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Intelligent Adaptive Control of a Tailless Advanced Fighter Aircraft Under Wing Damage

Jovan D. Bošković* and Raman K. Mehra†
Scientific Systems Company, Inc., Woburn, Massachusetts 01801

In this paper we propose an intelligent adaptive reconfigurable control scheme for a Tailless Advanced Fighter Aircraft (TAFA) in the presence of wing damage. The scheme consists of failure detection using multiple observers, multiple reference models for changing the desired performance on-line in the case of damage, on-line estimation of the percentage-of-damage parameter, and the corresponding adaptive reconfigurable controller augmented with an output error feedback term. The overall scheme results in fast and accurate failure detection and identification and control reconfiguration and is demonstrated analytically to be stable in the sense that all signals are bounded and the output error converges to zero asymptotically even in the case of 100% wing damage. The properties of the proposed intelligent adaptive controller are evaluated through numerical simulations on a TAFA model in the presence of large noise, actuator dynamics, position and rate limits on the control effectors, and 100% wing damage, and the proposed approach results in excellent overall performance.

I. Introduction

THE existing approaches to adaptive reconfigurable flight control, for instance, Refs. 1–5 among many others, are mainly concerned with control reconfiguration in the presence of control effector failures. Control reconfiguration in the presence of wing damage of a Tailless Advanced Fighter Aircraft (TAFA) from Ref. 6 was considered in Refs. 7 and 8. This problem is complex because the aircraft considered in Ref. 6 is open-loop unstable, and fast and robust control reconfiguration is needed to maintain the stability of the overall system in the presence of wing damage. The approach from Ref. 7 is based on multiple model failure detection and identification (FDI) and fast switching among multiple controllers based on the on-line information obtained from the FDI subsystem. However, because a finite number of models was used and if none of the models coincides with the actual damage, the resulting control system can only assure that the output errors are bounded, but not that they tend to zero asymptotically. In addition, performance of the overall system is difficult to study and is highly sensitive to control input saturation and noise. The approach from Ref. 8 is based on direct adaptive control using a neural network for compensation of different failures including structural or battle damage. Because the $e_1 - \theta$ modification[9] is used to adjust the parameters of the network, it is difficult to establish conditions under which the output error will tend to zero asymptotically. In addition, the overall neural-network controller needs to be tuned carefully in different flight regimes to achieve the desired flight performance.

In both of the preceding cases, the reconfigurable control designs do not take into account position and rate saturation of the control effectors, and the overall closed-loop system is required to maintain the same level of flight performance as in the no-damage case despite the control reconfiguration immediately following the failure.

As it is well known, control reconfiguration caused by a severe failure can saturate the control surfaces, which may lead to substantial performance deterioration and even to the loss of aircraft. Although saturation of control effectors has been studied in the general context of flight control, a detailed study of the relationship between control reconfiguration and control effector saturation is lacking. This problem is difficult because control reconfiguration at different time instants even during a single maneuver can have very different effects on control effector saturation.

Even if the control surfaces do not saturate during control reconfiguration, the resulting positions of the control effectors can yield substantially lower available control input redundancy as compared to the case prior to reconfiguration. The effect of control reconfiguration on available control redundancy is an important practical problem that has not been extensively studied in the literature. This is the case despite the fact that a decrease in the available redundancy can very adversely affect the aircraft dynamics and performance in subsequent segments of a mission. For instance, as observed through numerous simulations, in a particular flight regime a prespecified level of flight performance (flying qualities) can be maintained even after control reconfiguration following a severe failure; however, performance caused by subsequent failures or during transitions to other flight regimes, as well as the overall aircraft maneuverability, can substantially deteriorate because of low available redundancy.

In this context the following question can be posed: Is it possible to arrive at a strategy for partially lowering the desired flight performance in the case of failure so that the control redundancy after reconfiguration is sufficient for achieving a lowered (but still acceptable) performance, and under which conditions can this be achieved without saturating the control surfaces? In this context partial lowering of the desired flight performance in the presence of damage refers to the case when the control objective is relaxed only for noncritical state variables, whereas the critical ones are required to achieve the same level of performance as in the no-damage case. The control objective for the noncritical state variables is relaxed to the extent of satisfying some prespecified minimum tolerable performance requirements.

In this paper we will address this problem using the multiple model-based FDI in conjunction with on-line estimation of percentage-of-damage parameter, corresponding adaptive reconfigurable controller, and newly developed concepts of multiple reference models, we will illustrate our approach through simulations of control reconfiguration for a TAFA from Ref. 6 in the presence of wing damage. As discussed in Ref. 6, based on numerical modeling and numerous wind-tunnel experiments, researchers from Boeing developed aircraft models for different wing damage conditions, including the case of no damage, and the cases of increments of certain percentage of wing damage up to the 100% damage. For percentages of damage in between the corresponding matrix norms, in Refs. 6 and 10 the authors suggested a polynomial approximation in terms of percentage-of-damage parameter $\rho \in [0, 1]$ and carried out interpolation that resulted in acceptable approximation with a fifth-order matrix polynomial in ρ. Our proposed approach is based on this model and is summarized next:

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*Senior Research Engineer, 500 W. Cummings Park, Suite 3000; jovan@ssci.com.
†Founder and President, 500 W. Cummings Park, Suite 3000; rkm@ssci.com.

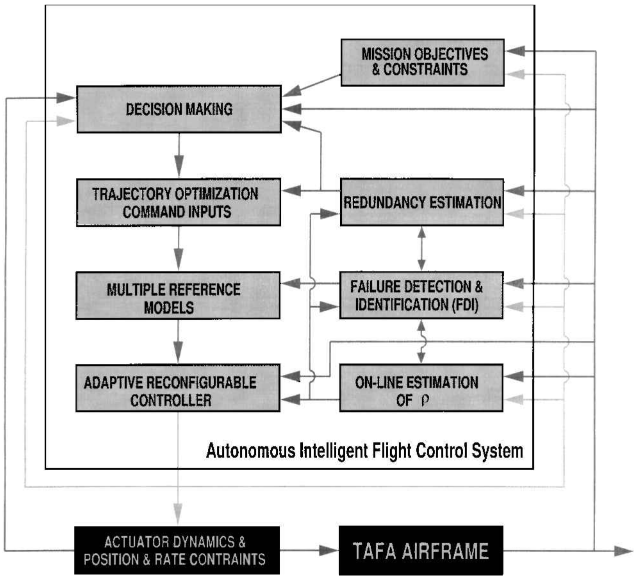

Fig. 1 Structure of the Autonomous Intelligent Flight Control System.

1) We first chose a nominal reference model to specify the flight performance for a particular flight condition and the no-damage case.

2) Based on available damage models, we next tested several reference models corresponding to a lower level of performance of noncritical state variables. The testing was carried out using the baseline controller and TAFA models for the cases between no damage and 100% wing damage.

3) Our analysis revealed that, for the case of 100% wing damage and a lower-performance reference model, there exists an output-error feedback gain matrix that stabilizes an arbitrary number of discrete models between 0 and 100% wing damage.

4) Because this does not imply that the closed-loop system will be stable if the actual damage falls in between these discrete models and to achieve fast and accurate detection and identification of the percentage of wing damage, we designed an intelligent flight control system consisting of a fast on-line FDI subsystem, based on multiple models and on-line estimation of ρ, the corresponding controller, and a suitable mechanism for switching among multiple reference and damage models. We also demonstrated asymptotic stability and robustness of the overall intelligent control system.

