Linear Parameter-Varying Detection Filter Design for a Boeing 747-100/200 Aircraft

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We present a fault detection and isolation (FDI) filter design using a linear parameter-varying (LPV) model of the longitudinal dynamics of a Boeing 747 series 100/200. The LPV FDI filter design is based on an extension of the fundamental problem of residual generation concepts elaborated for linear, time-invariant systems. Typically, the FDI filters are designed for open-loop models, and applied in closed loop. An application is shown of an LPV FDI filter for actuator failure detection and isolation in the closed-loop longitudinal LPV system to the full nonlinear Boeing 747 aircraft simulation, which represents the “true” system.

I. Introduction

MODERN control systems and algorithms are becoming increasingly complex and sophisticated. Consequently, the issues of availability, reliability, and operating safety are of major importance. These issues are especially important for safety-critical systems such as nuclear reactors, cars, and aircraft flight-control systems. For safety-critical systems, the consequence of faults can be extremely serious in terms of human mortality and environmental impact. Therefore, there is a growing need for on-line supervision and fault diagnosis to increase the reliability of safety-critical systems.

A traditional approach to fault diagnosis in the wider application context is based on hardware redundancy methods that use multiple sensors, actuators, computers, and software to measure and control a particular variable. In analytical redundancy schemes, the resulting difference generated from the consistency checking of different variables is called a residual signal. The residual should be zero when the system is normal and should diverge from zero when a fault occurs in the system. This zero and nonzero property of the residual is used to determine whether or not faults have occurred. Analytical redundancy makes use of a mathematical model and the goal is the determination of faults of a system from the comparison of available system measurements with a priori information represented by the mathematical model through generation of residual quantities and their analysis.

There are various approaches to residual generation [see, e.g., the parity space approach,7 the multiple model method, detection filter design using geometric approach2 or on frequency domain concepts,2 unknown input observer concept (Ref. 6, Chap. 3) and dynamic inversion-based detection.7 Most of the design approaches refer to linear time-invariant (LTI) systems, but references to nonlinear cases can be found in Ref. 4.

The geometric approach to the design detection filters was initiated by Massoumnia for LTI systems2 and was applied by Edelmayer et al. to linear time varying (LTV) systems in Ref. 6. These concepts have been used to build a linear parameter-varying (LPV) fault detection and isolation (FDI) design procedure.7,8 Related results on FDI filter design based in the geometric approach appeared recently for bilinear systems,9 whereas Persis and Isidori considered input affine nonlinear systems.10,11

Aircraft models are usually nonlinear and time varying. One approach to flight control is to derive a family of linear models based on linearization around given setpoints and synthesize a flight controller that is gain scheduled throughout the flight envelope. A more efficient and theoretically sound approach is to rewrite the models into LPV or quasi-LPV (QLPV) models that have an LTI or LTV form:

\[
\dot{x}(t) = A(p)x(t) + B(p)u(t) + \sum_{j=1}^{m} L_j(p)v_j(t)
\]

\[
y(t) = Cx(t)
\]

where \(x\) is the state variable and \(p(t) = [\rho_1(t), \ldots, \rho_q(t)]^T\) is a known function up to time \(t\). It is assumed that each parameter \(\rho_i\) ranges between known extremal values \(\rho_i(t) \in [-\bar{\rho}_i, \bar{\rho}_i]\). This parameter set will be denoted by \(\mathcal{P}\). The case when the \(\rho_i\) functions depend on the state(s) of the system or its components is called QLPV.

The fault models appear linearly in the LPV model, Eq. (1): their direction is given by \(L_j(p)\) and the failures to be detected are modeled by the unknown functions \(v_j(t)\).
It is worth noting that all input affine nonlinear models can be rewritten in QLPV form and very effective control system design methods have been developed for LPV and QLPV systems. These methods have been successfully applied to various aerospace control applications.

If the control system is designed for this model class, it is reasonable to design FDI algorithms and possible reconfiguration design strategies for LPV and QLPV systems. Because these models are basically time varying or nonlinear, use of time domain FDI design approaches based on geometric concepts is well suited as a solution. This is the approach investigated in this paper with development of an actuator FDI system for a Boeing 747 aircraft.

