Performance-Based Fault Detection for Model-Free Automatic Control Systems

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***Abstract*—This paper is dedicated to the performance-based fault detection problem for model-free automatic control systems, where the infinite-horizon quadratic index is adopted to describe the concerned system performance. Different from most of the observed-based fault detection methods, the designed performance-based approach mainly focuses on the performance degradations induced by faults. To be specific, the performance index embedded with the information of system dynamics is first reformulated. The performance residual, which is adopted as the evaluation function, is derived based on the Bellman equation. In order to remove the requirements for accurate system model and full state measurements, the performance residual is further represented by the input and output sequences. The relevant unknown matrix is identified based on the measurable process data. Finally, the validity of the theoretical results is demonstrated by the simulation studies on a ship propulsion system.**

***Index Terms*—fault detection, data-driven, performance residual, Bellman equation.**

I. Introduction

To achieve high-precision tasks, modern automatic control systems are becoming more and more complicated. Associated with this trend, the fault detection (FD) techniques have been recognized as indispensable tools to monitor the system safety and reliability [1], [2]. As the pioneer work, the observer-based FD methods have built the mainstream of relevant studies, whose essential idea is to check the residual signal representing the divergence between system output variables and their estimations [3], [4]. During the past years, significant attention has been paid to the performance-based FD by assessing the concerned system performance, such as the product quality [5], system stability [6], model predictive control performance [7], and performance index over an infinite horizon [8], which is motivated by the increasing demands for the key system performance and aims to investigate whether the occurred faults will undermine the key performance indicators [9].

Generally, the existing FD methods can be categorized as the model-based ones and the data-driven ones. The former methods focus on integrating the system model into the FD mechanism. Their applications to the performance-based FD could be found in [6], where the internal system stability has been adopted as the performance indicator and the FD scheme has been proposed. In [10], the quadratic index over the infinite horizon has been considered, and the performance-based FD approach has been deigned for systems embedded with dynamic output feedback controllers. However, for the complex processes in the absence of precise mathematical models, the model-based technologies can barely provide effective solutions. On the other hand, the data-driven FD methods primarily rely on the correlation of process variables [11]. They are dedicated to extracting the important features from the normal process data, and then constructing proper test statistics and thresholds to realize the FD. Among the involved studies, the least squares (LS) method [12], the partial least squares (PLS) method [13], [14] and the canonical correlation analysis (CCA) method [15] have been widely dedicated to computing and monitoring the system key performance indicators. It is noteworthy that statistical assumptions are generally posed on the process variables, which indicates that these approaches can hardly perform well for dynamic systems with various operation conditions. In fact, most of the data-driven methods, especially for these multivariate statistical analysis (MVA) methods, tend to construct soft models between the overall system performance and the measurable process variables, while neglect the intrinsic physical models of the process variables.

Based on the above observations, the model-based approaches and the data-driven approaches both have their merits and demerits. The combination of the two is expected to take advantage of the process knowledge and the process data, thus improve the FD strategy. In [16], by considering simultaneously the soft model of system performance and the physical model of process, the key performance supervised hierarchical FD scheme has been proposed for dynamic processes with the help of data-driven techniques. To monitor the performance over the infinite horizon, the temporal difference error (TDE) has been adopted to be the evaluator for feedback control systems in [8], where the relevant parameters have been identified via a neural network. Nevertheless, this work

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requires that the full state variables be measurable. Besides, it is conservative in practical fields since the external reference signal is not considered.

Motivated by the above limitations, the objective of this paper is to discuss the issues of performance-based FD for model-free automatic control systems by using data-driven skills. To this end, the quadratic index over the infinite horizon is utilized to indicate the concerned system performance, and then reformulated by embedding the system dynamics. The performance residual, which is adopted to be the evaluation function, is derived according to the Bellman equation. To remove the requirements for known system model and state measurements, the performance residual is constructed with regard to the observed input and output variables. The proposed FD approach is independent of the system inputs, with which the change of operation conditions and occurrence of faults are distinguished. Compared with the MVA-based FD methods, the proposed approach is applicable for dynamic systems through taking advantage of both the system knowledge and the process data.

