An infinite horizon model predictive control based active fault tolerant adaptive control scheme

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Abstract: This paper proposes an adaptive infinite horizon model predictive control (IHMPC) integrated with active fault tolerance properties due to the performance degradation of the model predictive control (MPC) caused by operational faults. The proposed scheme includes a fault supervision layer composed of fault diagnosis and accommodation methods to provide the ability to update the nominal model of the controller. The simulation results in a nonlinear industrial reactor subject to process faults illustrate that the proposed approach achieves better dynamic performance and has a reduced computational cost compared to a robust IHMPC.

Keywords: model predictive control, adaptive control, active fault-tolerant control, computational cost, performance improvement

1. INTRODUCTION

Model predictive control (MPC) is one of the main advanced control classes used in control engineering applications due to its optimal control performance, as well as the ability to handle constrained multivariate systems (Mayne, 2014). Despite industrial success, notably in the process industry, dealing with model mismatch due to changes in plant dynamics remains the main obstacle to maintain optimal performance of the MPC. The plant dynamics can be changed over time due to several factors, a major cause of this situation is operational faults (Blanke et al., 2016). Fault is an unacceptable deviation from some characteristic property of the system, which can occur in any element of the control loop (sensor, actuator or process) and according to Albalawi et al. (2018) faults cause significant degradation in control performance.

Faults can be modeled as uncertain systems, which in a theoretical perspective leads to the formulation of robust MPC (RMPC). In general, the RMPC is designed to meet all uncertainty conditions in the plant, including those least likely to occur in practice. This can result in a control law with conservative performance (Lorenzen et al., 2017). In addition, the computational cost of the robust MPC to solve online optimization problems is significant, some of them by nonlinear programming (NLP). Thus, the practical implementation in the controller hardware can be expensive (Di Cairano, 2016).

Another framework to deal with model uncertainty is through adaptive control and, particularly, for systems subject to faults, it is directly associated with the active fault tolerant control (AFTC) approach. The AFTC automatically compensates faults by redesigning the controller based on information provided by a fault diagnosis module, in order to maintain the closed-loop stability and acceptable control performance in fault situations (Blanke et al., 2016). The adaptive MPC allows fault tolerance to be incorporated into the optimization problem by redefining the constraints, updating the nominal model or changing the control objectives (Jain et al., 2018). However, AFTC approach based on the conventional MPC, as presented in Bavili et al. (2015), although it can provide improved control performance, there is not a priori guarantee of stability of the closed-loop system, which is a desirable feature in AFTC systems.

A popular approach to obtain a nominally stable MPC consists of adopting an infinite prediction horizon, which can be reduced to a finite horizon cost function by defining an appropriate terminal state penalty (Rawlings and Muske, 1993). However, other important characteristics of an IHMPC, such as recursive feasibility and offset elimination, depend on model and control law adequate structures. A formulation with these characteristics can be found in the IHMPC proposed by Odloak (2004), which considers artificial integrating modes to eliminate the offset of the closed-loop system and the one-step formulation is always feasible due to the slack variables included in the optimization problem. The method of Odloak (2004) has been extended to different types of dynamic systems (Martins and Odloak, 2016) and recently it has been embedded in real-time systems, as seen in Santana et al. (2019). However, the challenge related to preserving the performance of the IHMPC remains an open field of research, especially in plants subject to operational faults.

In this context, this paper proposes an AFTC scheme based on the IHMPC proposed by Odloak (2004) integrated with a fault supervision layer, in order to improve control performance in plants subject to operational faults.

The supervision layer consists of fault diagnosis and fault accommodation methods. The active fault tolerance is obtained by updating the nominal model of the controller to incorporate the fault dynamics in the optimization problem based on quadratic programming (QP).

In comparison with existing works in the literature, the contributions of this paper are: (1) an adaptive IHMPC with active fault tolerance proprieties; (2) AFTC strategy with reduced computational cost compared to robust MPC strategies; (3) achieve better control performance compared to the NLP-based robust IHMPC strategy.

This paper is organized as follows. The problem formulation is described in section 2. While in section 3, the adaptive IHMPC-based AFTC scheme for time delay stable systems is presented. Simulated results of control performance in a nonlinear reactor subject to process faults are presented in Section 4, as well as the comparative analysis of performance and computational cost in relation to robust strategy. In Section 5, the paper is concluded.

