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Intelligent fault-tolerant control using adaptive and learning methods

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Abstract

Stimulated by the growing demand for improving system performance and reliability, fault-tolerant system design has been receiving significant attention. This paper proposes a new fault-tolerant control methodology using adaptive estimation and control approaches based on the learning capabilities of neural networks or fuzzy systems. On-line approximation-based stable adaptive neural/fuzzy control is studied for a class of input–output feedback linearizable time-varying nonlinear systems. This class of systems is large enough so that it is not only of theoretical interest but also of practical applicability. Moreover, the fault-tolerance ability of the adaptive controller has been further improved by exploiting information estimated from a fault-diagnosis unit designed by interfacing multiple models with an expert supervisory scheme. Simulation examples for a fault-tolerant jet engine control problem are given to demonstrate the effectiveness of the proposed scheme. © 2002 Published by Elsevier Science Ltd.

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1. Introduction

The last two decades have seen continuous improvement in systems and control techniques resulting from the spectacular progresses in control theory and computer technologies. Meanwhile, stimulated by the growing demand for improving the reliability and performance of systems, many fault-diagnosis and fault-tolerant control methods have been developed which have the capability of detecting the occurrence of faults and retaining satisfactory system performance in the presence of faults (Frank, 1990; Stengel, 1991; Patton, 1997).

Fault tolerance of dynamic systems can be achieved either from system robustness to faults as well as other uncertainties, or from controller reconfiguration (or restructuring) in response to specific faults. Actually, a well-designed control system may have some fault-tolerance capabilities in that it can be designed (e.g., by properly choosing feedback gains) to compensate for some system uncertainties such as disturbances and noise, and the fault can be considered as a certain kind of system uncertainty. Since no information about faults is typically utilized by control systems (e.g., in linear "robust control"), this type of control system may be referred to as a "passive fault-tolerant control system" (Veillette, Medani, & Perkins, 1992; Chen, Patton, & Chen, 1997). However, the magnitude of faults that can be accommodated by a fixed control structure and parameters without using the knowledge of faults is often limited and more restricted than that of a reconfigurable controller (at least that is what has been found via current simulation studies). By utilizing the fault information obtained from fault detection and identification, "reconfigurable control" modifies the control function (parameters or structures) in response to the faults so that it is referred to as "active fault-tolerant control". An active fault-tolerant control system can be obtained by control law re-scheduling (Moerder, Halyo, Broussard, & Caglayan, 1989; Aubrun, Noura, & Sauter, 1994), linear-quadratic control (Looze, Weiss, Eterno, & Barrett, 1985; Huang & Stengel, 1990), pseudo-inverse methods (Gao & Antsaklis, 1991), or adaptive control methods (Kwong, Passino, Laukonen, & Yurkovich, 1995; Bodson & Groszkiewicz, 1997; Boskovic & Mehra, 1998; Polycarpou, 1999; Diao & Passino, 2001a, b). As most plants are inherently nonlinear and the faults may often amplify the nonlinearities by driving the plants from a relatively "linear" operating point into a more nonlinear

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operating region, the study of fault-tolerant control for nonlinear systems has become a very active research topic for both theoretical and practical reasons.

In the attempt to solve the fault-tolerant control problem for systems with significant nonlinearities and a wide operating range, methods such as neural networks and fuzzy systems have been receiving considerable attention due to their capabilities of forming arbitrarily accurate approximation to any continuous nonlinear functions. In particular, the idea of using function approximation structures with universal approximation properties (such as neural networks or fuzzy systems) to deal with arbitrary continuous nonlinearities has been widely used in adaptive control for nonlinear systems (Spooner, Ordonez, Maggiore, & Passino, 2002; Liu & Chen, 1993; Polycarpou & Mears, 1998; Spooner & Passino, 1996). The neural and fuzzy approaches are most of the time equivalent, differing between each other mainly in the structure of the approximator chosen. Indeed, to try to bridge the gap between the neural and fuzzy approaches, several researchers (e.g., in Spooner & Passino, 1996) introduce adaptive schemes using a class of parameterized functions that include both neural networks and fuzzy systems.

Since the faults are naturally time varying, it becomes necessary to study fault-tolerant control in the context of time-varying systems (not only are input and output variables varying over time, but the input–output relationships are also changing with respect to time, usually, on a time scale slower than that for the variables). However, due to the difficulties of formulating the problem and designing a control law with guaranteed performance, compared to the relatively mature field of linear (or even nonlinear) time-invariant systems, fault-tolerant control for nonlinear time-varying systems is still an open problem. There are some attempts of using adaptive control for time-varying systems. In a monograph, Tsakalis and Ioannou (1993) presented a major work on the topic of adaptive control for linear time-varying systems using model reference adaptive control and adaptive pole placement control schemes. Usually, the parameters are required to be varying slowly and smoothly, or discontinuously (i.e., jumps) but the discontinuities occur over large intervals of time. The assumption of slow parameter variations may be relaxed if some information about the fast varying parameters is available a priori (Marino & Tomei, 1998a, 1999). Adaptive control for nonlinear time-varying systems has also been studied by some researchers, but only restricted classes of systems are considered and only limited results exist so far. Marino and Tomei (1993) designed a robust state feedback control using the backstepping design method for a class of nonlinear time-varying systems in the strict feedback form (with unknown unmodeled time-varying parameters or disturbances whose bounds are known). This result has been extended to adaptive control in Marino and Tomei (1998b, 1997) by adaptive output feedback control). Although many theoretical results have been reported for the class of nonlinear systems in the strict feedback form (Wu & Chou, 1999; Lin, 1997; Ordonez & Passino, 2001a, b), this class of systems may be restricted in the sense that some practical systems, such as the jet engine, do not belong to this class.

Furthermore, although a well-designed control system may have some fault-tolerance capabilities, it will become more "active" if the fault information can be exploited. However, note that most fault-diagnosis results in the literature are only developed for linear systems. There are some nonlinear fault-diagnosis methods being developed but they lack theoretical analysis. To our knowledge, only the group of Polycarpou has studied the theoretical aspects (e.g., robustness, fault sensitivity, and stability conditions) of nonlinear fault-diagnosis (Polycarpou & Helmicki, 1995; Vemuri & Polycarpou, 1997).

In this paper, we propose an intelligent fault-tolerant system design methodology using adaptive estimation and control for nonlinear time-varying systems. The paper is organized as follows. In Section 2 we present on-line approximation-based stable neural/fuzzy control for a class of input–output feedback linearizable time-varying nonlinear systems. This class of system is large enough (compared to the nonlinear system in the strict feedback form) so that it may have more practical applicability. (This will be shown via our jet engine example where a model in the strict feedback form cannot be used to adequately represent the engine whereas our feedback linearizable model can do this quite well.) Under certain assumptions on the time-varying dynamics, uniform asymptotic tracking of a reference signal and uniform boundedness of all internal signals are achieved. Section 3 presents a model-based estimation system for robust fault diagnosis by interfacing multiple models with an expert supervisory scheme. The current system status is recognized by comparing the residuals of a bank of system models which characterize the system behaviors in different situations. Both robustness and fault-sensitivity results are given for this fault-diagnosis scheme. In Section 4 we introduce the strategies of incorporating fault diagnosis with adaptive control to achieve active fault-tolerant control, and in Section 5 the proposed methodology is applied to a turbine engine (General Electric XTE46) to demonstrate its effectiveness.

2. On-line approximation-based adaptive neural/fuzzy control

In this section, we present an indirect adaptive control method for a class of nonlinear time-varying systems which is input–output feedback linearizable. The problem formulation is given first. Later, the adaptive control approach using the on-line learning capabilities of radial basis function neural networks is presented, which guarantees that all internal signals of the system are uniformly bounded and the tracking error is uniformly asymptotically stable.

Consider the following single-input–single-output nonlinear time-varying system:

$$\dot{x} = f(x,t) + g(x,t)u, \tag{1}$$

$$y = h(x,t), \tag{2}$$

where $x = [x_1, x_2, \ldots, x_n]^{\mathrm{T}}$ is the state vector, u is the (scalar) input and y is the (scalar) output of the system. The functions $f: D \times [0, \infty) \to \Re^n$, $g: D \times [0, \infty) \to \Re^n$ and $h: D \times [0, \infty) \to \Re$ are smooth time-varying functions, and $D \subset \Re^n$ is a domain that contains the origin $x = 0$. For convenience, we assume that if $u = 0$, $\forall t \geqslant 0$, the origin is an equilibrium point at $t = 0$ and for all subsequent times, that is, $f(0,t) = 0$, $\forall t \geqslant 0$.