The detection filter design method will be described for LPV and QLPV systems where the state-space matrices depend affinely on the following parameters:

\[ A(\rho) = A_0 + \rho_1 A_1 + \cdots + \rho_N A_N \] (2)  
\[ B(\rho) = B_0 + \rho_1 B_1 + \cdots + \rho_N B_N \] (3)  
\[ L_j(\rho) = L_{j,0} + \rho_1 L_{j,1} + \cdots + \rho_N L_{j,N} \] (4)

The contribution of this paper is the first application of LPV FDI filtering to a full nonlinear aircraft model. The complete FDI design process, including an example, and experiences on the LPV FDI filter design and its application to the closed-loop aircraft system are presented. The paper is organized as follows. Section II provides a very quick review of the fundamental problem of residual generation (FPRG).18

II. Fundamental Problem of Residual Generation for Linear Time-Invariant and Linear Parameter-Varying Systems

Let us consider the following LTI system, which has two failure events:

\[ \dot{x}(t) = Ax(t) + Bu(t) + L_1 v_1(t) + L_2 v_2(t) \]
\[ y(t) = Cx(t) \] (5)

where \( x(t) \in \mathcal{X} \) is the state variable, \( u(t) \in \mathcal{U} \) is the known control input, \( y(t) \in \mathcal{Y} \) is the known output, and the arbitrary time-varying functions \( v_i(t) \in \mathcal{L}_i \) are the unknown failure modes. The term \( L_1 v_1(t) \) represents the faulty behavior of the actuator that we are trying to monitor; that is, a nonzero \( v_1(t) \) should show up in the output of the residual generator \( r(t) \). Similarly, \( L_2 v_2(t) \) represents the faulty behavior of the other actuator, which should not affect \( r(t) \). The task of designing a residual generator that is sensitive to \( L_1 \) and insensitive to \( L_2 \) is called the fundamental problem of residual generation (FPRG).18

Let us denote by \( S^* \) the smallest unobservability subspace (UOS) containing \( \mathcal{L}_2 \) where \( \mathcal{L}_2 = \text{Im} L_2 \); \( S^* \) is the largest UOS in \( \text{Ker} C \) containing \( \mathcal{L}_2 \).

The \( S^* \) can be computed by the unobservability subspace algorithm (UOSA):19

\[ S_0 = \mathcal{X} \] (6)  
\[ S_i = \mathcal{W}^* + (A^{-1} S_{i-1}) \cap \text{Ker} C \] (7)

where \( \mathcal{W}^* \) is the minimal \((\mathcal{C}, \mathcal{A})\)-invariant subspace containing \( \mathcal{L}_2 \). As is well known for LTI models, a subspace \( \mathcal{W} \) is \((\mathcal{C}, \mathcal{A})\)-invariant if \( A(\mathcal{W} \cap \text{Ker} C) \subseteq \mathcal{W} \), which is equivalent with the existence of a matrix \( D \) such that \((A + D C) \mathcal{W} \subseteq \mathcal{W} \).

Proposition 1: FPRG has a solution if and only if \( S^* \cap \mathcal{L}_1 = 0 \); moreover, if the problem has a solution, the dynamics of the residual generator can be assigned arbitrarily.

The equation \( S^* \cap \mathcal{L}_1 = 0 \) indicates that \( v_2 \) should not affect the output of the residual generator \( r(t) \).

It can be proved (see, e.g., Ref. 2) that the residual generator has the form

\[ u(t) = Nu(t) - Gy(t) + Fu(t) \]
\[ r(t) = Mw(t) - Hy(t) \] (8)

where \( H \) is a solution of \( \text{Ker} HC = \text{Ker} C + S^* \) and \( M \) is a unique solution of \( MP = HC \), where \( P \) is the projection \( P : \mathcal{X} \rightarrow \mathcal{X} / S^* \).

To obtain the matrices in Eq. (8), consider \( D_0 \) such that \((A + D_0 C) \mathcal{S}^* \subseteq \mathcal{S}^* \) [i.e., \( D_0 \) makes \( \mathcal{S}^* \) a \((\mathcal{C}, \mathcal{A})\)-invariant subspace] and denote \( A_0 = A + D_0 C |_{\mathcal{X}/S^*} \). By construction, the pair \((M, A_0)\) is observable; hence, there exists a \( D_1 \) such that the poles of \( N = A_0 + D_1 M \) can be assigned arbitrarily. Then set \( G = PD_0 + D_1 H \) and \( F = PB \).