2. PROBLEM FORMULATION

The faults that affect the system are represented by a variation of system parameters (Noura et al., 2009), whose discrete time invariant state space model is:

$$x_f(k+1) = A_f x_f(k) + B_f u(k) \tag{1}$$
$$y(k) = C_f x(k) \tag{2}$$

where the matrices of the faulty system are defined by $A_f = (A_h + \delta A)$, $B_f = (B_h + \delta B)$ and $C_f = (C_h + \delta C)$, whilst $x_f \in R^n$, $u \in R^{n_u}$ and $y \in R^{n_y}$ are the state, input and output vectors at time instant k, respectively, $A_h \in R^{n\times n}$, $B_h \in R^{n\times n_u}$ and $C_h \in R^{n_y\times n}$ are healthy matrices of appropriate dimensions, δA, δB and δC correspond to the deviation of the system parameters with respect to the nominal values. The model $\Theta = (A_f, B_f, C_f)$ represent a given plant dynamics, and process, actuator and sensor faults can affect A_f, B_f and C_f.

To characterize model uncertainty, it is adopted the multi-plant system (Badgwell, 1997), where the plant model in (1) and (2) is not exactly known, however it is known to lie within a discrete set Ω of possible stable plants with the same dimensions. In this case, each model Θ_n corresponds to a particular plant $\Theta_n = (A_{fn}, B_{fn}, C_{fn})$, for $n = 1, \ldots, L$, where L is the total number of models.

$$\Theta_n \in \Omega = \{\Theta_1, \Theta_2, \ldots, \Theta_L\}, \quad n = 1, \ldots, L \tag{3}$$

In the uncertainty domain considered here, it is assumed that the plant can operate under several different operating conditions. In particular, there is one healthy operating point (without fault) represented by $\Theta_1 \in \Omega$, whilst $\Omega_f = \{\Theta_2, \ldots, \Theta_L\} \subset \Omega$ represents different operational points with faults. The definition of set Ω is a decision to be taken during the design phase of the process system and depends on the desired operational policy as well as on the study of possible faults that may occur in the plant.

Considering the system (1) and (2) and uncertainty domain (3), the objective is to solve a control problem with constraints, while guarantee recursive feasibility, nominal closed-loop stability and better control performance in faults situations.

3. ACTIVE FAULT TOLERANT ADAPTIVE IHMPC

The proposed control scheme consists of two layers: control and supervision, as shown in Fig. 1. In the control layer, an IHMPC is designed to meet the desired performance requirements of the plant, deal with constraints and guarantee the nominal stability of the closed-loop system. On the other hand, the supervision layer seeks to monitor plant faults to redesign the controller, in order to improving performance.

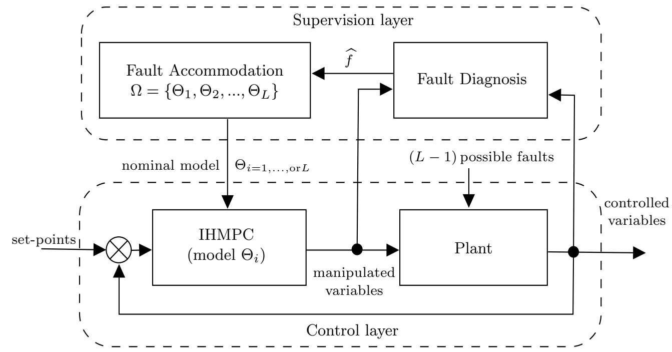

Figure 1. Adaptive IHMPC-based AFTC scheme.

After the occurrence of a specific fault between $n_f = L - 1$ possible faults, at time step k_f, the operating point of the plant is changed from the healthy model Θ_1 to the corresponding faulty dynamics of model $\Theta_i \in \Omega$, for $i = 2, \ldots, \text{or}\, L$. The fault diagnosis obtains information about the fault $\widehat{f}$ at time step k_d, where $k_d > k_f$, through the concept of analytical redundancy, evaluating inputs and outputs of the plant to verify dynamic inconsistencies (residual) between the expected behavior and the current plant dynamics. Posteriorly, the fault accommodation method updates the model, at time step k_a, where $k_a > k_d$, in the optimization problem of the IHMPC to compensate the effects of the fault in the plant.