Note that the standard Lie derivative (i.e., $L_g h(x) = (\partial h/\partial x)^{\mathrm{T}} g(x)$, $L_g^2 h(x) = L_g(L_g h(x))$, etc.) and strong relative degree for time-invariant systems (Khalil, 1996) are not adequate for time-varying systems; modifications need to be made to explicitly account for the time variability of the system. Let $\bar{L}_f^d h(x,t)$ be the dth *modified* Lie derivative of $h(x,t)$ with respect to $f(x,t)$. In particular, define $\bar{L}_f h(x,t) = (\partial h/\partial t) + (\partial h/\partial x)^{\mathrm{T}} f(x,t)$ and, for example, $\bar{L}_f^2 h(x,t) = \bar{L}_f[\bar{L}_f h(x,t)] = (\partial \bar{L}_f h/\partial t) + (\partial \bar{L}_f h/\partial x)^{\mathrm{T}} f(x,t)$. Next, we define the "strong relative degree" of the time-varying system. A system is said to have strong relative degree d, $1 \leqslant d \leqslant n$, in a region $D_0 \subset D$ if $L_g h(x,t) = L_g \bar{L}_f h(x,t) = \cdots = L_g \bar{L}_f^{d-2} h(x,t) = 0$ and $L_g \bar{L}_f^{d-1} h(x,t) \neq 0$ for all $x \in D_0$ and $t \in [0, \infty)$. (Note that we use both the standard and the modified Lie derivatives above to provide a compact representation of the definition.) Under the above definitions, if the system represented by (1) and (2) has strong relative degree d, then the system dynamics may be written in the normal form (Sastry & Isidori, 1989) as

$$\begin{aligned}
\dot{\xi}_1 &= \xi_2 = \bar{L}_f h(x,t) \\
\dot{\xi}_2 &= \xi_3 = \bar{L}_f^2 h(x,t) \\
&\vdots \\
\dot{\xi}_{d-1} &= \xi_d = \bar{L}_f^{d-1} h(x,t) \\
\dot{\xi}_d &= \bar{L}_f^d h(x,t) + L_g \bar{L}_f^{d-1} h(x,t) u = \alpha(\xi,\pi,t) + \beta(\xi,\pi,t) u \\
\dot{\pi} &= f_0(\xi,\pi,t)
\end{aligned}$$

with $\xi \in \Re^d$, $\pi \in \Re^{n-d}$, and $\xi_1 = y$. The normal form decomposes the system states into an external part ξ and an internal part π. For the external part, if we let $y^{(d)}$ denote the dth derivative of y, it may be rewritten as

$$y^{(d)} = [\alpha_k(t) + \alpha(x,t)] + [\beta_k(t) + \beta(x,t)]u, \tag{3}$$

where $\alpha_k(t)$ and $\beta_k(t)$ are "known" dynamics of the system (which are assumed to be bounded if x is bounded), and $\alpha(x,t)$ and $\beta(x,t)$ represent nonlinear time-varying dynamics of the plant that are unknown. We assume that for some known $\beta_0 > 0$, we have $|\beta_k(t) + \beta(x,t)| \geqslant \beta_0$ so that it is always bounded away from zero (for convenience, we further assume that $\beta_k(t) + \beta(x,t) > 0$; however, the following analysis may easily be modified for systems which are defined with $\beta_k(t) + \beta(x,t) < 0$). The external part may be stabilized by the control u (which we will show later), while the internal part is made unobservable by the same control. By having $\xi = 0$ in the inner part, the "zero dynamics" of the system are given by $\dot{\pi} = f_0(0,\pi,t)$. If the plant is of relative degree $d = n$, then there are no zero dynamics. Alternatively, if the relative degree $d < n$, we assume that the zero dynamics are uniformly exponentially attractive so that if we have some control u to let ξ uniformly bounded, this also ensures uniform boundedness of π and thus x.

The on-line learning abilities of neural networks are considered here to approximate the time-varying dynamics of the nonlinear system. In particular, the linear in the parameter radial basis function networks may take the form of

$$\hat{\alpha}(x,t) = \theta_\alpha^{\mathrm{T}}(t)\phi_\alpha(x),$$

$$\hat{\beta}(x,t) = \theta_\beta^{\mathrm{T}}(t)\phi_\beta(x),$$

where the vectors $\theta_\alpha(t)$ and $\theta_\beta(t)$ are updated on-line and are assumed to be defined within the compact parameter sets Ω_α and Ω_β, respectively. (An explanation of how neural networks or fuzzy systems can be put into this form is contained in Passino & Yurkovich, 1998.) In addition, we define the subspace $S_x \subseteq \Re^n$ as the space through which the state trajectory may travel under closed-loop control (we are making no a priori assumptions here about the size of S_x). Note that besides the tunable parameters contained in the vectors $\theta_\alpha(t)$ and $\theta_\beta(t)$ that are adjusted on-line by the update laws, it is also very important to properly specify the structure parameters such as the centers and shapes of the membership functions (or receptive fields). Although these structure parameters are defined in advance and will not affect the stability of the adaptive controller, the choice of these parameters should have a reasonable cover (e.g., with uniformly distributed centers) of the state space S_x so as to accurately approximate the system dynamics.

We also define the actual system as

$$\alpha(x,t) = \theta_\alpha^{*\mathrm{T}}(t)\phi_\alpha(x) + \omega_\alpha(x,t),$$

$$\beta(x,t) = \theta_\beta^{*\mathrm{T}}(t)\phi_\beta(x) + \omega_\beta(x,t),$$

where $\theta_\alpha^*(t) = \mathrm{argmin}_{\theta_\alpha \in \Omega_\alpha}(\sup_{x \in S_x} |\theta_\alpha^{\mathrm{T}}\phi_\alpha(x) - \alpha(x,t)|)$ and $\theta_\beta^*(t) = \mathrm{argmin}_{\theta_\beta \in \Omega_\beta}(\sup_{x \in S_x} |\theta_\beta^{\mathrm{T}}\phi_\beta(x) - \beta(x,t)|)$ are the optimal time-varying parameters, and $\omega_\alpha(x,t)$ and $\omega_\beta(x,t)$ are approximation errors which arise when $\alpha(x,t)$ and $\beta(x,t)$ are represented by finite size approximators. We assume that $|\omega_\alpha(x,t)| \leqslant W_\alpha(x)$ and $|\omega_\beta(x,t)| \leqslant W_\beta(x)$, where $W_\alpha(x)$ and $W_\beta(x)$ are known state-dependent time-invariant bounds on the error in representing the actual system with approximators. This assumption generally holds according to the universal approximation property of neural networks and fuzzy systems by properly defining the approximator structures and parameters. (In practice, $W_\alpha(x)$ and $W_\beta(x)$ are treated as design parameters and tuned when we design the adaptive controller.)

We view adaptive control to be a tracking problem, that is, to design a control system which will cause the output $y(t)$ and its derivatives $\dot{y}(t), \ldots, y^{(d)}(t)$ to track a desired reference trajectory $y_m(t)$ and its derivatives $\dot{y}_m(t), \ldots, y_m^{(d)}(t)$, respectively, which we assume to be bounded. The reference trajectory may be defined by a reference signal whose first d derivatives may be measured, or by any reference input $r(t)$ passing through a reference model, with the relative degree being equal to or greater than d. In particular, a linear reference model may be

$$\frac{Y_m(s)}{R(s)} = \frac{q(s)}{p(s)} = \frac{q_0}{s^d + p_{d-1}s^{d-1} + \cdots + p_0},$$

where $p(s)$ is the pole polynomial with stable roots.

As illustrated in Fig. 1, the indirect adaptive control law

$$u = u_{ce} + u_{si} \tag{4}$$

is comprised of a "certainty equivalence" control term

$$u_{ce} = \frac{1}{\beta_k(t) + \hat{\beta}(x,t)}(-(\alpha_k(t) + \hat{\alpha}(x,t)) + v(t)) \tag{5}$$

where $\beta_k(t) + \hat{\beta}(x,t)$ is bounded away from zero (which will be ensured later using projection) so that u_{ce} is well-defined, and a "sliding mode" control term u_{si}

$$u_{si} = \frac{(W_\alpha(x) + W_\beta(x)|u_{ce}|)}{\beta_0}\operatorname{sgn}(e_s) + \frac{W_\gamma}{\beta_0}\operatorname{sgn}(e_s) \tag{6}$$

The certainty equivalence term is used to exploit the approximated system dynamics $\hat{\alpha}(x,t)$ and $\hat{\beta}(x,t)$ to construct the feedback controller. It may also take advantage of a priori knowledge of system dynamics $\alpha_k(t)$ and $\beta_k(t)$ so as to simplify the unknown dynamics and facilitate the on-line learning process. Noting the existence of approximation inaccuracy, the sliding mode control term is introduced to compensate for approximation errors, improve system robustness, and guarantee system stability.

We define the error function $v(t) = y_m^{(d)} + \eta e_s + \bar{e}_s$ (with $\eta > 0$ as a design parameter) for the reason of guaranteeing the stability. Let the tracking error be $e(t) = y_m(t) - y(t)$ and a measure of the tracking error be $e_s(t) = e^{(d-1)}(t) + k_{d-2}e^{(d-2)}(t) + \cdots + k_1\dot{e}(t) + k_0 e(t)$, that is, in the frequency domain, $e_s(s) = L(s)e(s)$ with $L(s) = s^{(d-1)} + k_{d-2}s^{(d-2)} + \cdots + k_1 s + k_0$ whose roots are chosen to be in the (open) left-half plane. Also, we let $\bar{e}_s(t) = \dot{e}_s(t) - e^{(d)}(t)$. Note that our control goal is to drive $e_s(t) \to 0$ as $t \to \infty$ and the shape of the error dynamics is dictated by the choice of the design parameters in $L(s)$.

Consider the gradient-based update laws:

$$\dot{\theta}_\alpha(t) = -Q_\alpha^{-1}\phi_\alpha(x)e_s, \tag{7}$$

$$\dot{\theta}_\beta(t) = -Q_\beta^{-1}\phi_\beta(x)e_s u_{ce}, \tag{8}$$

where Q_α and Q_β are positive definite and diagonal and serve as adaptation gains for the parameter updates.