5) As shown through simulations, our approach resulted in excellent performance of TAFA in the presence of 100% wing damage. Such a performance was achieved even in the case when actuator dynamics and position and rate limits on control effectors were included in the simulation. Control reconfiguration based on the lower-performance reference model also resulted in a sufficiently high level of control redundancy, which enabled successful subsequent control reconfiguration and transition to other flight regimes.

The resulting Intelligent Adaptive Flight Control System is shown in Fig. 1.

As seen from the figure, the FDI information is used to choose the most suitable reference model and the corresponding controller; the latter is reconfigured based on on-line estimation of the damage parameter ρ.

The paper is organized as follows: the problem statement is given in Sec. II, followed by the baseline control strategy in Sec. III. The discussion regarding the multiple models, switching and tuning methodology, and the new concept of multiple reference models is included respectively in Secs. IV and V. Section VI contains a detailed description of the stable adaptive controller, followed by simulations, and conclusions.

II. Problem Statement

In this paper we will consider a linearized model of a TAFA in the presence of wing damage. The generalized aircraft model is of the form

$$\dot{x} = A_D(t)x + B_D(t)u \qquad (1)$$

where $x \in \mathbb{R}^n$ and $u \in \mathbb{R}^m$ denote, respectively, the state and control input vectors, $A_D: \mathbb{R}^+ \to \mathbb{R}^{n\times n}$, and $B_D: \mathbb{R}^+ \to \mathbb{R}^{n\times m}$.

The time-varying nature of matrices A_D and B_D is caused by the wing damage, which affects the dynamics of the aircraft in an abrupt fashion. In Ref. 6 the following form of these matrices was proposed:

$$A_D[\rho(t)] = A_{D0} + A_{D1}\rho(t) + A_{D2}\rho^2(t) + A_{D3}\rho^3(t) + A_{D4}\rho^4(t) + A_{D5}\rho^5(t) \qquad (2)$$

$$B_D[\rho(t)] = B_{D0} + B_{D1}\rho(t) + B_{D2}\rho^2(t) + B_{D3}\rho^3(t) + B_{D4}\rho^4(t) + B_{D5}\rho^5(t) \qquad (3)$$

where $\rho \in [0, 1]$ denotes the damage parameter. The preceding model sufficiently and accurately covers all cases from $\rho = 0$ (no-damage case) to $\rho = 1$ (100% wing damage).[6]

In this paper our objective is to design a suitable control strategy for the preceding aircraft model such that the desired performance is achieved despite the presence of severe wing damage. In particular, our strategy will include guaranteed robustness along with on-line reconfiguration in the case when $\rho(t)$ abruptly switches within the set [0, 1].

We will first make the following assumptions:

Assumption 1: There exists a nonsingular transformation matrix T that transforms the model (1) to the form

$$\dot{x}_1 = \bar{A}x \qquad (4)$$

$$\dot{x}_2 = A(t)x + B(t)u \qquad (5)$$

where x_1 is an $(n-p)$ vector, x_2 is a p vector, $\bar{A}$ is a $[(n-p)\times n]$ matrix independent of ρ, A and B are respectively $p\times n$ and $p\times m$ matrices, and

$$A[\rho(t)] = A_0 + A_1\rho(t) + A_2\rho^2(t) + A_3\rho^3(t) + A_4\rho^4(t) + A_5\rho^5(t) \qquad (6)$$

$$B[\rho(t)] = B_0 + B_1\rho(t) + B_2\rho^2(t) + B_3\rho^3(t) + B_4\rho^4(t) + B_5\rho^5(t) \qquad (7)$$

Assumption 2:

1) The state of the aircraft is available at every instant.

2) $m > p$.

3) The aircraft dynamics is minimum phase for all $\rho \in [0, 1]$.

4) $B(\rho)B^T(\rho)$ is a full-rank matrix for all $\rho \in [0, 1]$.

5) $\dot{\rho}(t) \in \mathcal{L}^2 \cap \mathcal{L}^\infty$, and $\ddot{\rho}(t) \in \mathcal{L}^\infty$.

Assumption 1 essentially states that the x_1 subsystem is characterized by a matrix of simple integrators and is not directly affected by ρ. Assumptions 2(1) and (2) are justified in the case of modern fighter aircraft, where a large number of state variables are measured on-line and where the number of control effectors exceeds the number of variables that can be affected by the controls as, for instance, in the case of the TAFA from Ref. 6. Also, assumptions 2(3) and (4) are justified in majority of flight regimes of such aircraft. Assumption 2(5) is just an analytical statement of the fact that derivative of $\rho(t)$ will eventually tend to zero regardless of the number of times that $\rho(t)$ switches (unidirectionally) from zero to values from (0, 1].

In this paper we will consider the case when the desired behavior of the plant is specified by suitably chosen reference models of the form

$$\dot{x}_{m1} = \bar{A}x_m \qquad (8)$$

$$\dot{x}_{m2} = A_m x_m + B_{mj}r_j, \qquad j = 0, 1, 2, \ldots, M \qquad (9)$$

where $x_{m1} \in \mathbb{R}^{(n-p)}$, $x_{m2} \in \mathbb{R}^p$, $[\bar{A}^T \;\; A_m^T]^T$ is an asymptotically stable $(n\times n)$ matrix, B_{mj} denote $[p\times(l-j)]$ matrices $(l \le p)$, and r_j denote $(l-j)$ vectors of bounded piecewise continuous reference inputs, $j = 1, 2, \ldots, M$. Matrices B_{mj} are obtained by zeroing the jth column of B_m, where $j = 1, 2, \ldots, M$, $M < p$. Further, $j = 0$ corresponds to the desired dynamics in the no-damage case.

Such a definition of reference models implies that, for a particular maneuver, the desired dynamics of $(p - M)$ variables (critical state variables) are the same for any $0 \leq j \leq M < p$, whereas the desired performance for the remaining variables (noncritical state variables) is lower for larger j, but is still acceptable even in the case corresponding to $\rho = 1$. The problem of relating the best possible performance that can be achieved in the case when $\rho = 1$ with a particular reference model is a difficult one and is beyond the scope of this paper. We will assume that the reference models corresponding to different values of ρ are given in advance.

We further partition the state of the plant as $x = [x_c^T \; x_r^T]^T$, and $x_m = [x_{mc}^T \; x_{mr}^T]^T$, where x_c and x_{mc} denote respectively the $(p - M)$ subvector of critical state variables and its desired vector and x_r and x_{mr} denote the M subvector of the remaining states and their desired vector.

The control objective is now formally stated as follows:

Control Objective: Design a control law $u(t)$ for the plant (4), (5) such that the following is true:

1) All signals in the system are bounded.

2) $\lim_{t\to\infty}[x_c(t) - x_{mc}(t)] = 0$.

3) $\|x_r(t) - x_{mr}(t)\| \leq \delta_j, \; \forall t$, in the presence of variations of $\rho(t)$ within [0, 1] that satisfy assumption 1(5).

In the preceding control objective constants $\delta_j > 0$ are prespecified for a particular maneuver. Even in the case of 100% damage, the speed of the desired trajectories for the critical state variables is the same as in the no-damage case.

III. Baseline Control Strategy

Because, by virtue of assumption 2, the plant is invertible and minimum phase, we suggest the control law based on dynamic inversion for the overactuated case, which is also referred to as the pseudoinverse control.[11] We will refer to this control law as the Inverse Dynamics Control Law (IDCL). Let j be fixed. We further denote by C_j the $(l \times n)$ matrix of virtual control inputs.[11] This matrix has ones corresponding to critical state variables, and all other elements are zero. In the case of aircraft, the number of rows of C_j is up to six.