In this scheme, the control performance is improved and still preserves the nominally stabilizing properties of the controller. Moreover, the proposed control structure has a simpler numerical solution to address model uncertainty than a traditional solution with the robust IHMPC.

3.1 Control layer

The formulation of the stabilizing MPC presented here is based on the state-space model in the analytical form of the step response of system with open-loop stable modes, proposed by Odloak (2004), and extended to the time delay system, as discussed in Martins and Odloak (2016). However, different from Odloak (2004), here it is proposed a cost function with an adaptive nominal model, according to changes that may occur in the plant due to faults.

In this model formulation, a discrete time state-space model in incremental form of the inputs, $\Delta u(k)$, is written from the corresponding step response at each time k of the system in (1) and (2):

$$x(k+1) = Ax(k) + B\Delta u(k) \tag{4}$$
$$y(k) = Cx(k) \tag{5}$$

where:

$$x(k) = \begin{bmatrix} x^s(k) & x^{st}(k) & z_1(k) & z_2(k) & \cdots & z_p(k) \end{bmatrix}^T \in C^{n_x}$$

$$A = \begin{bmatrix} I_{n_y} & 0 & B_1^s & B_2^s & \cdots & B_{p-1}^s & B_p^s \\ 0 & F & B_1^{st} & B_2^{st} & \cdots & B_{p-1}^{st} & B_p^{st} \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & I_{n_u} & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & I_{n_u} & 0 \end{bmatrix} \in R^{n_x \times n_x},$$

$$B = \begin{bmatrix} B_0^s & B_0^{st} & I_{n_u} & 0 & \ldots & 0 \end{bmatrix}^T \in R^{n_u \times n_x},$$

$$C = \begin{bmatrix} I_{n_y} & \Psi & 0_{n_y \times (n_y + n_u \cdot p)} \end{bmatrix} \in R^{n_y \times n_x}, \quad p = \max_{i,j} \gamma_{i,j},$$

$$n_x = n_y + n_{st} + p \cdot n_u, \quad n_{st} = n_y \cdot n_u \cdot \max(n_a)$$

The incremental form of the inputs introduces artificial integrating modes, $x^s \in R^{n_y}$, that provides integral action that eliminates offset at steady-state. The state vector also has a component related to the stable modes, $x^{st} \in R^{n_{st}}$, of the system, where $n_{st} = n_y \cdot n_u \cdot \max(n_a)$ and n_a distinct stable poles. The states z_1 to z_p represents the past input move delayed by the time period of zero until the largest process delay, p. The diagonal matrix F contains components corresponding to the stable poles. Whilst the matrices B_l^s and B_l^{st}, for $l = 0, \ldots, p$, are expressions of the coefficients of the partial fraction expansion of the step response. The details for obtaining these matrices can be found in Martins and Odloak (2016).

That way, for time delay stable systems and for the case of reference tracking, the IHMPC solves, considering here the adaptive nominal model (most likely) Θ_i, $i = 1, \ldots$ or L, the following optimization problem:

Problem 1.

$$\min_{\Delta u_k, \delta_{y,k}} V_k(\Theta_{i=1,\ldots or\ L}),$$

$$V_k(\Theta_i) = \sum_{j=0}^{m+p} \|e(k+j|k) - \delta_{y,k}(\Theta_i)\|_Q^2 + \sum_{j=0}^{m-1} \|\Delta u(k+j|k)\|_R^2 + \left\|x^{st}(k+m+p|k)\right\|_{Q(\bar{\Theta}_i)}^2 + \|\delta_{y,k}(\Theta_i)\|_S^2$$

subject to (4), (5) and

$$\Delta u(k+j|k) \in U, \quad j = 0, \ldots, m-1 \tag{6}$$

$$U = \left\{ \begin{matrix} -\Delta u_{max} \leq \Delta u(k+j|k) \leq \Delta u_{max} \\ u_{min} \leq \Delta u(k-1) + \sum_{i=0}^{j} \Delta u(k+i|k) \leq u_{max} \\ \Delta u(k+j|k) = 0 \quad j \geq m \end{matrix} \right\}$$

