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FAULT DIAGNOSIS OF NETWORKED CONTROL SYSTEMS

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Networked Control Systems (NCSs) deal with feedback control systems with loops closed via data communication networks. Control over a network has many advantages compared with traditionally controlled systems, such as a lower implementation cost, reduced wiring, simpler installation and maintenance and higher reliability. Nevertheless, the network-induced delay, packet dropout, asynchronous behavior and other specificities of networks will degrade the performance of closed-loop systems. In this context, it is necessary to develop a new theory for systems that operate in a distributed and asynchronous environment. Research on Fault Detection and Isolation (FDI) for NCSs has received increasing attention in recent years. This paper reviews the state of the art in this topic.

Keywords: networked control systems, fault diagnosis, fault tolerant control, network-induced time delays, packet losses, limited communication.

1. Introduction

In recent years, an increasing amount of research addresses the problem of NCSs. For this class of systems, a communication network is used as a feedback medium as shown in Fig. 1. The role of the communication network is to ensure data transmission and coordinating manipulation among spatially distributed components. Compared with conventional point-to-point control systems, the advantages of NCSs are less wiring, a lower installation cost, as well as greater flexibility in diagnosis and maintenance. Thanks to these distinctive benefits, typical applications of these systems range over various fields, such as automotive, mobile robotics, advanced aircraft, and so on. However, the introduction of communication networks in the control loops makes the analysis and synthesis of NCSs complex. There are several network-induced effects that arise when dealing with an NCS, such as time delays, packet losses and limited bandwidth. Because of the inherent complexity of such systems, an increasing amount of research addresses the problem of distributed control of NCSs by taking into account network-induced effects. For instance, the stability and stabilization problems of NCSs were investigated in (Halevi and Ray, 1988; Nilsson *et al.*, 1998; Branicky *et al.*, 2000; Zhang *et al.*, 2001; Li *et al.*, 2005) for network-induced delays, in (Ling and Lemmon, 2002; Seiler and Sengupta, 2005) for packet losses, in (Hu and Zhu, 2003; Yue *et al.*, 2005; Li *et al.*, 2006b) for network-induced delays and packet losses, in (Nair and Evans, 1997; Hristu, 1999; Ishii and Francis, 2002) for limited communication. The decision, coordination and task schedulings were addressed in (Tipsuwan and Chow, 2003; Hokayem and Abdallah, 2004; Yang, 2006).

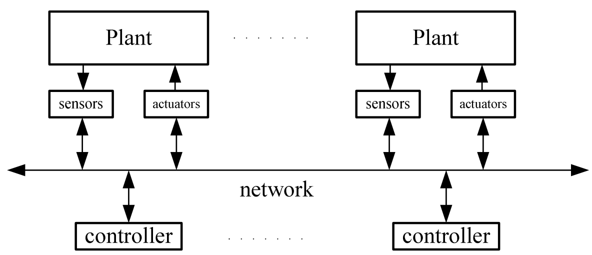

Fig. 1. NCS architecture.

Due to an increasing complexity of dynamic systems, as well as the need for reliability, safety and efficient operation, model-based fault diagnosis has became an important subject in modern control theory and practice, see, e.g., (Willsky, 1976; Frank, 1990; Gertler, 1998; Chen and Patton, 1999; Mangoubi and Edelmayer, 2000; Zhang and Jiang, 2003) and the references therein. Owing to the network-induced effects, the theories for traditional point-to-point systems should be revisited when dealing with NCSs. However, only a few studies of the impact of the communication network on the diagnosis performances have been recently published (Ding and Zhang, 2006; Llanos *et al.*, 2006). The main idea of these approaches is to minimize the false alarms caused by transmission delays. In this case, a network-induced delay is considered when designing the FDI filter.

The general configuration of NCSs considered in our works is shown in Fig. 2, wherein an NCS consists of a plant and a spatially distributed sensor, a controller and an actuator. When sampling and control data are transmitted over the network, many network-induced effects such as time delays and packet losses will naturally arise. Our work addresses the issues of modeling, analysis and synthesis of the NCS and takes into account the network-induced effects from the viewpoint of fault diagnosis and fault-tolerant control. In the sequel, the main ideas and results on these topics will be summarized.

The paper is organized as follows: Section 2 studies the fault diagnosis problems of NCSs with network-induced effects focusing on time delays, packet losses and limited communication. Fault-tolerant control of NCSs is addressed in Section 3. Section 4 gives the conclusions and indicates some future work.

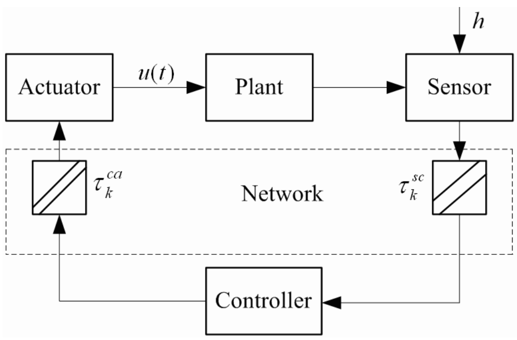

Fig. 2. General configuration of an NCS.

2. Fault diagnosis of NCSs with network-induced effects

2.1. Fault diagnosis of NCSs with network-induced time delays. Time delays in an NCS consist of: (a) a communication delay between sensors and controllers τ^{sc}, (b) a communication delay between controllers and actuators τ^{ca}, (c) computational time in controllers τ^{c}. Generally speaking, the computational time of controllers can be included in the communication delay between controllers and actuators. Different industrial networks have different communication delay features and real-time performances, e.g., the delay feature of the Ethernet is an uncertain stochastic delay; the delay feature of a token-type field bus is a deterministic bounded delay. These delays with different features can degrade the performance of control systems and even destabilize the systems. Thus, fault diagnosis for NCSs, taking into account network-induced time delays have gained attention from many researchers.