Note that the important step in the design of the filter is to assign the image of the first failure signature \( L_1 \) to the UOS of the residual \( r(t) \). Also the necessary condition simply states that the image of the first failure signature \( L_1 \) should not intersect with the UOS of the residual generator to ensure that the failure of the first actuator shows up in the residual \( r \).

FPRG results can be extended to the case of multiple events. This has a solution if and only if \( S^*_i \cap \mathcal{L}_i = 0 \), where \( S^*_i \) is the smallest UOS containing

\[ \bar{\mathcal{L}}_i = \sum_{j \neq i} \mathcal{L}_j \]

For the case of multiple faults, a bank of filters is designed such that each one of them is sensitive to a particular fault and completely insensitive to the others. This provides a complete isolation of the fault effects from each other.

These results can be extended to the parameter-varying case. To derive the filter synthesis procedure it is necessary to generalize the notions of invariant subspaces, \((\mathcal{C}, \mathcal{A})\)-invariant subspaces, and UOSs to the parameter-varying situation. We introduce the definition of parameter-varying \((\mathcal{C}, \mathcal{A})\)-invariant subspaces as follows.

Definition 1: Let \( \mathcal{C}(\rho) \) denote \( \text{Ker} C(\rho) \). Then a subspace \( \mathcal{W} \) is a parameter-varying \((\mathcal{C}, \mathcal{A})\)-invariant subspace if, for all the parameters \( \rho \in \mathcal{P} \),

\[ A(\rho) \mathcal{W} \cap \mathcal{C}(\rho) \subseteq \mathcal{W} \] (9)

As in the classical case one has the following characterization of the parameter-varying \((\mathcal{C}, \mathcal{A})\)-invariant subspaces.8

Proposition 2: \( \mathcal{W} \) is a parameter-varying \((\mathcal{C}, \mathcal{A})\)-invariant subspace if and only if for any \( \rho \in \mathcal{P} \) there exists a state feedback matrix \( D(\rho) \) such that

\[ [A(\rho) + D(\rho) C(\rho)] \mathcal{W} \subseteq \mathcal{W} \] (10)

The set of all parameter-varying \((\mathcal{C}, \mathcal{A})\)-invariant subspaces containing a given subspace \( \mathcal{B} \) admits a minimum denoted by

\[ \mathcal{W}^*(B) := \min \{ \mathcal{W}(\mathcal{C}(\rho), A(\rho), B) \} \] (11)

The notion of “UOS” extends to LPV systems as the largest subspace such that there exists a parameter-dependent gain matrix \( D(\rho) \) and constant-output mixing map \( H \) such that

\[ [A(\rho) + D(\rho) C] \mathcal{S} \subseteq \mathcal{S} \quad \text{for all} \quad \rho \in \mathcal{P} \] (12)

\[ \mathcal{S} \subseteq \text{Ker} HC \] (13)

For the LPV systems defined in Eq. (1), one can obtain the following algorithms.8
The Boeing 747-100/200 aircraft is an intercontinental widebody fidelity nonlinear model of a Boeing 747 series 100/200 aircraft. The longitudinal nonlinear model it represents to avoid model uncertainty. There are several theoretical issues of importance related to the LPV modeling stage in the FDI approach proposed (e.g., persistence of excitation and linear independency of the scheduling variables) but these are open questions outside the scope of this paper. The engineering solution found to address the linear condition was to introduce a fictitious input set always to 1 rad, which multiplies those terms from the equations of motion that could not be rewritten as linear combinations of any of the states or existing control inputs. To provide an LPV model that is a good approximation to the nonlinear model, it is assumed that the four elevator segments move and fail together. The body-axis aerodynamic forces and moments are given by

\[ F_z = -\bar{q} \alpha \cdot (CD_s \cdot c_{\alpha} - CL_s \cdot c_{\alpha}) + \sum_{i=1}^{4} T_{ni} - mg \cdot s_0 \]  

where \( \bar{q} \) is the dynamic pressure; \( S \) is reference surface area; \( \bar{q} \) is the angle of attack, respectively.

\[ M_x = \bar{q} \bar{c} \bar{\delta} \cdot \left\{ \bar{c}_m - \frac{1}{\bar{c}} (CD_s \cdot c_{\alpha} + CL_s \cdot c_{\alpha}) \bar{\delta}_{cg} \right. \]

\[ - (CD_s \cdot c_{\alpha} - CL_s \cdot c_{\alpha}) \bar{\delta}_{cg} + \frac{\bar{c} \bar{c}_m}{\bar{c}} \left( \bar{c}_m - \bar{\delta}_{cg} \cdot CL_s \cdot c_{\alpha} \right) \]

\[ + \sum_{i=1}^{4} T_{ni} \cdot \bar{\delta}_{cg} \]  