$$x^s(k+m+p|k) - y_{sp} - \delta_{y,k}(\Theta_i) = 0 \tag{7}$$

where $e(k+j|k) = y(k+j|k) - y_{sp}$ is the output prediction error vector at time step $k+j$ computed at time step k, taking into account the effects of the future control actions, $y(k+j|k)$ is the output prediction vector, $y_{sp,k}$ is the output reference vector, m is the control horizon and $\delta_{y,k} \in R^{n_y}$ is the slacks vector that aims to extend the domain of attraction of the controller and provides recursive feasibility to the method. $Q \in R^{n_y \times n_y}$ is a positive definite weighting matrix of the controlled outputs, $R \in R^{n_u \times n_u}$ is positive semi-definite weighting matrix associated with the move suppression on manipulated variables, and matrix $S_y \in R^{n_y \times n_y}$ is positive definite weighting matrix corresponding to slacks and must have adequate values to avoid the unnecessary use of the slacks in the optimization problem. The terminal weighting matrix, $\bar{Q}(\Theta_i)$, is determined from the solution of a Lyapunov equation:

$$\bar{Q}(\Theta_i) - F^T(\Theta_i)\bar{Q}(\Theta_i)F(\Theta_i) = F^T(\Theta_i)\Psi^T Q \Psi F(\Theta_i) \tag{8}$$

The constraint (7) is imposed to limit the cost function of the controller and the use of slacks in the optimization problem is only performed if this restriction is not satisfied with null slack variable. The Problem 1 is solved by quadratic programming (QP) and it recursively feasible, see proof in Odloak (2004), and asymptotically stable in the terms of the stability arguments proposed by Rawlings and Muske (1993).

3.2 Supervision layer

The supervision layer is flexible regarding the specification of the fault diagnosis method. However, for the implementation of analytical redundancy, model-based approaches, notably with observer, has been relevant for fault diagnosis (Gao et al., 2015). Specifically in this paper, it is considered the unknown input fault detection observer (UIFDO) proposed by Sotomayor and Odloak (2005).

For the development of UIFDO, a fault vector $f \in R^{n_f}$ is added to the system model (1) and (2), representing possible faults in the plant. In this way, from an adequate transformation matrix T, see Santos et al. (2019) for more details, the faulty model can be written in terms of a new state $w(k) = Tx(k)$, which can be separated into two parts $w(k) = [w_1(k)\ w_2(k)]^T$, where $w_1(k)$ is related to the faults that will be insensitive to the detector and $w_2(k)$ contains the faults that will be monitored. Now, with the assistance of Luenberger observer, an UIFDO can be written as:

$$\hat{w}_2(k+1) = \bar{A}\hat{w}_2(k) + \bar{B}u(k) + \bar{E}\bar{y}_1(k) + Kr(k) \tag{9}$$

$$r(k) = \bar{y}_2(k) - \bar{C}\hat{w}_2(k) \tag{10}$$

$$\hat{f}(k-1) = (\bar{E}_{11})[\hat{w}_1(k) - \bar{A}_{11}\hat{w}_1(k-1) - \bar{A}_{12}\hat{w}_2(k-1)) - \bar{B}_1 u(k-1)] \tag{11}$$

where r is the residual, $\hat{f}$ is the estimated fault magnitude, $\hat{w}_2$ is the estimate of the fault-sensitive state, $\bar{y}_1$ and $\bar{y}_2$ are the outputs of the transformed system, $\bar{A}$, $\bar{A}_{11}$, $\bar{A}_{12}$, $\bar{B}$, $\bar{B}_1$, $\bar{C}$, $\bar{E}$ and $\bar{E}_{11}$ are transformed system matrices, and K the observer gain, which was determined here through the adaptive Kalman filter, as indicated in (12) and (13), where P is the prediction error covariance matrix.

$$K(k) = (\bar{A}P(k-1)\bar{C}^T)(I + \bar{C}P(k-1)\bar{C}^T)^{-1} \tag{12}$$

$$P(k) = (\bar{A} - K(k)\bar{C})P(k-1)\bar{A}^T \tag{13}$$

Remark 1. *The probability of simultaneous occurrence of faults was considered insignificant.*

The fault diagnosis is implemented through a bank with n_f UIFDO in order to produce a structured residual set. The design of each UIFDO takes into account a specific fault in the plant with model contained in (3). In addition, the observer has the characteristic of being insensitive to one fault and sensitive to others.