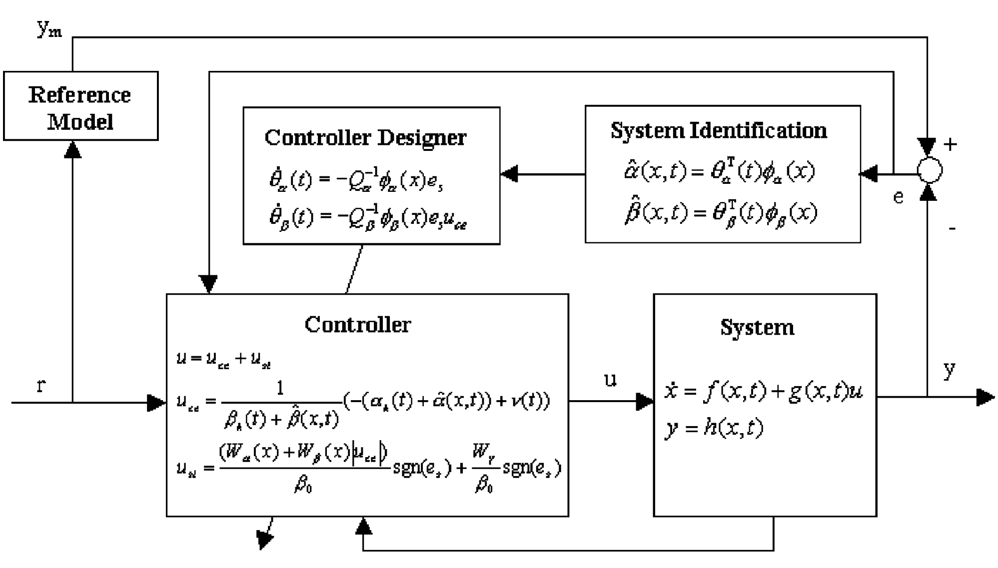

Fig. 1. Indirect adaptive control.

Note that the above adaptation laws do not guarantee that $\theta_\alpha \in \Omega_\alpha$ and $\theta_\beta \in \Omega_\beta$ so that we will use a projection method to ensure this, in particular, to make sure that $\beta_k(t) + \hat{\beta}(x,t) \geqslant \beta_0$.

To develop a stable adaptive controller for nonlinear time-varying systems, some assumptions about the characteristics of the time-varying dynamics are necessary. Here, we assume that

$$|\dot{\theta}^*_{\alpha,i}| \leqslant k|e_s|,$$

$$|\dot{\theta}^*_{\beta,j}| \leqslant k|e_s|,$$

where $\dot{\theta}^*_{\alpha,i}$ and $\dot{\theta}^*_{\beta,j}$ are components of the vectors of $\dot{\theta}^*_\alpha$ and $\dot{\theta}^*_\beta$, respectively, and k is a positive constant. This assumption is reasonable because the tracking error is usually large if the plant parameters vary fast. Under the above assumption, we can have

$$-[\tilde{\theta}^{\mathrm{T}}_\alpha Q_\alpha \dot{\theta}^*_\alpha + \tilde{\theta}^{\mathrm{T}}_\beta Q_\beta \dot{\theta}^*_\beta] \leqslant W_\gamma |e_s|,$$

where $\tilde{\theta}_\alpha(t) = \theta_\alpha(t) - \theta^*_\alpha(t)$ and $\tilde{\theta}_\beta(t) = \theta_\beta(t) - \theta^*_\beta(t)$ are the parameter errors, and $W_\gamma > 0$ is a constant indicating the bounds of parameter rate of change with respect to $|e_s|$. (Similar to linear time-varying systems (Tsakalis & Ioannou, 1993), a common assumption regarding to adaptive control for nonlinear time-varying systems is to assume the boundedness of parameter variations, that is, we assume $\dot{\theta}^*_\alpha$ and $\dot{\theta}^*_\beta$ are bounded. However, under this assumption, the tracking error e can only be proved as "small in the mean" (Diao & Passino, 2000c).)

The stability result of the above indirect adaptive controller is summarized as follows. Consider the nonlinear time-varying system (1) and (2) with strong relative degree d. Assume that (i) $\alpha_k(t)$ and $\beta_k(t)$ in (3) are bounded if x is bounded, (ii) $\beta_k(t) + \beta(x,t) \geqslant \beta_0$ for some known $\beta_0 > 0$, (iii) $|\omega_\alpha(x,t)| \leqslant W_\alpha(x)$ and $|\omega_\beta(x,t)| \leqslant W_\beta(x)$ with known $W_\alpha(x)$ and $W_\beta(x)$, (iv) $y_m(t), \dot{y}_m(t), \ldots, y_m^{(d)}(t)$ are measurable and bounded, (v) $x(t), y(t), \dot{y}(t), \ldots, y^{(d-1)}(t)$ are measurable, (vi) $1 \leqslant d < n$ with the zero dynamics uniformly exponentially attractive or $d = n$, and (vii) $|\dot{\theta}^*_{\alpha,i}| \leqslant k|e_s|$ and $|\dot{\theta}^*_{\beta,j}| \leqslant k|e_s|$. Under these conditions there exist indirect adaptive control law (4–6) and update law (7,8) such that all internal signals are uniformly bounded and the tracking error e is uniformly asymptotically stable. (Refer to Diao and Passino (2000c) for the proof.)

Note that although the indirect adaptive control law is based on the approximation of system dynamics, the condition of persistency of excitation is not required for the control input or the reference trajectory. This is because the objective of the adaptive law here is not to have the approximator converge to the actual system dynamics, but to have the tracking error converge to zero. Using the Lyapunov method and without the persistency of excitation condition, we can prove that the tracking error is uniformly asymptotically stable, while the approximation errors are only uniformly bounded (Diao & Passino, 2000c).

3. Model-based estimation for robust fault diagnosis

Although the adaptive controller developed above may serve as a fault-tolerant controller, its performance can generally be further improved by exploiting the information from a fault-diagnosis unit. This section presents a model-based estimation and reasoning system for robust fault diagnosis interfacing multiple models with an expert supervisory scheme (illustrated in Fig. 2). Issues of incorporating fault diagnosis with adaptive

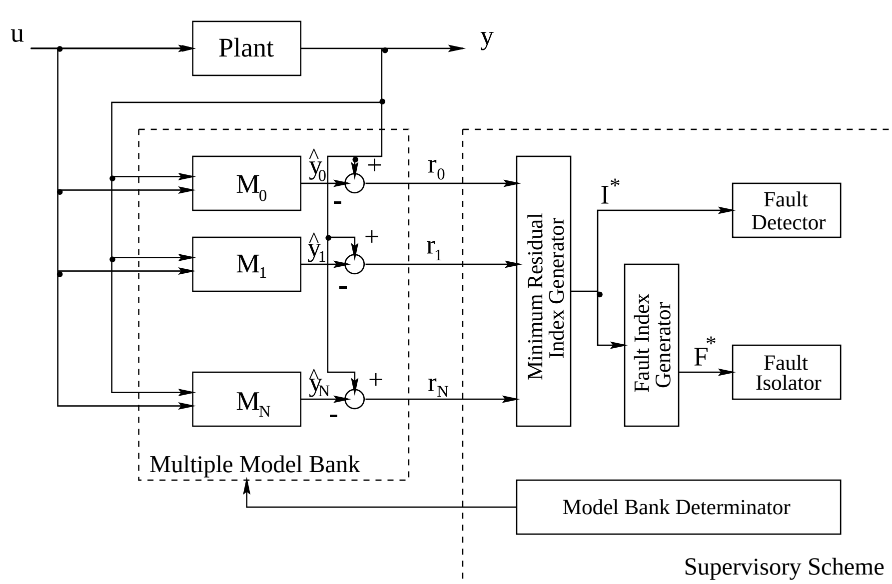

Fig. 2. Structure of the fault-diagnosis scheme.

control to achieve integrated fault-tolerant control will be discussed in the next section.

3.1. Residual generation using multiple models

Note that the plant may operate in many situations: no fault or different types of faults, possibly with manufacturing differences and deterioration. Usually, the faults result in changes of input–output characteristics of the system so that the faults may be detected by evaluating the residual which is generated by comparing the model output with the system output. However, this residual may be affected by the existence of different faults so that by inspecting the residual, the faults can only be detected but not isolated. In such situations, a "multiple model" method may be preferable. The multiple model approach utilizes different models to identify different fault situations, and then isolates faults by comparing the residuals corresponding to different models.

Assume that there are N possible fault situations and we have $(N+1)$ models $\{M_i\}_{i=0}^{N}$, where the nominal model M_0 corresponds to the situation with no fault, and the fault models M_i, $i = 1, 2, \ldots, N$ represent the ith fault situations. These models may be obtained by using nonlinear system identification with Takagi–Sugeno fuzzy systems (as explained later in Section 5). By running a bank of models on-line (which are selected by the expert supervisory scheme as we will explain later), the residuals r_i are generated by $r_i = y - \hat{y}_i$, where y is the system output and $\hat{y}_i$ is the output of the model M_i which corresponds to the ith fault situation. (More discussion on the forms of the system and models will be given later in the section of performance evaluation.)

3.2. Decision making with an expert supervisory scheme

The determination of on-line model bank composition and the evaluation of residual signals are conducted using an expert supervisory scheme. The advantage of using an expert system is that the heuristic knowledge of faults and our experience in handling faults can be easily incorporated into the expert system in the form of rules, and the operation of the expert system is transparent so that we may investigate the residual evaluation process of the expert system.