2.1.1. Low-pass post-filtering. The plant to be controlled through the digital communication network, and which may be subject to faults, is described by

$$\begin{aligned} \dot{x}(t) &= A_c x(t) + B_u u(t) + B_d d(t) + B_f f(t), \\ y(t) &= C x(t), \end{aligned} \tag{1}$$

where $x(t)$, $u(t)$, $y(t)$ and $d(t)$ are respectively the state vector, the control and output signals, and the disturbances. The vector $f(t)$ represents the faults which may act on the process. We assume that the signals have appropriate dimensions and that the matrices A_c, B_u, B_d, B_f, C have accordingly compatible dimensions but are not endowed with a particular structure. If we further assume that the unknown delay induced by the digital network is random and shorter than one sampling period, then the network-based controlled plant with unknown inputs d and faults f can be modeled as a discrete-time system (Aström and Wittenmark, 1984):

$$\begin{aligned} x(k+1) &= \bar{A}x(k) + \bar{\Gamma}_0 u(k) + \bar{\Gamma}_1 u(k-1) \\ &\quad + \bar{B}_d d(k) + \bar{B}_f f(k), \\ y(k) &= \bar{C}x(k), \end{aligned} \tag{2}$$

where the matrices of the discrete-time model are easily obtained from those of the continuous time model. The discrete-time model can be further written as (Li *et al.*, 2006a; Wang *et al.*, 2006a; Ye *et al.*, 2006)

$$\begin{aligned} &x(k+1) \\ &\quad = \bar{A}x(k) + \bar{B}u(k) + g(k) + \bar{B}_d d(k) + \bar{B}_f f(k), \end{aligned} \tag{3}$$

where

$$g(k) = -\bar{\Gamma}_1 \Delta u_k, \ \Delta u_k = u(k) - u(k-1). \tag{4}$$

There exists a time-varying term $g(k)$ in the state evolution equation of the system (3) and (4). When the total delay τ_k combining τ^{sc} and τ^{ca} is random, the variable $g(k)$ can be regarded as a random disturbance in (3). Therefore, it is natural to adopt a low-pass filter to reduce the impact of $g(k)$ on the residual signal. However, the technique cannot be applied by simply designing a traditional optimal residual generator and adding a low-pass filter to its output. The optimality of the global fault detection filter, which consists of a residual generator and a post filter, is not ensured anymore when the system comes to be networked. So it is necessary to consider the residual generator and the low-pass filter when designing the fault detection system (Ye and Ding, 2004).

As an extension of the results in (Ye *et al.*, 2004), a fault detection approach based on the parity space and the Stationary Wavelet Transform (SWT) for an NCS with a random network-induced delay was introduced in (Ye and Ding, 2004), which is briefly presented as follows:

Let

$$\star_{s,k} = \begin{bmatrix} \star^T(k-s) & \star^T(k-s+1) & \cdots & \star^T(k) \end{bmatrix}^T, \tag{5}$$

where '$\star$' may represent $u,\ y,\ d$ or f.

Set

$$H_{u,s} = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ \bar{C}\bar{B} & 0 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \bar{C}\bar{A}^{s-1}\bar{B} & \cdots & \bar{C}\bar{B} & 0 \end{bmatrix}, \tag{6}$$

and define $H_{d,s},\ H_{f,s},\ H_{g,s}$ as the matrices obtained by replacing $\bar{B}$ in (6) with $\bar{B}_d$, $\bar{B}_f$ and the identity matrix I, respectively. Let

$$H_{o,s} = \begin{bmatrix} \bar{C}^T & \bar{A}^T\bar{C}^T & \cdots & (\bar{A}^s)^T\bar{C}^T \end{bmatrix}^T.$$

Then a parity space and an SWT based residual generator is defined as the SWT of the output of a traditional parity space based residual generator, i.e.,

$$r_{s,k} = v_s(y_{s,k} - H_{u,s}u_{s,k}), \tag{7}$$

$$r^{WT}_{s,k} = WT^a_{r_s}(j_m, k), \tag{8}$$

whose dynamics are governed by

$$r_{s,k} = v_s(H_{d,s}d_{s,k} + H_{f,s}f_{s,k} + H_{g,s}g_{s,k}), \tag{9}$$

$$r^{WT}_{s,k} = WT^a_{r_s}(j_m, k), \tag{10}$$

where v_s is the parity vector to be designed, which should be selected from the parity space P_s defined by $P_s = \{v_s | v_s H_{o,s} = 0\}$, and $WT^a_{r_s}(j_m, k)$ denotes the approximation coefficients of the SWT of $r_{s,k}$, under scale j_m, which can be regarded as a kind of low-pass filtering of $r_{s,k}$. It can be proved that the dynamics (9) and (10) can be written in the following explicit form (Ye and Ding, 2004):

$$\begin{aligned} r^{WT}_{s,k} = & v_s(H_{d,s}N^d_{l,j_m}d_{s+i_{set},k} + H_{f,s}N^f_{l,j_m}f_{s+i_{set},k} \\ & + H_{g,s}N^g_{l,j_m}g_{s+i_{set},k}), \end{aligned}$$

where $N^d_{l,j_m},\ N^f_{l,j_m},\ N^g_{l,j_m}$ are known and constant matrices determined by the SWT filter, whose definitions can be found in (Ye and Ding, 2004).

Similarly to traditional parity space-based methods, the following optimization problem taking into account the influence of the delay can be defined and solved to determine the optimal parity vector v_s:

$$\begin{aligned} \min_{v_s \in P_s} J^{WT}_s = \min_{v_s \in P_s} \Bigg[& \frac{v_s H_{d,s} N^d_{l,j_m} (N^d_{l,j_m})^T H^T_{d,s} v^T_s}{v_s H_{f,s} N^d_{l,j_m} (N^f_{l,j_m})^T H^T_{f,s} v^T_s} \\ & + \frac{v_s H_{g,s} N^g_{l,j_m} (N^g_{l,j_m})^T H^T_{g,s} v^T_s}{v_s H_{f,s} N^d_{l,j_m} (N^f_{l,j_m})^T H^T_{f,s} v^T_s} \Bigg]. \end{aligned} \tag{11}$$

Finally, the residual signal can be calculated according to (7) and (8). The approach is robust to network-induced delays due to the utilisation of the SWT-based low-pass filter. Moreover, it has optimal robustness to d and sensitivity to f in the sense of (11).

2.1.2. Structure matrix of a network-induced time delay. With respect to (3) and (4), (Wang *et al.*, 2006a; Ye *et al.*, 2006; Ye and Ding, 2004; Liu *et al.*, 2005) proposed the so-called structure matrix of τ_k to address the fault diagnosis for NCSs. The procedure is decomposed into two steps:

(a) decompose $g(k)$ into two parts: (known part)$\times$(unknown part), where the "known part", expressed as the known information (such as A_c, B_u, Δu_k), is extracted from $g(k)$ and the "unknown part" includes the unknown information related to τ_k;

(b) use traditional robust fault detection methods to achieve robustness to τ_k.