The fault accommodation method is based on a decision-making algorithm, which checks information about the faults diagnosed to update the nominal model in Problem 1 to the most likely dynamics of the plant contained in (3).

4. SIMULATION RESULTS

This section presents the simulated results of the application of the fault tolerant adaptive IHMPC in an industrial styrene polymerization reactor. The dynamic performance and computational cost of the proposed control scheme are compared with the robust IHMPC proposed by Odloak (2004), which has no active fault tolerance characteristics.

4.1 Styrene polymerization reactor

It is considered here the industrial process for free-radical solution polymerization of styrene in a jacketed continuous stirred tank reactor (CSTR), whose phenomenological model is nonlinear, subject to three possible situations of abrupt process faults. In this system process, the polymer intrinsic viscosity η (y_1) and temperature of the reactor T (y_2) are the controlled variables and flow rate of initiator Q_i (u_1) and flow rate of cooling jacket fluid Q_c (u_2) are the manipulated variables. The definition of the parameters, variables, equations and process operation points can be consulted in Maner et al. (1996).

The faults scenarios analyzed correspond to abrupt changes in three nominal parameters of the reactor: frequency factor for termination reaction A_t, temperature of the reactor feed T_f and initiator efficiency f_i. For modeling purposes, the following magnitude of faults was adopted: decrease of 10% in parameter A_t, additive disturbance of $1.65\,K$ in T_f and 15% reduction in initiator efficiency. A set of linear models was obtained empirically to approximate the nonlinear plant, as showed in Table 1.

Table 1. Set of linear models of the plant

		$u_1(Q_i)$[L/h]	$u_2(Q_c)$[L/h]
Θ_1 (healthy)	$y_1(\eta)$[L/g]	$\frac{-45.47}{5.79s+1}e^{-0.44s}$	$\frac{3.75}{9.29s+1}e^{-2.81s}$
	$y_2(T)$[K]	$\frac{122.14}{7.09s+1}e^{-0.10s}$	$\frac{-39.01}{7.33s+1}e^{-0.62s}$
Θ_2 (fault A_t)	$y_1(\eta)$[L/g]	$\frac{-42.62}{5.76s+1}e^{-0.44s}$	$\frac{3.18}{8.59s+1}e^{-2.80s}$
	$y_2(T)$[K]	$\frac{119.96}{6.93s+1}e^{-0.10s}$	$\frac{-33.04}{6.83s+1}e^{-0.61s}$
Θ_3 (fault T_f)	$y_1(\eta)$[L/g]	$\frac{-45.46}{5.66s+1}e^{-0.46s}$	$\frac{2.69}{8.14s+1}e^{-2.73s}$
	$y_2(T)$[K]	$\frac{121.92}{6.46s+1}e^{-0.11s}$	$\frac{-28.20}{6.37s+1}e^{0.56s}$
Θ_4 (fault f_i)	$y_1(\eta)$[L/g]	$\frac{-38.64}{5.50s+1}e^{-0.42s}$	$\frac{3.68}{8.96s+1}e^{-2.81s}$
	$y_2(T)$[K]	$\frac{95.51}{6.75s+1}e^{-0.12s}$	$\frac{-38.71}{7.23s+1}e^{-0.61s}$

The controlled variables have a fixed setpoint $y_{sp} = [2.9091\,(\text{L/g})\ 323.55\,(\text{K})]^T$, whilst the inputs and input movements must be within the specified limits by $u_{max} = [144\,(\text{L/h})\ 748\,(\text{L/h})]^T$, $u_{min} = [72\,(\text{L/h})\ 400\,(\text{L/h})]^T$ and $\Delta u_{max} = [18\,(\text{L/h})\ 87\,(\text{L/h})]^T$. The tuning parameters of the adaptive IHMPC, for $\Delta T = 1$ h, are shown in Table 2.