The states of the system are angle of attack \( \alpha \) (rad), pitch rate \( \dot{\theta} \) (rad/s), true airspeed \( V_T \) (m/s), and altitude \( h_e \) (m). Longitudinal control is performed through a movable horizontal stabilizer \( \delta_{cg} \) (deg). For the purpose of this research it is assumed that the four elevator segments move and fail together.

The body-axis aerodynamic forces and moments are given by

\[ F_z = -\bar{q} \alpha \cdot (CD_s \cdot c_{\alpha} - CL_s \cdot c_{\alpha}) + \sum_{i=1}^{4} T_{ni} - mg \cdot s_0 \]  

\[ M_x = \bar{q} \bar{c} \bar{\delta} \cdot \left\{ \bar{c}_m - \frac{1}{\bar{c}} (CD_s \cdot c_{\alpha} + CL_s \cdot c_{\alpha}) \bar{\delta}_{cg} \right. \]

\[ - (CD_s \cdot c_{\alpha} - CL_s \cdot c_{\alpha}) \bar{\delta}_{cg} + \frac{\bar{c} \bar{c}_m}{\bar{c}} \left( \bar{c}_m - \bar{\delta}_{cg} \cdot CL_s \cdot c_{\alpha} \right) \]

\[ + \sum_{i=1}^{4} T_{ni} \cdot \bar{\delta}_{cg} \]  

where \( \bar{c} \) is the wing chord; \( c_T = 1/I_{yy} \) is an inertial coefficient; \( \bar{c} \) is dynamic pressure; \( S \) is reference surface area; \( \bar{q} \) is the angle of attack, respectively.

In Ref. 21, the longitudinal nonlinear model of the Boeing 747-100/200 is simplified by reducing the complexity of the aerodynamic coefficients. The simplified model maintains a high degree of accuracy and all the important nonlinear characteristics of the full set of aerodynamic coefficients. This simplification of the nonlinear model was performed to facilitate the LPV modeling task.

The LPV model developed for FDI filter design is nonstandard in the sense that for control design the number of scheduling variables is usually kept small (because the computational requirement for controller synthesis increases with the number of scheduling variables). In the present case (i.e., LPV FDI design based on FPRG concepts) it is important for the LPV model to be affine in the scheduling variables (and of course linear in the states and control inputs vectors) and also to be an accurate representation of the nonlinear model it represents to avoid model uncertainty. There are several theoretical issues of importance related to the LPV modeling stage in the FDI approach proposed (e.g., persistence of excitation and linear independency of the scheduling variables) but these are open questions outside the scope of this paper. The engineering solution found to address the linear condition was to introduce a fictitious input set always to 1 rad, which multiplies those terms from the equations of motion that could not be rewritten as linear combinations of any of the states or existing control inputs. To provide an LPV model that is a good approximation to the nonlinear model, the number of scheduling variables was significantly increased, up to nine parameters. See Appendix B for an example of a nonlinear state transformation into the affine LPV model format.
The states of the LPV model are the same as the nonlinear longitudinal model. The output measurements are angle of attack $\alpha$, pitch rate $\dot{q}$, true velocity $V_T$, pitch angle $\theta$, and altitude $h_z$. The inputs are elevator deflection $\delta_e$, stabilizer deflection $\delta_h$, throttle $T_n$, and an ideal fictitious input, $\delta_{fict}$, assumed to be always equal to 1 rad. The LPV model used for LPV filter design depends affinely on nine scheduling parameters, $\rho$. The general form of the LPV model is given by Eq. (1), where the system matrices are given by $A(\rho) \in \mathbb{R}^{5 \times 5}$ and $B(\rho) \in \mathbb{R}^{4 \times 4}$ and $N = 9$.