These results are further summarized as the Taylor approximation (Ye and Ding, 2004), eigendecomposition and the Padé approximation (Wang *et al.*, 2006a), the accurate structure matrix of τ_k and PCA (Ye *et al.*, 2006).

A. Taylor approximation. Consider a simpler NCS model defined as follows:

$$\begin{aligned} x(k+1) &= \bar{A}x(k) + \bar{B}u(k) + g(k) + f(k), \\ y(k) &= \bar{C}x(k). \end{aligned} \tag{12}$$

When the sampling period h is sufficiently small compared with the system's time constants, by using the Taylor approximation of $e^{A_c h}$, $g(k)$ will be approximated by

$$g(k) \approx \bar{E}_{\tau,k}\tau_k, \quad \bar{E}_{\tau,k} = -B_u \Delta u_k. \tag{13}$$

So $g(k)$ has been transformed into an approximate form in which the first part is a known structure vector $\bar{E}_{\tau,k}$ and the second part is unknown τ_k (Ye and Ding, 2004). A time-varying parity space-based residual generator is defined as

$$r_{s,k} = v_{s,k}(y_{s,k} - H_{u,s}u_{s,k}), \tag{14}$$

whose dynamics are governed by

$$r_{s,k} = v_{s,k}(H_{\tau,s,k}\tau_{s,k} + H_{f,s}f_{s,k}) \tag{15}$$

when $v_{s,k} \in P_s$, where
$H_{\tau,s,k} =$

$$\begin{bmatrix} 0 & 0 & \cdots & 0 & 0 \\ \bar{C}\bar{E}_{\tau,k-s} & 0 & 0 & 0 & 0 \\ \bar{C}\bar{A}\bar{E}_{\tau,k-s} & \bar{C}\bar{E}_{\tau,k-s+1} & \ddots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \bar{C}\bar{A}^{s-1}\bar{E}_{\tau,k-s} & \bar{C}\bar{A}^{s-2}\bar{E}_{\tau,k-s+1} & \cdots & \bar{C}\bar{E}_{\tau,k-1} & 0 \end{bmatrix} \tag{16}$$

To satisfy $v_{s,k} \in P_s$ and to decouple the residual signal from the vector $\tau_{s,k}$ consisting of network-induced delays, the parity vector is determined in each sampling period by solving

$$v_{s,k}H_{o,s} = 0, \quad v_{s,k}H_{\tau,s,k} = 0. \tag{17}$$

It is shown that the approach has good robustness to unknown network-induced delays only if both h and τ_k are small enough. In addition, since τ_k in (13) is a scalar signal, the existence condition of $v_{s,k}$ in (17) is not difficult to be satisfied in most cases.

B. Eigendecomposition and the Padé approximation. The NCS model considered in (Wang *et al.*, 2006a) is assumed to be similar to (12) and the matrix A_c in the continuous-time plant model is assumed to be diagonalizable. Based on eigendecomposition and the first-order Padé approximation of $e^{\lambda_i t}$, where $\lambda_1, \dots, \lambda_n$ are the eigenvalues of A_c, $g(k)$ will be approximated by

$$g(k) \approx \bar{E}_{\tau,k}\tau_k, \tag{18}$$

where the structure vector $\bar{E}_{\tau,k}$ is defined as

$$\bar{E}_{\tau,k} = -P\mathrm{diag}(P^{-1}B_u\Delta u_k)\left[\frac{2+\lambda_1 h}{2-\lambda_1 h}\cdots\frac{2+\lambda_n h}{2-\lambda_n h}\right]^{\tau}, \tag{19}$$

P being obtained through the eigendecomposition of A_c, i.e., $A_c = P\Lambda P^{-1}$.

The matrix $\mathrm{diag}(P^{-1}B_u\Delta u_k)$ denotes the diagonal matrix which is composed of the elements of the vector $P^{-1}B_u\Delta u_k$.

Comparing (18) with (13), it is seen that the two terms have the same form. Thus, the residual generation and its design are quite similar to the approach based on the Taylor approximation. Moreover, the full decoupling problem (17) does not need a strong condition in most cases since τ_k in (18) is still a scalar signal.

As demonstrated in (Wang *et al.*, 2006a), since the structure matrix of the network-induced delay (i.e., $\bar{E}_{\tau,k}$) in (Wang *et al.*, 2006a) has a much better accuracy than that in (Ye and Ding, 2004), the method in (Wang *et al.*, 2006a) is much more robust to the unknown network-induced delay than that in (Ye and Ding, 2004).

C. Accurate structure matrix of τ_k and PCA. (Ye *et al.*, 2006) proposed an approach to fault detection for NCSs which includes not only the unknown network-induced delay but also the ordinary unknown disturbance input d.

By the Cayley-Hamilton theorem,

$$\begin{aligned} e^{A_c t} &= I + A_c t + \cdots + \frac{1}{n!}A_c^n t^n + \cdots \\ &= \sum_{i=0}^{n-1} \alpha_i(t)A_c^i, \end{aligned} \tag{20}$$

where A_c is the matrix in the continuous NCS model and n is the dimension of the state x. Then $g(k)$ can be transformed into the following form accurately (Ye *et al.*, 2006):

$$g(k) = \bar{E}_{\tau,k}\beta_{\tau,k}, \tag{21}$$

where

$$\bar{E}_{\tau,k} = \begin{bmatrix} B_u & A_cB_u & \cdots & A_c^{n-1}B_u \end{bmatrix} \cdot \begin{bmatrix} \Delta u_k & & \\ & \ddots & \\ & & \Delta u_k \end{bmatrix} \in \mathbb{R}^{n\times n},$$

$$\beta_{\tau,k} = \begin{bmatrix} \eta_0^{\tau_k} & \eta_1^{\tau_k} & \cdots & \eta_{n-1}^{\tau_k} \end{bmatrix}^T \in \mathbb{R}^{n\times 1},$$

$$\eta_i^{\tau_k} = -\int_{h-\tau_k}^{h} \alpha_i(t)\,\mathrm{d}t \in \mathbb{R}, \quad i = 0, \dots, n-1.$$

Thus, in (21), $g(k)$ is separated into a known structure matrix $\bar{E}_{\tau,k}$ and an unknown vector $\beta_{\tau,k}$ determined by the network-induced delay τ_k. The structure matrix $\bar{E}_{\tau,k}$ in (21), different from the form expressed in (13) or (18), is accurate. A time-varying parity space based residual generator is defined as

$$r_{s,k} = v_{s,k}(y_{s,k} - H_{u,s}u_{s,k}).$$

It can be proved that when $v_{s,k} \in P_s$, the dynamics of the residual generator are governed by

$$r_{s,k} = v_{s,k}(H_{d,s}d_{s,k} + H_{f,s}f_{s,k} + H_{\tau,s,k}\Psi_{\tau,s,k}),$$

where $\Psi_{\tau,s,k} = \begin{bmatrix} \beta_{\tau,k-s}^T & \beta_{\tau,k-s+1}^T & \cdots & \beta_{\tau,k}^T \end{bmatrix}^T$ and $H_{\tau,s,k}$ takes the same form as (16).

