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Fault diagnosis of networked control systems

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Abstract

Networked control systems (NCS) are feedback systems closed through data networks. NCS have many advantages compared with traditional systems; however, the network-induced delay and other characteristics of data networks may degrade the performance of feedback systems designed without taking the network into account. Supported by the National Nature Science Foundation of China, we studied the fault diagnosis and fault-tolerant control theory for NCS in recent years. This paper summarizes our main ideas and results on fault diagnosis of NCS, including the fundamentals of fault diagnosis for NCS with information-scheduling, fault diagnosis approaches based on the simplified time-delay system models, and the quasi T–S fuzzy model and fault diagnosis for linear and nonlinear NCS with long delay.

Keywords: Fault diagnosis; Fault detection; Networked control systems; Time-delay systems; Optimization; Fault tolerance; Fuzzy modelling; Periodic systems

1. Introduction

Motivated by the fast advance of network technology and the accelerating technological convergence of communications, control and computing, research in and applications of networked control systems (NCS) have become increasingly popular. Generally speaking, NCS are comprised of a large amount of actuators, sensors and controllers which are all equipped with network interfaces, and are equal nodes of the network. All the signals, including real-time sensing, controller outputs, command, coordination, and supervision signals are transmitted through shared computer networks. The system elements of NCS are typically distributed over a wide area and are connected by wired or wireless, band-limited and possibly noisy communication channels. For some NCS, although there is no geographical separation between the elements, still all elements are connected via a shared communication channel that is being used along with other users in the same local area.

Networked control systems are not new in industry. They are becoming very popular today; more and more control systems are operating over a network. Usually, NCS in industry utilizes networks with specialized protocols, such as CAN for automotive and industrial automation, Fieldbus for process control, and so on (Lian, Moyne, & Tilbury, 2001).

Industrial control is only one application domain where networked real-time systems are becoming increasingly important. New applications of NCS are coming forth continuously, such as remote control over the Internet, *ad hoc* networks of autonomous mobile agents (for example, unmanned ground and air vehicles and clusters of satellites), mobile sensor networks, and arrays of micro-devices (Antsaklis & Baillieul, 2004a). These complicated systems are supposed to work through a shared data network, wireless network, or even the Internet.

Computer networks have been used for control systems for quite a long time, the first DCS (distributed control system), TDC2000, was developed by Honeywell in 1975, that is about 30 years ago. A networked control system is also a distributed control system itself, but NCS are totally different from these traditional DCS. DCS generally consists of process stations, operator stations and various auxiliary stations for process control, supervision, data logging and process optimization. But in these systems, all these modules are only loosely connected through some network, and most of the real-time control tasks are carried out within the individual process stations. Only on/off signals, monitoring and alarm information

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and the likes are transmitted on the network. Especially, the feedback loops are not closed through the network. In contrast to DCS, all components of a networked control system are connected to a shared computer network, and work together closely to perform control tasks, and feedback loops are closed through the network. Fig. 1 shows a typical feedback loop in NCS.

New and interesting challenges arise when feedback loops are closed via networks. The network itself is a dynamical system that exhibits characteristics which traditionally have not been taken into account in control system design. For example, the network-induced delay, packet dropout, asynchronous clock among network nodes and other characteristics of networks could degrade the performance of closed-loop systems and even destabilize them. Although NCS is not new to industry, theoretical research on NCS is still new to the academic control community. We have many new opportunities in this exciting field. As pointed by the Report of the Panel on Future Directions in Control, Dynamics and Systems, entitled ‘‘Control in an Information Rich World’’, it is necessary to develop theory and practice for control systems that operate in a distributed, asynchronous, and packet-based environment (Murray, Astrom, Boyd, Brockett, & Stein, 2003). Research on NCS has received increasing attention in recent years, and hundreds of papers came forth in journals and conferences, which deal with the modelling, design and analysis of NCS (Antsaklis & Baillieul, 2004b; Bushnell, 2001; Li & Fang, 2006a, 2006b; Ma & Fang, 2005a, 2005b, 2006a; Nilsson, 1998; Tipsuwan & Chow, 2003).

Fault diagnosis (FD) and fault-tolerant control (FTC) are very important issues for practical control systems, particularly in safety-critical systems. The rapid growth of applications of NCS in industry and military domains has created a demand to develop new fault diagnosis and fault-tolerant control theory for these kinds of large-scale distributed control systems. The theory and practice of fault diagnosis and fault-tolerant control for NCS are different from the ones for traditional control systems in many aspects. For example, (1) it is apparent that network-induced delay, packet dropout and other characteristics of networks could influence the performance of a fault diagnosis system designed without taking them into account; (2) usually, data networks are very robust to unpredicted changes in topology such as loss of a node or a link, and far more reliable than other control system components. This is in

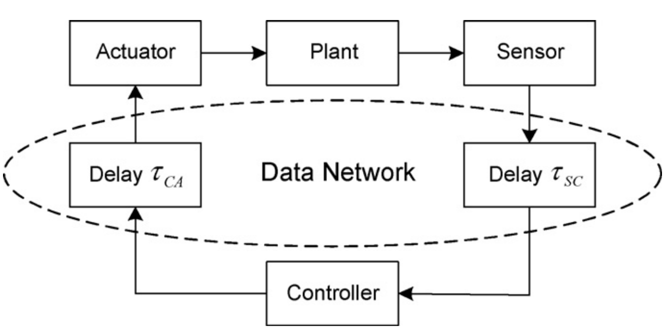

Fig. 1. Typical feedback loop in NCS.

contrast with traditional control systems, which are usually only as reliable as their weakest link; (3) with good architecture and protocol design, the networked swarm of smart sensors and actuators could be very robust to component failure. In this system, sensors and controllers asynchronously send and process packets. Communication links can break. Sensors and actuators can become unavailable. New sensors, actuators, and processors can be added to the system automatically. As long as there are enough sensors and actuators available, and enough packets are received, the system will still work. The fault-tolerant ability of such systems is of course very strong (Murray et al., 2003). The designer of fault diagnosis and fault-tolerant control for such systems should take all these network-induced characteristics and limitations into account.

Supported by the National Nature Science Foundation of China, we studied the fault diagnosis and fault-tolerant control theory for NCS in recent years. In this work, we mainly focused on NCS as depicted in Fig. 1, which is a typical feedback loop in NCS; it consists of a plant, sensors, actuators, and controller, as in a traditional control system, however, the sensor data packets reach the controller, and the control data packets arrive at the actuators via data network. In such a setting, the network load and the limited communication bandwidth could cause random time delays, packet dropout and other issues.

Our work included modelling, analysis, fault detection and fault-tolerant control of NCS with information scheduling and network-induced delay. This paper summarizes our main ideas and results on the fault diagnosis theory part of this research; the fault-tolerant control part (Huo, 2006) and many important contributions from other authors (for instance, Patton, Kambhampati, Casavola, & Franze, 2006) are not included here.

We group the results into three categories: fault diagnosis for NCS with information scheduling, fault diagnosis for NCS with network-induced delay, and the modelling and fault diagnosis for NCS with long delay time.

NCS with information scheduling have far more potential to efficiently use the communication capacity and reduce the network-induced delay. The NCS with information scheduling was modelled as a periodic discrete-time system; this way many basic ideas of existing fault diagnosis approaches could be extended to these cases by taking the periodic property into account.

With a different assumption, the NCS was modelled as a simplified delay system; then many existing methods, such as state observer, filtering algorithms, etc., developed originally for ordinary time-delay systems could be used for or extended to fault diagnosis of NCS. Further, new algorithms dedicated to NCS have been presented based on these models.

For linear and nonlinear NCS with long random delay time, the so called quasi T–S fuzzy models were presented; based on these models many existing fault diagnosis and fault-tolerant control approaches could be extended to linear or nonlinear NCS with long random delay time.