II. Background and Problem Formulation

A. System Description and Performance Evaluation

In this paper, the linear discrete-time system is considered as

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) \\ y(k) = Cx(k) + Du(k) \end{cases} \tag{1}$$

where $x \in \mathbb{R}^n$ denotes the vector of system state variables, $u \in \mathbb{R}^p$ denotes the process input vector, and $y \in \mathbb{R}^m$ denotes the process output vector. A, B, C, D represent the unknown matrices with compatible dimensions. Without loss of generality, the system (1) is assumed to be stable and observable. The following value function, which depends on the system output and the control input over the infinite horizon, is adopted as the performance index of system (1)

$$V(k) = \sum_{i=k}^{\infty} \gamma^{i-k} \theta^T(i)\theta(i) \tag{2}$$

$$\theta(k) = W_1 y(k) + W_2 u(k). \tag{3}$$

Here, W_1 and W_2 denote the coefficient matrices, and $0 < \gamma < 1$ indicates the discounted factor. Since the index (2) evaluates the system performance along the operational trajectory from current time instant k to infinity, it holds that

$$V(k) = \gamma V(k+1) + \theta^T(k)\theta(k) \tag{4}$$

which is called the Bellman equation.

B. Input-Output Representation of Dynamic System

To detect faults in model-free circumstance, the input-output model plays an important role. Let $\lambda(k) \in \mathbb{R}^{\lambda}$ denote a certain vector, and introduce the sequence set

$$\lambda_q(k) = \begin{bmatrix} \lambda^T(k-q) & \cdots & \lambda^T(k-1) \end{bmatrix}^T \in \mathbb{R}^{q\lambda}, \tag{5}$$

then the input-output representation of system dynamics (1) is described by

$$\begin{bmatrix} x(k) \\ y_q(k) \end{bmatrix} = \begin{bmatrix} A^q & \Gamma_{u,q} \\ \Gamma_{x,q} & G_{u,q} \end{bmatrix} \begin{bmatrix} x(k-q) \\ u_q(k) \end{bmatrix} \tag{6}$$

where

$$\Gamma_{u,q} = \begin{bmatrix} A^{q-1}B & \cdots & AB & B \end{bmatrix}$$

$$\Gamma_{x,q} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{q-1} \end{bmatrix}, G_{u,q} = \begin{bmatrix} D & 0 & \cdots & 0 \\ CB & D & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ CA^{q-2}B & \cdots & CB & D \end{bmatrix}$$

with $\Gamma_{u,q} \in \mathbb{R}^{n \times qp}$, $\Gamma_{x,q} \in \mathbb{R}^{qm \times n}$, and $G_{u,q} \in \mathbb{R}^{qm \times qp}$.

C. Problem Formulation

In the following context, we will investigate: 1) Building up a performance-based FD scheme for system (1); 2) Constructing a data-driven realization algorithm for the designed FD scheme, without the knowledge of matrices A, B, C, D and the state vector x.

III. Main Results

A. Performance-Based FD Scheme

In order to monitor the system conditions regarding the concerned performance, (2) is firstly reformulated by embedding the system dynamics into the construction of the evaluation function.

Theorem 1: For the linear discrete-time system (1), assume that the positive-definite matrix $P \in \mathbb{R}^{n \times n}$ is the solution to the following Lyapunov equation

$$\gamma A^T P A - P + C^T W_1^T W_1 C = 0, \tag{7}$$

then the performance index (2) can be formulated as

$$V(k) = x^T(k)Px(k) + V_\chi(k) \tag{8}$$

$$V_\chi(k) = \sum_{i=k}^{\infty} \gamma^{i-k} \chi^T(i) P_{x,u} \chi(i) \tag{9}$$

$$\chi(k) = \begin{bmatrix} x(k) \\ u(k) \end{bmatrix}, P_{x,u} = \begin{bmatrix} 0 & V_{x,u} \\ * & V_{u,u} \end{bmatrix} \tag{10}$$

$$V_{x,u} = C^T W_1^T (W_1 D + W_2) + \gamma A^T P B \tag{11}$$

$$V_{u,u} = (W_1 D + W_2)^T (W_1 D + W_2) + \gamma B^T P B \tag{12}$$

where $*$ represents the symmetric elements.

