Improving System Availability using Overlapping Decomposition-based Robust Control

Haris M. Khalid, *Member, IEEE* and Zimran Rafique

***Abstract*—High availability is always expected for the continuation of operations in a plant. However, this objective is unable to attain due to the unplanned breakdowns, which could lead to unusual variations and faults. This paper works on improving the availability of system by accurately handling the fault information. This was made possible by proposing a subsystem-based robust control. The overlapping decomposition was employed to tackle the variations independently for each state. The stability of the system was proved further using a Lyapunov stability criteria. Performance evaluation was then conducted on an interconnected continuous time stirred tank reactor (CSTR) with recycle. The proposed scheme effectively controlled the faults to avoid costly failures.**

***Keywords*—Actuator failure, availability, closed loop, CSTR, failure detection, fault analysis, fault detection, interconnected system, overlapping decomposition, reliability, robust control, sensor failure, system failure and recovery.**

I. Introduction

Industries aim to improve the availability of plant components, decrease the operating cost, and optimize the maintenance cost [1]. One of the important components are liquid level-based systems. They are widely used due to their ability to produce high forces and torques with reduced vibration and low inertia [2]. To maintain high availability while not compromising on the safety of continuous operation, information is a key element to monitor the activity of every system component [3]–[5]. An incomplete or a delay in information may limit the working mechanism, thereby affecting the performance of the plant. Critical scenarios can be a burnt-out thermocouple, a broken transducer or a stuck valve, which could propagate further to effect a production line or a monitoring unit. In literature, various techniques are proposed to predict generic system faults and failures [6]–[15], as well as performing fault diagnosis [16]–[19]. Prognostic and health management systems were also published to improve the reliability and extend the remaining useful life of system components [20]–[23]. Nevertheless, these techniques rely on the procedures of accurate fault detection and prognosis. To the best of authors' knowledge, a common challenge among published methods is to control a plant in the presence of an undetected fault or variation.

This paper demonstrates the challenge of controlling faults using a nonlinear stirred tank reactor system. The contribution is to enhance the availability of overall system by controlling nonlinear transitions. An overview of the proposed scheme is illustrated in Fig. 1. The proposed method is developed by considering an observation model for all state variables. The state model is decomposed using overlapping decomposition. This divides the main system into independent subsystems of each state, such that the dynamics can be individually addressed. Subsequently, the information gathered from each state is given to an adaptive H_2-based controller, which is applied independently on each state. The proposed scheme provides a novel and convenient way to enhance the parametric estimations at states that are dominated by nonlinearity and system perturbations. Note among the undetected fault and variations, only leakage fault is considered in this formulation.

The paper is organized as follows: The proposed improved availability scheme is presented in Section II, followed by the implementation and evaluation of the proposed scheme in Section III. Finally conclusions are drawn in Section IV.

