, by replacing $y(\kappa)$ with $y_f(\kappa)$ in (28), the output equation (30) is obtained as follows

$$y(\kappa) = (I+\gamma_s)^{-1}C\chi(\kappa) - (I+\gamma_s)^{-1}y_{f0} \quad (55)$$

By defining $C_{new} = (I+\gamma_s)^{-1}C$, the equation (55) is written as

$$y(\kappa) = C_{new}\chi(\kappa) - (I+\gamma_s)^{-1}y_{f0} \quad (56)$$

For compensating the sensor partial failure, by using of information about γ_s, C_{new} is constructed, then NMPC is redesigned. Also the bias term $-(I+\gamma_s)^{-1}y_{f0}$ can be compensated by correction of equation (13) in NMPC formulation. Thus, by constructing the $g(\chi(\kappa))_{new}$ and C_{new} in each sample time, the NMPC is updated and the simultaneous fault in actuators and sensors, are compensated. Also it should be noted, the fault in plant that modeled by (25), create mismatch between plant and model; but by FC in NMPC, plant fault is compensated automatically.

D. FTC ARCHITECTURE

The block diagram of the proposed FTC based on NMPC and EKF is depicted in Fig. 3. In every sample time, the EKF estimates the control and output effectiveness factors $\hat{\gamma}_a$, $\hat{\gamma}_s$ and states of plant $\hat{\chi}$. Then $\hat{\gamma}_a$, $\hat{\gamma}_s$ are sent to supervisor unit. Supervisor replaces the new faulty model with old fault-free model used in the NMPC. In addition, the estimated states of plant also used in NMPC formulation when the states are not measurable. Then, NMPC using this new information, updates the optimization problem and computes $\Delta u(\kappa)$. Thus the actuator and sensor faults are compensated by an AFTC system. Also, by FC in NMPC, the proposed controller is robust through plant faults and uncertainties. In brief, the whole procedure of implementation the presented FTC scheme can be summarized as follow

1) Develop the discrete, affine nonlinear model of process.
2) Construct NMPC controller with FC considering the nonlinear affine model of the plant and the real constraints (this step needs some trial and error for setting the NMPC weight matrices, prediction horizon).
3) Construct the EKFs for augmented systems (this step needs some trial and error for setting the best tuning parameters of EKF).

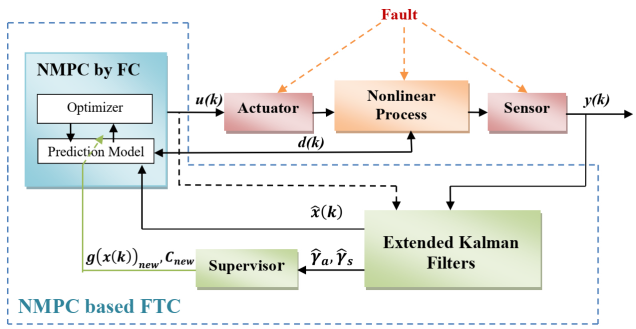

FIGURE 3. Architecture of proposed FTC based on NMPC.

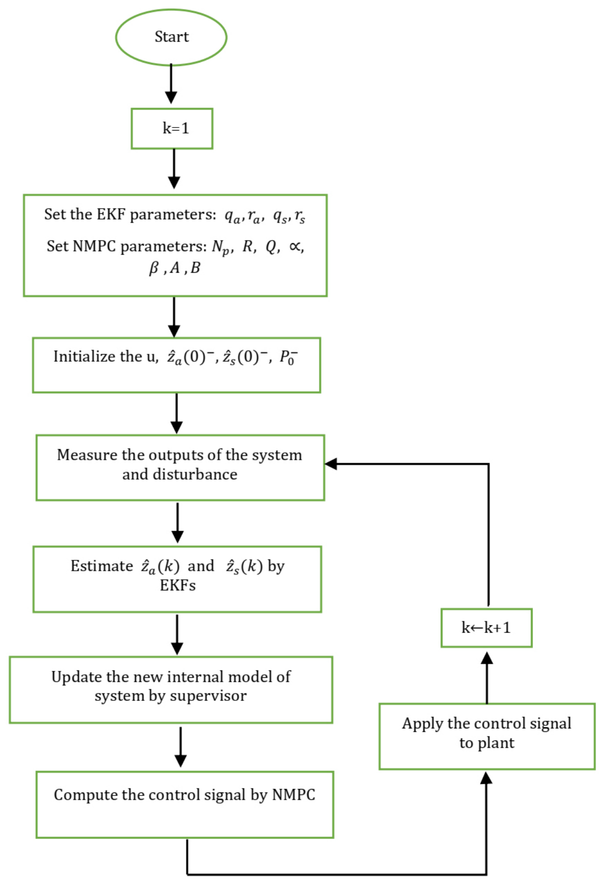

FIGURE 4. Flowchart of proposed FTC scheme.