Proof. The proof can be implemented via the backward recursion procedures. For the sake of simplicity, denote

$$P_{x,u}^1(i) = \begin{bmatrix} 0 & A^T P(i) B \\ * & B^T P(i) B \end{bmatrix} \tag{13}$$

$$P_{x,u}^2 = \begin{bmatrix} 0 & C^T W_1^T (W_1 D + W_2) \\ * & (W_1 D + W_2)^T (W_1 D + W_2) \end{bmatrix}. \tag{14}$$

Consider the final time instant f $(f \to \infty)$, there is

$$V(f) = \theta^T(f)\theta(f) = x^T(f)P(f)x(f) + V_\chi(f) \tag{15}$$

$$P(f) = C^T W_1^T W_1 C, V_\chi(f) = \chi^T(f) P_{x,u}^2 \chi(f). \tag{16}$$

In light of the Bellman equation

$$V(f-1) = \gamma V(f) + \theta^T(f)\theta(f) \tag{17}$$

and the system dynamics (1), the performance index at the $(f-1)$-th instant is calculated by

$$V(f-1) = x^T(f-1)P(f-1)x(f-1) + V_\chi(f-1) \tag{18}$$
$$P(f-1) = \gamma A^T P(f)A + C^T W_1^T W_1 C \tag{19}$$
$$V_\chi(f-1) = \chi^T(f-1)(\gamma P^1_{x,u}(f) + P^2_{x,u})\chi(f-1) + \gamma V_\chi(f).$$

Repeat the above backward recursions till the time instant k, the expression of $V(k)$ can be derived as

$$V(k) = x^T(k)P(k)x(k) + V_\chi(k) \tag{20}$$
$$P(k) = \lim_{f\to\infty} \sum_{i=k}^{f} \gamma^{i-k}(A^{i-k})^T C^T W_1^T W_1 C A^{i-k} \tag{21}$$
$$V_\chi(k) = \lim_{f\to\infty}\left(\sum_{i=k}^{f-1}\gamma^{i-k}\chi^T(i)P_{x,u}(i+1)\chi(i) + \gamma^{f-k}V_\chi(f)\right) \tag{22}$$

where $P_{x,u}(i+1) = \gamma P^1_{x,u}(i+1) + P^2_{x,u}$. Under the assumption that A is Schur stable, $P(k) = P$ turns out to be the solution of the Lyapunov equation (7). On this basis, the value function (22) could be formulated into $V_\chi(k) = \sum_{i=k}^{\infty}\gamma^{i-k}\chi^T(i)P_{x,u}\chi(i)$ by observing that $\lim_{f\to\infty}\gamma^{f-k}V_\chi(f) = 0$. ■

Based on Theorem 1, the performance residual calculated via the Bellman equation (4) can be constructed as

$$\begin{aligned} r_V(k) &= V(k) - \gamma V(k+1) - \theta^T(k)\theta(k) \\ &= \chi^T(k)P_\chi\chi(k) - \gamma x^T(k+1)Px(k+1) - \theta^T(k)\theta(k) \end{aligned} \tag{23}$$

with

$$P_\chi = \begin{bmatrix} P & V_{x,u} \\ * & V_{u,u} \end{bmatrix} \in \mathbb{R}^{(n+p)\times(n+p)}. \tag{24}$$

Since in fault-free situation, it holds that

$$\frac{V(k) - \gamma V(k+1)}{\theta^T(k)\theta(k)} = 1, \theta^T(k)\theta(k) \neq 0. \tag{25}$$

Therefore, $r_V(k)$ can be adopted as the evaluation function for the FD purpose, and the threshold of (23) can be determined as

$$r_{V,th}(k) = \xi\theta^T(k)\theta(k) \tag{26}$$

where $\xi > 0$ denotes the tolerant band preseted. In real applications, ξ can be selected as a small constant by considering the fault detection rate as well as the false alarm rate. As a result, the following decision logic is utilized to detect the occurred fault

$$\begin{cases} |r_V(k)| \leq r_{V,th}(k) \ \Rightarrow \ \text{no alarm} \\ |r_V(k)| > r_{V,th}(k) \ \Rightarrow \ \text{alarm}. \end{cases} \tag{27}$$