This paper is organized as follows. The main ideas of fault detection for NCS with information scheduling are summarized in Section 2. Then the summary for fault diagnosis of NCS with network-induced delay and quasi T–S model based fault detection for linear and nonlinear-networked control systems with long random delay time are presented in Sections 3 and 4 respectively. Finally, some further research topics and concluding remark are drawn in Section 5.

2. Fault diagnosis for NCS with information scheduling

Network congestion, which is the main reason causing time delay, could be reduced or even avoided by decreasing the number of information packets transmitted over networks. NCS with information scheduling will have the potential to efficiently use the communication capacity, reduce the network-induced delay and improve the performance of control systems. For instance, the states of a large-scale control system can be grouped into subsystems, then share the communication resource periodically. In another situation, for a MIMO system which is controlled by a digital controller, the controller does not simultaneous access all inputs and outputs of the controlled plant, but takes turns to send one group of the inputs to and receive one group of the measurements from the plant periodically. The packets from sensors and controllers are transmitted sequentially in a predetermined order. The performance of such kinds of systems is affected by the scheduling strategy; the stability issues have been discussed in literature (Xie & Fang, 2004; Xie, Fang, & Wang, 2004, Xie, Ji, Pan, & Fang, 2005). The theory of mode-based fault detection for NCS with information scheduling has been investigated; the main ideas are summarized below (Xie, 2004).

A networked control system with information scheduling is depicted in Fig. 2.

Here G is the continuous-time plant of NCS, S_i and H_i are ideal sampler and hold, respectively, and Sc represents the information scheduling scheme. $\bar{y}_k$, $\bar{u}_k$, y_k and u_k are the sampled signals of the plant output (sensor signal), plant input, controller input, and controller output (control signal), respectively. They are all discrete-time signals.

The state variable equation of plant G is given by

$$\dot{x}(t) = Ax(t) + B\bar{u}(t) + B_{\mathrm{d}}d(t) + B_{\mathrm{f}}f_{\mathrm{a}}(t),$$
$$\bar{y}(t) = Cx(t) + D_{\mathrm{d}}d(t) + D_{\mathrm{f}}f_{\mathrm{s}}(t)$$

where $x(t) \in R^{n}$, $\bar{u}(t) \in R^{n_{\mathrm{u}}}$, $\bar{y}(t) \in R^{n_{\mathrm{y}}}$ are state variables, control signal and output signal; $d(t) \in R^{\mathrm{d}}$, $f_{\mathrm{a}}(t) \in R^{f_{\mathrm{a}}}$, $f_{\mathrm{s}}(t) \in R^{f_{\mathrm{s}}}$ are external disturbances and fault signals,

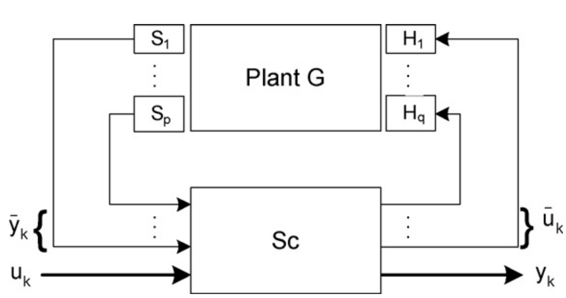

Fig. 2. NCS with information-scheduling.

respectively. The corresponding discrete-time system G_{d} with sampling period h is

$$x(k+1) = \bar{A}x(k) + \bar{B}\bar{u}(k) + \bar{B}_{\mathrm{d}}d(k) + \bar{B}_{\mathrm{f}}f_{\mathrm{a}}(k),$$
$$\bar{y}(k) = \bar{C}x(k) + \bar{D}_{\mathrm{d}}d(k) + \bar{D}_{\mathrm{f}}f_{\mathrm{s}}(k)$$

where $\bar{A} = \mathrm{e}^{Ah}$, $\bar{B} = \int_0^h \mathrm{e}^{As}B\,\mathrm{d}s$, $\bar{B}_{\mathrm{d}} = \int_0^h \mathrm{e}^{As}B_{\mathrm{d}}\,\mathrm{d}s$, $\bar{B}_{\mathrm{f}} = \int_0^h \mathrm{e}^{As}B_{\mathrm{f}}\,\mathrm{d}s$, $\bar{C} = C$, $\bar{D}_{\mathrm{d}} = D_{\mathrm{d}}$, $\bar{D}_{\mathrm{f}} = D_{\mathrm{f}}$.

The information-scheduling scheme Sc can also be described by state variable equations

$$\bar{x}(k+1) = \bar{\bar{A}}_j\bar{x}(k) + \bar{\bar{B}}_{1j}\bar{y}(k) + \bar{\bar{B}}_{2j}u(k),$$
$$\bar{u}(k) = \bar{\bar{C}}_{1j}\bar{x}(k) + \bar{\bar{D}}_{11j}\bar{y}(k) + \bar{\bar{D}}_{12j}u(k),$$
$$y(k) = \bar{\bar{C}}_{2j}\bar{x}(k) + \bar{\bar{D}}_{21j}\bar{y}(k) + \bar{\bar{D}}_{22j}u(k)$$

where j is the step number of information-scheduling $j \in \{1, 2, \ldots, N\}$; N is the period of information scheduling; $\bar{\bar{A}}_j$, $\bar{\bar{B}}_{1j}$, $\bar{\bar{B}}_{2j}$, $\bar{\bar{C}}_{1j}$, $\bar{\bar{C}}_{2j}$, $\bar{\bar{D}}_{11j}$, $\bar{\bar{D}}_{12j}$, $\bar{\bar{D}}_{21j}$, $\bar{\bar{D}}_{22j}$ are all constant matrices determined by the information-scheduling scheme. A very simple example of information-scheduling is the switching scheduling scheme, that is, the signals of sensors and controllers are transferred through the network alternatively:

$$y(k) = \begin{cases} \bar{y}(k) & k \text{ is even} \\ \bar{y}(k-1) & k \text{ is odd} \end{cases},$$
$$\bar{u}(k) = \begin{cases} u(k-1) & k \text{ is even} \\ u(k) & k \text{ is odd} \end{cases}$$

where $j \in \{1, 2\}$, scheduling period $N = 2$. For a SISO system G, we have the following

- when k is even: $\bar{\bar{A}}_k = 0$, $\bar{\bar{C}}_{1k} = 1$, $\bar{\bar{C}}_{2k} = 0$, $\bar{\bar{B}}_{1k} = 1$, $\bar{\bar{B}}_{2k} = 0$, $\bar{\bar{D}}_{12k} = 0$, $\bar{\bar{D}}_{21k} = 1$, $\bar{\bar{D}}_{11k} = \bar{\bar{D}}_{22k} = 0$;
- when k is odd: $\bar{\bar{A}}_k = 0$, $\bar{\bar{C}}_{1k} = 0$, $\bar{\bar{C}}_{2k} = 1$, $\bar{\bar{B}}_{1k} = 0$, $\bar{\bar{B}}_{2k} = 1$, $\bar{\bar{D}}_{12k} = 1$, $\bar{\bar{D}}_{21k} = 0$, $\bar{\bar{D}}_{11k} = \bar{\bar{D}}_{22k} = 0$.