In order to achieve the robustness of $r_{s,k}$ with respect to the network-induced delay vector $\Psi_{\tau,s,k}$ and to ensure that $v_{s,k}$ belongs to the parity space P_s, it is expected that $v_{s,k}$ should satisfy

$$v_{s,k} \in P_s, \quad v_{s,k} H_{\tau,s,k} = 0. \tag{22}$$

But since $\beta_{\tau,k}$ in (21) is an n-dimensional vector, the solution of (22) may not exist in any case. Thus, (Ye *et al.*, 2006) developed the following objective to determine the parity vector (22) by Principal Component Analysis (PCA):

$$v_{s,k} \in P_s, \quad v_{s,k} \Lambda^{m_k}_{\tau,s,k} = 0, \tag{23}$$

where $\Lambda^{m_k}_{\tau,s,k}$ is defined as the matrix which is composed of the first m_k main Principal Component (PC) vectors of the matrix $H_{\tau,s,k}$.

In (Ye *et al.*, 2006) it is argued that due to the good characteristics of PCA, usually suitable m_k which is much smaller than the column number of $H_{\tau,s,k}$, can be found to produce the solution to (23). Moreover, it satisfies (22) with a good accuracy. After solving (23), we may further take advantage of the remaining degree of freedom of $v_{s,k}$ to achieve optimal robustness to d and optimal sensitivity to f in the following sense:

$$\min_{v_{s,k} \in P_s, v_{s,k}\Lambda^{m_k}_{\tau,s,k}=0} J_{s,k}, \tag{24}$$

where

$$J_{s,k} = \frac{v_s H_{d,s} H^T_{d,s} v^T_s}{v_s H_{f,s} H^T_{f,s} v^T_s}.$$

The advantages of (Ye *et al.*, 2006) lie in (a) the adoption of an accurate structure matrix of the network-induced delay and its inclusion of an ordinary unknown input d, (b) the known information on the network-induced delay (i.e., its structure matrix), which makes it different from the prior work in (Ye and Ding, 2004; Ye and Wang, 2006; Wang *et al.*, 2006b).

2.1.3. Robust deadbeat fault filter. In (Li *et al.*, 2006a), the authors assume that the statistical behavior of the network-induced delay τ_k is random and governed by the Markov chain

$$\theta_k \in \mathcal{S} = \{1, 2, \ldots, s\}, \quad \forall k \in \mathbb{Z}_+, \tag{25}$$

with the transition probabilities $\lambda_{ij} = \mathbf{Pr}[\theta_{k+1} = j | \theta_k = i]$, $\lambda_{ij} \geq 0$ and $\sum_{j=1}^{s} \lambda_{ij} = 1$ for any $i \in \mathcal{S}$. For notational simplicity, B_{1,τ_k} is denoted by B_{1,θ_k} and Δu_k $w(k)$. Then, the discrete-time model (3) of the network-based controlled plant is replaced by the state space system with the following particular Markov jump linear system:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + Ff(k) \\ &\quad + B_{1,\theta_k} w(k), \\ y(k) &= Cx(k). \end{aligned} \tag{26}$$

The following filter is presented as the residual generator of the NCS (26):

$$\begin{aligned} \hat{x}(k+1) &= A\hat{x}(k) + Bu(k) + K(y(k) \\ &\quad - C\hat{x}(k)), \\ \alpha_k &= L(y(k) - C\hat{x}(k)), \end{aligned} \tag{27}$$

where $\hat{x}(k)$ is the state of the filter, α_k the residual generator or the fault indicator. The filter gain $K \in \mathbb{R}^{n\times m}$ and the projector $L \in \mathbb{R}^{q\times m}$ are unknown matrices to be found for the solution of the fault detection and isolation problem.

From (26) and (27), the state estimation error $e(k) = x(k) - \hat{x}(k)$ and the output of the filter α_k propagate as

$$\begin{aligned} e(k+1) &= (A - KC)e(k) \\ &\quad + Ff(k) + B_{1,\theta_k} w(k), \\ \alpha_k &= LCe(k). \end{aligned} \tag{28}$$

Let $G_{f\alpha}(z)$ be the transfer function from $f(k)$ to the output residual α_k. Then the following theorem is presented to design K and L such that

$$\begin{aligned} G_{f\alpha}(z) &= LC(zI - (A - KC))^{-1}F \\ &= \mathrm{diag}\{z^{-\rho_1}, \ldots, z^{-\rho_q}\}, \end{aligned} \tag{29}$$

which ensures the isolation of multiple faults (Li *et al.*, 2006a).

Under the condition $\mathrm{rank}(\Psi) = q$, the solutions of (29) can be parameterized as $K = \omega\Pi + \bar{K}_{\theta_k}\Sigma$, $L = \Pi$, with $\Sigma = \beta(I - \Psi\Pi), \Pi = \Psi^+, \omega = AD$ and $\Psi = CD$, where $\bar{K}_{\theta_k} \in \mathbb{R}^{n\times m-q}$ is the vector of free parameters to be designed, Ψ^+ is the pseudo-inverse of Ψ, and β is an arbitrary matrix chosen so that $\mathrm{rank}(\Sigma) = m - q$.