B. Data-Driven Realization of Performance-Based FD

Note that the system model and state variables are required when constructing and computing the performance residual (23). In practice, however, it can be difficult to obtain the accurate mathematical models for complex real processes, and the system states are generally unmeasurable. In this subsection, we show how to formulate the performance residual (23) based merely on the observed data, i.e., the input sequence and the output sequence, and then provide the identification method for the parameter matrix involved in the FD in the data-driven context.

Theorem 2: For the linear discrete-time system (1), the performance residual (23) is given in terms of the measured input and output sequences by

$$\begin{aligned} r_V(k) = &z^T_{q,u}(k)\bar{P}_\chi z_{q,u}(k) - \gamma z^T_{q,0}(k+1)\bar{P}_\chi z_{q,0}(k+1) \\ &- \theta^T(k)\theta(k) \end{aligned} \tag{28}$$

where

$$z_{q,u}(k) = \begin{bmatrix} u_q(k) \\ y_q(k) \\ u(k) \end{bmatrix}, z_{q,0}(k) = \begin{bmatrix} u_q(k) \\ y_q(k) \\ 0 \end{bmatrix} \in \mathbb{R}^{n_z} \tag{29}$$

for some symmetric matrix $\bar{P}_\chi \in \mathbb{R}^{n_z\times n_z}, n_z = q(p+m)+p$.

Proof. Denote $\chi_0(k+1) = [x^T(k+1) \ \ 0]^T \in \mathbb{R}^{n+p}$, then (23) can be rewritten as

$$\begin{aligned} r_V(k) = &\chi^T(k)P_\chi\chi(k) - \gamma\chi_0^T(k+1)P_\chi\chi_0(k+1) \\ &- \theta^T(k)\theta(k). \end{aligned} \tag{30}$$

Note that the considered system is observable, hence there must exist q satisfying the rank condition $\mathrm{rank}(\Gamma_{x,q}) = n$, which indicates that $\Gamma_{x,q}$ is of full column rank and its left inverse can be calculated as $(\Gamma^T_{x,q}\Gamma_{x,q})^{-1}\Gamma^T_{x,q}$ [17]. Therefore, by virtue of (6), the state vector is constructed as

$$x(k) = M_q\begin{bmatrix} u_q(k) \\ y_q(k) \end{bmatrix} = \begin{bmatrix} M_{u,q} & M_{y,q} \end{bmatrix}\begin{bmatrix} u_q(k) \\ y_q(k) \end{bmatrix} \tag{31}$$
$$M_{y,q} = A^q(\Gamma^T_{x,q}\Gamma_{x,q})^{-1}\Gamma^T_{x,q} \tag{32}$$
$$M_{u,q} = \Gamma_{u,q} - A^q(\Gamma^T_{x,q}\Gamma_{x,q})^{-1}\Gamma^T_{x,q}G_{u,q}. \tag{33}$$

Substitute (31) and (29) into (30), we obtain

$$\begin{aligned} r_V(k) &= z^T_{q,u}(k)\begin{bmatrix} M_q^T & 0 \\ 0 & I \end{bmatrix} P_\chi \begin{bmatrix} M_q & 0 \\ 0 & I \end{bmatrix} z_{q,u}(k) \\ &\quad - \gamma z^T_{q,0}(k+1)\begin{bmatrix} M_q^T & 0 \\ 0 & I \end{bmatrix} P_\chi \begin{bmatrix} M_q & 0 \\ 0 & I \end{bmatrix} z_{q,0}(k+1) \\ &\quad - \theta^T(k)\theta(k) \\ &= z^T_{q,u}(k)\bar{P}_\chi z_{q,u}(k) - \gamma z^T_{q,0}(k+1)\bar{P}_\chi z_{q,0}(k+1) \\ &\quad - \theta^T(k)\theta(k) \end{aligned} \tag{34}$$

where

$$\bar{P}_\chi = \begin{bmatrix} M_q^T P M_q & M_q^T V_{x,u} \\ * & V_{u,u} \end{bmatrix}. \tag{35}$$

This completes the proof. ■

Theorem 2 expresses $r_V(k)$ with regard to the system inputs and outputs from time instant $k-p$ to instant $k-1$. It should be keep in mind that the information of system dynamics is unknown, hence the matrix $\bar{P}_\chi$ should be obtained based on the observed data, instead of using the matrices A, B, C, D.