The combination of G and Sc brings us the full system model G_Sc of NCS:

$$X(k+1) = \tilde{A}_kX(k) + \tilde{B}_ku(k) + \tilde{B}_{\mathrm{d}k}d(k) + \tilde{B}_{\mathrm{f}k}f_{\mathrm{a}}(k),$$
$$y(k) = \tilde{C}_kX(k) + \tilde{D}_{\mathrm{d}k}d(k) + \tilde{D}_{\mathrm{f}k}f_{\mathrm{s}}(k) \qquad (1)$$

where

$$X(k) = \begin{bmatrix} x(k) \\ \bar{x}(k) \end{bmatrix}, \qquad \tilde{A}_k = \begin{bmatrix} \bar{A} & \bar{B}\bar{\bar{C}}_{1k} \\ \bar{\bar{B}}_{1k}\bar{C} & \bar{\bar{A}}_k \end{bmatrix},$$
$$\tilde{B}_k = \begin{bmatrix} \bar{B}\bar{\bar{D}}_{12k} \\ \bar{\bar{B}}_{2k} \end{bmatrix}, \qquad \tilde{B}_{\mathrm{d}k} = \begin{bmatrix} \bar{B}_{\mathrm{d}} \\ \bar{\bar{B}}_{1k}\bar{D}_{\mathrm{d}} \end{bmatrix},$$
$$\tilde{B}_{\mathrm{f}k} = \begin{bmatrix} \bar{B}_{\mathrm{f}} \\ \bar{\bar{B}}_{1k}\bar{D}_{\mathrm{f}} \end{bmatrix}, \qquad \tilde{C}_k = [\bar{\bar{D}}_{21k}\bar{C} \quad \bar{\bar{C}}_{2k}],$$
$$\tilde{D}_{\mathrm{d}k} = \bar{\bar{D}}_{21k}\bar{D}_{\mathrm{d}}, \qquad \tilde{D}_{\mathrm{f}k} = \bar{\bar{D}}_{21k}\bar{D}_{\mathrm{f}}$$

This combined system G_Sc is a periodic time varying discrete-time system with the period being equal to the number of steps of information-scheduling.

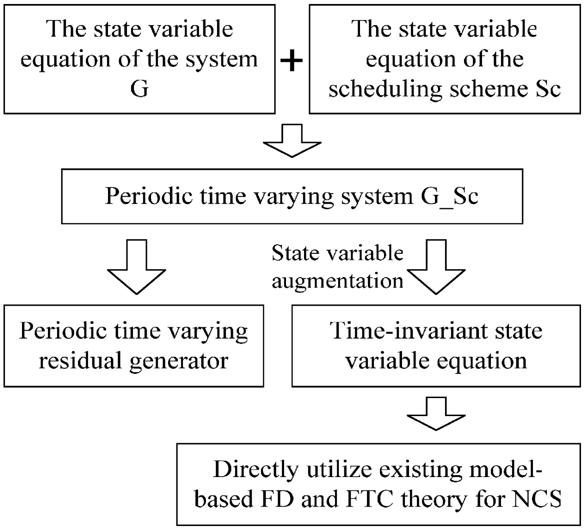

Fig. 3. Design outline for NCS with information-scheduling.

Utilizing the combined system model, the model-based fault diagnosis systems could be developed. Fig. 3 shows the outline of the design procedure.

The model of system G plus the model of the scheduling scheme Sc provide a full system model which is a periodic time varying system. Based on this model, we have two choices to develop fault diagnosis systems.

- The first approach is to develop periodic time varying residual generators for NCS. For example, a series of observers can be designed for each subsystem, and then a periodic time varying observer is constructed by combining all these sub-observers, and this observer will be an asymptotic observer under some assumptions; then an observer-based fault detection system can be implemented in the traditional way.
- In another approach, the full periodic time varying system model (1) is transformed into a time-invariant system by state variable augmentation, and then we can directly utilize the existing model-based fault diagnosis and fault-tolerant control theory for NCS with information-scheduling.

The residual generators designed with these two approaches have different benefits, the periodic one is more complicated than the time-invariant one, but the time-invariant one has higher dimension (Xie, 2004; Fang, Fang, & Yang, 2006).

3. Fault diagnosis for NCS with network-induced delay

Network-induced delay is the key issue in the investigation of NCS. Fig. 1 depicts a typical feedback loop in NCS. There are two delays, sensor to controller delay and controller to actuator delay. These two delays can be combined together when the controller is linear and time-invariant. It is evident that the network-induced delay in NCS could influence the performance of traditional fault diagnosis systems. For example, it is shown in Ye and Ding (2004) and Ye, He, Liu, and Wang (2006), that the network-induced delay will prevent a traditional observer based fault detection system from satisfying the essential requirement of a qualified residual generator, i.e., with the delay, the residual signal of a traditional residual generator will not be able to be decoupled from the control input any longer.

In this section, we will model NCS as classes of simplified delay systems and then attack the fault diagnosis problem for NCS with time delay in three ways, i.e. extending or directly using the existing state estimation and observer theory of time delay systems to develop a dedicated fault diagnosis method for NCS (Section 3.1), developing fault diagnosis methods witch are robust to an unknown item produced by network-induced random delay (Sections 3.2 and 3.3), and directly utilizing the fault diagnosis theory of delay systems (Section 3.4).

3.1. Approaches based on existing state estimation and observer theory for time-delay systems

Based on various assumptions, the NCS can be modelled as simplified time-delay systems (Ray & Halevi, 1988; Zhang, 2001, Zhang, Branicky, & Phillips, 2001; Zheng, Fang, Wang, & Xie, 2003). Many existing observer, filtering and state estimation methods developed originally for time-delay systems could be utilized or extended to formulate fault diagnosis algorithms for NCS. Fig. 4 is the outline of this design procedure.

Modelling NCS as a simplified time-delay system and selecting some suitable state estimation or observer method developed originally for time-delay systems, a residual generator for NCS can be obtained with the usual way for traditional systems.

For example, as shown in Fig. 1, the time delays τ_{sc} and τ_{ca} are random variables. If the controller node is clock-driven, then at sample instant kh the packet arriving at the controller/actuator and its sequence will not be determined, so that it is difficult to get the distinct state model of the NCS. In order to overcome this difficulty, event-driven mode (Branicky, Phillips, & Zhang, 2000) for the controller node can be utilized; once the sensor's packet arrives at the controller, the controller starts immediately and computes the control signals and sends them to the actuators. To eliminate data loss and keep the packet's sequence, the transmission buffers are set up, the lengths of which are longer than the maximum delay time. In this way, the

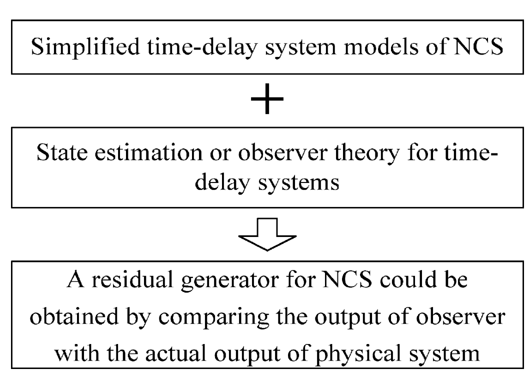

Fig. 4. Design outline of FD based on time-delay system models.

integrity and sequence of the information transmission is guaranteed. Then the discrete state model of the system with network-induced delay can be described as

$$\begin{aligned} x(k+1) &= \bar{A}x(k) + \bar{B}_0 u(k-l) + \bar{B}_1 u(k-l+1) + \bar{B}_{\rm d} d(k) + \bar{B}_{\rm f} f_{\rm a}(k), \\ y(k) &= \bar{C}x(k) + f_{\rm s}(k) \end{aligned} \tag{2}$$

This is a familiar discrete-time system with input time delays. A reduced-order memoryless state observer with a γ-stability margin for linear discrete-time systems with multiple delays in both the state and the control variable was presented by Trinh and Aldeen (1997). Utilizing this state observer, an observer-based fault detection method was suggested for system (2) by comparing the output of the observer with the actual output of the practical system (Zheng, Fang, Wang, & Xie, 2003). The residual function for this approach is

$$r(z) = Q\bar{C}P^{-1}\bar{B}_{\rm d}d(z) + Q\bar{C}P^{-1}\bar{B}_{\rm f} f_{\rm a}(z) + [Q - Q\bar{C}P^{-1}(zI_n - \bar{A})V(zI_{\rm r} - \Lambda_{\rm r})^{-1}L] f_{\rm s}(z)$$

where

$$P = (zI_n - \bar{A})[I_n + V(zI_{\rm r} - \Lambda_{\rm r})^{-1}L\bar{C}]$$

To remove the effect of the disturbance, it is required that

$$Q\bar{C}P^{-1}\bar{B}_{\rm d} = 0$$

Simulation results demonstrating the feasibility of this approach can be found in Zheng (2003) and Zheng, Fang, Wang, and Xie (2003).