3.2.1. On-Line model bank determination

Our experience of working with the monitored system may provide us some a priori knowledge of the faults, for instance, the possible types of the faults and the possible combinations of these faults. According to this, $(N+1)$ models have been established which correspond to different no-fault or fault situations. Besides, we may know that there are some relationships among these situations. For instance, suppose fault i is happening at present, then the next possible fault situation may be the existence of fault i together with fault j (a fault that could occur in the presence of fault i), but not the situations where there exist three faults under the assumption that no two faults can occur simultaneously, or no fault exists if we know that the fault cannot be self-recovered. Therefore, at each time instant only a subset of $(N+1)$ situations may happen and thus only a subset of models are required to be on-line to generate the residuals, which can be summarized as the rule: *IF fault situation i is currently in existence THEN a subset of models* (S_i) *will be used as the on-line model bank to generate residuals afterwards*. In particular, the rules may include the following:

- *IF there is no fault in existence THEN the model bank consists of no fault model and all possible single fault models.*
- *IF there is a single fault in existence THEN all single fault models except the one that has been isolated will be removed from the model bank, and the multiple fault models including the isolated fault and another possible fault will be added.*
- *IF there are two faults in existence THEN the on-line model bank includes the model corresponding to the situation with these two faults, and the models corresponding to the situations with three faults, i.e., these two faults and another possible fault.*

The advantage of using the fault knowledge to select the on-line model bank is to reduce the computational complexity caused by using this multiple model fault diagnosis approach.

3.2.2. Fault decision logic

Once the residuals are generated, the fault decision logic is used to diagnose the faults. A sequence of "minimum residual indices" is first generated by

$$I^*(k) = \arg \min_{i \in S_i} (r_i(k)),$$

where $I^*(k)$ denotes the index of the model whose residual is the minimum, which corresponds to the most appropriate model to represent the system at time instant k. Note that the change of fault situations results in the change of the input–output characteristics of the system. Therefore, the change of index, i.e., the change of most suitable model, may be used to indicate the change of fault situations, i.e., the occurrence of new faults.

The change of index may serve as a fault detector, but not a fault isolator. Actually, the new index may not indicate that the new fault is the one corresponding to this index. This is because during the transient phase, the residuals corresponding to the on-line models may change drastically and some of them may happen to be very small for a short time (and become large afterwards since they are not the one corresponding to the new fault situation). In order to isolate the fault situations correctly, some logic rules are used to guarantee that a fault will be isolated only if its corresponding index remains to be the minimum index at least for T_0 seconds (to indicate the suitability of the model). The time delay term T_0 will be used to ensure robustness of fault diagnosis (which we will discuss later) and its value may be obtained by trial and error to balance the robustness and sensitivity of fault isolation. The results of isolation is represented by a fault index F^* as shown in Fig. 2. Actually, the fault-diagnosis strategy of using a time delay term may affect fault sensitivity to some extent but it is often useful in isolating faults accurately (which is more important), and it generally does not affect the sensitivity of fault detection. As a result, we will have a fault-diagnosis scheme that can detect a fault relatively fast, but isolate the fault type a little more slowly but accurately, which is quite reasonable.

3.2.3. Performance evaluation

To evaluate the above fault-diagnosis method, an analytical framework has been developed to study its performance, in particular, the robustness and the fault sensitivity (Diao & Passino, 2000a, b). The robustness of fault diagnosis refers to the ability to prevent false alarms in the presence of modeling uncertainties, that is, if the system is in the ith fault situation, the fault-diagnosis system should indicate the ith fault situation rather than the jth fault situation where $j \neq i$. The robustness of the above fault-diagnosis system can be proved by studying the error dynamics under certain assumptions of system uncertainty and modeling accuracy, i.e., the ith model can represent the system dynamics in the ith fault situation accurately enough compared to the modeling uncertainties, and the difference between the jth model ($j \neq i$) and the ith fault situation is large enough compared to the modeling uncertainties. Moreover, the time delay term T_0 in the fault-isolation scheme is used to consider the case where the estimated output of a ‘‘wrong’’ model approaches the system output for a short period of time and then departs again. Note that the effects of the faults are usually large; hence, the above assumptions can often be satisfied in real applications. (Refer to Diao and Passino (2000a) for the proof.) Fault sensitivity of fault diagnosis refers to the ability to correctly determine the existence of a fault and then isolate its type. The fault-sensitivity result of the above fault-diagnosis scheme can also be achieved using a similar approach (Diao and Passino, 2000b).

4. Achieving active fault-tolerant control

Without any knowledge of the faults, the adaptive controller is capable of accommodating the faults by learning and adaptation. In addition, since the adaptive control approach does not rely on explicit fault information, it may tolerate the faults that have not been anticipated. However, since no fault information is explicitly used, the fault-tolerance ability of this adaptive control framework solely depends on the adaptation of parameters. Although the adaptive scheme may work fine for some incipient faults, for the faults that significantly change the system dynamics, the speed of adaptation may be inadequate. (Note that even small faults may cause drastic changes in system dynamics.) This motivates us to incorporate the fault information into the adaptive controller so as to make the fault-tolerant controller more active. Specifically, recall the form of the nonlinear system

$$y^{(d)} = [\alpha_k(t) + \alpha(x,t)] + [\beta_k(t) + \beta(x,t)]u$$

and the certainty equivalence control law

$$u_{ce} = \frac{1}{\beta_k(t) + \hat{\beta}(x,t)}(-(\alpha_k(t) + \hat{\alpha}(x,t)) + v(t)),$$

where the terms $\alpha_k(t)$ and $\beta_k(t)$ can be used to represent the known system dynamics. Thus, if we specify (switch) the $\alpha_k(t)$ and $\beta_k(t)$ to be the models corresponding to different fault situations, according to the results from fault diagnosis, then the fault information can be explicitly used by the adaptive controller, i.e., adopting the known system (fault) dynamics to reinforce the certainty equivalence control term and to reduce the burden of adaptation (by starting from a ‘‘closer’’ point).

Hence, we propose a general fault-tolerant control system framework, as illustrated in Fig. 3, which is composed of four main parts: the stable adaptive controller, the robust fault diagnosis unit, the supervision scheme, and the multiple-model bank. This active method of incorporating fault diagnosis and adaptive control is expected to be effective when large ‘‘jump’’ faults occur. The stable adaptive neural/fuzzy controller serves as a robust baseline controller to maintain stability, while the fault-diagnosis unit uses the multiple model approach to locate and identify the possible fault. Once the fault is identified, the supervision scheme will utilize the fault information and pre-computed models to reconfigure the adaptive controller. By choosing the ‘‘correct’’ known dynamics $\alpha_k(t)$ and $\beta_k(t)$, the major changes of system dynamics may be captured faster (compared to only relying on the adaptation scheme), so that the adaptive controller will ‘‘jump’’ to a closer region and compensate for modeling errors afterwards.

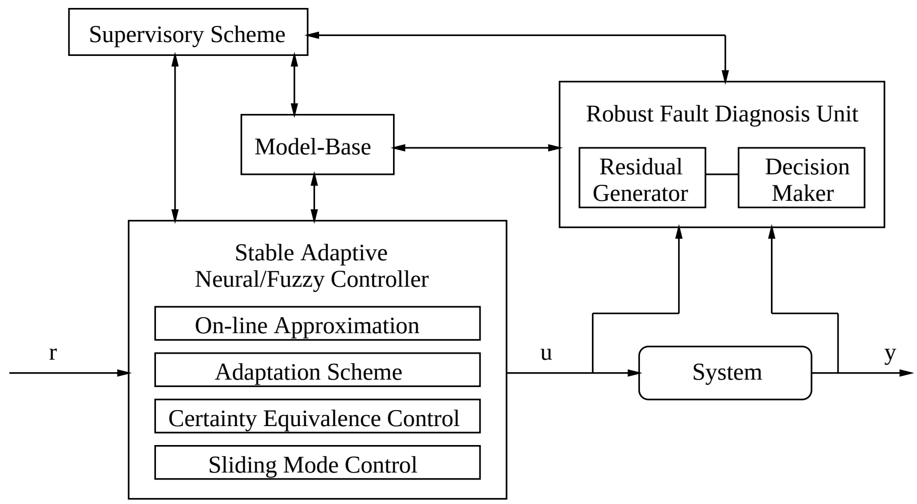

Fig. 3. Integrated fault-tolerant control.

5. Simulation examples: fault-tolerant engine control

5.1. Model development for the XTE46 engine

To study the effectiveness of the proposed fault-tolerant control method, we apply it to the component level engine cycle model (CLM) of an aircraft jet engine (General Electric XTE46), which is a simplified, unclassified version of the original "Integrated High Performance Turbine Engine Technology" (IHPTET) engine (Adibhatla & Lewis, 1997). The CLM of the XTE46 is a thermodynamic simulation package developed by General Electric Aircraft Engines (GEAE). This is a sophisticated highly nonlinear dynamic model where each engine component is simulated. The reason that GEAE developed such a "paper engine" was in order to facilitate the design and analysis of engine control systems before installing them for actual flights. Thus, the component level model is quite complicated and so accurate that it can be used as the "truth model" in the control simulation to represent the real engine.