In the healthy (faultless) situation the nominal model of the adaptive IHMPC is Θ_1, in the case of a specific faults this model is updated to the corresponding fault $\{\Theta_2$, Θ_2, $\Theta_3\}$. Regarding the robust IHMPC, the prediction model is fixed Θ_1 and the other models used for contracting-cost constraints of the optimization problem. Differently adaptive IHMPC, the optimization problem of robust IHMPC is solved by nonlinear programming (NLP), see Odloak (2004) for more details. Finally, the current model of the plant is nonlinear subject to faults.

Table 2. Tuning parameters of the controller.

model	Θ_1	Θ_2	Θ_3	Θ_4
m		3		
h_p		∞		
Q_y	[4.0 0.5]	[4.0 0.5]	[4.0 0.3]	[6.0 0.6]
R	[400 200]	[400 200]	[400 200]	[400 100]
S_y		$[10^4\ 10^4]$		

4.2 Fault scenario - A_t

The variation of the parameter A_t may occur due to the diffusion limitations in the monomer conversions. Thus, a reduction of 10% is considered, similar to an abrupt process fault. As seen in Fig. 2, the fault occurs at time 20 h and the fault diagnosis performed in approximately 2 sampling time. It is noted that an alarm is generated from the residuals r_{T_f} and r_{f_i}, and not by the residual r_{A_t}, due to the insensitivity characteristic of the detector fault. We use a decision limit $T = 0.2$. It is also verified that the estimate of the fault magnitude is coherent with the abnormality that occurred in the process.

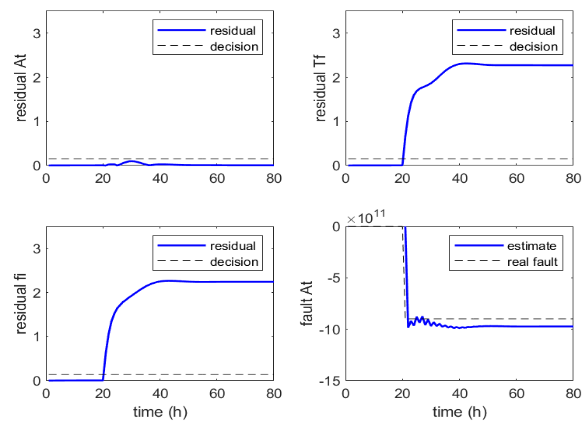

Figure 2. Fault diagnosis for abrupt fault in parameter A_t.

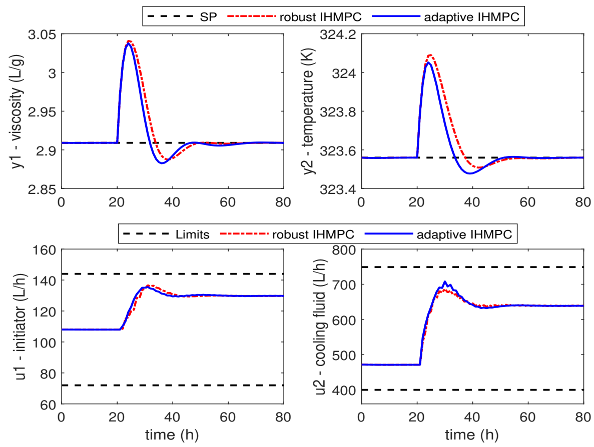

Figure 3. Performance of the controllers - fault A_t.

The control performance of the adaptive and robust IHMPC are shown in Fig. 3. Specifically, for the adaptive IHMPC, after online fault diagnosis, the fault accommodation module updates the model from Θ_1 to Θ_2, meanwhile the robust IHMPC remains with the model Θ_1. The two control strategies are able to converge the outputs to the respective setpoints, however the performance of adaptive IHMPC has less variation in the controlled variables.

4.3 Fault scenario - T_f

A sudden change in the feed temperature T_f affects the reactor temperature evolution and, consequently, influences the polymer properties and the process productivity. In this fault scenario, it is considered a abrupt increase of 1.65 K. The results of the fault diagnosis are presents in Fig. 4, observing that the residuals r_{At} and r_{fi} are sensitive and residual r_{Tf} is insensitive to this fault. The fault is properly isolated and its magnitude is estimated perfectly with respect to the real fault in the process.