This observer-based fault detection approach for NCS is only serving as a typical example. With different assumptions and simplified models of NCS, many existing observer, filtering and state estimation methods developed originally for time-delay systems can be utilized or extended to formulate fault diagnosis algorithms for NCS, such as the results presented in Huo and Fang (2005a, 2005b), Xie, Ji, & Fang (2005), Zheng, Fang, Wang, and Li (2003), Zheng, Fang, Xie, and Wang (2003), Zheng, Fang, Xie, and Cao (2003), Zheng, Fang, and Wang (2004a), and Zheng, Hu, Fang, and Wang (2005).

3.2. Approaches based on low-pass post-filtering

Suppose that the network-induced delay of an NCS is random and unknown, and is smaller than the sampling period, then the plant model of the NCS with unknown inputs d and faults f can be described by the following discrete-time model (Zhang, Branicky, et al., 2001):

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

which can be further expressed as (Ye et al., 2006):

$$x(k+1) = \bar{A}x(k) + \bar{B}u(k) + g(k) + \bar{B}_{\rm d}d(k) + \bar{B}_{\rm f} f(k) \tag{3}$$

where

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

Eqs. (3) and (4) show that the unknown network-induced delay τ_k has introduced an unknown item $g(k)$ into the discrete-time plant model. The fault diagnosis system should be robust to this term.

If we use a traditional parity relation based residual generator for NCS with network-induced delay then, as it has been shown in Ye, Zhang, Ding, and Wang (2000), when the parity vector has a low-pass frequency response, the fault detection system will be robust to the term g, but when the parity vector is high-pass or band-pass, then the term g, the delay, may strongly degrade the performance of the fault detection system. So, in order to reduce the influence of delay, a natural thought is to add a low-pass post-filter to the residual generator.

Recently, based on the study of the frequency domain characteristics of the parity space approach (Ye et al., 2000; Zhang, Ye, Ding, Wang, & Zhou, 2006), a new fault detection approach using parity space and Stationary Wavelet Transform (SWT) has been proposed (Ye, Wang, & Ding, 2004). This can ensure good performance and low online computational effort simultaneously by adding SWT filters to an ordinary parity space based residual generator and considering both the parity space based residual generator and the SWT filters in the optimal design.

Although the motive for the work in Ye et al. (2004) was not to deal with NCS, it has already provided an effective way for us to design an optimal fault detection system consisting of an observer based residual generator and SWT based post-filters.

So based on the main results in Ye et al. (2004), a method for fault detection of NCS with random network-induced delay has been introduced in Ye and Wang (2006), which can be regarded as an application of the method of the former in fault detection of NCS. The difference between the design procedures lies in that the SWT based post-filter is forced to be low-pass in Ye and Wang (2006), but could be located at any frequency in Ye et al. (2004). The following are the main results of the low-pass design.

Let

$$u_{{\rm s},k} = [\, u^{\rm T}(k-s) \quad u^{\rm T}(k-s+1) \quad \cdots \quad u^{\rm T}(k) \,]^{\rm T} \tag{5}$$

and define $y_{{\rm s},k}$, $d_{{\rm s},k}$, $f_{{\rm s},k}$ and $g_{{\rm s},k}$ as the vectors obtained by replacing u in Eq. (5) with y, d, f and g, respectively. Let

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

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

$$H_{\rm 0,s} = [\, \bar{C}^{\rm T} \quad \bar{A}^{\rm T}\bar{C}^{\rm T} \quad \cdots \quad (\bar{A}^{s})^{\rm T}\bar{C}^{\rm T} \,]^{\rm T}$$

Then a parity space and 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 is governed by

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

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

where v_s is the parity vector to be designed which should be selected from the parity space P_s defined by $P_s = \{v_s | v_s H_{0,s} = 0\}$, 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) may be written in the following explicit form (Ye et al., 2004)

$$r^{WT}_{s,k} = v_s(H_{d,s}N^{d}_{l,j_m}d_{s+i_{set},k} + H_{f,s}N^{f}_{l,j_m}f_{s+i_{set},k} + H_{q,s}N^{q}_{l,j_m}q_{s+i_{set},k})$$

where N^{d}_{l,j_m}, N^{f}_{l,j_m}, N^{q}_{l,j_m} are known and constant matrices determined by the SWT filter, whose definitions can be found in Ye et al. (2004).

An optimal residual generator may not remain optimal when an extra post-filter is added, so an integrated optimization of the residual generator and the filter should be carried out. The optimal parity vector v_s is determined by this optimization problem.

$$\min_{v_s \in P_s} J^{WT}_s = \min_{v_s \in P_s} \frac{v_s H_{d,s} N^{d}_{l,j_m} (N^{d}_{l,j_m})^T H^T_{d,s} v^T_s}{v_s H_{f,s} N^{f}_{l,j_m} (N^{f}_{l,j_m})^T H^T_{f,s} v^T_s} \tag{11}$$

It is similar to the traditional one, but N^{d}_{l,j_m}, N^{f}_{l,j_m} are determined by the SWT filter, so this is an integrated optimization. Finally, the residual signal can be calculated according to Eqs. (7) and (8).

3.3. Approaches based on the structure matrix of g(k)

According to Eqs. (3) and (4), a key difference between $g(k)$ and the unknown input $d(k)$ is that the structure matrix $\bar{\Gamma}_1$ of term $g(k)$ is an unknown matrix, but the one for term $d(k)$ is assumed to be a known matrix. If we can transform the term $g(k)$ into (known part) × (unknown part) form, where the known part can extract the known information (such as A, B, Δu_k) from $g(k)$ as much as possible, and the unknown part includes the unknown information related to τ_k, then we can use traditional robust fault detection approaches to design a residual generator which is robust to the unknown part, thus also is robust to the time-delay.

Since the role of the known part is similar to that of the structure matrix $\bar{B}_d$ for disturbance $d(k)$, so we call the known part as the structure matrix of term $g(k)$. Several approaches to do the transformation have been presented (Liu, Cheng, & Ye, 2005; Wang, Ye, & Wang, 2006, Wang, Ye, Cheng, & Wang, 2006; Ye & Ding, 2004; Ye et al., 2006).

3.3.1. Approach based on Taylor approximation

The method was proposed in Ye and Ding (2004), in which a simpler NCS model is considered, i.e.

$$x(k+1) = \bar{A}x(k) + \bar{B}u(k) + g(k) + f(k), \qquad y(k) = \bar{C}x(k) \tag{12}$$

When the sampling period h is sufficiently small compared with the system's time constants, by using the Taylor approximation of e^{At}, where A is the matrix in the continuous NCS model, i.e. $\bar{A} = e^{Ah}$ (Zhang, Branicky, et al., 2001), there is

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

So $g(k)$ has been transformed into an approximate form whose left part is a known structure vector $\bar{E}_{\tau,k}$ and whose right part is the unknown τ_k.

In Ye and Ding (2004), a time-varying parity space based residual generator is defined as

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

whose dynamics is governed by

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

where $v_{s,k} \in P_s$ and

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

$$\tau_{s,k} = [\tau_{k-s} \quad \tau_{k-s+1} \quad \cdots \quad \tau_k]^T \tag{14}$$

and the other matrices have the same definitions as those in Section 3.2, respectively.

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

$$v_{s,k}H_{0,s} = 0 \quad \text{and} \quad v_{s,k}H_{\tau,s,k} = 0 \tag{15}$$

The approach has good robustness to unknown network-induced delay only when both h and τ_k are small enough. In addition, since τ_k in Eq. (13) is a scalar, the existence condition of $v_{s,k}$ in Eq. (15) is not difficult to satisfy in most cases.