Let

$$\eta(x, \rho, t) = C_j[-A(\rho)x + \Lambda(x - x_m) + A_m x_m + B_{mj} r_j] \quad (10)$$

The control law is now of the form

$$u = W^{-1}[C_j B(\rho)]^T [C_j B(\rho)] W^{-1} \left\{[C_j B(\rho)]^T\right\}^{-1} \eta(x, \rho, t) \quad (11)$$

where W is a diagonal $(m \times m)$ matrix with strictly positive elements. We will assume that Λ can be chosen such that the matrix

$$\Lambda_0 = \begin{bmatrix} \bar{A} \\ C_j \Lambda \end{bmatrix} \quad (12)$$

is asymptotically stable. We note that the preceding IDCL is augmented with the output error feedback term $C_j \Lambda(x - x_m)$.

The preceding control law can be readily shown to achieve the objective for a known operating regime of the plant and a given j. Let $e = x - x_m$ denote the output error vector. From Eqs. (4), (5), (8), (9), and (11) we obtain that $\dot{e} = \Lambda_0 e$. This system is exponentially stable because Λ_0 is asymptotically stable. In addition, Λ_0 can be chosen to achieve the desired response of the closed-loop system.

The preceding control law assumes complete prior knowledge of matrices A and B. Because this assumption is not realistic in the case when $\rho > 0$, we will further consider control designs for the model (4), (5) in the case when $\rho(t)$ abruptly switches within (0, 1].

IV. Multiple Models, Switching, and Tuning

The problem of control reconfiguration for the TAFA in the presence of wing damage was addressed in Ref. 7 using the concept of multiple models, switching, and tuning (MMST) from Ref. 12, Fig. 2.

The main idea behind this approach is to build multiple observers corresponding to different operating regimes of a plant, and, based on a suitably chosen estimation error criterion, find the one closest to the current regime and switch to the corresponding controller.

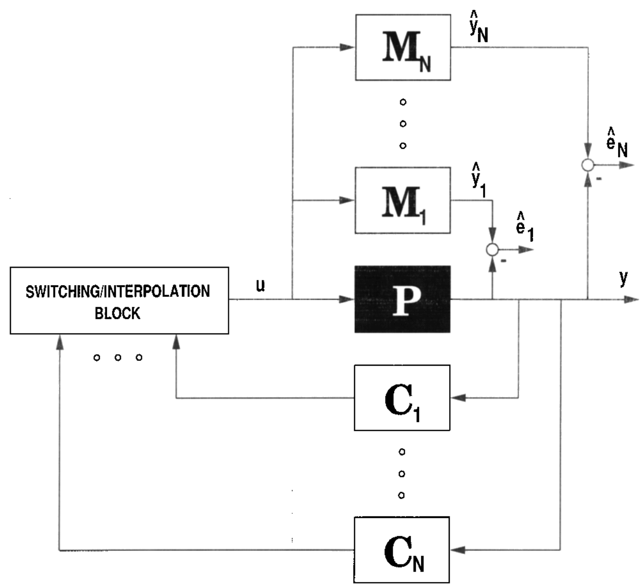

Fig. 2 Structure of the MMST controller: parallel observers are used to find the model closest to the current plant dynamics, and switch to the corresponding controller.

In the case of wing damage, parallel observers correspond to models of the TAFA dynamics for different percentage of damage. Using this approach, in Ref. 7 we extracted 11 models from the model (4), (5) for a particular flight condition and for $\rho = (i - 1)/10$, $i = 1, 2, \ldots, 11$, and designed the corresponding IDCL controllers. The assumption was made that the closed-loop system should achieve the same performance in all cases of damage, and, hence, only one reference model was used to implement the controller. To make the overall system sufficiently robust to the cases of damage that do not coincide with the 11 models, a robustifying output error feedback term was added to the multiple controllers. As shown in Ref. 7 through numerical simulations, such an approach yields excellent performance of the overall system in the presence of up to 100% wing damage. However, our further research has revealed that, in some cases, the performance of the overall system may not be acceptable when measurement noise, actuator dynamics and position and rate limits on the control effectors were included in the simulation. In addition, even in the cases when the response was acceptable, the remaining control redundancy can be too low to guarantee the stability of the overall system in the case of subsequent failures.

For these reasons in this paper we propose an intelligent adaptive reconfigurable control strategy for TAFA in the presence of wing damage; the strategy is based on multiple reference models, as described next.

V. Multiple Reference Models and Output Error Feedback

After studying the problem of wing damage for TAFA and its solution using the MMST, the following observations can be made:

1) The FDI subsystem consists of multiple observers and a suitably chosen error criterion and is, to a large extent, independent of the current control input, as long as the latter is bounded. The role of this subsystem is to generate a suitable switching signal.

2) Control reconfiguration is based on the switching signal obtained from the FDI subsystem.

3) In the case when the actual damage does not coincide with any of the models, the system is characterized by infinite switching between the neighboring models (chattering).

4) This effect can be reduced by adding an output feedback term to the controllers to ensure small tracking error for a set of initial conditions around the corresponding model. However, choosing the output error feedback gain matrix for each of the controllers such that the small tracking error is achieved is a formidable task. In addition, the output error feedback is essentially a high-gain term and is highly sensitive to measurement noise and input saturation.

Hence our approch is focused on achieving the control objective in the presence of wing damage by using on-line FDI and parameter estimation and multiple damage and reference models. The approach consists of several steps, one of which is reducing the performance requirements for noncritical state variables. This step is carried out off-line and is based on the analysis of desired dynamics for different cases of wing damage.

For instance, in the case of no damage the desired dynamics of TAFA for the terrain-following maneuver during ingress and the TAFA response with the baseline controller and a full-performance reference model are shown in Fig. 3. The requirement for all state variables is to follow the desired trajectories generated by the full-performance reference model, and the baseline controller achieves this objective.

In the case when the control objective is relaxed for some of the noncritical control variables, the desired and actual response is shown in Fig. 4. The performance in this case is just slightly lower than in the case of no damage. In this particular example, the performance requirements are relaxed for the forward velocity and roll rate; other choices of noncritical state variables can be made for different maneuvers.

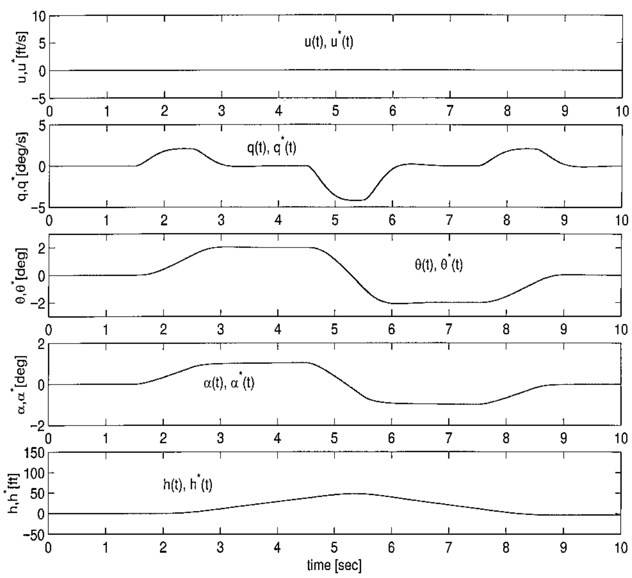

Fig. 3 Actual and desired TAFA response in the no-damage case.