Then, the filter (27) can be written as

$$\begin{aligned} \hat{x}(k+1) &= A\hat{x}(k) + Bu(k) + \omega\alpha_k \\ &\quad + \bar{K}_{\theta_k}\Sigma(y(k) - C\hat{x}(k)), \\ \alpha_k &= \Pi(y(k) - C\hat{x}(k)), \end{aligned} \tag{30}$$

where α_k is a deadbeat filter for the fault $f(k)$ given by

$$\alpha_k = \breve{\alpha}_k + \begin{bmatrix} n^1_{k-\rho_1} & \cdots & n^i_{k-\rho_i} & \cdots & n^q_{k-\rho_q} \end{bmatrix}^T, \tag{31}$$

where $\breve{\alpha}_k$ is the fault indicator signal without faults. It propagates from the fault-free state estimation error $\bar{e}(k) = \tilde{x}(k) - \hat{x}(k)$ as

$$\begin{aligned} \bar{e}(k+1) &= (\bar{A} - \bar{K}_{\theta_k}\bar{C})\bar{e}(k) + B_{1,\theta_k} w(k), \\ \breve{\alpha}_k &= \Pi C \bar{e}(k), \end{aligned} \tag{32}$$

where $\bar{A} = A - \omega\Pi C$, $\bar{C} = \Sigma C$ and $\tilde{x}(k)$ is the fault-free state. The transfer function from $w(k)$ to $\breve{\alpha}_k$, when freezing θ_k, is then given by

$$G_{w\breve{\alpha}}(z) = \Pi C(zI - (\bar{A} - \bar{K}_{\theta_k}\bar{C}))^{-1} B_{1,\theta_k}. \tag{33}$$

Let $\hat{\alpha}_k$ be the fault indicator signal without disturbances. From Eqn. (29), the transfer function $G_{f\hat{\alpha}}(z)$ from the fault f to the fault indicator $\hat{\alpha}_k$ is a pure delay and

$$\|G_{f\hat{\alpha}}(z)\|_\infty := \sup_{\theta_0\in\mathcal{S}} \sup_{0\neq f\in\ell_2} \frac{\|\hat{\alpha}\|_2}{\|f\|_2} = 1, \tag{34}$$

where $\|s\|_{\ell_2} = (\sum_{k=0}^{\infty} \|s\,(k)\|)^{1/2}$ is the ℓ_2 norm of the signal $s\,(k)$.

Then, the free parameters $\bar{K}_{\theta_k}$ are designed to satisfy the following two constraints:

C1. The $\mathcal{H}_\infty$-norm of $G_{w\breve{\alpha}}(z)$ is less than a prescribed scalar $\gamma > 0$.

C2. The eigenvalues of $(\bar{A} - \bar{K}_{\theta_k}\bar{C})$ are located within a prescribed region in the complex plane so that the residual dynamical has the given transient properties.

The following theorem solves these two constraints (Li *et al.*, 2006a): For given discs $D_i(\xi_i, \delta_i)$, if there exist matrices $P_i = P_i^T > 0$, G_i and Y_i for prescribed scalars $\gamma > 0$, $-1 < -\xi_i + \delta_i < 1$, $\forall i = \theta_k \in \mathcal{S}$ such that

$$\begin{bmatrix} -P_i & 0 & \bar{A}^T G_i^T - \bar{C}^T Y_i^T & C^T\Pi^T \\ 0 & -\gamma^2 I & B_{1,i}^T G_i^T & 0 \\ G_i\bar{A} - Y_i\bar{C} & G_i B_{1,i} & \bar{P}_i - G_i - G_i^T & 0 \\ \Pi C & 0 & 0 & -I \end{bmatrix} < 0, \tag{35}$$

$$\begin{bmatrix} -\delta_i^2 P_i & \bar{A}^T G_i^T - \bar{C}^T Y_i^T - \xi_i G_i^T \\ G_i\bar{A} - Y_i\bar{C} - \xi_i G_i & P_i - G_i - G_i^T \end{bmatrix} < 0, \tag{36}$$

where $\bar{A} = A - \omega\Pi C$, $\bar{C} = \Sigma C$, then the free parameters are designed as $\bar{K}_i = G_i^{-1} Y_i$ and ensure the second-moment stability of the error system (32) and the constraints C1 and C2.

Given discs $D_i(\xi_i, \delta_i)$, $i = \theta_k \in \mathcal{S}$, the search problem of the lowest possible value of γ can be formulated as the following convex optimization problem:

$$\begin{aligned} \mathcal{OP}: &\min_{P_i = P_i^T > 0, G_i, Y_i} \gamma, \\ &\text{s.t. LMI (35), (36),} \end{aligned} \tag{37}$$

which can be effectively solved by the existing Matlab LMI toolbox (Gahinet *et al.*, 1995).

2.1.4. Adaptive residual evaluation strategy. In (Sauter and Boukhobza, 2006), the multiple input plant is considered as

$$\begin{aligned} \dot{x}(t) &= Ax(t) + \sum_{i=1}^{m} B_i u_i(t) + Ef(t), \\ y(t) &= Cx(t). \end{aligned} \tag{38}$$

Assume that the network-induced time delay is shorter than one sampling period. Then the discrete-time model of the plant is given by

$$\begin{aligned} x(k+1) &= \Phi x(k) + \sum_{i=1}^{m} \Gamma u_i(k) \\ &\quad - \sum_{i=1}^{m} \Gamma_{1i}\Delta u_i(k) + \Xi f(k), \\ y(k) &= Cx(k), \end{aligned} \tag{39}$$

with $\Delta u_i(k) = u_i(k) - u_i(k-1)$, and the computation of the matrices are straightforward. A classical observer-based residual generator is given as

$$\begin{aligned} \hat{x}(k+1) &= \Phi\hat{x}(k) + \sum_{i=1}^{m} \Gamma_i u_i(k) + L(y(k) - \hat{y}(k)), \\ \hat{y}(k) &= C\hat{x}(k). \end{aligned} \tag{40}$$

From (39) and (40), the estimation error $e(k) = x(k) - \hat{x}(k)$ and the residual vector $r(k)$ propagate as

$$\begin{aligned} e(k+1) &= (\Phi - LC)e(k) + \sum_{i=1}^{m} \Gamma_{1i}(\tau_i)\Delta u_i(k) \\ &\quad + \Xi f(k), \\ r(k) &= TCe(k). \end{aligned} \tag{41}$$

Clearly, it appears that the residual signal is corrupted with uncertainties, that is, the unknown term $\sum_{i=1}^{m} \Gamma_{1i}(\tau_i)\Delta u_i(k)$, caused by the network-induced delays.