3.3.2. Approach based on eigendecomposition and Padé approximation

This approach was proposed in Wang, Ye, Cheng, et al. (2006), in which the NCS model is also supposed to be described by Eq. (12) and the matrix A in the continuous NCS model is supposed to be diagonalizable.

Based on eigendecomposition and the first-order Padé approximation of $e^{\lambda_i t}$, where $\lambda_1, \ldots \lambda_n$ are the eigenvalues of A, it has been proved in Wang, Ye, Cheng, et al. (2006) that there is

$$g(k) \approx \bar{E}_{\tau,k}\tau_k \tag{16}$$

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

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

in which P is obtained through the eigendecomposition of A, i.e. $A = P\Lambda P^{-1}$, and $\mathrm{diag}(P^{-1}B\Delta u_k)$ denotes the diagonal matrix which is composed of the elements of the vector $P^{-1}B\Delta u_k$.

Since Eq. (16) has the same form as Eq. (13), the residual generator and its design is also as same as that in the approach based on Taylor approximation. And again, since τ_k in Eq. (16) is still a scalar, the full decoupling problem (15) does not need a strong condition in most cases.

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

3.3.3. Approach based on Cayley–Hamilton formula and principal component analysis

Both of the methods in Ye and Ding (2004) and Wang, Ye, Cheng, et al. (2006) use approximate structure matrices of network-induced delay, and neither of them includes the traditional unknown input $d(k)$ in their model.

In Ye et al. (2006), an approach for fault detection of NCS was proposed, in which an accurate structure matrix of network-induced delay was deduced. In the method, it is supposed that the NCS model to be monitored is described by Eqs. (3) and (4), which includes not only the unknown network-induced delay but also the ordinary unknown input d.

Based on the Cayley–Hamilton theorem, there is

$$e^{At} = I + At + \cdots + \frac{1}{n!}A^n t^n + \cdots = \sum_{i=0}^{n-1}\alpha_i(t)A^i$$

where A is the matrix in the continuous NCS model and n is the dimension of the state x. Then it has been proved that $g(k)$ can be transformed into the following form accurately,

$$g(k) = \bar{E}_{\tau,k}\beta_{\tau,k} \tag{17}$$

where

$$\bar{E}_{\tau,k} = [B \quad AB \quad \cdots \quad A^{n-1}B]\begin{bmatrix}\Delta u_k & & \\ & \ddots & \\ & & \Delta u_k\end{bmatrix} \in R^{n\times n},$$

$$\beta_{\tau,k} = [\eta_0^{\tau_k} \quad \eta_1^{\tau_k} \quad \cdots \quad \eta_{n-1}^{\tau_k}]^{\mathrm{T}} \in R^{n\times 1},$$

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

Now Eq. (17) has decomposed $g(k)$ into a known structure matrix $\bar{E}_{\tau,k}$ and an unknown vector $\beta_{\tau,k}$ determined by the network-induced delay τ_k. Unlike Eq. (13) or (16), the structure matrix $\bar{E}_{\tau,k}$ in Eq. (17) is accurate.

In the method, 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 is 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

$$\psi_{\tau,s,k} = [\beta_{\tau,k-s}^{\mathrm{T}} \quad \beta_{\tau,k-s+1}^{\mathrm{T}} \quad \cdots \quad \beta_{\tau,k}^{\mathrm{T}}]^{\mathrm{T}}$$

$H_{\tau,s,k}$ takes the same form as Eq. (14), and the other matrices have the same definitions as those in Section 3.2, respectively.

To achieve the robustness of $r_{s,k}$ to the vector of network-induced delay $\psi_{\tau,s,k}$ and ensure that $v_{s,k}$ belongs to the parity space P_s, it is expected that $v_{s,k}$ satisfies

$$v_{s,k} \in P_s \quad \text{and} \quad v_{s,k}H_{\tau,s,k} = 0 \tag{18}$$

But since $\beta_{\tau,k}$ in Eq. (17) is a vector of dimension of n, the solution of Eq. (18) may not exist in many cases. So in Ye et al. (2006), based on Principal Component Analysis (PCA), the following objective is used to determine the parity vector in place of (18):

$$v_{s,k} \in P_s \quad \text{and} \quad v_{s,k}\Lambda_{\tau,s,k}^{m_k} = 0 \tag{19}$$

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

It has been discussed that, due to the good characteristics of PCA, usually a suitable m_k which is much smaller than the column number of $H_{\tau,s,k}$ may be found to make the solution of Eq. (19) exist on one hand, and to make Eq. (18) hold approximately with a good accuracy on the other hand.

After solving Eq. (19), we may further take advantage of the remaining freedom of $v_{s,k}$ to achieve the optimal robustness to d and optimal sensitivity to f in the following sense

$$\min_{\substack{v_{s,k}\in P_s \\ v_{s,k}\Lambda_{\tau,s,k}^{m_k}=0}} J_{s,k} = \min_{\substack{v_{s,k}\in P_s \\ v_{s,k}\Lambda_{\tau,s,k}^{m_k}=0}} \frac{v_s H_{d,s}H_{d,s}^{\mathrm{T}}v_s^{\mathrm{T}}}{v_s H_{f,s}H_{f,s}^{\mathrm{T}}v_s^{\mathrm{T}}}$$

Compared with the methods in Ye and Ding (2004) and Wang, Ye, Cheng, et al. (2006), the advantage of the method lies in the adoption of an accurate structure matrix of network-induced delay and the inclusion of the ordinary unknown input d. Compared with the method in Ye and Wang (2006), the merit of this method is that it takes full advantage of the known information on network-induced delay (i.e. its structure matrix).

3.3.4. Other related work

In Wang, Ye, et al. (2006), a method for fault detection of NCS with unknown network-induced delay, which may be greater than h, is proposed. In the method, an NCS model for unknown network-induced delay which may be greater than h (Halevi & Ray, 1988; Hu & Zhu, 2003) has been adopted, and the idea for handling multiplicative faults (Gertler, 1998) has been used to deal with the network-induced delay. However, from another point of view, the method in Wang, Ye, et al. (2006) 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.

Additionally, research on fault detection of sampled-data systems has received increasing attention in recent years, which considers the influence of the dynamics of unknown inputs and faults between sampling instants and therefore has better performance than other indirect methods (Zhang, Ding, Wang, & Zhou, 2001). Since an NCS with unknown inputs and faults is a kind of typical sampled-data systems, the ideas in the approaches for fault detection of sampled-data systems can be used to improve the performance of a fault detection system for NCS. So in Liu et al. (2005), a method which combines the method for fault detection of NCS in Ye and Ding (2004) and that for fault detection of sampled-data systems in Zhang, Ding, et al. (2001) has been introduced.

3.4. Direct utilization of existing fault diagnosis theory of time-delay system

Based on a simplified time-delay model of NCS, many existing fault diagnosis methods for time-delay systems can be extended to, or utilized directly for, NCS with network-induced delay. Some of these results are briefly introduced in the following.

3.4.1. Unknown input decoupling

The work by Yang and Saif (1998) is the first paper to deal with the fault detection problem for time-delay systems. A reduced-order unknown input observer was proposed to detect and identify the actuator and sensor faults for a class of state-delayed dynamic systems, in which the faults as well as other effects such as disturbances and higher-order nonlinearities were considered as unknown inputs. With some assumptions on the structure of system and distribution matrices, decoupling of the completely unknown input from the residual is achieved.

3.4.2. H_∞-norm-model matching formulation

In Ding, Ding, and Jeinsch (2002), a weighting transfer function matrix was first developed to describe the desired behaviour of the residual with respect to the fault, and an observer-based fault detection filter for a class of linear systems with time-varying delays was designed, in such a way that the error between the generated residual and fault (or, more generally weighted fault) is as small as possible in the sense of the H_∞-norm. The design of the observer-based fault detection filter was then formulated into an H_∞-model matching problem and, with the aid of an optimization tool, such as the linear matrix inequality technique, the problem was solved.