II. Proposed Improved Availability Scheme

A. Benchmark Example of Interconnected CSTR with Plant Model

The proposed scheme is built on a benchmark example of plant which is composed of interconnected units with recycle [24]. It is composed of two well-mixed, non-isothermal CSTRs with interconnections at time-instant t. Three parallel irreversible elementary exothermic reactions of the form $A(t) \xrightarrow{k(1,t)} B(t)$, $A(t) \xrightarrow{k(2,t)} U(t)$, $A(t) \xrightarrow{k(3,t)} R(t)$ took place, where $A(t)$ is the reactant species, and $B(t)$ is the desired product. $U(t)$ and $R(t)$ are the undesired by-products respectively. The feed to CSTR 1 consists of two streams as shown in Fig. 1: 1) one contains fresh $A(t)$ at flow rate $F(0,t)$, molar concentration $C(A(0),t)$ and temperature $T(0,t)$. 2) The other contains the recycled $A(t)$ from the second reactor at flow rate $F(r,t)$, molar concentration $C(A(2),t)$ and temperature $T(2,t)$. Similarly, the feed to CSTR 2 consists of of four streams as shown in Fig. 1: 1) the output of CSTR 1, 2) an additional fresh stream feeding pure $A(t)$ at flow rate $F(3,t)$, 3) molar concentration $C(A(03),t)$, and 4) temperature $T(03,t)$. Note a jacket is used to remove and provide heat to both reactors. This is due to the non-isothermal nature of the reactions. Under standard modeling assumptions, a plant model of the following form can be derived as follows in equations (1)-(4). Here $\Big(R(i,t)\ T(j,t)\Big) = \Big(k(i(0),t)\ exp(-E(i,t)/R(t)T(j,t))\Big)$, where $G(i,t)\ T(j,t)$ for $j = 1,2$. $T(j,t)$, $C(A(j),t)$, $Q(j,t)$, and $V(j,t)$ denote the temperature of the reactor, the concentration of $A(t)$, the rate of heat input to the reactor, and the reactor volume, respectively. $\triangle\ H(i,t)$, $k(i,t)$, $E(i,t)$, $i = 1,2,3$ denote the enthalpy, pre-exponential constants and activation energies of the three reactions, respectively. $c(p,t)$ and $\rho(t)$ denote the heat capacity and density of fluid in the reactor respectively. For the typical values of the process parameters, the plant with $Q(1,t) = Q(2,t) = 0$, $C(A(0),t) = C^s(A(0),t)$, $C(A(03),t) = C^s(A(03),t)$ and a recycle ratio of $r = 0.5$, has three

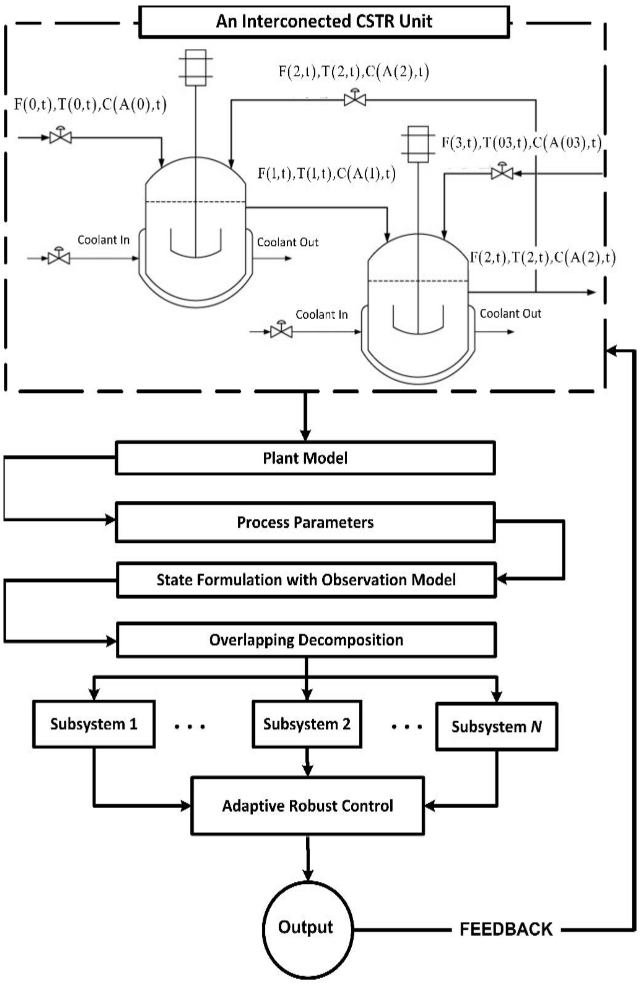

Fig. 1. Proposed scheme for improving system availability

steady-states: 1-2) two locally asymptotically stable, and 3) one unstable at $\Big(T^s(1,t)$, $C^s(A(1,t)\Big)$, $T^s(2,t)$, $C^s(A(2),t)$ = $(457.9K, 1.77 kmol/m^3$, $415.5\ K$, $1.75\ kmol/m^3)$. As stated in [24], the control objective is to stabilize the plant using the manipulated inputs from both the reactors. This control objective is to be achieved with minimal data exchange between the local control systems of the reactors over the communication network.