In order to be able to distinguish the faults from these uncertainties induced by the delays, a threshold is defined on the basis of an evaluation function taken as the time-varying functional $\Psi(kh) = \|r(kh)\|$. Note that from the dynamics (41), this functional may be viewed as a continuous function of the unknown vector of time-delays $\tau = [\tau_1^*, \ldots, \tau_m^*]^T$, i.e., we may write alternatively $\Psi(kh) = \|r(kh)\| = \Psi(\tau)$. As the time-delays are assumed to be bounded, that is, $0 \leq \tau_i \leq \tau_i^{\max}$ for some positive reals $\tau_i^{\max}$, $i = 1, \ldots, m$, the unknown vector τ actually belongs to a compact set $\mathfrak{T}$ of $\mathbb{R}^m$. The time-dependent variable

$$Th(kh) = \max_{f=0;\tau\in\mathfrak{T}} \Psi(kh) \tag{42}$$

is therefore well defined and is considered as the detection threshold, i.e.,

$$\begin{cases} \Psi(kh) \geq Th(kh) & \text{for } f \neq 0, \\ \Psi(kh) < Th(kh) & \text{for } f = 0. \end{cases} \tag{43}$$

This threshold can be computed, through an optimization problem, via the following continuous-time dynamical system:

$$\begin{aligned}\dot{e}(t) &= (A - LC)e(t)\\ &\quad + \sum_{i=1}^{m} B_i(u_i(t,\tau_i) - u_i(t,0)) + Ef(t), \qquad (44)\\ r(t) &= TCe(t),\end{aligned}$$

where

$$\begin{aligned} u_i(t,\tau_i) &= u_i\,(kh-1)\,, && kh \le t < kh+\tau_i,\\ u_i(t,\tau_i) &= u_i\,(kh)\,, && kh+\tau_i \le t < (k+1)h.\end{aligned} \qquad (45)$$

The rationale behind this continuous time dynamics is that the discrete-time system (41) can be seen as resulting from a zero-order hold discretization of the system (44) and the optimization problem is more easily handled in the continuous-time framework. With respect to (42), the optimization problem is to find the time-delays τ_i^* in the control (45) running on the time interval $[kh,\ (k{+}1)h]$ such that the performance index $\Psi(\tau) = \|r(t_{k+1})\|$ is maximal on that interval, where we have set $t_{k+1} = (k+1)h$. Note that the problem has been reduced to a terminal-cost optimization with respect to τ over an interval of one period. For that purpose, the Hamiltonian

$$\begin{aligned} H = \lambda^T[(A-LC)e(t) + \sum_{i=1}^{m} B_i(u_i(t,\tau_i) - u_i(t,0))]\\ + \lambda^T Ef(t) \end{aligned} \qquad (46)$$

is introduced, where λ is the co-state vector. The solution to the optimization problem is given by the m-dimensional vector of time-delays ((Lawden, 2006))

$$\begin{aligned}\tau^* &= [\tau_1^*, \dots, \tau_m^*]^T\\ &= \arg \min_{\tau_i \in [0,\ \tau_i^{\max}]} \Big(\lambda^T \sum_{i=1}^{m} B_i \Delta u_i(t,\tau_i)\Big),\end{aligned} \qquad (47)$$

with λ satisfying the adjoint equations

$$\dot{\lambda}^T = -\frac{\partial H}{\partial e} = -\lambda^T\,(A - LC) \qquad (48)$$

with terminal conditions

$$\lambda(t_{k+1}) = TC \begin{bmatrix} \mathrm{sign}(e_1(t_{k+1}))\\ \vdots \\ \mathrm{sign}(e_n(t_{k+1})) \end{bmatrix}. \qquad (49)$$

Since the inputs over the time interval considered are stepwise, the optimization procedure can be iterated over several sampling intervals.

2.1.5. Other work. It is worth noting that in the references cited above the total maximum of the network-induced delays is assumed to be less than one sampling interval. However, in practice, the delay may be more than one sampling period. In worse cases, this long time delay may distort the timing order of the message arriving at the receiver (Hu and Zhu, 2003; Lincoln and Bernhardsson, 2000; Li *et al.*, 2004; Ray and Halevi, 1988).

In this way, the integrity and sequence of the information transmission are guaranteed. Then the discrete state model of the system with a network-induced delay can be described as

$$\begin{aligned} x(k+1) &= \bar{A}x(k) + \bar{B}_0 u(k-1) + \bar{B}_1 u(k-l+1)\\ &\quad + \bar{B}_d d(k) + \bar{B}_f f_a(k),\\ y(k) &= \bar{C}x(k) + f_s(k),\end{aligned} \qquad (50)$$

which is a familiar discrete time system with input time delays. An observer-based fault detection method was presented for the system (50) by comparing the output of the observer with the actual output of the actual system (Zheng, 2003). The residual function for this approach is

$$\begin{aligned} r(z) &= Q\bar{C}P^{-1}\bar{B}_d d(z) + Q\bar{C}P^{-1}\bar{B}_f f_a(z)\\ &\quad - Q\bar{C}P^{-1}(zI-\bar{A})V(zI-\Lambda_r)^{-1}Lf_s(z)\\ &\quad + Qf_s(z),\end{aligned} \qquad (51)$$

where $P = (zI-\bar{A})[I + V(zI-\Lambda_r)^{-1}L\bar{C}]$.

The effect of the disturbance is decoupled from the residual if the following conditions hold:

$$Q\bar{C}P^{-1}\bar{B}_d = H(zI - P^T)^{-1}\bar{B}_d = 0.$$

The simulation results demonstrating the feasibility of this approach can be found in (Zheng, 2003).

In (Wang *et al.*, 2006b), a method for fault detection of an NCS with an unknown network-induced delay, which may be greater than h, is also proposed. In the method, an NCS model for an unknown network-induced delay which may be greater than h (Ray and Halevi, 1988; Hu and Zhu, 2003) was adopted, and the idea for handling multiplicative faults (Gertler, 1998) was used to deal with the network-induced delay. However, from another point of view, the method in (Wang *et al.*, 2006b) can also be regarded as an extension of the one-dimensional Taylor approximation used in (Ye and Ding, 2004) into a multi-dimensional Taylor approximation.

2.2. Fault diagnosis of NCSs with packet losses. Packet losses happen when packets are dropped due to a link failure or when packets are purposefully dropped in order to avoid congestion or to guarantee the most recent data to be sent. Although a single packet loss neither deteriorates the system performance nor destabilizes the system, the consecutive packet losses have an adverse impact on the overall performance. Therefore, it is necessary to discuss how packet losses influence the fault diagnosis of NCSs. Generally speaking, packet losses can be modeled in either a deterministic or stochastic sense. In the following, both cases will be discussed.