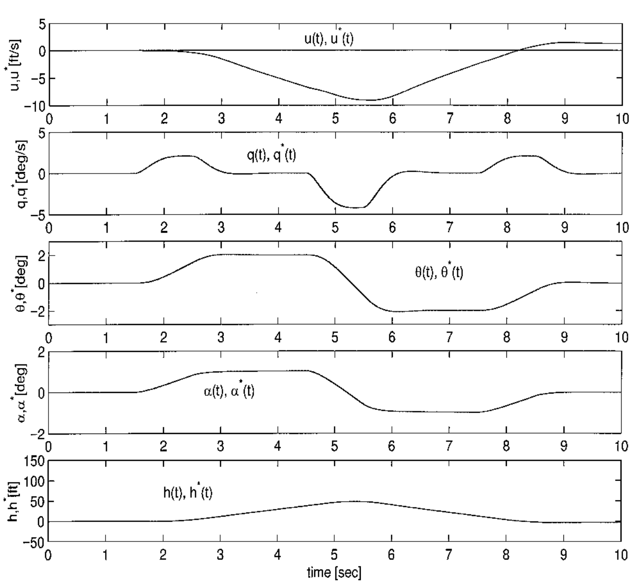

Fig. 4 Actual and desired TAFA response in the case of nonzero damage.

However, the use of the lower-performance reference model has dramatic impact on the control design. Our analysis revealed that there exists an output error feedback gain matrix for the baseline controller such that the closed-loop system is stable for all cases of damage from zero to 100%, even though the response is not acceptable in the case when there is 100% wing damage at $t = 2.5$ s (Figs. 5–8). Hence one of the objectives is to improve this response. In addition, even in the case of 100% wing damage, the control objective can be achieved even in the presence of actuator dynamics and control input saturation. This was the main motivation for the approach used in this paper. The overall approach is described next.

Proposed Approach: The overall intelligent control system consists of the following components:

1) A suitable mechanism for switching between the full-performance and lower-performance reference models. Our analysis has revealed that, in the case of TAFA, the preceding two reference models were sufficient to cover all cases from zero to 100% wing damage. The mechanism operates in such a fashion that, in the case when the scheme detects that $\rho(t)$ is greater than zero, the system in turn switches to the lower-performance reference model.

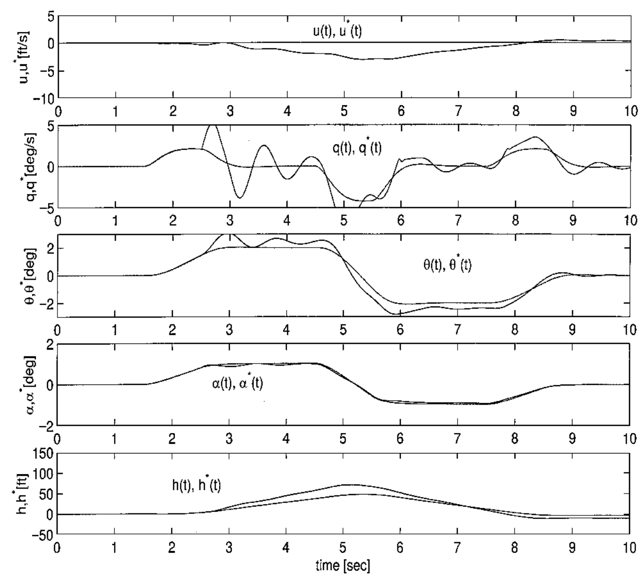

Fig. 5 TAFA state response with the baseline controller and output error feedback in the presence of 100% damage, actuator dynamics, and position and rate limits.

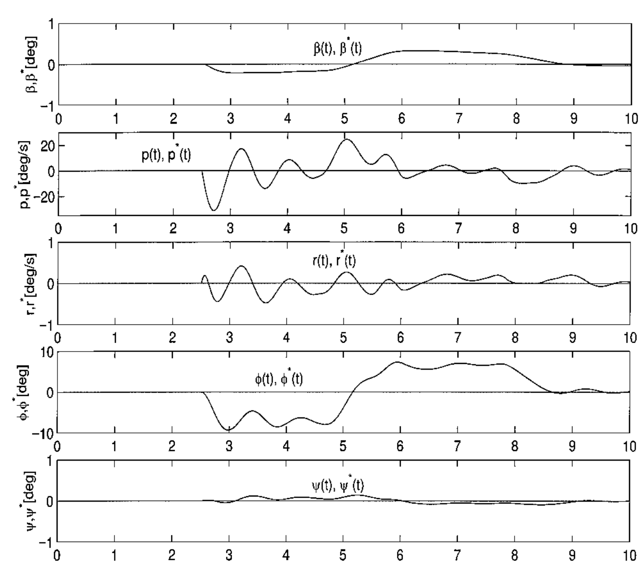

Fig. 6 TAFA state response with the baseline controller and output error feedback in the presence of 100% damage, actuator dynamics and position and rate limits (cont.).

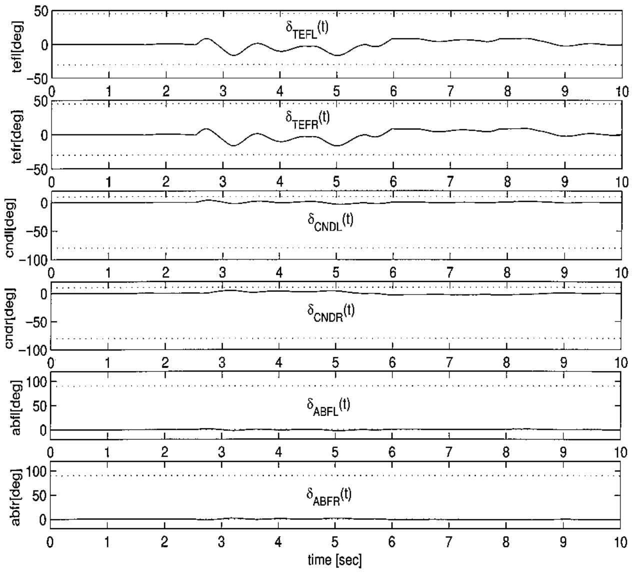

Fig. 7 TAFA input response with the baseline controller and output error feedback in the presence of 100% damage, actuator dynamics, and position and rate limits.

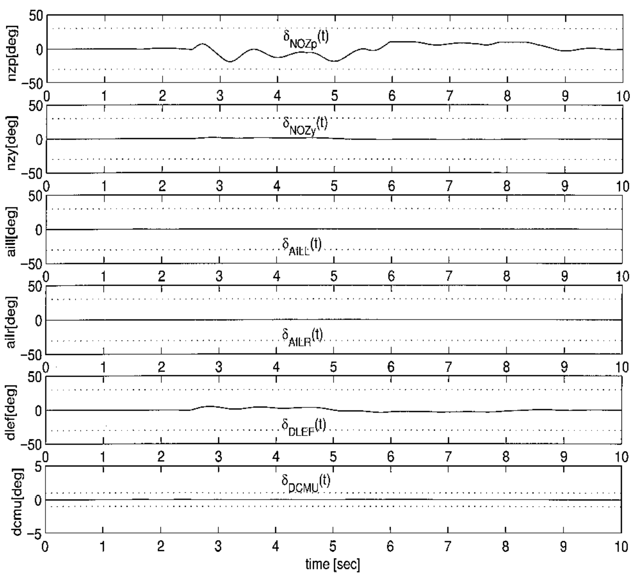

Fig. 8 TAFA input response with the baseline controller and output error feedback in the presence of 100% damage, actuator dynamics, and position and rate limits (cont.).

2) The multiple reference model subsystem obtains the information that ρ is greater than zero from the multiple model-based failure detection subsystem. This subsystem consists of 11 observers based on 10 damage models plus the no-damage model and is described in detail in Ref. 7. Its role is only to generate the information that a failure has occured. From that point of view, even a smaller number of observers could be sufficient to achieve this objective.