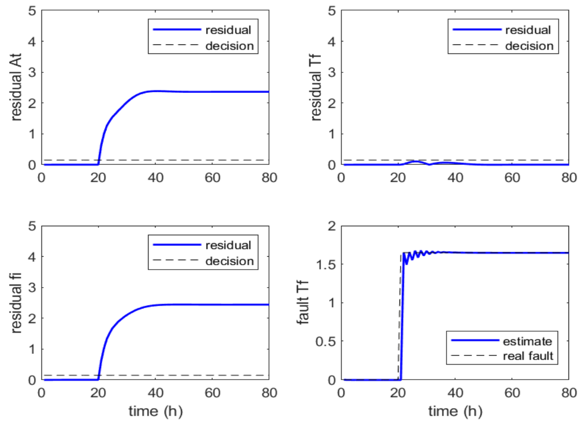

Figure 4. Fault diagnosis for abrupt increase in T_f.

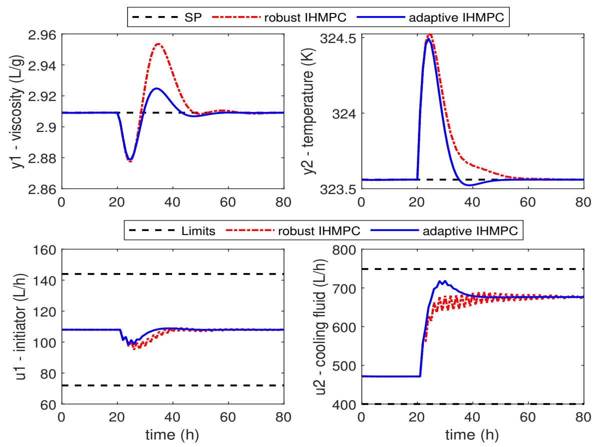

Figure 5. Performance of the controllers - fault T_f.

In this situation, adaptive IHMPC is redesigned online by changing the model from Θ_1 to Θ_3. The performance of the control strategies is shown in Fig. 5. It is possible to verify qualitatively that the adaptive IHMPC has the better dynamic performance in the process control, because it regulates the controlled variables with less deviation from the setpoints and also manipulates the control valves less aggressively. It is important to note that, before the redesign of the adaptive IHMPC, the control action of both controllers basically follow the same performance, however, after fault diagnosis and accommodation, the adaptive controller responds with a more effective control action.

4.4 Fault scenario - f_i

In a given context, the overall efficiency of the initiator may decrease due to imperfect mixing with a reaction fluid. For this scenario, it is simulated an abrupt fault with reduction of 15% in the efficiency of the initiator. As shown in Fig. 6, the fault is diagnosed correctly. Only the residual r_{fi} is not sensitized, which characterizes the referred fault, and the fault magnitude is estimated according to expectations. In this situation, the nominal model of the adaptive IHMPC is updated from Θ_1 to Θ_4.

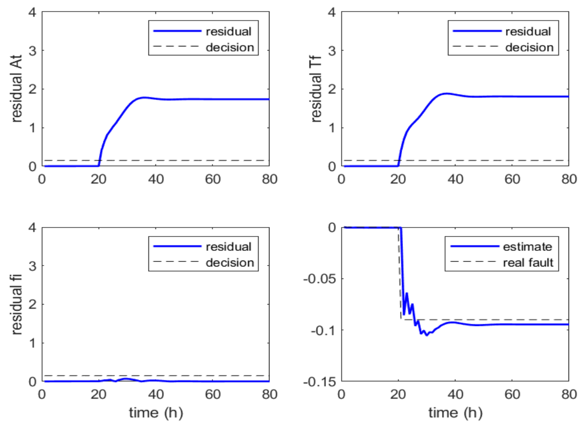

Figure 6. Fault diagnosis for abrupt increase in f_i.