B. Process Parameters

The typical process parameters are collected from [24] as: $F(0,t) = 4.998\ m^3/h$, $F(1,t) = 39.996\ m^3/h$, $F(3,t)$ = $30.0\ m^3/h$, $F(r,t) = 34.998\ m^3/h$, $V(1,t) = 1.0\ m^3$, $V(2,t) = 3.0\ m^3$, $R(t) = 8.314\ kJ/kmolK$,$T(0,t) = 300.0\ K$, $T(03,t) = 300.0\ K$, $C^s(A(0,t)) = 4.0\ kmol/m^3$, $C^s(A(03,t)) = 4.0\ kmol/m^3$, $\Delta H_1 = -5.0 \times 104\ kJ/kmol$, $\Delta\ H(2,t) = -5.2 \times 104\ kJ/kmol$, $\Delta\ H(3,t) = -5.4 \times 104\ kJ/kmol$, $k(10,t) = 3.0 \times 10^6/h$, $k(20,t) = 3.0 \times 10^5/h$, $k(30,t) = 3.0 \times 10^5/h$, $E(1,t) = 5.0 \times 10^4\ kJ/kmol$, $E(2,t)$ = $7.53 \times 10^4\ kJ/kmol$, $E(3,t) = 7.53 \times 10^4\ kJ/kmol$, $\rho(t) = 1000.0\ kg/m^3$, $C(p,t) = 0.231\ kJ/kgK$, $T^s(1,t)$ = $457.9\ K$, $C^s(A(1),t) = 1.77\ kmol/m^3$, $T^s(2,t) = 415.5$ K, $C^s(A(2),t) = 1.75\ kmol/m^3$.

C. State Formulation with Observation Model

The state-space model is formulated based on the data available at each sensor. Assume that the process is nonlinear and the model has the capacity to collect observations as:

$$x(t+1) = f(x(t), u(t), d(t) + \nu(t),\ t = 0, 1, ..., T \quad (5)$$

$$z(t) = H(t)x(t) + w(t) \quad (6)$$

where $x(t) \in \mathbf{R}^{n\times 1}$ denote the plant's state at time-instant t. Superscript n is the size of state vector in subspace $\mathbf{R}$. $f(.)$ in the nonlinear representing the plant state $x(t)$, control input $u(t)$, and random process noise $\nu(t) \in \mathbf{R}^{n\times 1}$ respectively. In the observation model (6), $z(t) \in \mathbf{R}^{m\times 1}$ is the number of simultaneous observations obtained from m sensor of set $S = \{1, 2, ...m\}$ at time-instant t. The observations were $H(t) \in \mathbf{R}^{m\times m}$. $w(t) \in \mathbf{R}^{m\times 1}$ is the observation noise. It has been initially assumed that noises $\Big(\nu(t)$ and $w(t)\Big)$ are all uncorrelated. They are treated as zero-mean white Gaussian such that:

$$\mathbf{E}[w(t)] = \mathbf{E}[\nu(t)] = \mathbf{E}[w(g,t)\nu^*(h,t)] = 0,\ \forall\ t \quad (7)$$

$$\mathbf{E}[w(g,t)w^*(h,t)] = R(t)\delta(gh,t),\ \forall\ t \quad (8)$$

$$\mathbf{E}[\nu(g,t)\nu^*(h,t)] = Q(t)\delta(gh,t),\ \forall\ t \quad (9)$$

Note $\delta(gh,t)$ is a Kronecker delta, which is one when variables g and h are the same.

Since the observation model gives accumulative results of the full system, a method is required to decompose the plant into subsystems that represent local states. As a result, the overlapping decomposition [25] is used to decentralize the subsystems.