3) On-line estimation of the percentage-of-damage parameter ρ is carried out using the approach from Refs. 13 and 14 for nonlinearly parameterized plants. The approach is based on linearization of the corresponding error model with respect to the parameter error. The use of adaptive algorithms with projection assuress boundedness of the estimate $\hat{\rho}$ of ρ.

4) Control reconfiguration is based on the use of on-line estimates of ρ in the control law at every instant. As shown in the following section, the resulting system is stable, and the output error tends to zero asymptotically.

VI. Adaptive Control Design

In this section we will discuss the design of an on-line scheme for estimation of ρ, as well as the corresponding reconfigurable controller, and study the stability of the overall system.

We recall that the TAFA model is of the form (4), (5), where A and B are given by Eqs. (6) and (7). Because the parameter ρ is unknown (i.e., the extent of damage and its time instant of occurence is assumed unknown), we next build an observer for estimating ρ on-line and design a corresponding adaptive controller, as shown next.

Observer: The observer is chosen in the form

$$\dot{\hat{x}}_1 = \bar{A}\hat{x} \tag{13}$$

$$\dot{\hat{x}}_2 = \Lambda\hat{e} + \hat{A}x + \hat{B}u \tag{14}$$

where $\hat{e} = \hat{x} - x$, $\hat{x} = [\hat{x}_1 \;\; \hat{x}_2]^T$ and

$$\hat{A} = A_0 + A_1\hat{\rho} + A_2\hat{\rho}^2 + A_3\hat{\rho}^3 + A_4\hat{\rho}^4 + A_5\hat{\rho}^5 \tag{15}$$

$$\hat{B} = B_0 + B_1\hat{\rho} + B_2\hat{\rho}^2 + B_3\hat{\rho}^3 + B_4\hat{\rho}^4 + B_5\hat{\rho}^5 \tag{16}$$

where $\hat{\rho}$ denotes the estimate of ρ.

Controller: Let $\hat{\eta} = C_j[-\hat{A}x + \Lambda(x - x_m) + A_m x_m + B_m r]$. The baseline control law is now modified as follows:

$$u = W^{-1}(C_j\hat{B})^T\left\{C_j\hat{B}W^{-1}\left[(C_j\hat{B})^T\right]\right\}^{-1}\hat{\eta} \tag{17}$$

On-line estimation of ρ: Because it is assumed that $\rho \in [0, 1]$, we will also adjust its estimate within the interval [0, 1] using the adaptive algorithms with projection (see the Appendix). This will also ensure that the properties (3) and (4) from assumption 2 are retained even when the true value of ρ is replaced by its estimate in the control law.

Let $\mathcal{S}$ denote the system consisting of the plant (4), (5) and the controller (17). Also let P denote a symmetric positive definite solution of the Lyapunov matrix equation $\Lambda_0^T P + P\Lambda_0 = -Q$, where $Q = Q^T > 0$ and Λ_0 is given by Eq. (12). We next consider the following theorem:

Theorem 1: If the estimate $\hat{\rho}$ is adjusted using the following adaptive law

$$\dot{\hat{\rho}} = \mathrm{Proj}_{[0,1]}[-\gamma\hat{e}^T P\Omega(x, u, \hat{\rho})] \tag{18}$$

where

$$\Omega(x, u, \hat{\rho}) = \sum_{i=1}^{5} i \cdot (A_i x + B_i u)\hat{\rho}^{i-1} \tag{19}$$

and $\gamma > 0$, then all of the signals in the system $\mathcal{S}$ are bounded and $\lim_{t\to\infty}[x(t) - x_m(t)] = 0$ in the presence of arbitrary variations of $\rho(t)$ within [0, 1].

Proof: Let $\hat{e}_j = \hat{x}_j - x$, $j = 1, 2$, and $\hat{e} = [\hat{e}_1^T \;\; \hat{e}_2^T]^T$. Upon subtracting Eqs. (4), (5) from (13), (14), we obtain

$$\dot{\hat{e}}_1 = \bar{A}\hat{e} \tag{20}$$

$$\dot{\hat{e}}_2 = \Lambda_0\hat{e} + \sum_{i=1}^{5}(A_i x + B_i u)(\hat{\rho}^i - \rho^i) = \Lambda_0\hat{e} + \Theta(x, u, \hat{\rho}, \phi) \tag{21}$$

where $\phi = \hat{\rho}_i - \rho$ denotes the parameter estimation error and

$$\Theta(x, u, \hat{\rho}, \phi) = \sum_{i=1}^{5}(A_i x + B_i u)[\hat{\rho}^i - (\hat{\rho} - \phi)^i] \tag{22}$$

The proof is based on the approach from Refs. 13 and 14 and will be carried out in several steps as given next.

Step 1: We first linearize Θ with respect to $\phi = 0$. By keeping only the first term in the corresponding Taylor's series, we obtain

$$\Theta(x, u, \hat{\rho}, \phi) \cong \Omega(x, u, \hat{\rho}) \cdot \phi \tag{23}$$

where $\Omega(x, u, \hat{\rho}) = \Omega_A(\hat{\rho})x + \Omega_B(\hat{\rho})$ and

$$\Omega_A(\hat{\rho}) = \sum_{i=1}^{5} i \cdot A_i \hat{\rho}^{i-1}, \qquad \Omega_B(\hat{\rho}) = \sum_{i=1}^{5} i \cdot B_i \hat{\rho}^{i-1} \quad (24)$$

Hence, for small ρ the error model (20), (21) takes the form

$$\dot{\hat{e}}_1 = \bar{A}\hat{e} \quad (25)$$

$$\dot{\hat{e}}_2 = \Lambda_0 \hat{e} + \Omega(x, u, \hat{\rho})\phi \quad (26)$$

Step 2: We choose the following tentative Lyapunov function:

$$V(\hat{e}, \phi) = \tfrac{1}{2}(\hat{e}^T P \hat{e} + \phi^2/\gamma) \quad (27)$$

Upon taking its first derivative along the motions of Eqs. (25) and (26), we obtain

$$\dot{V}(\hat{e}, \phi) = -\tfrac{1}{2}\hat{e}^T Q \hat{e} + \hat{e}^T P \Omega \phi_i + \phi\dot{\phi}/\gamma \quad (28)$$

Using the properties of adaptive algorithms with projection (see the Appendix) and because $\dot{\phi} = \dot{\hat{\rho}} - \dot{\rho}$, we further have

$$\dot{V}(\hat{e}, \phi) \leq -\tfrac{1}{2}\lambda_m \|\hat{e}\|^2 - \phi\dot{\rho}/\gamma \quad (29)$$

where λ_m denotes the minimum eigenvalue of Q.

Step 3: Our next objective is to prove that $\hat{e}$ is bounded. Parameter estimation error ϕ is bounded by the choice of the adaptive law, and $|\phi(t)| \leq 1$ for all t. Because from assumption 2(5) $\dot{\rho} \in \mathcal{L}^\infty$, it follows that there exists a constant $c > 0$ such that $|\dot{\rho}(t)| \leq c$ for all t. Hence we have

$$\dot{V}(\hat{e}, \phi) \leq -\tfrac{1}{2}\lambda_m \|\hat{e}\|^2 + \bar{c} \quad (30)$$

where $\bar{c} = c/\gamma$. We further have

$$\dot{V}(\hat{e}, \phi) \leq -\tfrac{1}{2}\lambda_m \|\hat{e}\|\{\|\hat{e}\| - 2\bar{c}/\lambda_m\} \quad (31)$$

Hence $\dot{V}$ is less than zero for $\|\hat{e}\| > 2\bar{c}/\lambda_m$ and can be greater than zero for $\|\hat{e}\| \leq 2\bar{c}/\lambda_m$. Because in the latter case the set of values of $\|\hat{e}\|$ includes the point $\hat{e} = 0$, it follows from LaSalle's extension of Lyapunov's method[15] that $\hat{e} \in \mathcal{L}^\infty$.