2.2.1. Deterministic packet losses. The deterministic packet losses were also discussed, either in terms of switching systems, by (Zhang *et al.*, 2001) or, in terms of delayed differential equations, by (Yue *et al.*, 2005; Yu *et al.*, 2005). As to fault diagnosis of NCSs with deterministic packet losses, to our best knowledge, no work has been done. However, many existing research results on fault diagnosis for switching and time delay systems can be extended or applied directly to NCSs. Some of these results are briefly introduced as follows:

- **Unknown input decoupling.** Yang and Saif (1998) addressed fault diagnosis for a class of state-delayed dynamic systems, in which the actuator and sensor faults, as well as other effects, such as disturbances and higher-order nonlinearities, were considered as unknown inputs. More recently, Koenig *et al.* (2005) dealt with the design problem of full-order observers for linear continuous delayed state and inputs systems with unknown input and time-varying delays. A method to design an Unknown Input Observer (UIO) for such systems was proposed based on delay-dependent stability conditions of the state estimation error system. A fault diagnosis scheme using a bank of such UIOs was also presented and tested on a fault diagnosis problem related to irrigation canals.
- **H_∞-norm model matching formulation.** Ding *et al.* (2000b) developed a weighting transfer function matrix to describe the desired behavior of residuals with respect to faults. The observer-based fault detection filter for a class of linear systems with time-varying delays was designed such that the error between the generated residual and the fault was as small as possible in the sense of the H_∞-norm. The design was then formulated as an H_∞-model matching problem, which can be solved by an optimization tool, such as a linear matrix inequality technique.
- **Two-objective optimization approaches.** Liu and Frank (1999) regarded the fault detection problem for linear systems with constant time delays as two-objective nonlinear programming, namely, enhancing the sensitivity of residuals to faults and, at the same time, suppressing the undesirable effects of unknown inputs and modeling errors. More recently, Jiang *et al.* (2003) extended the results of (Liu and Frank, 1999) to the case of discrete-time systems. Zhong *et al.* (2006) dealt with the robust fault detection filter problem for linear systems with time-varying delays and model uncertainty.
- **Unified optimization approach.** Zhong *et al.* (2005) extended the results of (Ding *et al.*, 2000a) to linear systems with L_2-norm bounded unknown input and multiple constant time delays. Then, an observer-based fault detection filter was developed such that a performance index based on the ratio of robustness and sensitivity was minimized. By an appropriate choice of a filter gain matrix and post-filter, a solution to the fault detection filter was derived in terms of a Riccati equation.
- **Adaptive observer-based fault detection and identification.** With a structure restriction on the fault distribution, Jiang *et al.* (2002) developed an adaptive observer for fault identification of both linear systems with multiple state time delays and a class of nonlinear systems. Jiang and Zhou (2005) proposed a new adaptive observer for robust fault detection and identification of uncertain linear time-invariant systems with multiple constant time-delays in both states and outputs. Chen and Saif (2006) investigated an iterative learning observer based on adaptive unknown input estimation with considering both the disturbances and possible faults as unknown inputs.

2.2.2. Stochastic packet losses. The simplest stochastic model assumes that losses are realizations of a Bernoulli process (Seiler, 2001; Sinopoli *et al.*, 2004). Underlying finite-state Markov chains can be used to model correlated packet losses (Smith and Seiler, 2003; Nilsson, 1998; Xiao *et al.*, 2000), and Poisson processes can be used to model stochastic losses in continuous time (Xu, 2006).

In (Zhang *et al.*, 2004), the fault detection problem of systems with stochastic packet losses is discussed. First, in order to cope with packet losses, the structure of the standard model based residual generator is modified and dynamic network resource allocation is suggested as

$$e(k+1) = \begin{cases} (A-LC)e(k)+(E_f-LF_f)f(k)+L\theta(k), & \gamma(k)=0,\\ (A-LC)e(k)+(E_f-LF_f)f(k), & \gamma(k)=1, \end{cases} \tag{52}$$

and

$$r(k) = \begin{cases} WCe(k)+WF_ff(k)-W\theta(k), & \gamma(k)=0,\\ WCe(k)+WF_ff(k), & \gamma(k)=1, \end{cases} \tag{53}$$

where $\theta(k)$ is the the difference between the real value of the measurement $y(k)$ and the value $y^a(k)$ used, namely,

$\theta(k) := y(k) - y^a(k)$. $\gamma(k)$ is a stochastic variable representing the data communication status. $\gamma(k) = 1$ means that the measurement at time point k arrives correctly, while $\gamma(k) = 0$ means that this measurement is lost. The dynamics of the residual generator are thus characterized by a discrete-time Markovian jump linear system.

To reduce the false alarm rate caused by a missing measurement, a residual evaluation scheme is then developed as

$$r_{\text{eval}} > J_{th}, \quad \text{a fault is detected,}$$
$$r_{\text{eval}} \leq J_{th}, \quad \text{no fault is detected,}$$

where $r_{\text{eval}} = \left(\sum_{j=0}^{\infty} r^T(j)r(j)\right)^{1/2}$. To compute the threshold J_{th}, a convex optimization problem is then developed to find the minimum of $\mathbf{E}[\|r\|_2]/\|\theta\|_2$, which is formulated as a disturbance attenuation problem of the Markovian jump linear systems (52) and (53). Further, a co-design approach of a time-varying residual generator and threshold is proposed to improve the dynamics and sensitivity of the fault detection system to the faults.

It should be noted that there are some research works which concern the NCS that take into account simultaneous time-delays and packet losses, see, e.g., (Yue *et al.*, 2005; Zhang *et al.*, 2005; Yu *et al.*, 2005). However, the obtained results may be somewhat conservative as they are based on worst-case scenarios. To the best of our knowledge, there is no previous work analyzing estimation where observation packets are subject to a simultaneous random delay and packet losses in a probabilistic framework.

2.3. Fault diagnosis of NCSs with limited communication. The capacity of the communication network and its ability to carry a reasonable amount of information per unit of time play an important role in characterizing the NCS stability. When introducing the network into the control loop, issues like the channel/network capacity, encoding/decoding schemes and quantization naturally arise. Examples of NCSs with limited communication include unmanned air vehicles owing to stealth requirements, wireless sensor networks due to long-lasting energy limitations, and so on.