The scheduling variables to be used in the LPV model are the following:

$$\rho = \begin{bmatrix} \bar{q}, \frac{\bar{q}}{V_T}, \frac{1}{V_T}, \gamma, C_{L_{max}} \frac{\bar{q}}{V_T}, \frac{\partial C_L}{\partial \delta_{el}}, \frac{\bar{q}}{V_T}, C_{D_{hach}} \frac{\bar{q}}{V_T}, \frac{\partial C_m}{\partial \delta_{el}}, \frac{\bar{q}}{V_T}, C_{m_{max}} \frac{\bar{q}}{V_T} \end{bmatrix}^T$$

This set of scheduling variables is formed by combining aircraft stability derivatives and physical variables (i.e., dynamic pressure $\bar{q}$, true airspeed $V_T$, and flight path angle $\gamma$). The term $C_{L_{max}}(\alpha, M)$ is the basic lift coefficient for the rigid airplane at the zero stabilizer angle in free air with the landing gear retracted; $(\partial C_L/\partial \delta_{el})(h_z, M)$ is the change in basic lift coefficient due to change in elevator; $C_{D_{hach}}(M, C_{2})$ is the Mach effect on drag coefficient; $(\partial C_m/\partial \delta_{el})(h_z, M)$ is the change in basic pitching moment coefficient due to change in elevator; and $C_{m_{max}}(\alpha, M)$ is the basic pitching moment coefficient for the rigid airplane at the zero stabilizer angle in free air with the landing gear retracted. All the scheduling variables depend nonlinearly, through lookup tables, on altitude $h_z$, wing angle of attack $\alpha_w$, defined as $\alpha_w = \alpha - 180/\pi + 2$ deg; and true airspeed $V_T$. The flight envelope described by the LPV model is based on these three parameters: $h_z \in [3000, 12000]$ m, $\alpha \in [-2, 10]$ $\pi/180$ rad, and $V_T \in [80, 300]$ m/s, which covers the up-and-away flight envelope used in Refs. 20 and 21 (see Table B1 for the scheduling variables limits). The scheduling variables should be measurable parameters and although it could be argued that for a real implementation some of the proposed parameters are not physically accessible it is always possible to use the lookup table descriptions and the available measurements of the altitude, angle of attack, and velocity to calculate these scheduling variables.

To validate the LPV model, open-loop time responses are obtained and compared to the transient response of the nonlinear model. Specifically, tests are performed to analyze and compare the short-period and phugoid characteristics of the models. Figure 1 shows open-loop time responses of the nonlinear system and the LPV model to an elevator pulse of 6 deg for 4 s. The simulation time is 100 s. To provide the correct thrust to excite the phugoid mode an engine model is included in the open-loop simulation. The engine model transforms engine pressure ratio (EPR) command inputs into thrust $T_n$ based on the true airspeed measurement. The trim flight condition used in this simulation is straight-level flight with angle of attack $\alpha = 0.0209$ rad, true airspeed $V_T = 241$ m/s, altitude $h_z = 9000$ m, $\dot{q} = 0$ rad/s, and $\theta = \alpha$ (i.e., flight path angle $\gamma = 0$ rad). This flight condition results in trim command inputs for the nonlinear model of EPR = 0.021 rad, $T_n = 39,439$ N, $\delta_e = 0.0348$ rad, and $\delta_h = -0.0094$ rad. The EPR and stabilizer deflection commands are held constant at the previous trim values during the open-loop simulation.

The phugoid or long-period mode is characterized by gradual changes in pitch angle, altitude, and velocity over long periods of time; these are clearly shown in the corresponding graphs in Fig. 1. The short-period dynamics are more important and are characterized for a short-period oscillation heavily damped affecting mainly angle of attack and pitch rate. The LPV model is an almost perfect approximation to the nonlinear model short period because there are no discernible differences in the corresponding graphs in Fig. 1. Additional flight conditions and maneuvers were tested yielding similar results, which are not included for brevity.

IV. Boeing 747-100/200 Longitudinal Linear Time-Invariant Controller

For closed-loop simulations, an LTI $H_\infty$ controller is obtained that is synthesized at the same equilibrium point at which the aircraft model is trimmed. In the subsequent closed-loop simulations the equilibrium point used to design the controller and initialize the models is given by an altitude of 7000 m and a true airspeed of 241 m/s. This section provides a brief description of the LTI control synthesis based on the controller presented in Ref. 23.