Step 4: Our next objective is to prove that $\hat{e} \in \mathcal{L}^2$. From Eq. (29) and because $\dot{\rho}(t) \geq 0$ and $|\phi_i(t)| \leq 1$ for all t, we have

$$\dot{V}(\hat{e}, \phi) \leq -\tfrac{1}{2}\lambda_m \|\hat{e}\|^2 + \dot{\rho}/\gamma \quad (32)$$

Upon integrating the preceding expression over the interval $t \in [0, \infty)$, we obtain

$$V(0) - V(\infty) \geq \frac{1}{2}\lambda_m \int_0^\infty \|\hat{e}(t)\|^2 \,\mathrm{d}t - \int_0^\infty \frac{\dot{\rho}(t)\,\mathrm{d}t}{\gamma} \quad (33)$$

Because $\hat{e}$ and ϕ are bounded, it follows that $V(\hat{e}, \phi)$ is also bounded. Hence the term on the left-hand side of the preceding expression is bounded. Further, from assumption 2(5) we have $\dot{\rho} \in \mathcal{L}^2 \cap \mathcal{L}^\infty$. Hence it follows that $\hat{e} \in \mathcal{L}^2$. In addition, because from the same assumption, $\ddot{\rho}_i \in \mathcal{L}^\infty$, and it follows from the Barbalat's Lemma (see, e.g., Ref. 9) that $\lim_{t\to\infty} \dot{\rho}(t) = 0$. However, the fact that $\hat{e} \in \mathcal{L}^2 \cap \mathcal{L}^\infty$ does not imply that either $\hat{x}$ or x are bounded, and further analysis is needed to establish this fact.

Step 5: We further substitute the control law (17) into Eq. (14), which yields

$$\dot{\hat{x}}_1 = \bar{A}\hat{x} \quad (34)$$

$$\dot{\hat{x}}_2 = \Lambda\hat{e} + C_j[\Lambda(x - x_m) + A_m x_m + B_m r] \quad (35)$$

We further define $\hat{e}_m = \hat{x} - x_m$ and $\hat{e}_{mi} = \hat{x}_i - x_{mi}$, $i = 1, 2$. From the preceding equations and Eqs. (8) and (9), we now have

$$\dot{\hat{e}}_{m1} = \bar{A}\hat{e}_m \quad (36)$$

$$\dot{\hat{e}}_{m2} = \Lambda\hat{e}_m \quad (37)$$

Because Λ_0 from Eq. (12) is asymptotically stable, the preceding system is exponentially stable. If the initial conditions of the observer are chosen equal to those of the reference model, the observer is identical to the reference model. Even when these initial conditions are different, $\hat{e}_m \in \mathcal{L}^\infty$, and $\lim_{t\to\infty} \hat{e}_m(t) = 0$. The former condition also implies that $\hat{x} \in \mathcal{L}^\infty$, which, along with boundedness of $\hat{e}$, also implies that $x \in \mathcal{L}^\infty$.

Step 6: Our final objective is to show that $\dot{\hat{e}}$ is bounded. Because ϕ is bounded, from Eqs. (25) and (26) it is sufficient to show that $\Omega(x, u, \hat{\rho})$ is bounded. Because x is bounded, from Eq. (17) it follows that u is bounded, which implies that $\Omega(x, u, \hat{\rho})$ is bounded as well. We can now conclude that $\dot{\hat{e}}$ is bounded. Using the Barbalat's Lemma,[9] from the fact that $\hat{e} \in \mathcal{L}^2 \cap \mathcal{L}^\infty$ and $\dot{\hat{e}} \in \mathcal{L}^\infty$ we can conclude that $\lim_{t\to\infty} \hat{e}(t) = 0$. Because $\lim_{t\to\infty} \hat{e}_m(t) = 0$, these two conditions imply that $\lim_{t\to\infty} [x(t) - x_m(t)] = 0$, which completes the proof. □

1) Because of the properties of adaptive algorithms with projection (see the Appendix), we can readily demonstrate that the system will be robust in the presence of large bounded external disturbances, noise, and some classes of unmodeled dynamics.

2) Because an error model linearized with respect to ϕ was used to design adaptive algorithms, the stability property of the overall system is local in nature, i.e., the approximation is valid for sufficiently small ϕ. Global stability can be demonstrated using the approach from Ref. 14, where the adaptive controller was combined with a variable-structure controller using multiple models. In the problem under consideration, numerous simulations revealed that the values $\phi \in [0, 1]$ are sufficiently small to guarantee the validity of the approximation and ensure excellent overall performance. Some representative simulations are included in the following section.

3) The problem of the false alarm is a major one in reconfigurable control design. Particularly prone to false alarms are schemes that are based on voting mechanisms and rule-based FDI. However, the scheme from the paper is based on analytic redundancy, i.e., on an explicit mathematical model of the aircraft, where the damage causes abrupt variations in its dynamics. In addition, the effect of wing damage is much more severe than any other type of failure (for instance, sensor, actuator, control effecor, or engine failures). Hence the possibility of false alarms in the presence of wing damage is very low, and the FDI capabilities of the scheme are limited only by the accuracy of the corresponding models. In the simulation section we will also include simulations that will demonstrate that the proposed scheme is highly robust to false alarms.

VII. Simulations

Because the response of the system shown in Sec. V is not acceptable, the objective was to improve it using our adaptive control design. The corresponding response in the case with no noise and 100% damage at $t = 2.5$ s is shown in Figs. 9–12. The resulting

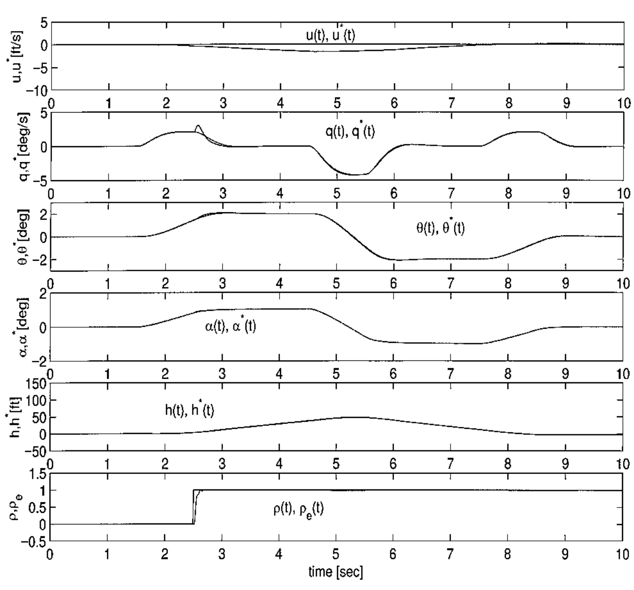

Fig. 9 TAFA state response with the intelligent adaptive controller.