4) Implement the control system as shown in Fig. 3. The general view on the proposed control scheme is illustrated in Fig. 4

It should be noted that in similar to the other MPC based FTC approaches, only by trial and error in choosing the parameters of NMPC, stability and desired performance can be obtained. The parameters of the proposed method are the NMPC parameters: N_p, α, β, R, Q which should be satisfied in $R, Q > 0$; $\alpha \in [0, 1)$; $\beta \in R^+$; $N_p > 1$ and EKFs parameters: $q_a, r_a, q_s, r_s > 0$ These parameters must be set to apply both to above criteria and to provide stability and desired performance in the closed-loop system.

Remark 5: The proposed FTC scheme is designed based on the basic approach such that the tracking error to be minimized and the constraints to be satisfied. However, for further stability analysis the recently presented methods can be applied such as [32].

IV. SIMULATION RESULTS

In order to demonstrate the performance of the proposed control method, the results of comparative simulation on CSTR system are given. The performance of the closed-loop system with proposed FTC is evaluated by Matlab simulation, compared to control method proposed in [19]. Both of method [19] and our method present the FTC based on predictive control and compensate the actuator and sensor faults simultaneously. Also, the proposed NMPC controller with analytical solution is compared to NMPC with SQP solution, from the computational cost point of view. The proposed FTC scheme is used to control of a continuous stirred-tank-reactor (CSTR), depicted in Fig. 5, which has a highly nonlinear model. Considering the constant liquid level, the dynamic model of CSTR is written as [33]:

$$\dot{C}_a = \frac{\mathbf{F}}{\mathbf{v}}(C_{a\mathbf{f}} - C_a) - \kappa_0 \,\mathbf{exp}\left(-\frac{E}{RT}\right) C_a \qquad (57)$$

$$\dot{T} = \frac{\mathbf{F}}{\mathbf{v}}(T_0 - T) + \frac{(-\Delta H)}{\rho C_p}\kappa_0 \exp\left(-\frac{E}{RT}\right) C_a + \frac{UA}{V\rho C_p}(T_\iota - T_d - T) \qquad (58)$$

The aforementioned model, represents an exothermic reaction, A $\rightarrow$ B, where, the concentration of A in the reactor (C_a) and the reactor temperature (T) are the outputs and the temperature of the coolant stream (T_ι) is the manipulated input by an external heat input/removal actuator. Also T_d, the loss of temperature because of heat dissipation is as input disturbance. The description of system parameters are presented in Table 2. The real constraints for system are

$$230 \leq \leq 600K, \quad 245 \leq T_\iota \leq 350K, \; 0 \leq C_a \leq 1\, mol/l \qquad (59)$$

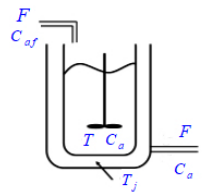

FIGURE 5. CSTR process.

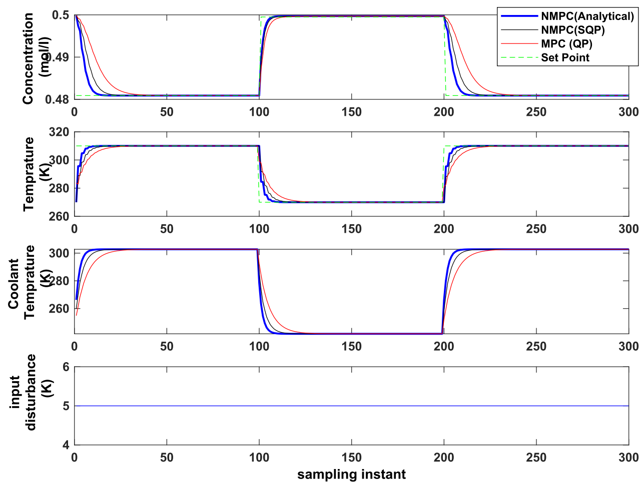

FIGURE 6. Control of CSTR system by NMPC controllers.