Inspired by the Shannon information theory, there is increasing attention to characterize the minimum bit rate which is needed to stabilize NCSs through feedback, see, e.g., (Sahai, 2000; Tatikonda, 2000; Savkin and Petersen, 2003) and the references therein. In order to describe the quantization effects on the performance of NCSs, great research efforts have been devoted to develop new a quantization scheme to achieve lower bit-rates, see, e.g., (Brockett and Liberzon, 2000; Delchamps, 1989; Elia and Mitter, 2000; Ishii and Francis, 2002; Wong and Brockett, 1997) and the references therein. For more details on this topic, we refer the reader to the survey (Hokayem and Abdallah, 2004).

In (Zhang and Ding, 2006), the fault detection problem of networked control systems with limited data transmission rates is considered. In order to reduce the network load and thus avoid the uncertainty caused by transmission delays and packet losses, the so-called periodic communication sequence is introduced as

$$y(k) = N_k y_p(k), \tag{54}$$
$$u_p(k) = M_k u(k), \tag{55}$$

where $y \in \mathbb{R}^{\omega_m}$ represents the sensor signals transmitted from the sensors to the central station through the network, $N_k \in \mathbb{R}^{\omega_m \times m}$ is a θ-periodic matrix formed by selecting ω_m rows of the identity matrix. $u \in \mathbb{R}^p$ represents the signal generated by the controller, $M_k \in \mathbb{R}^{p\times p}$ is a θ-periodic diagonal matrix with ω_p elements equal to 1 on the diagonal. The dynamics of the NCS are then characterized by

$$\begin{aligned} x(k+1) &= Ax(k) + BM_k u(k) + E_d d(k) + E_f f(k), \\ y(k) &= N_k(Cx(k) + DM_k u(k) + F_d d(k)) \\ &\quad + N_k F_f f(k). \end{aligned} \tag{56}$$

The input-output relation of the NCS (2.3) over a moving finite horizon $[k-s,\ k]$, where s is an integer representing the length of the horizon, can be expressed by

$$\begin{aligned} Y(k) &= H_{s,k}x(k-s) + H_{u,k}U(k) + H_{d,k}D(k) \\ &\quad + H_{f,k}F(k). \end{aligned} \tag{57}$$

Matrices $H_{o,k}, H_{u,k}, H_{d,k}, H_{f,k}$ in the parity relation (57) are θ-periodic with respect to k. The residual generator is then constructed as

$$r(k) = v_k(Y(k) - H_{u,k}U(k)), \tag{58}$$

where $v_k \in \mathbb{R}^{1\times(s+1)\omega_m}$ is the periodic parity vector to be designed such that $v_k H_{o,k} = 0$ for any k. The residual dynamics are not influenced by the initial state $x(k-s)$ and are governed by

$$r(k) = v_k(H_{d,k}D(k) + H_{f,k}F(k)). \tag{59}$$

There are two cases to be considered:

- If
$$\text{rank}\begin{bmatrix} H_{o,k} & H_{d,k} & H_{f,k} \end{bmatrix} > \text{rank}\begin{bmatrix} H_{o,k} & H_{d,k} \end{bmatrix}$$
for any k, then the residual signal can be decoupled from the unknown disturbances by designing v_k in such a way that
$$v_k \begin{bmatrix} H_{o,k} & H_{d,k} \end{bmatrix} = 0, \quad v_k H_{f,k} \neq 0$$
holds for any k.

- If a full decoupling is not achievable, then a suitable compromise between the robustness to unknown disturbances and the sensitivity to faults can be achieved by solving the optimization problem

$$\min_{v_k} J_k = \min_{v_k} \frac{v_k H_{d,k} H_{d,k}^T v_k^T}{v_k H_{f,k} H_{f,k}^T v_k^T}$$
$$\text{s.t. } v_k H_{o,k} = 0$$

  to get an optimal periodic parity vector v_k.

Then, the influence of the new communication pattern on fault detection, including a full decoupling and an optimal achievable performance, is analyzed. Finally, the optimal selection of the periodic communication sequence is discussed.

3. Fault-tolerant control of NCSs

Based on the fault diagnosis algorithm for NCSs in Section 2, fault-tolerant control of NCSs can be obtained. The existing methods of fault tolerant control techniques against actuator faults can be categorized into two groups: passive (Seo and Kim, 1996; Cheng and Zhao, 2004) and active approaches (Zhang and Jiang, 2002; Jiang and Zhang, 2006). Zheng (2003) proposed a passive controller for NCSs considering random time delays. Although the passive controllers are easy to implement, their performances are relatively conservative. The reason is that this class of controllers based on the presumed set of component failures and with a fixed structure and parameters is used to deal with all the possible different failure scenarios. If a failure occurs out of those considered in the design, the stability and performance of the closed-loop system is unanticipated. Such potential limitations of passive approaches motivate the research on Active FTC (AFTC).

AFTC procedures require an on-line and real-time fault diagnosis process and a controller reconfiguration mechanism. Because AFTC approaches propose a flexibility to select different controllers according to different component failures, better performance of the closed-loop system is expected. However, the above case holds true only if the fault diagnosis process does not provide an incorrect or delayed decision. Some preliminary results have been obtained on AFTC which tend to make the reconfiguration mechanism immune from imperfect fault diagnosis decison, see (Mahmoud *et al.*, 2003; Wu, 1997). Maki *et al.* (2004) further discussed the above issue by using the guaranteed cost control approach and on-line controller switching in such a way that the closed-loop system was stable at all times. However, Maki *et al.* (2004) did not consider the plant controlled over the network.

Li *et al.* (2007) addressed the stability guaranteed active fault tolerant control of NCSs. The design procedures are summarized as follows: (i) design a passive fault-tolerant controller such that the closed-loop system stability is maintained for all actuator failure modes; and (ii) under the assumption that a particular actuator is free from faults, repeatedly redesign the controller using only this actuator alone so that the robust performance is further improved without affecting the stability property of the design in (i). All the design theorems are formulated in terms of convex optimization problems which can be efficiently solved by existing software, e.g., the Matlab LMI toolbox.

4. Conclusion

In this paper we discussed and summarized model based FDI approaches to NCSs including observer-based and parity space methods. A fault tolerance principle for NCSs is also presented. The induced effect of the communication medium on the performance of the FDI algorithm, such as time delays and packet losses or limited communication, is taken into account in the filter design. Directional residual generator decoupling from the disturbances ensures the treatment of multiple faults occurring simultaneous or sequentially. It was pointed out that this domain is still in progress and the co-design method aiming at integrating the control and scheduling for NCS is a promising topic of research.

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