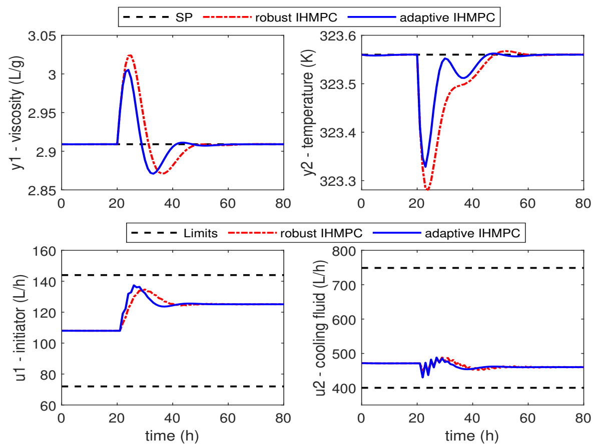

Figure 7. Performance of the controllers - fault f_i.

In this fault scenario, the adaptive IHMPC, again, results in better dynamic performance in the process control subject to fault, as seen in Fig. 7. It is noted that this control strategy provides a control action that results in less overshoot in the controlled variables, in addition to leading the process to steady-state more quickly than the robust strategy. The performance improvement achieved by the adaptive IHMPC directly influences the economic performance of the polymer production process.

4.5 Computational cost of the controllers

The computational cost associated with an MPC controller is an important parameter, given that at each sampling time the controller needs to solve an optimization problem. In this way, the computational cost of the QP-based adaptive IHMPC and NLP-based robust IHMPC are compared in terms of the solution time of the optimization problem at each time step k. In all the faulty scenarios, the computational cost of the adaptive controller is significantly lower compared to the robust controller. As seen in the histograms in Fig. 8, 9 e 10 the numerical performance of the adaptive IHMPC is concentrated in the time range of up to 0.03 s. On the other hand, the robust IHMPC provided irregular time values, with average time of 0.16 s, 0.30 s and 0.22 s, for faults A_t, T_f and f_i, respectively, and solution time of up to 1.4 s, as seen in Fig 10(b).

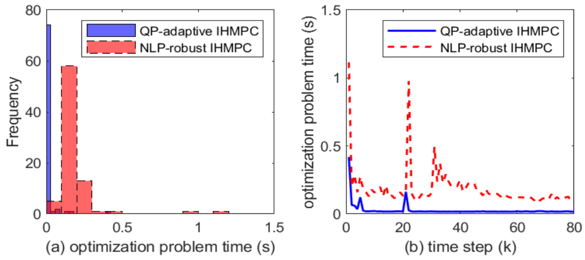

Figure 8. Computational cost - fault A_t.

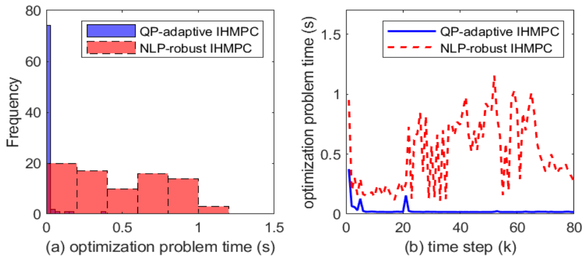

Figure 9. Computational cost - fault T_f.

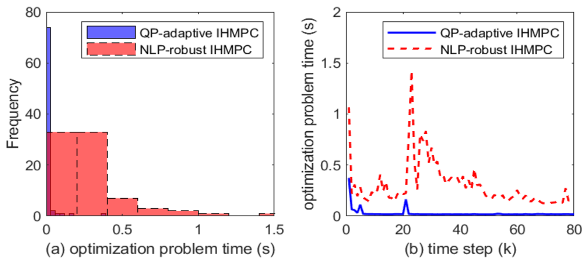

Figure 10. Computational cost - fault f_i.

5. CONCLUSIONS

This paper presents an active fault tolerant scheme based on the integration of an IHMPC with a fault supervision layer. One of the main characteristics of the proposed approach is its ability to guide a plant subject to faults to improve control performance. The simulation results in a nonlinear industrial reactor subject to three possible process faults illustrate that the adaptive approach achieves better control performance than a IHMPC robust. The adaptive IHMPC requires lower computational cost to deal with the uncertainty of the model. Finally, the application demonstrated practical implementation perspectives in a real case, with the possibility of integration in real systems that already employ the conventional IHMPC.

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