The simulation results of NMPCs control of CSTR system are shown in Fig. 6, and the parameters and computational load of NMPC with analytical solution used in this paper and NMPC with SQP used in [28], are compared in Table 3. The sample time is $\kappa_s = 0.5\, sec$ and for MPC design the system is linearized around the operation point OP1 ($C_a = 0.49, T = 290$). It can be seen that around the operation point OP1, each of the controllers have acceptable performance, but by attention to the Table 3, NMPC with analytical solution can reach the same control objectives and constraints with low computational time in comparison with other NMPC. The proposed method performs calculations in less time among nonlinear model predictive controllers. Obviously, MPC has less calculations time due to the simpler computational method, but, as mentioned earlier, it is not suitable for nonlinear systems. Compared to the rival NMPC, which use SQP for compute the

TABLE 2. The CSTR parameters values.

$UA = 50\,000\ J/min\ K$	Heat-transfer coefficient
$0.4 \ \leq C_{a\mathbf{f}} \leq 0.6 mol/l$	Inlet feed concentration
$E/R = 8750K$	Activation-energy
$\rho = 1000\ g/l$	Liquid density
$348 \leq T_0 \leq 352\ K$	Feed temperature
$\mathbf{F} = 100\ \ l/min$	Process flow rate
$\mathbf{v} = 100\ l$	Reactor volume
$C_p = 0.239 J/gK$	Specific-heat
$\kappa_0 = 7.20\ \times 10^{10} min^{-1}$	Reaction rate constant
$\Delta H = -50\,000\ J/mol$	Heat of reaction

TABLE 3. The NMPCs parameters and computation time.

Controller	Parameters	Average computation time (s)
MPC (QP)	$N_P = 2,\ \ N_c = 2\ R = 0.05 \cdot I\ ,\ Q = 0.1 \cdot I$	0.021
NMPC (SQP)	$N_P = 2,\ \ N_c = 2\ R = 0.05 \cdot I\ ,\ Q = 0.10 \cdot I$	0.127
NMPC (Analytical)	$N_P = 2,\ \ N_c = 2\ , R = 0.05 \cdot I\ ,\ Q = 0.10 \cdot I,\ \alpha = 0.5,\ \beta = 0.8$	0.023

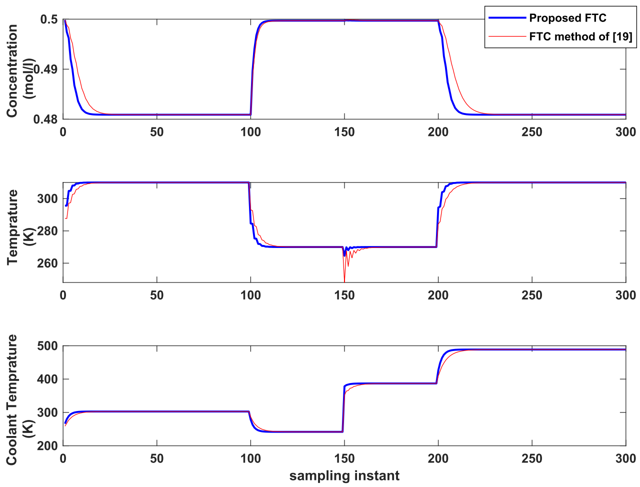

FIGURE 7. Control of CSTR system by the suggested FTC and the method of [19], for set point changes around OP1.