3.4.3. Two-objective optimization approaches

Enhancing the sensitivity of the residual to the fault and, at the same time, suppressing the undesirable effects of unknown inputs and modelling errors are two essential objectives of residual generation. The work by Liu and Frank (1999) regarded the fault detection problem for linear systems with constant time delays as a two-objective nonlinear programming. Jiang, Staroswiecki, and Cocquempot (2003) extended the results of Liu and Frank (1999) to the case of discrete-time systems. More recently, Zhong, Ye, Sun, and Wang (2006) dealt with the robust fault detection filter problem for linear systems with time-varying delays and model uncertainty, and an iterative linear matrix inequality algorithm was proposed.

3.4.4. A unified optimization approach

The work in Zhong, Ye, Wang, and Zhou (2005) dealt with the fault detection problem for linear systems with L_2-norm bounded unknown input and multiple constant time-delays. An observer-based fault detection filter was developed such that a robustness/sensitivity based performance index was minimized. The key idea of this study is the introduction of a new fault detection filter as residual generator and the extension of an optimized fault detection method for linear time-invariant systems in Ding, Jeinsch, Frank, and Ding (2000) and Ding, Zhong, and Tang (2001) to time-delay systems. A sufficient condition for the solvability of the fault detection filter has been derived in terms of the *Riccati* equation and a solution has been obtained by suitably choosing a filter gain matrix and post-filter.

In Zhong, Ding, and Lam (2004) the above mentioned optimized fault detection approach has been further modified to a class of neutral time-delay systems.

3.4.5. Adaptive observer based approaches

With a structure restriction on fault distribution, the work by Jiang, Staroswiecki, and Cocquempot (2002) developed an adaptive observer for the fault identification in both linear systems with multiple state time delays and a class of nonlinear systems.

More recently, a new adaptive observer was proposed, by Jiang and Zhou (2005), for the robust fault detection and identification of uncertain linear time-invariant systems with multiple constant time-delays in both states and outputs.

In Chen and Saif (2006), both the disturbance and the possible fault were considered as unknown input, then an iterative learning observer based adaptive unknown input estimation and fault-tolerant control scheme was investigated. The main contribution of Chen and Saif (2006) was the demonstration of a novel reconfigurable fault-tolerant control concept for additive faults. The states of the observer were updated by both the present and past output estimation error, and the control law was compensated by the estimated unknown input.

Some other work on the problem of fault detection for time-delay systems can also be found in Zhong, Ding, and Zhang (2003) and Zhong, Ye, et al. (2004). We believe that there are many other related results, which may be extended for NCS, but are not included in this article.

4. Quasi Takagi-sugeno fuzzy model based fault detection for NCS with long delay time

The previous discussions are mainly based on the assumption that the delay time is less than one sampling period. In this section, we turn to the system with network-induced delay greater than one sampling period. For linear and nonlinear NCS with long delay time, new models, so-called Quasi T–S fuzzy models, were presented in Fang, Zhang, Fang, and Yang (2006) and Zheng, Fang, and Wang (2006), which used the delay time as premise variables and the probability distribution of delay time as membership functions. Based on these models, fault diagnosis and fault-tolerant control schemes were developed. The main ideas of these results are summarized here.

It is assumed that the sensors and the actuators are clock-driven, the controller is event-driven, and the delay time may be greater than one sampling period. The time diagram of data packets is shown in Fig. 5. In each sampling period, the actuator may receive several control data packets, but only the latest one is accepted as plant input at the sampling time. Under such assumptions, the delay time becomes a random integer, and the transfer delay of the data packet, which is accepted by the actuator at the instant kh, is $\tau_k \in \{1, 2, \ldots, n\}$ periods, i.e., at the instant kh the actuators accept the controller dada packet that is based on the sensor packet sent out at the instant $(k - \tau_k)h$.

We assume that the plant in Fig. 1 is a nonlinear system with m operating points described by linear approximations of the state variable equation

$$\dot{x}(t) = A_i x(t) + B_i u(t - \tau_t),$$
$$y(t) = C_i x(t), \quad i = 1, 2, \ldots, m$$

where τ_t is the composite effect of network-induced delay. The linear plant is a special case of nonlinear plants with only one operating point.

Sampling the system with sampling period h, we obtain a simplified discrete-time system model under the above assumptions

$$x(k+1) = \bar{A}_i x(k) + \bar{B}_i u(k - \tau_k),$$
$$y(k) = \bar{C}_i x(k), \quad i = 1, 2, \ldots, m$$

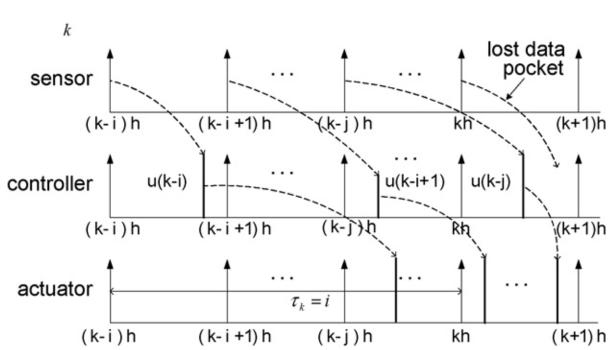

Fig. 5. Time diagram for data packets.

where all matrices in this set of equations have compatible dimension. The delay time τ_k is a discrete random variable, $\tau_k \in \{1, 2, \ldots, n\}$, and the probability distribution of this random variable is $p = \{p_1, p_2, \ldots, p_n\}$, where $p_i = P(\tau_k = i)$, $\sum_{i=1}^{n} p_i = 1$. In some cases, τ_{k+1} is only affected by τ_k and not by $\tau_1, \tau_2, \ldots, \tau_{k-1}$, then the series $\{\tau_1, \tau_2, \ldots, \tau_k, \ldots\}$can be described as a Markov chain (Nilsson, 1998).

When the NCS is a linear system, there is only one operating point described by

$$x(k+1) = \bar{A}x(k) + \bar{B}u(k - \tau_k),$$
$$y(k) = \bar{C}x(k), \quad \tau_k \in \{1, 2, \ldots, n\} \tag{20}$$

The T–S fuzzy models proposed by Takagi and Sugeno (Takagi & Sugeno, 1985; Tanaka & Wang, 2001) are used very broadly for nonlinear systems, which are described by fuzzy IF–THEN rules that represent local linear input-output relations for a nonlinear system. The system (20) is a linear system with random delay time, and we cannot use the T–S modelling approach directly. We extended the ideas in T–S modelling to present a new fuzzy model for system (20) (Fang, Zhang, et al., 2006, Zheng et al., 2006). This new modelling approach utilizes the network-induced delay as a premise variable and the probability distribution of delay time as membership function. This is different from the traditional T–S fuzzy modelling for nonlinear systems, so we name this modelling approach as quasi T–S fuzzy modelling.

The rth rule of this fuzzy model is the following:

$$\text{IF}(r-1)h < \tau_t \leq rh, \qquad \tau_k = r$$
$$\text{THEN}\begin{cases} x(k+1) = \bar{A}x(k) + \bar{B}u(k-r) \\ y(k) = \bar{C}x(k) \end{cases},$$
$$r = 1, 2, \cdots, n \tag{21}$$

Here, the delay time τ_t is used as premise variable, and each subsequent equation with a delay time $\tau_k = r$ is called a ‘‘subsystem’’. n is the maximum value of delay time and also is the number of rules.