D. Overlapping Decomposition

From the state model (5) and (6), $z(t)$ is related to $x(t)$ by (10), where $I(1,t), ..., I(4,t)$ are considered as states of the plant, and $I(5,t), I(6,t)$ are pump-throughputs of the system. T is the non-square matrix of dimension $\Big(n(1,t) + 2n(2,t) + 2n(3,t) + 2n(4,t) + 2n(5,t) + n(6,t)\Big) \times \Big(n(1,t) + n(2,t) + n(3,t) + n(4,t) + n(5,t) + n(6,t)\Big)$. Variables $I(1,t), I(2,t), I(3,t), I(4,t), I(5,t)$, and $I(6,t)$ are identity matrices with dimensions corresponding to the components $x(1,t), x(2,t), x(3,t), x(4,t), x(5,t)$ and $x(6,t)$ respectively. The term $T(I)$ is the generalized inverse of T. According to overlapping decomposition [25], the transformation defines the expanded system as:

$$\tilde{A}(t) = \mathcal{U}(t)A(t)U(t) + \mathcal{M}(t) \quad (11)$$

Note $\tilde{A}(t)$ is the new expanded state matrix, $U(t) = \Big(\mathcal{U}(t)T(t)\mathcal{U}(t)\Big)^{-1}\mathcal{U}^*(t)$ is chosen as the pseudo-inverse of $\mathcal{U}(t)$. In addition, $\mathcal{M}(t)$ is the complementary matrix. The expanded $\tilde{A}(t)$ is described by (12). By comparing with original matrix $A(t)$, the description of overlapping diagonal blocks remained invariant due to the choice of the complementary matrix $\tilde{M}(t)$ under the transformation. This invariant property of the expansion is crucial because the identity of overlapping subsystems is preserved in $\tilde{A}(t)$, and they now appear as disjoint. Subsequently, adaptive robust control can be applied to individual subsystem dynamics.

$$\dot{T}(1,t) = \frac{F(0,t)}{V(1,t)}(T(0,t)-T(1,t)) + \frac{F(T,t)}{V(1,t)}(T(2,t)-T(1,t)) + \sum_{i=1}^{3} G(i,t)(T(i,t)C(A(1),t) + \frac{Q(1,t)}{\rho C(p,t)V(1,t)}) \tag{1}$$

$$\dot{C}(A(1),t) = \frac{F(0,t)}{V(1,t)}(C(A(0),t)-C(A(1),t))+\frac{F(r,t)}{V(1,t)}(C(A(2),t)-C(A(1),t))-\sum_{i=1}^{3} R(i,t)(T(i,t)C(A(1),t)C(p,t)V(1,t)) \tag{2}$$

$$\dot{T}(2,t) = \frac{F(1,t)}{V(2,t)}(T(1,t)-T(2,t))+\frac{F(3,t)}{V(2,t)}(T(03,t)-T(2,t))+\sum_{i=1}^{3} G(i,t)(T(2,t)C(A(2),t)+\frac{Q(2,t)}{\rho C(p,t)V(2,t)}) \tag{3}$$

$$\dot{C}(A(2),t) = \frac{F(1.t)}{V(2,t)}(C(A(1),t)-C(A(2),t)) + \frac{F(3,t)}{V(2,t)}(C(A(03),t)-C(A(2),t)) - \sum_{i=1}^{3} R(i,t)(T(2,t)C(A(2),t)) \tag{4}$$

$$z(t) = Tx(t),\ T = \begin{bmatrix} I(1,t) & 0 & 0 & 0 & 0 & 0 \\ 0 & I(2,t) & 0 & 0 & 0 & 0 \\ 0 & I(2,t) & 0 & 0 & 0 & 0 \\ 0 & 0 & I(3,t) & 0 & 0 & 0 \\ 0 & 0 & I(3,t) & 0 & 0 & 0 \\ 0 & 0 & 0 & I(4,t) & 0 & 0 \\ 0 & 0 & 0 & I(4,t) & 0 & 0 \\ 0 & 0 & 0 & 0 & I(5,t) & 0 \\ 0 & 0 & 0 & 0 & I(5,t) & 0 \\ 0 & 0 & 0 & 0 & 0 & I(6,t) \end{bmatrix}, TT^{I} = I \tag{10}$$