To this end, rewrite (28) as

$$r_V(k) = vec(\bar{P}_\chi)^T(\varphi(k) - \gamma\varphi_0(k+1)) - \theta^T(k)\theta(k) \quad (36)$$

where $\varphi(k) = z_{q,u}(k) \otimes z_{q,u}(k)$, $\varphi_0(k+1) = z_{q,0}(k+1) \otimes z_{q,0}(k+1)$, $\otimes$ denotes the Kronnecker product and $vec(\cdot)$ the vectorization operator. Since $\bar{P}_\chi$ is symmetric, we extract its $n_z(n_z+1)/2$ upper portion elements as

$$\rho = \begin{bmatrix} \bar{p}_{\chi,11} & \bar{p}_{\chi,12} & \cdots & \bar{p}_{\chi,1n_z} & \cdots & \bar{p}_{\chi,n_z n_z} \end{bmatrix}^T \quad (37)$$

and denote

$$\begin{aligned} \tilde{\varphi}(k) &= \begin{bmatrix} z_{q,u,1}^2(k) & 2z_{q,u,1}(k)z_{q,u,2}(k) & \cdots & z_{q,u,n_z}^2(k) \end{bmatrix}^T \\ \tilde{\varphi}_0(k) &= \begin{bmatrix} z_{q,0,1}^2(k) & 2z_{q,0,1}(k)z_{q,0,2}(k) & \cdots & z_{q,0,n_z}^2(k) \end{bmatrix}^T. \end{aligned} \quad (38)$$

Then the unknown parameter ρ satisfies

$$\rho = \arg\min_\rho \{\rho^T(\tilde{\varphi}(k) - \gamma\tilde{\varphi}_0(k+1)) - \theta^T(k)\theta(k)\}^2. \quad (39)$$

By employing the least-squares algorithm, ρ can be obtained as

$$\rho = (\Psi_N \Psi_N^T)^{-1}\Psi_N \Theta_N^T \quad (40)$$

with

$$\begin{aligned} &\delta_{\tilde{\varphi}}(k) = \tilde{\varphi}(k) - \gamma\tilde{\varphi}_0(k+1) && (41)\\ &\Psi_N = \begin{bmatrix} \delta_{\tilde{\varphi}}(k) & \delta_{\tilde{\varphi}}(k+1) & \cdots & \delta_{\tilde{\varphi}}(k+N) \end{bmatrix} && (42)\\ &\Theta_N = \begin{bmatrix} \theta^T(k)\theta(k) & \cdots & \theta^T(k+N)\theta(k+N) \end{bmatrix} && (43)\\ &N \geq n_z(n_z+1)/2 - 1. \end{aligned}$$

As a consequence, the performance-based FD is achieved with the aid of the decision logic below

$$\begin{cases} |r_V(k)| \leq r_{V,th}(k) \ \Rightarrow \ \text{no alarm} \\ |r_V(k)| > r_{V,th}(k) \ \Rightarrow \ \text{alarm} \end{cases} \quad (44)$$

where $r_V(k)$ is calculated online according to (28).

To summarize, the detailed steps involved in the proposed data-driven FD method are presented into Algorithm 1.

Algorithm 1 Performance-based FD for model-free automatic control system (1)

Offline identification:

1. Collect historical process input and output data;
2. Construct Ψ_N and Θ_N according to (29), (38), (41)-(43);
3. Identify parameter vector ρ based on (40), and build the matrix $\bar{P}_\chi$;
4. Set the tolerant band ξ.

Online monitoring:

1. Collect the real-time input and output data;
2. Calculate the performance residual $r_V(k)$ according to (28);
3. Perform the decision logic (44).