The probability distribution of the random variable τ_k, $p = \{p_1, p_2, \ldots, p_n\}$, is used as the membership function $\mu = \{\mu_1, \mu_2, \ldots, \mu_n\}$, where

$$\mu_i = p_i, \quad i = 1, 2, \ldots, n$$

By fuzzy ‘‘blending’’ of all subsystems, the overall model of this linear NCS, the so called quasi T–S fuzzy model, is inferred as follows

$$x(k+1) = \sum_{r=1}^{n} \mu_r \{\bar{A}x(k) + \bar{B}u(k-r)\}$$
$$= \bar{A}x(k) + \bar{B}\sum_{r=1}^{n} \mu_r u(k-r), \qquad y(k)$$
$$= \sum_{r=1}^{n} \mu_r \{\bar{C}x(k)\} = \bar{C}x(k) \tag{22}$$

For nonlinear NCS with random delay time and m operating points, the two-layer quasi T–S fuzzy model was presented (Fang, Zhang, et al., 2006,).

Inner layer: At the ith operating point ($i = 1, 2, \ldots, m$), we use the quasi T–S fuzzy model for linear system to describe the linear approximation of the nonlinear NCS at that operating point:

$$\text{IF}(r-1)h < \tau_t \leq rh, \qquad \tau_k = r$$
$$\text{THEN}\begin{cases} x(k+1) = \bar{A}_i x(k) + \bar{B}_i u(k-r) \\ y(k) = \bar{C}_i x(k) \end{cases}, \quad r = 1, 2, \ldots, n$$

The quasi T–S fuzzy model for the ith operating point is inferred as follows:

$$x(k+1) = \bar{A}_i x(k) + \bar{B}_i \sum_{r=1}^{n} \mu_r u(k-r), \qquad y(k) = \bar{C}_i x(k)$$

Outer layer: We utilize the ordinary T–S fuzzy modelling approach for the overall nonlinear NCS, fuzzy 'blending' all the quasi T–S fuzzy models for the nonlinear NCS at each operating point, just as done with ordinary T–S fuzzy modelling for a nonlinear system.

The ith rule is described as

$$\text{IF}\, Z_1(K)\,\text{is}\, M_{i1}, z_2(k)\,\text{is}\, M_{i2}, \ldots, z_p(k)\,\text{is}\, M_{ip}, \quad i = 1, 2, \ldots, m$$
$$\text{THEN}\begin{cases} x(k+1) = \bar{A}_i x(k) + \bar{B}_i \sum_{r=1}^{n} \mu_r u(k-r) \\ y(k) = \bar{C}_i x(k) \end{cases}$$

The overall fuzzy model for the nonlinear NCS is inferred as follows, by fuzzy "blending" all these quasi T–S fuzzy models:

$$\begin{aligned} x(k+1) &= \frac{\sum_{i=1}^{m} \omega_i(k) \left\{ \bar{A}_i x(k) + \bar{B}_i \sum_{r=1}^{n} \mu_r u(k-r) \right\}}{\sum_{i=1}^{m} \omega_i(k)} \\ &= \sum_{i=1}^{m} \rho_i(k) \bar{A}_i x(k) + \sum_{i=1}^{m} \sum_{r=1}^{n} \rho_i(k) \mu_r \bar{B}_i u(k-r), \\ y(k) &= \frac{\sum_{i=1}^{m} \omega_i(k) \bar{C}_i x(k)}{\sum_{i=1}^{m} \omega_i(k)} = \sum_{i=1}^{m} \rho_i(k) \bar{C}_i x(k) \end{aligned} \tag{23}$$

Here M_{ij} $i = 1, \ldots, m, j = 1, \ldots, p$ are the fuzzy sets and m is the number of model rules; $z_1(k), \ldots, z_p(k)$ are known premise variables that may be functions of the state variables; $\omega_i(k)$ ($i = 1, 2, \ldots, m$) are traditional membership functions, and

$$\rho_i(k) = \frac{\omega_i(k)}{\sum_{i=1}^{m} \omega_i(k)}, \qquad \sum_{i=1}^{m} \rho_i(k) = 1.$$

All those fuzzy sets and membership functions have the same definitions and physical meaning as the ones defined in the traditional T–S fuzzy model for common nonlinear system (Tanaka & Wang, 2001).

The stability of a closed-loop networked control system described by these quasi T–S fuzzy models is governed by the following theorems presented in Fang, Zhang, et al. (2006).

With parallel-distributed compensation (Takagi and Sugeno, 1985; Tanaka & Wang, 2001), the closed-loop nonlinear networked control system described by the quasi T–S fuzzy model is given by

$$x(k+1) = \sum_{i=1}^{m} \rho_i(k) A_i x(k) + \sum_{i=1}^{m} \sum_{r=1}^{n} \rho_i(k) \mu_r B_i \bar{F}(k) x(k-r) \tag{24}$$

where

$$\bar{F}(k) = \sum_{i=1}^{m} \sum_{r=1}^{n} \rho_i(k) \mu_r F_{i,r},$$

and

$$u(k) = F_{i,r} x(k), \quad i = 1, 2, \ldots, m, \quad r = 1, 2, \ldots, n$$

are local control rules for each subsystem.

Theorem 1. *The equilibrium of a fuzzy control system (24) is globally asymptotically stable if there exist two common positive definite matrices R and S such that*

$$\begin{bmatrix} S - R & SA_i^{\mathrm{T}} \\ A_i S & \frac{1}{2} S \end{bmatrix} > 0, \quad i = 1, 2, \ldots, n,$$
$$\begin{bmatrix} R & M_{\alpha,r}^{\mathrm{T}} B_i^{\mathrm{T}} \\ B_i M_{\alpha,r} & \frac{1}{2} S \end{bmatrix} > 0,$$
$$i = 1, 2, \ldots, m; \quad \alpha = 1, 2, \ldots, m; \quad r = 1, 2, \ldots, n$$

with real matrixes $M_{\alpha,r} = F_{\alpha,r} S$, $\alpha = 1, 2, \ldots, m$, $r = 1, 2, \ldots, n$. □

The linear plant is a special case of the nonlinear plant with only one operating point. The closed-loop linear NCS described by the quasi T–S fuzzy model is given by

$$x(k+1) = Ax(k) + \sum_{r=1}^{n} \mu_r B \tilde{F}(k) x(k-r) \tag{25}$$

where

$$\tilde{F} = \sum_{r=1}^{n} \mu_r F_r$$

and $u(k) = F_r x(k)$, $r = 1, 2, \ldots, n$ are local control rules for each subsystem.

Theorem 2. *The equilibrium of a fuzzy control system (25) is globally asymptotically stable if there exist two common positive definite Matrices R and S, such that*

$$\begin{bmatrix} S - R & SA^{\mathrm{T}} \\ AS & \frac{1}{2} S \end{bmatrix} > 0, \qquad \begin{bmatrix} R & M_r^{\mathrm{T}} B^{\mathrm{T}} \\ BM_r & \frac{1}{2} S \end{bmatrix} > 0,$$
$$r = 1, 2, \ldots, n$$

where M_r are real matrixes, and $M_r = F_r S$, $r = 1, 2, \ldots, n$. □

Many existing fault detection and fault-tolerant control approaches, such as parity relation approach and observer-based approach, could be extended to linear or nonlinear NCS with random long delay time based on these models, by first designing residual generators (or fault-tolerant controllers) for each subsystem, then using the same membership function as the ones in the modelling procedure and fuzzy 'blending' all of the residual generators (or fault-tolerant controllers) in two layers to obtain the one for the overall system (Zheng, 2003; Zheng et al., 2006; Fang, Fang, et al., 2006, Fang, Yang, et al., 2006). Fig. 6 is the design outline based on quasi T–S fuzzy models for linear and nonlinear NCS with long delay.