$$\tilde{A}(t) = \begin{bmatrix} A(11,t) & A(12,t) & 0 & A(13,t) & \dots & \dots & \dots & \dots\dots & \dots & \vdots \\ A(21,t) & A(22,t) & 0 & A(23,t) & \dots & \dots & \dots & \dots\dots & \dots & \vdots \\ A(21,t) & 0 & A(22,t) & A(23,t) & \dots & \dots & \dots & \dots & \dots & \vdots \\ A(31,t) & 0 & A(32,t) & A(33,t) & \dots & \dots & \dots & \dots & \dots & \vdots \\ A(31,t) & \dots & \dots & \dots & A(33,t) & A(34,t) & \dots & \dots & \dots & \vdots \\ A(41,t) & \dots & \dots & \dots & A(43,t) & A(44,t) & \dots & \dots & \dots & \vdots \\ A(41,t) & \dots & \dots & \dots & \dots & \dots & A(44,t) & A(45,t) & \dots & \vdots \\ A(51,t) & \dots & \dots & \dots & \dots & \dots & A(54,t) & A(55,t) & \dots & \vdots \\ A(51,t) & \dots & \dots & \dots & \dots & \dots & \dots & \dots & A(55,t) & A(56,t) \\ A(61,t) & \dots & \dots & \dots & \dots & \dots & \dots & \dots & A(65,t) & A(66,t) \end{bmatrix} \tag{12}$$

E. Adaptive Robust Control (ARC)

In this paper, ARC has been formulated for each state. The hardy-space $H(2,t)$ is also considered in the design. The $H(2,t)$ norm can be defined with its transfer function $G(s,t)$ as:

$$\|G\|(2,t) = \sqrt{\frac{1}{2\pi}\int_{-\infty}^{\infty} \text{trace}\Big(G(H,jw), G(jw)\Big)dw} \tag{13}$$

The performance of the $H(2,t)$ norm is defined by Lemma *2.1*.

Lemma 2.1: Consider the model (5)-(6), with no control input, i.e. $u(t) = 0$. Suppose the system is asymptotically stable, and a transfer function has been developed from $w(t)$ to observation output $z(t)$. This implies that

- $\|G\|(2,t) \leq \gamma$
- There exist matrices $P(t) \geq 0$ and $Z(t) \geq 0$ such that

$$\begin{bmatrix} P(t)A(t) + A^{*}(t)P(t) & P(t)B(t) \\ B^{*}(t)P(t) & -I \end{bmatrix} \leq 0 \tag{14}$$

$$\begin{bmatrix} P(t) & H(t)^{*} \\ H(t)^{*} & Z(t) \end{bmatrix} \geq 0 \tag{15}$$

$$\text{trace}(Z) \leq \gamma^2 \tag{16}$$

By minimizing the trace, feedback gains for the adaptive controller can be obtained. The feedback of robust control is dependent upon the assumption that: The initial transition matrix $x(0)$ from each state and $w(t)$ are independent for all time instants t, such that $t \geq 0$. This asserts that $P(t)$ and $\hat{P}(t)$ are the same. Hence, both of them can be used to characterize the covariance matrix for the feedback. Considering this assumption, $P(t)$ satisfies the following Lyapunov differential equation:

$$\hat{Q}(t) \quad = \quad A(t)P(t) + P(t)A(t)^*, \;\; t \geq 0, \qquad (17)$$

where $P(0) = \mathbf{E}[x(0)x^*(0)] - \mathbf{E}[x(0)]\mathbf{E}[x^*(0)]$.