In order to apply the proposed adaptive control strategy to the jet engine, we start from developing a "design model". The CLM for the XTE46 aircraft engine is a multiple-input–multiple-output nonlinear system (involving schedules, look-up tables, and partial differential equations). However, GEAE (the authority on this engine) indicates that the key single-input–single-output loop (i.e., fuel flow to fan speed loop) is not tightly coupled with other loops. Therefore, to focus our theoretical studies, we could assume that the fundamental engine dynamic characteristics of interest are represented by a single-input–single-output, combustor fuel flow to fan rotor speed system (while the other two input variables, the exhaust nozzle area and the variable area bypass injector area, could be properly scheduled as functions of the power level and the inlet temperature). To develop the design model for the XTE46 engine, we conduct nonlinear system identification to approximate local engine dynamics. Based on the transient data generated by the CLM, a number of local nonlinear models are constructed, each of which is in the structure of Takagi–Sugeno fuzzy systems and is corresponding to a specific operating condition and engine health situation. In order to build a "global" engine model (actually, it is a "regional" model valid in the "climb" region), we conduct nonlinear interpolation among a grid of these local models. The global engine model can be viewed to have a hierarchical learning structure, where we perform local learning to approximate the local engine dynamics and interpolate these local models to generate the global model. Note that the nonlinearity of the engine is different at different operating conditions and for different engine health situations. Moreover, the operating condition of the engine is defined by four variables: the altitude (ALT), the Mach number (XM), the difference of temperature (DTAMB), and the throttle setting represented by power code (PC). The health of the engine is described by ten quality parameters including the flows and efficiencies of the fan (ZSW2 and SEDM2), the compressor tip and hub (ZSW7D, SEDM7D, ZSW27, and SEDM27), and the high/low pressure turbines (ZSW41, ZSE41, ZSW49, and ZSE49). Therefore, although it is theoretically possible to approximate the engine dynamics by building one fuzzy system, it is not feasible in practice because of the huge amounts of data; hence, a hierarchical model structure is favorable.

The general form of the model can be described as

$$\dot{x} = f(x, c, p) + g(x, c, p)u, \tag{9}$$

$$y = x_1 \tag{10}$$

and

$$f(x,c,p) = \frac{\sum_{i=1}^{N} \underline{f}(x,c_i,p_i)\mu_i(c,p)}{\sum_{i=1}^{N} \mu_i(c,p)},$$

$$g(x,c,p) = \frac{\sum_{i=1}^{N} \underline{g}(x,c_i,p_i)\mu_i(c,p)}{\sum_{i=1}^{N} \mu_i(c,p)},$$

$$\underline{f}(x,c_i,p_i) = \frac{\sum_{j=1}^{R}[a_{j,0}(c_i,p_i) + a_{j,1}(c_i,p_i)x_1 + a_{j,2}(c_i,p_i)x_2]\underline{\mu}_j(x_1)}{\sum_{j=1}^{R} \underline{\mu}_j(x_1)},$$

$$\underline{g}(x,c_i,p_i) = \frac{\sum_{j=1}^{R} a_{j,3}(c_i,p_i)\underline{\mu}_j(x_1)}{\sum_{j=1}^{R} \underline{\mu}_j(x_1)},$$

where $u = \mathrm{WF36}$ is the system input (the combustor fuel flow), and $x = [x1, x2]^T = [\mathrm{XNL}, \mathrm{XNH}]^T$ represents the system states (the fan rotor speed and core rotor speed), which are positive since the speed cannot be negative and $x \in S_x$ (a valid speed region). The vector $c = [\mathrm{ALT}, \mathrm{XM}, \mathrm{DTAMB}, \mathrm{PC}]^T$ represents the known operating condition of the engine, and $p = [\mathrm{ZSW2}, \mathrm{SEDM2}, \mathrm{ZSW7D}, \mathrm{SEDM7D}, \mathrm{ZSW27}, \mathrm{SEDM27}, \mathrm{ZSW41}, \mathrm{ZSE41}, \mathrm{ZSW49}, \mathrm{ZSE49}]^T$ represents the unknown quality parameter vector. The values of c_i and p_i specify the nodes where we establish the local models. The functions $f = [f_1, f_2]^T$ and $g = [g_1, g_2]^T$ are 2×1 function vectors obtained through fuzzy interpolation, and $\mu_i(c,p)$ are interpolating membership functions. The functions $\underline{f} = [\underline{f}_1, \underline{f}_2]^T$ and $\underline{g} = [\underline{g}_1, \underline{g}_2]^T$ are 2×1 function vectors obtained through nonlinear system identification and are in the form of Takagi–Sugeno fuzzy systems, where $a_{j,0}$, $a_{j,1}$, $a_{j,2}$, and $a_{j,3}$ are 2×1 parameter vectors of the (linear) consequent functions, and $\underline{\mu}_j(x_1)$ are membership functions describing local nonlinearity with respect to x_1. (Refer to Diao and Passino (2001b, 2001a) for more details on how we have developed the nonlinear engine model using Takagi–Sugeno fuzzy systems.)

By inspecting the parameters that result from the identification process we found that $a^1_{j,3}(c_i,p_i) > a^2_{j,3}(c_i,p_i) > 0$ and $a^2_{j,2}(c_i,p_i) < a^1_{j,2}(c_i,p_i) < 0$ for any $i = 1,2,\ldots,N, j = 1,2,\ldots,R$. Basically, these sign conditions explain some physical dynamics of the engine. In particular, the relationships among the state variables and the input variable are relevant for stability analysis of the system. For instance, we have both $a^1_{j,3}(c_i,p_i) > 0$ and $a^2_{j,3}(c_i,p_i) > 0$, which indicate that if the fuel flow is increased, both the fan rotor speed and the core rotor speed will be increased. These constraints on the model parameters are important to design and analyze the stable adaptive control system. For example, by knowing $a^1_{j,3}(c_i,p_i) > 0$ for any operating conditions and quality parameters (and $\underline{\mu}_j(x_1) > 0$ and $\sum_{j=1}^{R} \underline{\mu}_j(x_1) \neq 0$ by the definition of Takagi–Sugeno fuzzy systems), we obtain $\underline{g}^1(x,c_i,p_i) > 0$ and thus $g_1(x,c,p) > 0$ for all x, c, p. This implies the "relative degree" of the engine is one. In addition, more details on how to use these relationships to determine the exponentially attractive zero dynamics of the engine can be found in the stability analysis part of the paper (Diao & Passino, 2001b). Finally, note that via similar nonlinear identification studies, we showed that an interpolation of strict feedback form models could not adequately represent the engine dynamics.

5.2. Adaptive controller design

We develop an adaptive controller for the fault-tolerant engine control problem using the indirect method. We choose to design the indirect controller because we could facilitate the indirect adaptive controller by using our developed models to represent the system dynamics in different fault situations. Consider the engine in the form of

$$\begin{aligned}\dot{y} &= f_1(x,c,p) + g_1(x,c,p)u \\ &= [\alpha_k(c,p_0,t) + \alpha(x,c,p)] + [\beta_k(c,p_0,t) + \beta(x,c,p)]u,\end{aligned}$$

where $x(t)$ and $y(t)$ are measurable according to the properties of the component level engine model. By studying dynamics of the developed nonlinear model, we know that $g_1(x,c,p) > 0.32$ so that we can set $\beta_0 = 0.32$. We use our developed engine model to represent the nominal model dynamics $\alpha_k(c,p_0,t)$ and $\beta_k(c,p_0,t)$ by setting the quality parameters to be the nominal value p_0, and they are bounded if x is bounded since the model is in the form of a Takagi–Sugeno fuzzy system. The unknown dynamics $\alpha(x,c,p)$ and $\beta(x,c,p)$ describe both the model uncertainty caused by nominal model inaccuracy and system changes (time-varying characteristics) due to the fault effects. They will be approximated by two radial basis function networks $\hat{\alpha}$ and $\hat{\beta}$ with 11 receptive field units for each. The inputs to the neural networks include two state variables (XNL and XNH), and the parameters are updated on-line to capture the unknown time-varying dynamics affected by model inaccuracy and faults so that fault-tolerance can be achieved. Note that the stable adaptive controller will ensure the stability of x_1, and the uniform exponential attractivity of the engine zero dynamics will ensure the stability of the uncontrollable state x_2. Since the relative degree of the system is 1, the error dynamics are simple ($e_s(t) = e(t)$ and $\bar{e}_s(t) = 0$). The reference trajectory is defined by passing a reference signal through a linear reference model $Y_m(s)/R(s) = 3/(s+3)$ so that $y_m(t)$ and $\dot{y}_m(t)$ are measurable and bounded.

Taking into account the engine dynamics, the model uncertainty is described by $W_\alpha = 0.01$ and $W_\beta = 0.01$. Note that we cannot explicitly know the model uncertainty so that the parameters W_α and W_β are treated as design parameters and tuned by trial and error to achieve good control performance. As for the parameter W_γ in (6), since its effect on the sliding mode control term is the same as that of W_α, we just treat it as part of W_α and do not tune it explicitly. In addition, the adaptation gains are tuned to be $Q_\alpha^{-1} = 5e-8$ and $Q_\beta^{-1} = 1e-17$, and the design parameter $\eta = 1$. Since the time-varying dynamics caused by both incipient faults and jump-like faults satisfy the assumption on parameter rate of change, we could apply the stable adaptive control method developed above to solve the fault-tolerant engine control problem.

Generally, we start the tuning process based on the nonlinear engine model (the design model) that we have developed using nonlinear system identification techniques. We first remove the adaptation mechanism (by setting the adaptation gains to zero) and tune the approximation error bounds W_α and W_β in order to stabilize the system. At this initial step, the approximation error bounds are usually large because they quantify the unknown system dynamics at this moment. Next, we increase the adaption gains to add the on-line learning ability to the adaptive controller, and reduce the approximation error bounds subsequently. The above procedure is iterated until certain good control performance has been achieved and further increasing the adaptation gains may cause oscillation. Afterwards, we apply the controller to the component level model simulation of the XTE46 engine and do some further tuning. This XTE46 simulator has been developed by GEAE to be very complicated and accurate so that the simulation conducted on this simulator is very close to that on the real engine for actual flights.