In the aforementioned reference, a reconfigurable LPV controller for the longitudinal motion of the Boeing 747-100/200 is presented. The LPV controller has the particularity of scheduling on true airspeed, altitude, and the elevator fault signal produced by an FDI filter. The basis of the reconfiguration is to use an alternative control in case the elevator surfaces suffer a malfunction. The alternative control is provided by the horizontal stabilizer, which results in a loss in performance (i.e., a reduced speed of response.
V. Fault Detection and Isolation Filter Design Using Linear Parameter-Varying Model

This section deals with the design, simulation, and analysis of a fault detection LPV filter used to detect elevator and thrust faults for the longitudinal motion of the Boeing 747-100/200. The filter approach relies on open-loop LPV models of the aircraft (see Sec. III). Realistically these filters are implemented in a closed loop; hence, simulations are performed with the LTI $H_\infty$ controller and the nonlinear model to ensure its validity. From theoretical results (see Refs. 24 and 25) it is known that when there is no model uncertainty the filter in closed loop can be obtained by multiplying the open-loop filter by the inverse of the sensitivity function (i.e., $F_{\text{open}}^{-1}$). The open-loop and closed-loop designs can be directly in the synthesis of the controller but the controller should be robust enough to handle noncritical faults.

The controller objectives are to achieve decoupled tracking of flight-path angle command $\gamma$ and velocity command $V_c$ with setting times of 15 and 45 s, respectively, with the elevator surface fully functional and the rejection of gust disturbances for the up-and-away flight envelope. Figure 2 shows the controller architecture. The corresponding weights are performance $W_p$, uncertainty $W_u$, command scaling $W_{\text{act}}$, noise $W_n$, ideal models $T_{\text{id}}$, engine, elevator, and stabilizer dynamic models are given in the aforementioned reference. The controller has five measurements available: flight-path angle $\gamma$ (rad), acceleration $V$ (m·s$^{-2}$), pitch angle $\theta$ (rad), pitch rate $q$ (rad/s), and velocity $V$ (m/s). Note that these inputs are different from those of the plant; the latter are manipulated before being fed to the controller. There are two control outputs: elevator deflection $\delta_{\text{el}}$ (rad) and thrust $T_n$ (N). It was mentioned before that the plant inputs included the two controller outputs and a stabilizer input, $\delta_{\text{st}}$ (rad). The latter is used for trim purposes and is held constant at the corresponding trim value for the entire simulation when implemented with the FDI filter. These controller outputs and stabilizer input are passed through first-order actuators before going to the plant: the elevator actuator dynamics are given by $act_e = 27/(s + 27)$ and the engine dynamics and stabilizer actuator by $act_{T_n} = act_{T_0} = 1/(2s + 1)$.

The FDI filter is tested during an aircraft maneuver. The LPV FDI filters designed for the longitudinal motion of the Boeing 747-100/200 aircraft are sensitive to elevator and throttle failure. The LPV FDI filter inputs are the aircraft outputs (e.g., $\gamma_c$, $V_T$, $\theta$, $h_c$) and the actuator outputs ($\delta_e$, $\delta_{\text{st}}$, $T_n$). The output of each detection filter is a diagnostic signal known as a residual: one for the elevator fault, $res_e$, and the other for the thrust fault, $res_{T_n}$, respectively. The LPV model including elevator and throttle failure can be described as

$$\dot{x}(t) = A(\rho)x(t) + B(\rho)u(t) + L_{\text{el}}(\rho)v_{\text{el}}(t) + L_{T}(\rho)v_{T}(t)$$

$$y(t) = Cx(t)$$

where

$$A(\rho) = A_0 + \rho_1 A_1 + \cdots + \rho_6 A_6$$

$$B(\rho) = B_0 + \rho_1 B_1 + \cdots + \rho_6 B_6$$

$$L_{\text{el}}(\rho) = \rho_{1} b_{\text{el,1}} + \rho_{2} b_{\text{el,6}} + \rho_{3} b_{\text{el,8}}$$

$$L_{T} = b_{T,0}$$

The elevator failure signature is parameter dependent because the direction of the elevator depends on parameters. The direction of the throttle failure does not depend on parameters. The $b_{\text{el}}$ is that column of the $B$ matrix that represents the elevator actuator direction and $b_{T}$ is the column of the $B$ matrix associated with throttle direction. The FDI filter is tested during an aircraft maneuver. The $\gamma$ command used in the simulations is a square wave, starting at 25 s and ending at 100 s and the velocity command is a step signal starting at time $t = 30$ s as seen in Fig. 4. The fault scenarios applied in the elevator channel and in the throttle channel and the commands can be seen in the residual plots of Fig. 5. The failures are modeled as an additive term in Eq. (26) corresponding to a loss in effectiveness of the control

![Fig. 2 \( H_\infty \) LTI controller interconnection.](image-url)
Fig. 3 Closed-loop implementation.