The convergence of the above adaptive reconfiguration is guaranteed by the following theorem:

Theorem 2.1: Under the assumptions, the system (5-6) and following diagnostic algorithm.

$$\varDelta\varXi(f,t) \quad = \quad \varGamma(t)f^*(u(t),z(t),\hat{x}(t))R(t)e(z,t) \quad (18)$$

where $\varXi(t)$ is the variable representing any variation or fault, $R(t)$ is a variable representing the covariance of error $e(t)$, $\varGamma$ > 0 is a weighting scalar. $\varXi(t)$ can realize $lim_{t\to\infty}e(x,t) = 0$ and a bounded $e(0,t) \in L^2(0)$. Furthermore, $lim_{t\to\infty}e(\xi,t)$ $= 0$ under a persistent excitation.

1) Proof of theorem 2.1:
Consider the following Lyapunov function,

$$V(e(t)) \quad = \quad e(x,t)^*P(t)e(x,t) + \varGamma^{-1}e(\varXi,t)^2 \quad (19)$$

From (18), its first forward difference is:

$$\begin{aligned}
\varDelta V = \; & \mathbf{E}\{V(e(t+1)|e(t),P(t))\} - V(e(t)) \\
= \; & \mathbf{E}\{e^*(t+1)P(t)e(t+1)\} - e^*(t)P(t)e(t) \\
= \; & (A(e,t)e(x,t) + B(L(0),t)u^*(e,t))P(t) \\
& (A(e,t)e(x,t) + B(L(0),t)u(e,t)) \\
- \; & e^*(x,t)P(t)e(x,t) \\
= \; & e^*(t)[(P(t)(A(t) - K(t)H(t)) + (A(t) \\
- \; & K(t)H(t))^*P(t)) + P(t)B(t)[\varXi(f,t)f(u(t),z(t),x(t)) \\
- \; & \hat{\varXi}(t)f(u(t)\varXi(t),z(t),\hat{x}(t))]e(t) - 2e(\varXi,t) \\
& f^*(u(t),z(t),\hat{x}(t))R(t)e(z,t) \qquad (20)
\end{aligned}$$

which concludes the $\lim_{t\to\infty} e(\varXi,t) = 0$. This completes the proof. ∎

III. Implementation and Evaluation

In this study, the system suffered from two leakage fault scenarios. Leakage faults are created by changing system parameters at various time instances in the experimentation. The system inputs, outputs, and four states are corrupted by Gaussian noise with zero mean and a standard deviation of 0.1. The applied scenarios were random leakage faults as: 1) A single fault in CSTR 1 was created by changing the valve parameters from 1 cm^2 to 0.81 cm^2. This was triggered at 250 second after the start of the experiment. Note the value 0.81 correlates to 30 % of the cross-section of the outlet hole of CSTR 1. 2) Multiple faults involving CSTR 1 and 2 were generated by changing valve parameters from 1 cm^2 to 1.62 cm^2, and from 1 cm^2 to 0.54 cm^2 respectively. Here, the value 1.62 cm^2 equals to 60 % of the cross-section of the outlet holes of CSTR 2 at 10 second. Furthermore, 0.54 cm^2 is 20 % of the cross-section of the outlet holes of CSTR 2 at 350 second. In Fig. 2, the H_2 based robust controller was implemented on each state of the plant. All states were separated using the overlapping decomposition to analyze the performance of controller individually on each state. The fault profiles of both test cases and their resultant impacts on each state are also presented. Referring to Fig. 2, it is evident the proposed controller was able to make the system stable with the minimum over-shoot and response time. This is due to its robust and reconfigurable nature, allowing better compensation of the leakage faults generated in the system.

IV. Conclusions

In this paper, the control of plant in the presence of undetected incipient faults was tackled by the proposed controller. An effective adaptive controller to tolerate the faults was designed. The enhancements provided more resistance against fluctuations and noisy conditions. One observed limitation of the proposed method was the computational complexity. This was due to the calculations of control using the decomposed architectures. However, this may be resolved by reducing the number of iterations or alternatively changing the time sequence.

References

[1] M.C. Eti, S.O.T. Ogaji, and S.D. Probert, "Integrating reliability, availability, maintainability and supportability with risk analysis for improved operation of the Afam thermal power-station," *Applied Energy*, vol. 84, no. 2, pp. 202–221, Feb 2007.