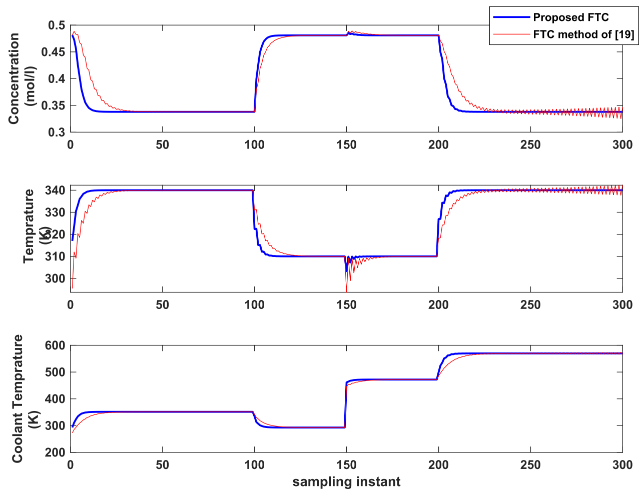

FIGURE 8. Control of CSTR system by the FTC and the method of [19], for set point changes around OP2.

optimization problem, our method with analytical solution, has significant less calculations time and can be implemented with industrial computers. For further complexity analysis the readers are referred to see a new approach in [34]. In the following, comparative simulations are presented. For this purpose, the proposed FTC approach based on NMPC with analytical solution is compared with FTC based on MPC as presented in [20], under simultaneous fault in actuator, sensor and plant; suppose that, the heat input/removal actuator has bias $T_{i0} = 10\ K$ and its effectiveness 40% degraded at instant $\kappa = 150$, and sensor1 lost 60% of its effectiveness simultaneously. Also the dynamic of plant changed by

$$f(\chi(\kappa))_f = f(\chi(\kappa)) + \delta f(\chi(\kappa)), \quad \delta f(\chi(\kappa)) = \begin{bmatrix} 0.005 \\ -1.5 \end{bmatrix} \tag{60}$$

The simulation results around two operation points OP1 ($C_a = 0.49, T = 290$) and OP2 ($C_a = 0.41, T = 325$) are shown in Fig. 7 and. 8 respectively. Also, the loss of effectiveness factor of actuator and sensor estimated by fault/state estimator are predicted in Fig. 9. By attention to Fig. 7 and Fig. 8, around both operation points specially in OP2, the FTC based on NMPC has more acceptable performance than FTC approach presented in [20], in the presence of the faults. Simulations verifies that the designed FTC based on NMPC with analytical solution accommodates the simultaneous faults in the closed-loop control system and can deal with constraints on control with low computational load in comparison with other FTC based on NMPC.

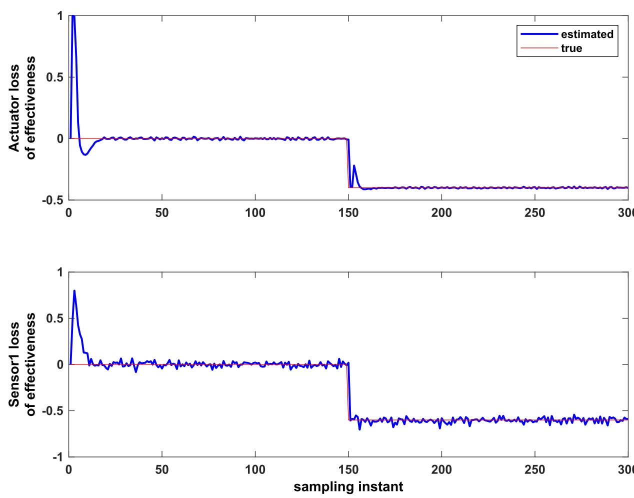

FIGURE 9. Control and output loss of effectiveness factor estimated by Fault/State estimator.

V. CONCLUSION

This study presents a new AFTC method on basis of NMPC and EKF for constrained affine nonlinear system. With fault estimating and correcting the internal model of NMPC in each sampling instant, the actuator and sensor faults were compensated. Also, by using FC in NMPC formulation, the proposed controller is robust in versus of plant faults and uncertainties. The advantages of the proposed FTC approach are: (1) its capability to handle the constraints and all types of faults in control system components simultaneously, (2) low on-line computational cost, (3) simplicity for real applications. To examine the capability, the suggested control approach is used to control of a continuous stirred-tank-reactor. Various faults such as degradation of sensors and actuators performance about 60% and suddenly dynamic changes are taken to account. It is shown that the suggested FTC-NMPC method well tackles the effect of faults and the output is well converged to the desired set point. Also, it is verified that the suggested approach has less computational cost. For our future work, this approach will be extended to MIMO constrained general nonlinear systems.

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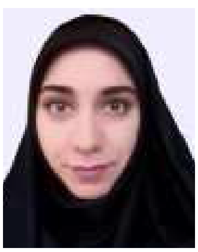

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