Note that the sliding mode control term can introduce a high-frequency signal to the plant which may excite unmodeled dynamics. To avoid this, we use a "smoothed" sliding mode control term

$$u_{si} = \frac{(W_\alpha(x) + W_\beta(x)|u_{ce}|)}{\beta_0}\,\mathrm{sat}(e_s/\varepsilon) + \frac{W_\gamma}{\beta_0}\,\mathrm{sat}(e_s/\varepsilon),$$

where $\varepsilon > 0$ and

$$\mathrm{sat}(x) = \begin{cases} 1, & \text{if } x \geqslant 1, \\ x, & \text{if } -1 < x < 1, \\ -1, & \text{if } x \leqslant -1. \end{cases}$$

By using this smoothed control action, the tracking error will converge asymptotically to an ε-neighborhood of $e = 0$ (Spooner & Passino, 1996). Here, we choose $\varepsilon = 10$.

5.3. Fault-diagnosis unit design

Note that the faults affect the engine dynamics through engine quality parameters, and the engine quality parameters are also affected by initial engine variation (due to manufacturing differences) and engine deterioration. Hence, the quality parameter vector p in Eq. (9) can be represented by $p = p_0 + p_{iev} + p_d + p_f$, which is composed of four parts: the nominal value ($p_0 = 1$), the initial engine variation due to manufacturing differences (p_{iev}), the quality parameter adjustment resulted from engine deterioration (p_d), and the quality parameter change due to the faults (p_f). Note that the engine quality parameters are actually unknown (and unmeasurable as well). Hence, we represent the engine dynamics of different fault situations as $f(x, c, p_i^0)$ and $g(x, c, p_i^0)$ with p_i^0 indicating the expected quality parameters with respect to the corresponding fault situation i. By this, we consider the effects of initial engine variation and engine deterioration as model uncertainty. Since the effects of engine faults are larger than the initial engine variation and engine deterioration, it is valid and the assumptions to guarantee the robustness of fault sensitivity of fault diagnosis can be satisfied. (For simplicity, by assuming that the engine deterioration affects ten quality parameters in the same way, we use a deterioration index I_d to represent the degree of deterioration. $I_d = 0$ indicates that there is no deterioration. $I_d = 1$ implies the maximum deterioration usually encountered.)

We build a series of models corresponding to different fault situations. For simplicity, we only consider two fault types: fan fault and compressor hub fault. The fan fault will affect two engine quality parameters: the fan flow (ZSW2) and the fan efficiency (SEDM2). The compressor hub fault will also affect two engine quality parameters: the compressor hub flow (ZSW27) and the compressor hub efficiency (SEDM27). Moreover, each fault may have three different levels: small fault (the corresponding variable in p_f is -1%), medium fault (the corresponding variable in p_f is -2%), and large fault (the corresponding variable in p_f is -3%). For example, a small fan fault is characterized by $p_{f,\mathrm{ZSW2}} = -1\%$ and $p_{f,\mathrm{SEDM2}} = -1\%$. (If there is no fault, the corresponding variable in p_f is 0.) Note that here we only consider the "local" fault, that is, only the physical characteristics (and thus the flow and efficiency parameters) of the corresponding engine component are affected. For instance, if a large compressor hub fault occurs, it will affect the flow ($p_{f,\mathrm{ZSW27}} = -3\%$) and efficiency ($p_{f,\mathrm{SEDM27}} = -3\%$) of the compressor hub accordingly, but have no effects on the flow ($p_{f,\mathrm{ZSW2}} = 0\%$) and efficiency ($p_{f,\mathrm{SEDM2}} = 0\%$) of the fan.

Using Takagi–Sugeno fuzzy systems we generated 16 models including one nominal model (no fault), six single-fault models (three models corresponding to small, medium, and large fan fault, respectively, and three models of small, medium, and large compressor hub fault), and nine double-fault models (small fan fault with small compressor hub fault, small fan fault with medium compressor hub fault, etc.). Not all these models need to be run on-line. They are picked by the model-bank determinator according to the current fault scenario.

5.4. Component level model simulation

We let the component level engine model run at the operating condition of ALT = 15000, XM = 0.7, DTAMB = 0, and PC = 46. For quality parameters of the engine, we set the initial engine variation to be $p_{iev} = [0.1\%, 0.1\%, 0.2\%, 0.1\%, -0.1\%, 0, -0.3\%, 0.2\%, -0.1\%, 0.1\%]$, and the engine deterioration index to be 0.1 (slight deterioration). We first consider a fault-free engine. Without any knowledge of the system, that is, $\alpha_k(c, p_0, t) = \beta_k(c, p_0, t) = 0$, the adaptive controller is capable of improving control performance by learning and adaptation, as shown in Fig. 4, even if it may take a relatively long time. (Note that we use a sinusoidal reference input signal to simulate a smooth change of the desired fan speed. The validation of applying this signal to the XTE46 engine has received approval from GE Aircraft Engines in the sense of studying the effects of fault accommodation.) Indeed, it is desirable to incorporate a nominal model (developed above using nonlinear system identification techniques) into the controller so as to start adaptation at a closer point and learn faster. As shown in Fig. 5, the incorporation of the knowledge on engine dynamics has effectively reduced the burden of adaptation and increased the control performance.

In the case where a small fault or an incipient fault occurs, the system dynamics may not change much or fast. Thus, we still expect the adaptive controller with the same nominal model (i.e., no model switching is involved according to the fault information from the fault-diagnosis unit) to perform well. For instance, Fig. 6 shows the control result for an engine with a small fan fault ($p_{f,\mathrm{ZSW2}} = -1\%$ and $p_{f,\mathrm{SEDM2}} = -1\%$), which is introduced at $T_f = 6$ s as an abrupt-type fault. The indirect adaptive controller is capable of quickly accommodating the fault. This is because its adaptation scheme can let the on-line approximators learn the profile of the fault so that the control law can be modified accordingly.

However, if the system changes drastically according to some large faults, the nominal model may not be suitable and the adaptation may not be fast enough. Thus, a fault-diagnosis unit is desired to determine the fault type and then reconfigure the adaptive controller by switching the nominal model into a corresponding fault model. Fig. 7 shows the performance of such an integrated fault-tolerant controller for a fault scenario, where an abrupt large compressor hub fault ($p_{f,\mathrm{ZSW27}} = -3\%$ and $p_{f,\mathrm{SEDM27}} = -3\%$) occurs at $T_f = 6$ s. The occurrence of abrupt large compressor hub fault affects the system performance significantly. However, the fault-tolerant controller accommodates for the faults quite well by identifying the fault type with the fault-diagnosis unit and then reinforce the adaptive controller by adopting the corresponding fault model.

The operation of the fault-diagnosis unit is illustrated in Fig. 8. Since the engine is started from the fault-free

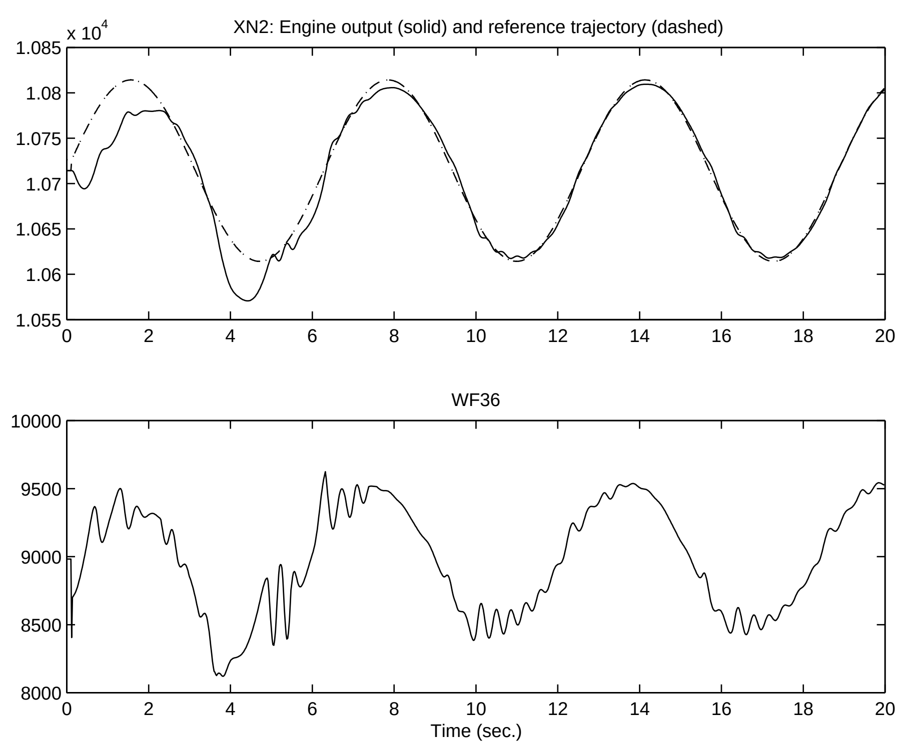

Fig. 4. Performance of the adaptive controller (without the nominal model) for a fault-free engine.