[2] M. Jelali, and H. Schwarz, "Nonlinear identification of hydraulic servodrive systems," *IEEE Control System Magazine*, vol. 15, no. 5, pp. 1722, Oct. 1995.

[3] Y. S. Juang, S. S. Lin, and H. P. Kao, "A knowledge management system for series/parallel availability optimization and design," *Expert System with Applications*, vol. 34, no. 1, pp. 181–193, Jan 2008.

[4] L. Sikos, J. Kleme, "Evaluation and assessment of reliability and availability software for securing an uninterrupted energy supply," *Clean Technologies and Environmental Policy*, vol. 12, no. 2, pp. 137–146, Apr 2010.

[5] O. Stephen, S. Suresh, S. Riti, and P. Douglas, "Novel approach for improving power-plant availability using advanced engine diagnostics," *Applied Energy*, vol. 72, no. 1, pp. 389–407, May 2002.

[6] S. K. Yang and T. S. Liu, "A petri net approach to early failure detection and isolation for preventive maintenance," *Quality and Reliability Engineering International*, vol. 14, pp. 319–330, 1998.

[7] W. Nelson, "Weibull prediction of a future number of failures," *Quality and Reliability Engineering International* vol. 16, pp. 23–26, 2000.

[8] S. N. Kher and G. M. Bubel, "Predicting system-failure risk from unanticipated fiber-breaks in manufacturing," *IEEE Transactions on Reliability*, vol. 47, no. 2, pp. 126–130, 1998.

[9] S. K. Yang, and T. S. Liu, "Implementation of petri nets using a field-programmable gate array," *Quality and Reliability Engineering International*, vol. 16, pp. 99–116, 2000.

[10] G. S. Hura and J. W. Atwood, "The use of petri nets to analyze coherent fault trees," *IEEE Transactions on Reliability*, vol. 37, no. 5, pp. 469–474, 1988.

[11] S. K. Yang, "A condition-based failure-prediction and processing-scheme for preventive maintenance," *IEEE Transactions on Reliability*, vol. 52, no. 3, Sep. 2003.

[12] M. S. Mahmoud, and H. M. Khalid, "Model prediction-based approach to fault tolerant control with applications", *Oxford University Press-IMA Journal of Mathematical Control and Information*, vol. 31, no. 2, pp. 217–244, October 2013.

[13] H. M. Khalid, and J. C.-H. Peng, "Tracking electromechanical oscillations: An enhanced maximum-likelihood based approach," *IEEE Transactions on Power Systems*, vol. 31, no. 3, pp. 1799–1808, May 2016.

[14] H. M. Khalid, and J. C.-H. Peng, "Improved recursive electromechanical oscillations monitoring scheme: A novel distributed approach," *IEEE Transactions on Power Systems*, vol. 30, no. 2, pp. 680–688, March 2015.