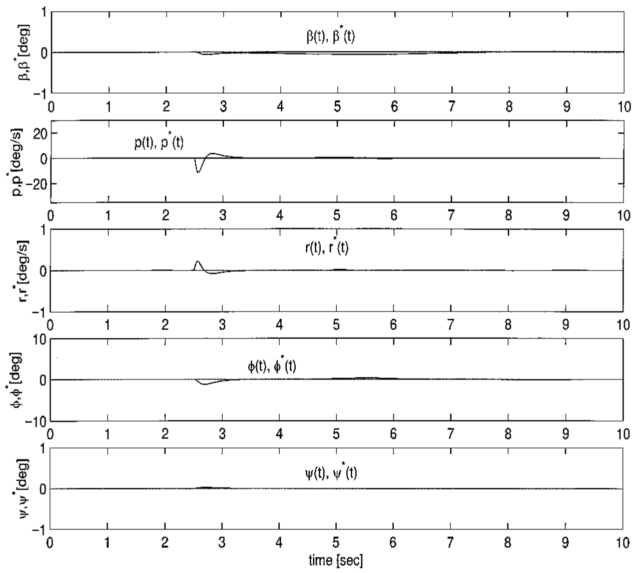

Fig. 10 TAFA state response with the intelligent adaptive controller (cont.).

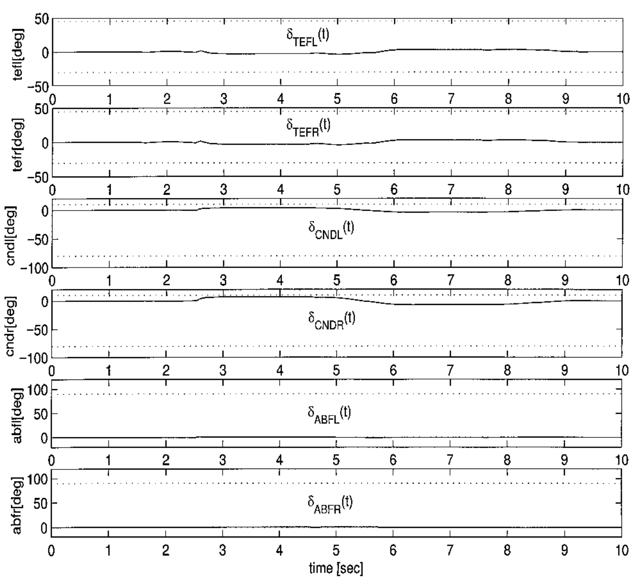

Fig. 11 TAFA input response with the intelligent adaptive controller.

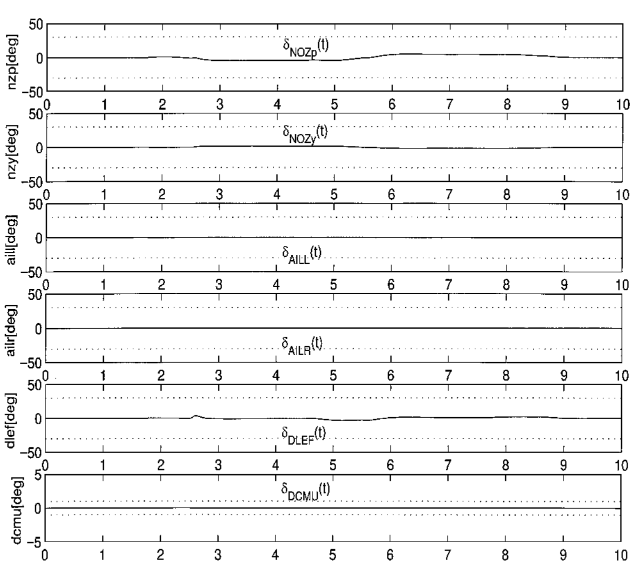

Fig. 12 TAFA input response with the intelligent adaptive controller (cont.).

response is excellent, and the actual value of ρ is accurately identified after only a few samples. Successful control reconfiguration is also seen to improve the response in forward velocity.

We next tested the robustness to false alarms by simulating the overall adaptive reconfigurable system in the case when there is no damage, but there is large process and measurement noise of magnitude 1.2 and 0.2 [deg/s], respectively. The resulting response is shown in Fig. 13. The scheme does not cause any false alarms despite such large process and measurement noise.

To demonstrate that the scheme will still be stable even in the presence of false alarms, we considered the case of false alarms as that of a sudden change in the initial condition of the estimate of the parameter ρ, which occures independently of the aircraft dynamics. For instance, this can be caused by a set of bad data points, causing a false alarm. This was simulated as a sudden change in the initial condition of $\hat{\rho}$ from zero to one at $t = 2.5$ (Fig. 14). As seen from the figure, because the scheme is stable for all initial conditions in $\hat{\rho}$ it will force this estimate to converge to the true value of ρ from any initial condition, and thus quickly recover from the false alarm.

We also simulated the case of the delay switch time as the case when the initial condition in $\hat{\rho}$ suddenly changes to one and stays at that value for a whole second, even though there is no damage.

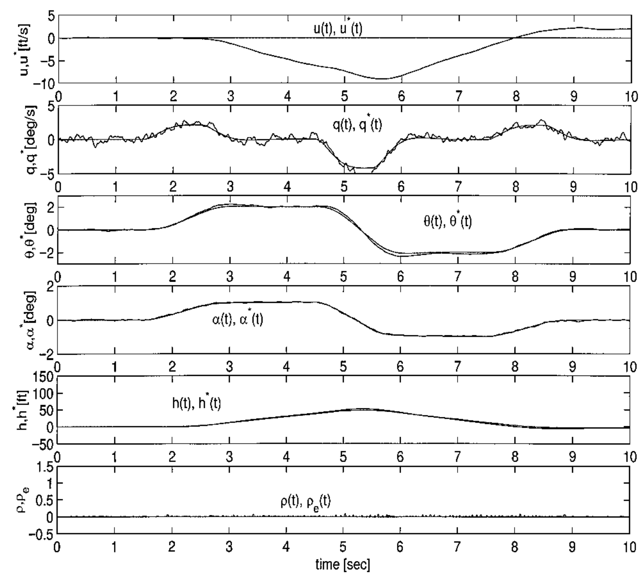

Fig. 13 Response in the no-damage case: large process and measurement noise.

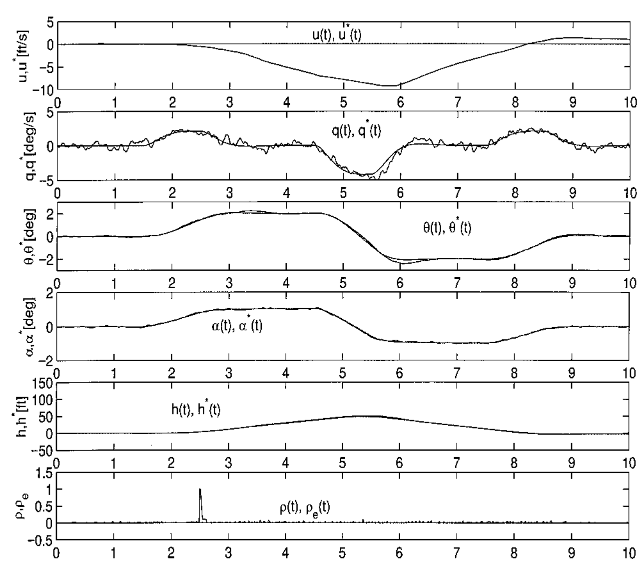

Fig. 14 Response in the no-damage case: recovery from a false alarm.