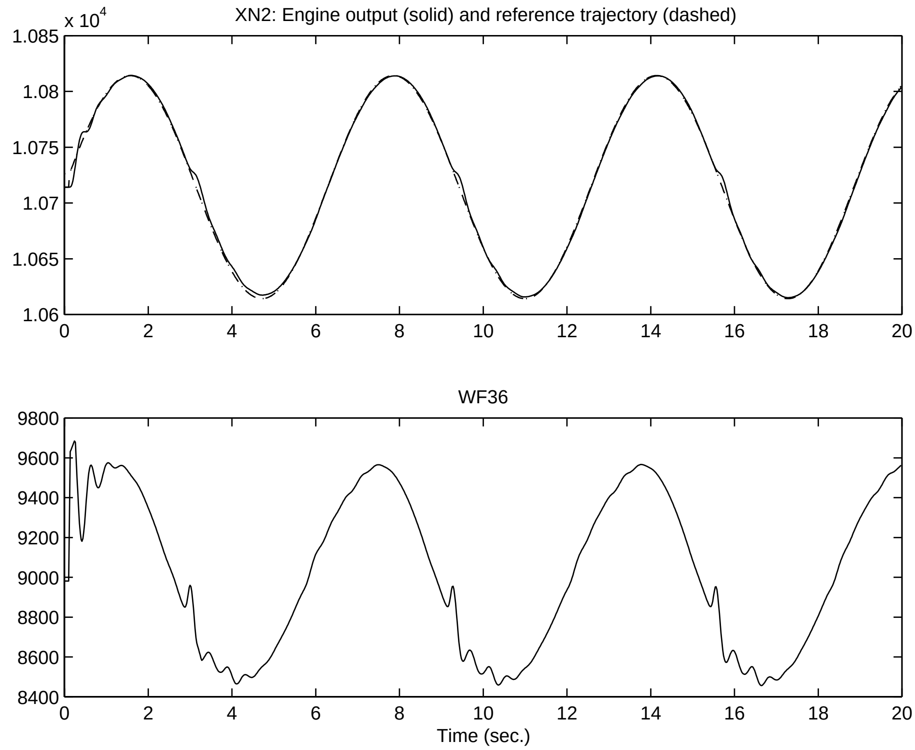

Fig. 5. Performance of the adaptive controller (with the nominal model) for a fault-free engine.

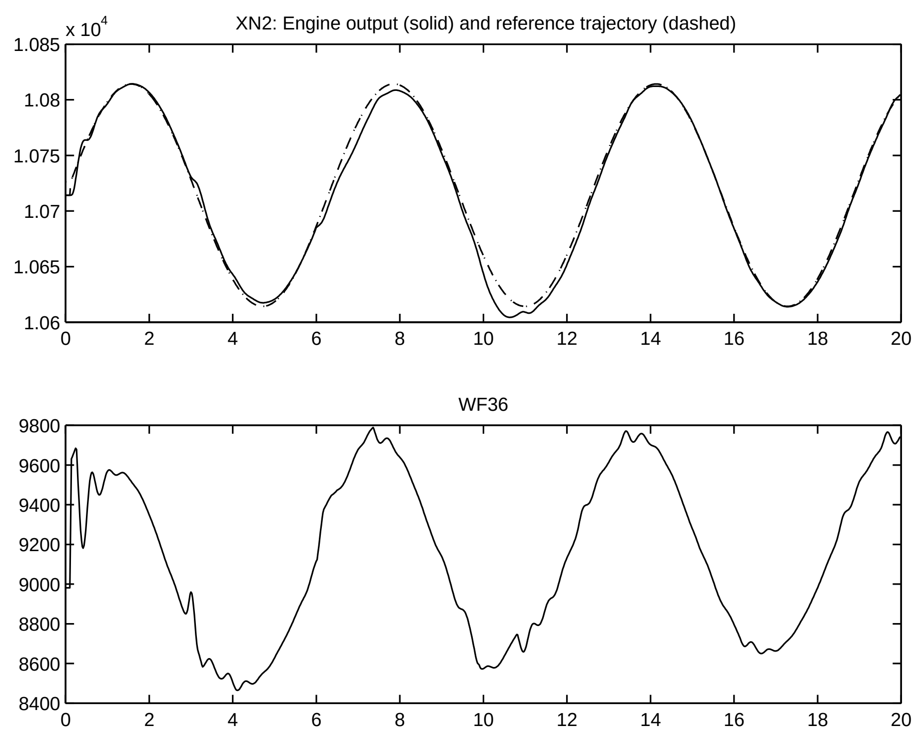

Fig. 6. Performance of the adaptive controller for a small fan fault.

situation, only seven models need to be applied on-line: three fan fault models corresponding to different fault sizes (small: Index 1, medium: Index 2, and large: Index 3), three compressor hub fault models corresponding to different fault sizes (small: Index 4, medium: Index 5, and large: Index 6), and one fault-free nominal model

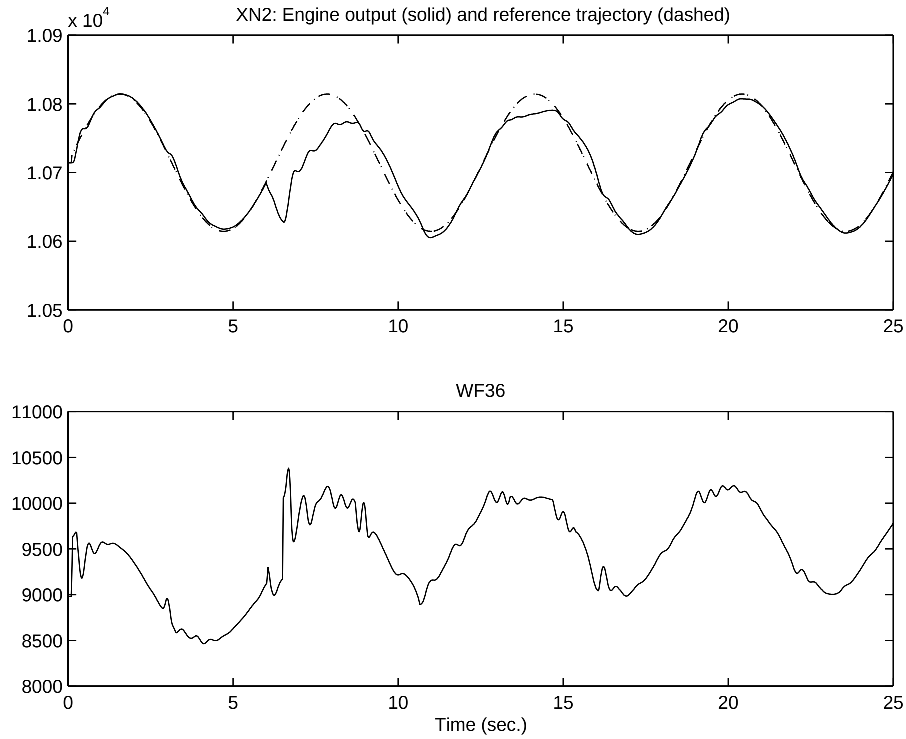

Fig. 7. Performance of the integrated fault-tolerant controller for a large compressor hub fault.

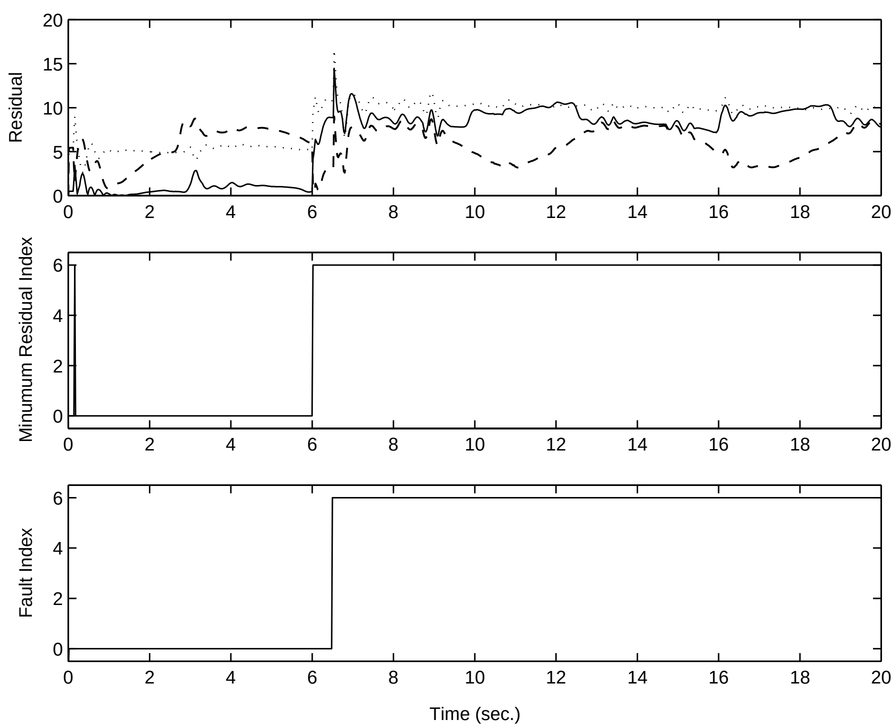

Fig. 8. Operation of the fault-diagnosis unit.

(Index 0). For clarity, in Fig. 8, we only show the residuals of three models: the fault-free model (indicated by the solid line), the large fan fault model (indicated by the dotted line), and the large compressor hub fault model (indicated by the dashed line). The fault is detected shortly after it occurs (indicated by the minimum residual index) and isolated at 6.5 s (indicated by the fault index, where we set the time delay term

$T_0 = 0.5$ s). Once the fault is identified, the known dynamics $\alpha_k(t)$ and $\beta_k(t)$ in the adaptive control law (the certainty equivalence control term, Eq. (5)) are "switched" from the nominal (fault-free) model to the large compressor hub fault model. After that, the control performance is improved by using the adaptation scheme to compensate for model uncertainties.