For instance, the discrete-time system model with disturbance and fault signals at the ith operating point and with time delay r is

$$\begin{aligned} &x(k+1) = A_i x(k) + B_i u(k-r) + B_i^{\mathrm{d}} d(k) + B_i^{\mathrm{f}} f(k), \\ &y(k) = C_i x(k) + D_i^{\mathrm{f}} f(k), \qquad u(k) = F_{i,r} x(k), \\ &i = 1, 2, \ldots, m, \quad r = 1, 2, \ldots n \end{aligned} \tag{26}$$

where $d(k)$ is the disturbance and $f(k)$ is the fault signal.

The overall system is the fuzzy "blending" of all these subsystems in Eq. (26):

$$\begin{aligned} x(k+1) &= \sum_{i=1}^{m} \rho_i(k) \{A_i x(k) + B_i^{\mathrm{d}} d(k) + B_i^{\mathrm{f}} f(k)\} \\ &\quad + \sum_{i=1}^{m} \rho_i(k) \left\{ B_i \sum_{r=1}^{n} \mu_r u(k-r) \right\}, \\ y(k) &= \sum_{i=1}^{m} \rho_i(k) \left\{ C_i x(k) + D_i^{f} f(k) \right\}, \qquad u(k) = \bar{F} x(k) \end{aligned}$$

where $\bar{F}(k) = \sum_{i=1}^{m} \sum_{r=1}^{n} \rho_i(k) \mu_r F_{i,r}$.

The local residual generators (Fang, Yang, et al., 2006; Zheng et al., 2006) can be derived from the local parity equation for each subsystem (26)

$$\begin{aligned} R_{i,r}(z) &= Q_{i,r}(z) \\ &\quad \times [(I + C_i \tilde{A}_i^{-1} \tilde{B}_i^{\mathrm{d}}) y(z) \\ &\quad - C_i \tilde{A}_i^{-1} (I - \tilde{B}_i^{\mathrm{d}} C_i A_i^{-1}) B_i z^{-r} u(z)] \\ &i = 1, 2, \ldots, m, \quad r = 1, 2, \ldots, n \end{aligned}$$

where $\tilde{B}_i^{\mathrm{d}} = B_i^{\mathrm{d}} (C_i A_i^{-1} B_i^{\mathrm{d}})^{+}$, $\tilde{A}_i = z(I - \tilde{B}_i^{\mathrm{d}} C_i A_i^{-1}) - A_i$ and $Q_{i,r}(z)$ is any stable rational function.

All premise variables, fuzzy sets and membership functions are the same as the ones in the quasi T–S fuzzy model, and then we use the following fuzzy rules:

IF $z_1(k)$ is M_{i1}, $z_2(k)$ is M_{i2}, ..., $z_p(k)$ is M_{ip}, $i = 1, 2, \ldots, m$; and $(r-1)h < \tau_t \le r_h$, $\tau_k = r$

$$\begin{aligned} &\text{THEN} \quad R_{i,r}(z) \\ &= Q_{i,r}(z) \\ &\times [(I + C_i \tilde{A}_i^{-1} \tilde{B}_i^{\mathrm{d}}) y(z) - C_i \tilde{A}_i^{-1} (I - \tilde{B}_i^{\mathrm{d}} C_i A_i^{-1}) B_i z^{-r} u(z)] \end{aligned} \tag{27}$$

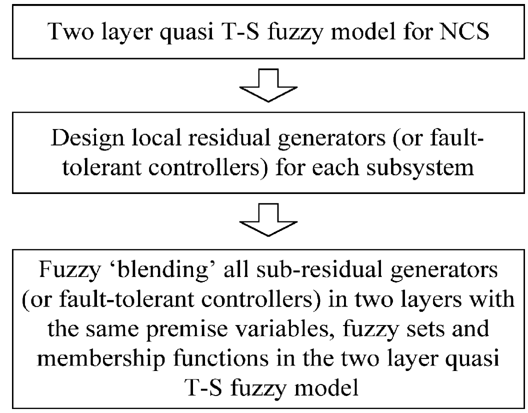

Fig. 6. Design outline based on quasi T–S fuzzy models.

The overall residual is the fuzzy "blending" of all these local residuals in Eq. (27)

$$\begin{aligned} R(z) &= \sum_{i=1}^{m} \sum_{r=1}^{n} \rho_i \mu_r R_{i,r}(z) \\ &= \sum_{i=1}^{m} \sum_{r=1}^{n} \rho_i \mu_r Q_{i,r}(z) \\ &\quad \times [(I + C_i \tilde{A}_i^{-1} \tilde{B}_i^{\mathrm{d}}) y(z) \\ &\quad - C_i \tilde{A}_i^{-1} (I - \tilde{B}_i^{\mathrm{d}} C_i A_i^{-1}) B_i z^{-r} u(z)] \end{aligned}$$

The fault can be detected by comparing the residual with a threshold function $T(k)$.

$$\begin{cases} |r(k)| \le T(k) & \text{Normal} \\ |r(k)| > T(k) & \text{Faulty} \end{cases}$$

where the $r(k)$ is the inverse z-transform of $R(z)$.

These quasi T–S fuzzy models can also describe nonlinear systems with multiple random delays, so that all results in this section are not only applicable to NCS but also applicable to nonlinear systems with multiple random delays.

5. Concluding remarks

Model-based fault diagnosis for NCS has been discussed and summarized in this paper. With different assumptions, the NCS were modelled as different simplified time-delay systems. Based on these models, many existing results, such as state observer and filtering theory, developed originally for time-delay systems, could be utilized for fault diagnosis of NCS. Also, some new fault detection approaches dedicated to NCS were presented, and many existing results of fault diagnosis for time-delay systems could be used for NCS directly.

Based on the fault detection algorithms and the simplified models for NCS, active and passive fault-tolerant control can be obtain (Kong & Fang, 2005; Huo & Fang, 2005c, 2006a, 2006b; Huo, 2006; Ma & Fang, 2006b; Ma, 2006; Zheng & Fang, 2004; Zheng, Fang, & Wang, 2004b).

The results included in this paper are mainly focusing on network-induced delay. Many other features of NCS have not been concerned. There are some further research topics.

5.1. FD and FTC theory based on new models of NCS

As the new models of NCS are coming forth continuously, such as switched system model (Yu, Wang, & Xue, 2006), stochastic system model (Ma, 2006; Ma & Fang, 2006b), systems with time-varying interval delays (Yue, Han, & Peng, 2004, Yue, Han, & Lam, 2005), we have opportunities to develop new fault diagnosis and fault-tolerant control strategies for NCS.

5.2. FD and FTC theory for nonlinear NCS

Similarly to linear systems, the effect produced by network-induced delay, packet dropout, asynchronous clock and other features of the network should be discussed for nonlinear NCS, and new fault diagnosis and fault-tolerant control theory for nonlinear NCS should also be developed.

5.3. FD and FTC theory for NCS with all other network-induced issues

For NCS with network-induced delay, we have modeled NCS as a simplified linear or nonlinear time-delay system, then developed analysis and design tools. NCS with packet dropout we could model as a switched system, and then develop the related theory. For NCS with asynchronous clock among network nodes, it is not clear yet what the suitable mathematic description is and how the fault diagnosis and fault-tolerant control problems can be dealt with. Especially, how to deal with the combined impacts of all these features? This is really a big challenge for the research community.

5.4. FD and FTC theory based on integrated modelling of all components of control system and communication channel

Research on NCS is progressing in two directions. One is based on control and system theory, and some results about fault diagnosis theory are summarized in this paper. Another one is based on system architecture and protocols of communication channels; this approach results in the development of NCS in industry, over CAN, Fieldbus, industry Ethernet, and the likes. However, NCS is an integration of sensors, actuators, controllers, plants and communication channels, which are working together closely. So the combination of the ideas, strategies, results, etc. in the two directions, integrated modelling for all components of the control system and the communication channel, research based on newly developed integrated models will bring us more useful fault diagnosis and fault-tolerant control theory.

Fault diagnosis and fault-tolerant control of networked control systems are current, active, and fertile research topics offering interesting challenges in both theory and applications. Although there are some achievements, we still have a long way to go.

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