IV. Simulation Studies

In this section, the simulation studies are presented to demonstrate the proposed FD approach. Consider the model of ship propulsion system as follows [18]

$$\begin{cases} \dot{x}(t) = \begin{bmatrix} -0.3154 & 0.1964 \\ 0.0056 & -0.0149 \end{bmatrix} x(t) + \begin{bmatrix} -2.2936 & 4.5480 \\ 0.1424 & 0 \end{bmatrix} u(t) \\ y(t) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} x(t) \end{cases}$$

where the system state vector $x = [\omega \ V]^T$ with ω being the transmission shaft speed and V the ship speed, the input vector $u = [u_1 \ u_2]^T = [\vartheta \ \eta]^T$ with $\vartheta \in (0,1)$ being the propeller pitch and $\eta \in (0,1)$ the fuel index, and the output vector $y = [y_1 \ y_2]^T = x$.

By choosing the sampling time $T_s = 1$ second, the resulting discrete-time system is obtained as

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) \\ y(k) = Cx(k) \end{cases} \quad (45)$$

where

$$A = \begin{bmatrix} 0.7299 & 0.1672 \\ 0.0048 & 0.9857 \end{bmatrix}, B = \begin{bmatrix} -1.9549 & 3.9013 \\ 0.1356 & 0.0114 \end{bmatrix}$$
$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

The coefficient matrices of the index (2) are chosen to be $W_1 = [1 \ \ 1]$, $W_2 = [10 \ \ 0]$, and the discounted factor $\gamma = 0.8$. The tolerant band in the threshold function is set as $\xi = 0.005$. Then, by solving the Lyapunov equation (7) based on the system matrices, we obtain that

$$P = \begin{bmatrix} 1.7707 & 2.8389 \\ 2.8389 & 8.0283 \end{bmatrix}$$

and

$$V_{x,u} = \begin{bmatrix} 8.1864 & 4.0956 \\ 6.0706 & 9.7343 \end{bmatrix}, V_{u,u} = \begin{bmatrix} 104.3277 & -9.6431 \\ -9.6431 & 21.7641 \end{bmatrix}.$$

Since the state variables are measurable here, the matrix $\bar{P}_\chi$ equals P_χ of the form

$$\bar{P}_\chi = \begin{bmatrix} P & V_{x,u} \\ * & V_{u,u} \end{bmatrix}.$$

By employing the identification procedures in Algorithm 1, we obtain the parameter matrix as follows

$$\bar{P}_\chi = \begin{bmatrix} 1.7462 & 2.9072 & 8.1194 & 3.9206 \\ * & 8.0511 & 6.0841 & 9.7404 \\ * & * & 104.1735 & -9.4857 \\ * & * & * & 21.0546 \end{bmatrix}. \quad (46)$$

Compared with the analytic values of P, $V_{x,u}$ and $V_{u,u}$, it can be seen that the identified $\bar{P}_\chi$ (46) possesses acceptable accuracy.

For demonstration purpose, the actuator fault is first simulated by setting $u_a = 85\%u$ from the 400-th time instant, where u denotes the real input signal and u_a the effective