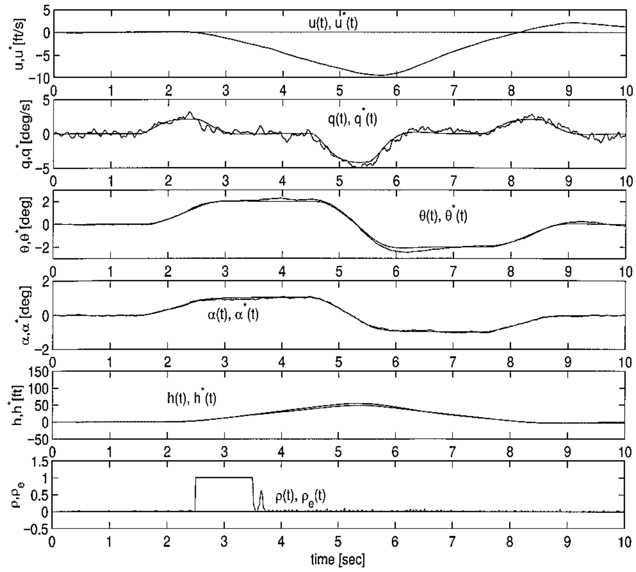

Fig. 15 Response in the no-damage case: recovery from a switch delay.

As seen from Fig. 15, the overall system is highly robust to such a delay switch time.

The simulation results, along with the fact that actuator dynamics and position and rate limits on the control effectors were included in the simulation, demonstrate the robustness and practical viability of the proposed intelligent control scheme.

VIII. Conclusion

In this paper we developed an intelligent adaptive reconfigurable control scheme for a TAFA in the presence of wing damage. The scheme consists of a failure detection subsystem based on multiple observers, multiple reference models for changing the desired performance on-line in the case of damage, on-line estimation of the percentage-of-damage parameter, and the corresponding adaptive reconfigurable controller augmented with an output error feedback term. The overall scheme results in fast and accurate failure detection and identification and control reconfiguration and was demonstrated analytically to be stable in the sense that all signals are bounded, and the output error converges to zero asymptotically even in the case of 100% wing damage. The properties of the proposed intelligent adaptive controller are evaluated through numerical simulations on a TAFA model in the presence of large noise, actuator dynamics, position and rate limits on the control effectors, and 100% wing damage, and the proposed approach results in excellent overall performance.

Our further research will be focused on the problem of relating the actual flight performance with control input redundancy and the design of corresponding reference models for different cases of subsystem failures and structural damage.

Appendix: Properties of Adaptive Algorithms with Projection

Properties of such adaptive algorithms will be illustrated on the example of a simple error model given next:

$$\dot{e} = -\lambda e + \phi\omega(t, x) \tag{A1}$$

where $\lambda > 0$, $e = x - x_m$, $x_m: \mathbb{R}^+ \rightarrow \mathbb{R}$ is a smooth bounded function, $\omega(t, x)$ is bounded for bounded x and for all time; $\phi = \theta - \theta^*$ denotes the parameter error; θ is an adjustable parameter; and $\theta^* \in [\theta_{\min}, \theta_{\max}]$ is constant. The objective is to adjust $\theta(t)$ within $[\theta_{\min}, \theta_{\max}]$ so that $\lim_{t\rightarrow\infty} e(t) = 0$.

Theorem A1: If $\theta(t)$ is adjusted using the adaptive algorithm with projection of the form

$$\dot{\theta} = \mathrm{Proj}_{[\theta_{\min},\theta_{\max}]}\{-\gamma e\omega\}, \qquad \theta(0) \in [\theta_{\min}, \theta_{\max}] \tag{A2}$$

where the projection operator is defined as

$$\mathrm{Proj}_{[\theta_{\min},\theta_{\max}]}\{-\gamma e\omega\} =$$

$$\begin{cases} -\gamma e\omega, & \text{if} \quad \theta(t) = \theta_{\max}, \quad e\omega > 0 \\ 0, & \text{if} \quad \theta(t) = \theta_{\max}, \quad e\omega \leq 0 \\ -\gamma e\omega, & \text{if} \quad \theta_{\min} < \theta(t) < \theta_{\max} \\ 0, & \text{if} \quad \theta(t) = \theta_{\min}, \quad e\omega \geq 0 \\ -\gamma e\omega, & \text{if} \quad \theta(t) = \theta_{\min}, \quad e\omega < 0 \end{cases}$$

then $\lim_{t\rightarrow\infty} e(t) = 0$.

Proof: Let the tentative Lyapunov function for the system be

$$V(e, \phi) = \tfrac{1}{2}(e^2 + \phi^2/\gamma) \tag{A3}$$

Its derivative along the motions of the system yields

$$\dot{V}(e, \phi) = -\lambda e^2 + e\phi\omega + \phi\dot{\phi}/\gamma$$

To assure that $\dot{V}$ is negative semidefinite, our objective is to show that in all cases

$$\phi\dot{\phi} \leq -\gamma e\phi\omega$$

i.e., that $\phi\dot{\phi} + \gamma e\phi\omega \leq 0$. We will further consider each individual case. We note that because θ^* is constant $\dot{\theta}(t) \equiv \dot{\phi}(t)$.

1) $\theta(t) = \theta_{\max}$. When $e\omega > 0$, $\dot{\phi} = -\gamma e\omega$, and $\phi\dot{\phi} = -\gamma e\phi\omega$. Because $\phi = \theta - \theta^*$ and $\theta^* \in [\theta_{\min}, \theta_{\max}]$, in this case $\phi = \theta_{\max} - \theta^* \geq 0$. When $e\omega \leq 0$, $\dot{\phi} = 0$, and $\phi\dot{\phi} + \gamma e\phi\omega = \gamma e\phi\omega \leq 0$.

2) $\theta_{\min} < \theta(t) < \theta_{\max}$. In this case $\phi\dot{\phi} = -\gamma e\phi\omega$.

3) $\theta(t) = \theta_{\min}$. For $e\omega < 0$, $\dot{\phi} = -\gamma e\omega$, and $\phi\dot{\phi} = -\gamma e\phi\omega$. Because in this case $\phi = \theta_{\min} - \theta^* \leq 0$, for $e\omega \geq 0$, $\dot{\phi} = 0$, and $\phi\dot{\phi} + \gamma e\phi\omega = \gamma e\phi\omega \leq 0$.

The adaptive algorithms with projection ensure that the condition $\phi\dot{\phi} \leq -\gamma e\phi\omega$ is satisfied for all values of arguments. This implies that $\dot{V}(e, \phi) \leq -\lambda e^2 \leq 0$. Using the arguments from Ref. 9, we can now readily demonstrate that $\lim_{t\rightarrow\infty} e(t) = 0$. □

Our next objective is to demonstrate that when the adjustment law (A2) is used, the overall system will be robust to bounded external disturbances, time-varying parameters, and parametric uncertainty. Let the error model be of the form

$$\dot{e} = -\lambda e + \xi(t, x) + \phi\omega(t, x) + z \tag{A4}$$

where $|\xi(t, x)| \leq a|x| + b$ for all (t, x) denotes a term caused by unmodeled dynamics and/or parametric uncertainty; $a, b > 0$ and $a < \lambda$; $\theta^*(t) \in [\theta_{\min}, \theta_{\max}]$ for all t; $|\dot{\theta}^*(t)| \leq c_\theta$ for all t; and $|z(t)| \leq c_z$ for all t denotes a disturbance. We also let $|x_m(t)| \leq c_{xm}$ for all t.

Theorem A2: Adaptive algorithm (A2) ensures that e is bounded.

Proof: Let the tentative Lyapunov function be of the form [Eq. (A3)]. Because $\dot{\phi} = \dot{\theta} - \dot{\theta}^*$, its first derivative yields

$$\dot{V}(e, \phi) \leq -\lambda e^2 + e\xi + ez - \phi\dot{\theta}^*/\gamma$$

$$\leq -(\lambda - a)e^2 + (ac_{xm} + b + c_z)|e| + (\theta_{\max} - \theta_{\min})c_\theta/\gamma$$

Because $\lambda > a$, using the arguments from Ref. 15 we can readily show that e is bounded, which completes the proof. □

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