Fig. 4 Time responses, LPV model with faults: ---, command and ——, responses.

Fig. 5 Controller and FDI filter outputs, LPV model: ---, fault and ——, residual.
input channels. This means that the actuator effectiveness has been reduced to a constant value. In case of failures, the actuators are assumed to be able to work when faults have occurred. Although the actuator loses its effectiveness, the aircraft motion can be controlled with increased control action.

The simulation results of the LPV FDI filter for the case of the closed loop with the LPV model is shown in Fig. 4. It is observed that the controller guarantees the tracking performance despite the fault. Even though the command decoupling objective is achieved, the impact of the faults affects the responses of the controller. Figure 5 shows the control inputs and the outputs of the FDI filters. The first residual, $\delta_{e}$ residual, detects the elevator fault while the second diagnostic signal, the $T_n$ residual, is the throttle fault residual. The effect of the failures is decoupled and the residuals give an exact estimation of elevator and throttle fault. The impact of the flight-path angle command on the residuals is negligible.

Next, the situation is studied when the FDI filter is applied to the nonlinear longitudinal model, which represents the “true” system. Figure 6 shows the simulation results of the LPV FDI filter for the case of the closed-loop nonlinear system. The residual outputs for the nonlinear simulation are shown in Fig. 7.

The fault scenarios are the same as before. The effect of the failures is decoupled and the FDI filters tell us the magnitude of the failures and also at what time the failures have occurred in the system. In the case of the nonlinear Boeing 747 aircraft closed loop, the fault estimation error is larger than for the LPV model case. Moreover, there are transients at 25 and 100 s in the elevator fault residual. The reason for these transients is that the LPV FDI filter is simulated using the square wave $\gamma$ command: during climbing mode the trim conditions are changing, thereby resulting in a transient signal at the residual outputs. This result is a function of the difference between the LPV and nonlinear model, which is illustrated best in the $\theta$ variable at 20 s into the simulation in Figs. 4 and 6. However, when the $\gamma$ command goes back to zero, indicating that the aircraft has reached its commanded altitude, and the trim conditions no longer change, the fault residuals of FDI filter show only the effective faults. Unfortunately, if the trim conditions change in a long time duration (e.g., when we use a long $\gamma$ command for takeoff) then a transient fault signal may appear for an extended period of time. Therefore, knowledge of the trim value would need to be accounted for in the current formulation of the LPV FDI filter to reduce the potential for false alarms.

VI. Conclusions

In this paper, a LPV FDI filter design based on the extension of the fundamental problem of residual generation concepts elaborated for LTI systems has been presented through the application of the
LPV longitudinal model of a Boeing 747-100/200. The LPV FDI filter used in this paper is sensitive to elevator and throttle failure. The LPV FDI filter is designed for an open-loop LPV model of the aircraft and is applied to the full nonlinear Boeing 747 closed-loop aircraft. In case of nonlinear closed-loop simulation, the impact of the flight-path angle command appears in the residuals as transients, but this does not destroy the reliable operation of the LPV detection filter. For steady-state trim conditions the LPV FDI filter performs very well, accurately isolating as well as estimating the magnitude of the faults.

Appendix A: Example of LPV Detection Filter Design Procedure

We consider a simple example in which the matrices are given by

\[ A(\rho) = A_0 + \rho(t)A_1 \]

\[ B = L = [L_1 \ L_2] = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \] (A1)

Given \( A, B, C, L_1, \) and \( L_2 \) (in the present example we use \( A = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, B = 0, C = 0.5 \)) the design process goes as follows. The subspaces \( W^+_i \) and \( S^+_i \) containing \( L_i \) (with \( i = 1, 2 \)) are determined first using (\( C, A \))-invariant subspace algorithm (CAISA) and UOSA, respectively.

Since \( \ker C = \text{span}(0 \ 1)^T \) and \( L_1, L_2 \) are not in \( \ker C \), using CAISA immediately obtains \( W^+_i = L_i, i = 1, 2 \). Computation of the UOS \( S^+_i \) is as follows. The (determination of \( S^+_i \) is identical.) Using UOSA we get

\[ S_1 = W^+_1 + (A_0^{-1}W^+_2 \cap \ker C) \cap (A_1^{-1}W^+_2 \cap \ker C) \]

(A2)

It can be seen that one has to compute subspace additions, intersections, and inverse images. The latter can be computed using the following result.