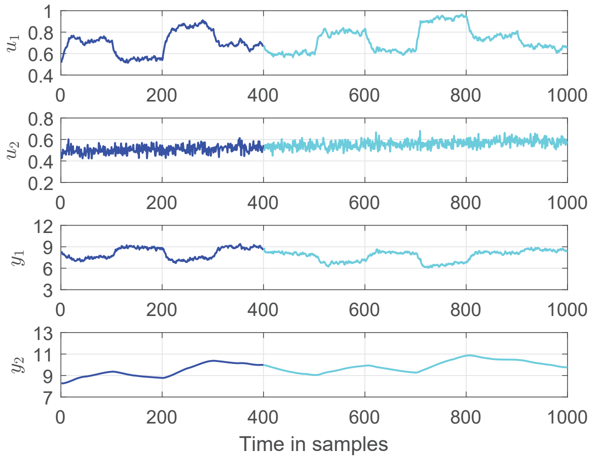

Fig. 1. Input and output trajectories in the case of actuator fault

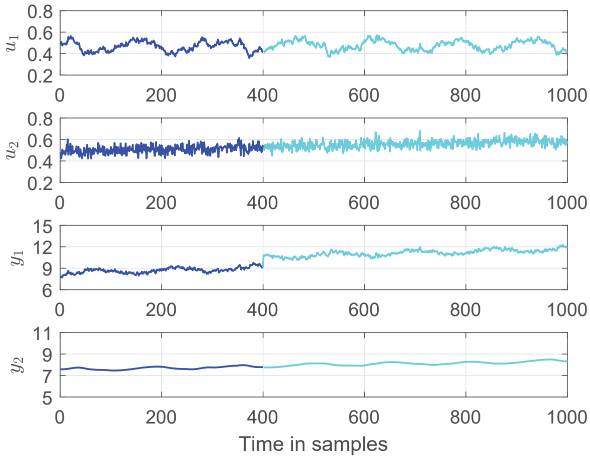

Fig. 3. Input and output trajectories in the case of sensor fault

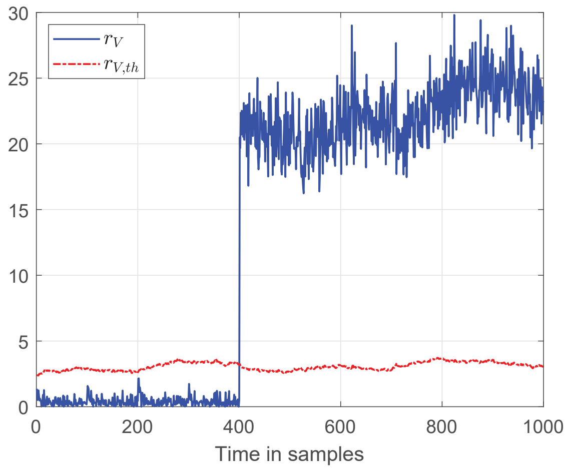

Fig. 2. FD results for the actuator fault

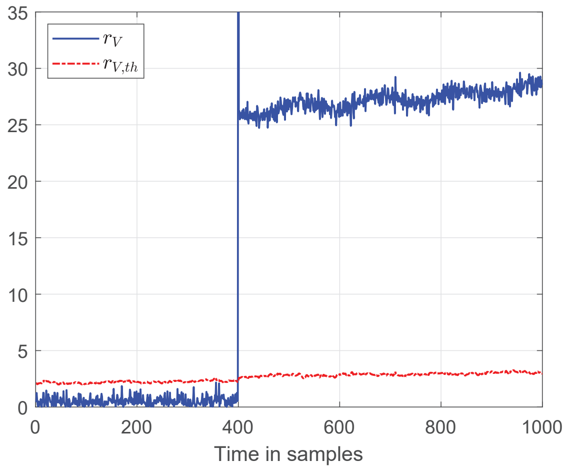

Fig. 4. FD results for the sensor fault

part. The input and output trajectories are given in Fig. 1, and the FD outcomes are illustrated in Fig. 2. Then, the second fault scenario considers the sensor fault which leads to $y = y_r + f_s,\ f_s = [1.5 \quad 0]^T$ from the 400-th time instant. Here, y_r, y denote the real and measured system output. f_s denotes the measurement drift. The input and output data, and the associated FD performance are presented respectively in Fig. 3 and Fig. 4. It could be observed that the degradations of system performance caused by both the actuator fault and sensor fault are detected by the designed FD approach.

V. Conclusion

This paper has studied the performance-based fault detection issues for automatic control systems via data-driven approaches. By taking advantage of the system knowledge and the process data, the performance residual has been established as the evaluation function and the fault detection strategy has been put forward for dynamic processes. Since the fault detection strategy relies on the precise system model and the state variables, which are not possible in real applications, the data-driven realization algorithm has been developed using the measurable input and output sequences. The validity of the devised fault detection method has been illustrated by simulation studies on a practical system. The future research perspective will be dedicated to the performance-based fault detection for systems subjected to external uncertainties/disturbances.

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