Note that in order to obtain a sensitive fault-detection scheme, any changes in the minimum residual index (i.e., the change of the most suitable model) will be considered as indicating the occurrence of new faults; hence, the minimum residual index is used to detect the fault promptly. Furthermore, considering the presence of modeling uncertainties, the time delay term T_0 is included to achieve the robustness of the fault isolation scheme. In general, there is a trade-off between robustness and sensitivity of fault isolation. Improving the robustness to modeling uncertainties may cause the fault-isolation scheme to be insensitive.

Also note that above we applied seven models on-line. Alternatively, the on-line model bank can only be composed of models corresponding to large faults but not small or medium faults. This would help to reduce the number of on-line models and is valid because for those small or medium faults, the adaptive controller itself can learn the fault effects quickly so that there is no need for model switching guided by the fault-diagnosis unit.

The effectiveness of integrating the fault-diagnosis unit with the adaptive controller can be further demonstrated by comparing its performance with that of a fault-tolerant controller which uses an adaptive control scheme but is not enhanced by the fault-diagnosis unit. As shown in Fig. 9, although it does achieve fault accommodation, a much longer time is needed.

Indeed, the adaptive controller plays the major role in achieving system stability and robustness in the presence of uncertainties such as engine-to-engine manufacturing differences, engine deterioration during normal operation, and the occurrence of faults. Here, we examine an engine with larger initial engine variation (p_{iev} = [0.3%, 0.5%, 0.2%, 0.5%, 0.4%, 0.3%, −0.3%, 0.5%, − 0.5%, 0.5%]) and severe engine deterioration (the engine deterioration index is 0.7). The component level engine model is run at the same operating condition (ALT = 15000, XM = 0.7, DTAMB = 0, and PC = 46) with same fault scenario (where an abrupt large compressor hub fault occurs at $T_f = 6$ s). As shown in Fig. 10, the fault-tolerant controller is still well capable of accommodating the fault.

Actually, we have also tested the fault-tolerant controller on many other cases, i.e., different operating conditions, different initial engine variation and engine deterioration, different fault sizes, and different fault types (jump faults or incipient faults). The effectiveness of the proposed intelligent fault-tolerant controller has

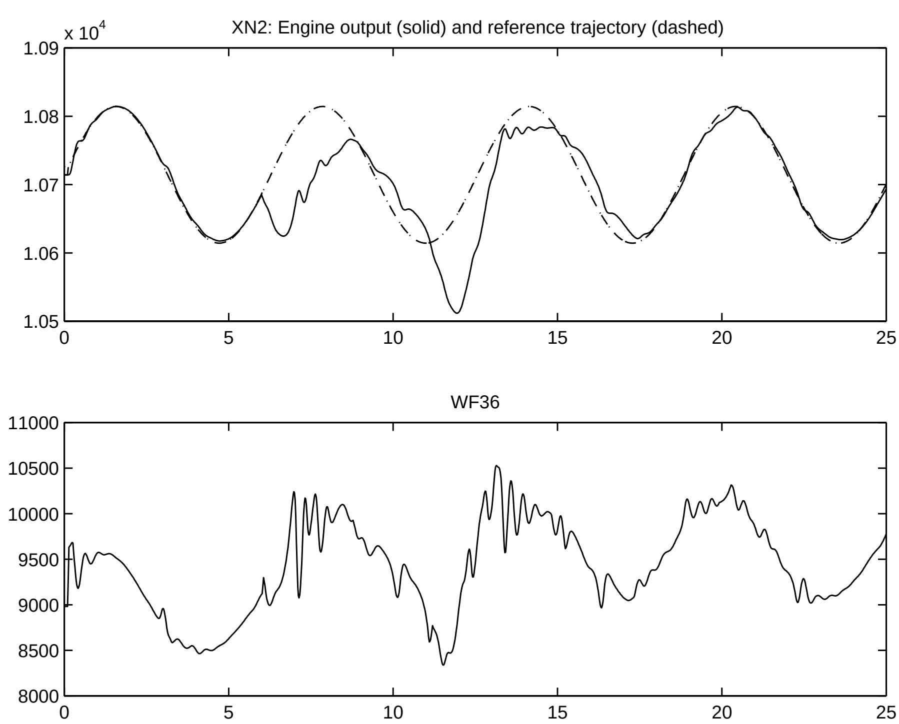

Fig. 9. Performance of the adaptive controller not enhanced by the fault-diagnosis unit.

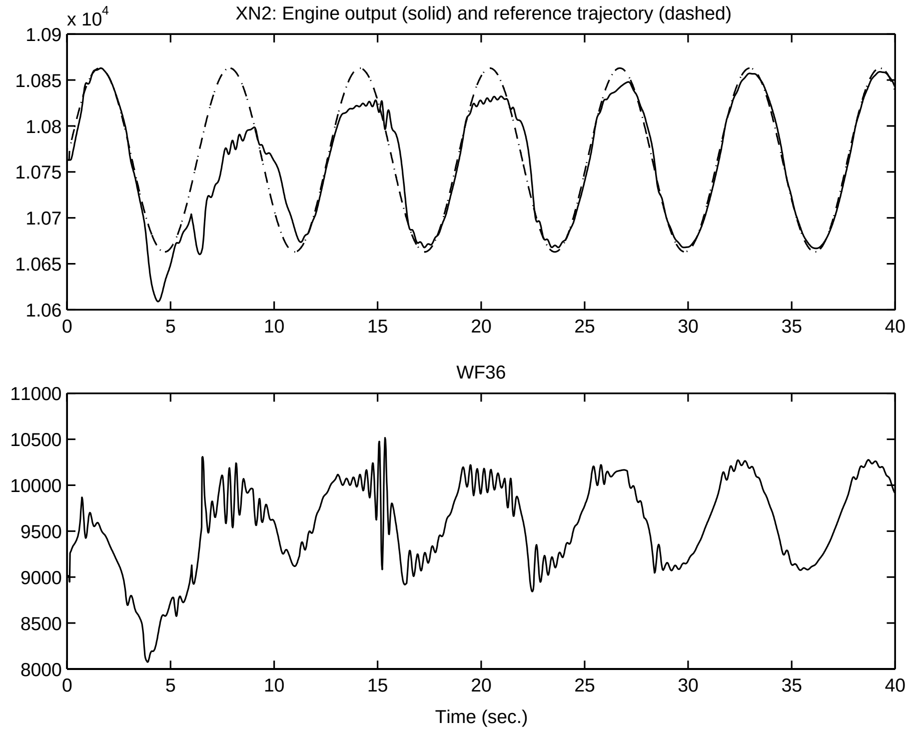

Fig. 10. Performance of the integrated fault-tolerant controller for a "poor" engine.

been demonstrated for all the tested cases, but in the interest of brevity we do not show those results here. It is also worth mentioning that this integrated fault-tolerance scheme is mostly favorable for large jump faults, whereas for incipient faults or small jump faults, the adaptive controller may be capable of learning the fault effects relatively quickly and maintain good performance so that the fault-diagnosis unit may not be needed.

6. Conclusion

Fault-tolerant system design for nonlinear time-varying systems can be quite challenging. Most existing studies on fault-diagnosis and fault-tolerant control have relied on a linear nominal model of the plant. In practical situations, however, plants are nonlinear and the faults often force plants away from local linear behaviors into a nonlinear operating region. Furthermore, the existing work in the literature mainly considers fault-tolerant control in the context of time-invariant systems as if a fault has already occurred, while the reality is that both incipient and abrupt faults are naturally time-varying phenomena. In this paper, we have achieved fault-tolerant control via on-line approximation-based stable adaptive neural/fuzzy control methods which is designed for a general class of nonlinear time-varying systems (in the input–output feedback linearizable from). This class of systems is large enough so that it is not only of theoretical interest but also of practical applicability (e.g., to the fault-tolerant control problem of the General Electric XTE46 engine that we encountered in a project funded by NASA). Uniform boundedness of all internal signals and uniform asymptotic tracking of a reference signal have been obtained under the assumption of bounded parameter rate of change. This adaptive controller has also been incorporated with a robust fault-diagnosis unit to achieve active fault-tolerant control. Since the issue of incorporating (switching) known system dynamics (corresponding to the fault information) has already been considered in the model form and adaptive control laws, the stability of the integrated system is guaranteed.

Note that this paper is not only motivated by the status of the literature but also with the application to fault-tolerant control for the General Electric XTE46 engine. Due to the complexity of modeling jet engines, only local linear models are reported to be used, which are relatively easy to build but generally not accurate. The fault-tolerant system design presented in this paper is based on a hierarchical learning structure of nonlinear system modeling. This modeling strategy is quite general so that not only has it been used to construct the model of the jet engine but also it can be applied to many other applications. Moreover, the resulting model is an input–output feedback linearizable form so that we can apply nonlinear adaptive control to it.

The effectiveness of the fault-tolerant system design methodologies proposed in this paper has been demonstrated via the component level model simulation of the XTE46 engine. Unlike the typical engine models that are used in some of the literature, this XTE46 simulator has been developed by GEAE to be very complicated and accurate so that the simulation conducted on this simulator is very close to that on the real engine for actual flights. According to the generality of the methodology, the proposed fault-tolerant controller may be applied to many other applications such as fault-tolerant aircraft control or longitudinal control of a vehicle within an automated highway system. However, similar to the jet engine control problem, since the controller properties are derived based on the mathematical model of the actual physical system, if the system model is reasonably accurate, as for the nonlinear model developed for the XTE46 engine, then the performance metrics (i.e., stability, robustness, fault sensitivity) will take on real physical meanings. Otherwise, the value of mathematical analysis may be limited.

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