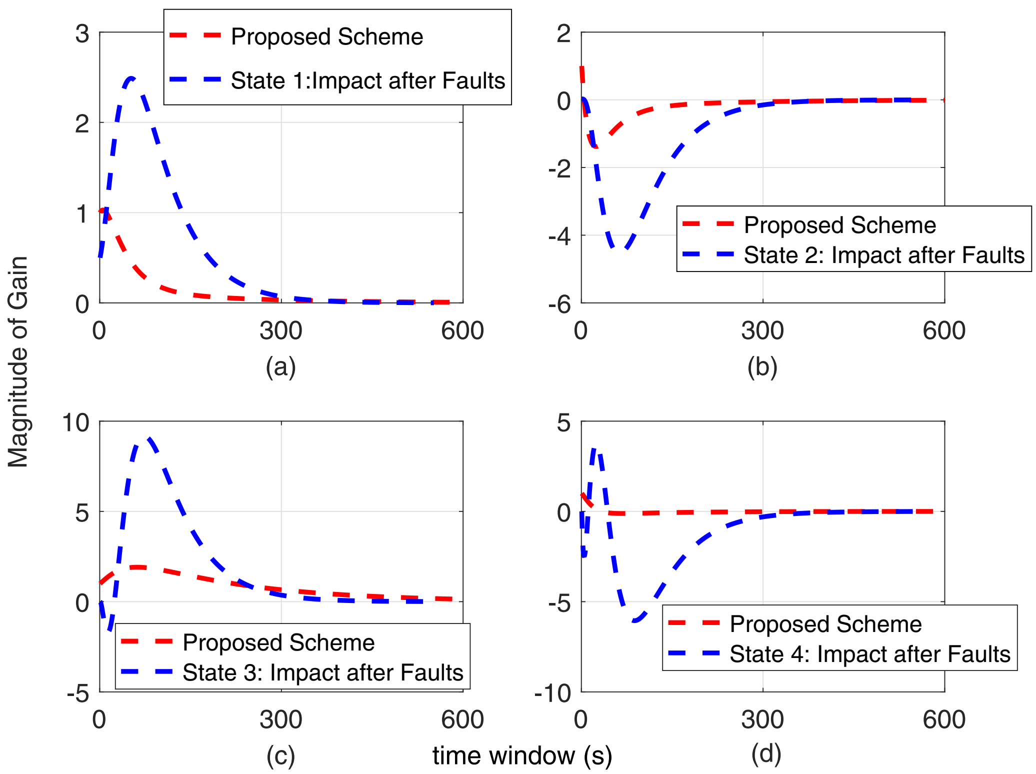

Fig. 2. (a-d) Comparison of fault control for each state

[15] H. M. Khalid, and J. C.-H. Peng, "Immunity towards data-injection attacks using track fusion-based model prediction," *IEEE Transactions on Smart Grid*, vol. 8, no. 2, pp. 697–707, March 2017.

[16] F. Cadini, E. Zio, and G. Peloni, "Particle filtering for the detection of fault onset time in hybrid dynamic systems with autonomous transitions," *IEEE Transactions on Reliability*, vol. 61, no. 1, March 2012.

[17] P. Wang, X. M. Chen, and T. Aldermir, "DSD: A generic software package for model-based fault diagnosis in dynamic systems," *Reliability Engineering and System Safety*, vol. 75, pp. 31–39, 2002.

[18] T. Aldemir, "Computer-assisted Markov failure modeling of process control systems," *IEEE Transactions on Reliability*, vol. 36, pp. 133–144, 1987.

[19] M. Marseguerra and E. Zio, "Monte Carlo approach to PSA for dynamic process systems," *Reliability Engineering and System Safety*, vol. 52, pp. 227–241, 1996.

[20] E. Scanff, K. L. Feldman, S. Ghelam, P. Sandborn, M. Glade, and B. Foucher, "Life cycle cost impact of using prognostic health management (PHM) for helicopter avionics," *Microelctronics Relibility*, vol. 47, pp. 1857–1864, Dec. 2007.

[21] M. Lebold and M. Thurston, "Open standards for condition-based maintenance and prognostic systems," *Proceedings of Maintenance and Reliability Conference*, 2001.

[22] P. S. Laura, E. C. James, S. L. Kelly, and B. D. Adele, "Algorithm development for prognostics and health management (PHM)," *Sandia National Laboratories*, Technical Report (SAND2003-3820), Oct. 2003.

[23] Z. S. Chen, Y. M. Yang, and Z. Hu, "A technical framework and roadmap of embedded diagnostics and prognostics for complex mechanical systems in prognostics and health management systems," *IEEE Transactions on Reliability*, vol. 61, no. 2, pp. 314–322, Jun. 2012.

[24] Y. Sun, N. H. El-Farra, "Quasi-decentralized model-based networked control of process systems," *Computers and Chemical Engineering*, vol. 32, no. 9, pp. 2016–2029, 2008.

[25] M. Ikeda, D. D. Siljak, "Overlapping decompositions, expansions, and contractions of dynamic systems," *Large Scale Systems*, vol. 1, no. 1, pp. 29–38, 1980.