**Proposition A1:** Let \( A : \mathbb{R}^n \to \mathbb{R}^n, X \subset \mathbb{R}^n \) and \( \text{Im} X = X \); then

\[ A^{-1}X = \ker X A \]

(A3)

where \( X^\perp \) is a maximum solution (a solution with maximum rank) of \( X^\perp X = 0 \).

Let \( W = [0 \ 0 \ 1 \ 0]^T \); then for a matrix satisfying \( W^+ A_0 = 0 \) we get

\[ W^+ = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \]

resulting in \( (A_0^{-1}W^+_2 \cap \ker C) = \text{span}(1 \ -0.5)^T \) and \( (A_1^{-1}W^+_2 \cap \ker C) = \ker C \).

Using similar arguments one can conclude that \( (A_1^{-1}W^+_2 \cap \ker C) = \ker C \) and \( S_1^+ = W^+_2 \); that is,

\[ S_1^+ = \ker\begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \]

(A4)

Simple calculation shows that \( S_1^+ = W^+_1 = \ker\begin{bmatrix} 0 & 1 \ 0 & 1 \end{bmatrix}^T \).

Having the minimal parameter-varying UOSs containing \( L_2 \) we factorize the state space with this \( S_2^+ \) subspace and only look at the factor space to prevent any effect of \( L_2 \) on the observation of \( L_1 \). This is done via a \( P_i \) projection matrix whose kernel is the \( S_i^+ \) subspace. Choosing a basis in \( S_i^+ \) and considering the basis vectors as rows we can get suitable \( P_i \) matrices:

\[ P_1 = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad P_2 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \]

(A5)

The next step is to compute the gains \( D_0(\rho), D_1(\rho) \) that make \( S_i^+ \); \( i = 1, 2 \) respectively, \( (C, A) \)-invariant:

\[ \begin{bmatrix} A(\rho) + D_0(\rho) C \end{bmatrix} S_i^+ \subset S_i^+, \quad i = 1, 2 \] (A6)

where

\[ D_0(\rho) = D_0^{00} + \rho D_0^{01} \]

(A7)

Denote by \( S_i \) the matrix with columns forming a basis of \( S_i^+ \). Then using the preceding formulas we get \( S_i^+(A_j + D_{0j} C) = 0, i = 1, 2, j = 0, 1 \).

In the example we find that for \( i = 1 \) the element \( D_{01}(1, 2) = 0, D_{00}(1, 2) = 0 \), and all others are arbitrary. One possible choice for the remaining elements is to specify \( A_j + D_{0j} C = 0, j = 0, 1 \). This choice results in the following gain matrices:

\[ D_0(\rho) = \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix}, \quad D_1(\rho) = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + \rho \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \]

(A8)

Having the parameter-varying \( D(\rho) \) calculated we need the output mixing \( H \) for which \( \ker H C = \ker C + S_i^+ \), \( i = 1, 2 \). Let \( V_i \) be a matrix for which \( \text{Im} V_i = \ker C + S_i^+ \) and let the columns of \( V_i \) be based in \( \ker V_i^T \). Then for \( H_i \) we have

\[ C^T H_i^T = V_i \]

(A9)

It was supposed that \( C \) had full row rank; thus, a possible choice for \( H \) is \( H_i = [(C_i^T)^{-1} V_i] \). In our case,

\[ V_1 = [0, 1, 0]^T, \quad V_2 = [1, 0, 0]^T \]

(A10)

\[ H_1 = [0 \ 1], \quad H_2 = [1 \ 0] \]

(A11)

In the example, we find that

\[ M_1 = [1, 0], \quad M_2 = 1 \]

(A12)

The next step is to compute the restriction of the map \( A_0(\rho) = [A(\rho) + D_0(\rho) C]]X/S^+ \) using the formulas \( P_i (A_j + D_{0j} C) P_i^T \), \( i = 1, 2, j = 0, 1 \).

Computation of the stabilizing gain \( D_1(\rho) = D_{10} + \rho D_{11} \), \( i = 1, 2 \), will be performed using LMIs. For simplicity the index \( i \) will be omitted, but the subsequent LMI has to be solved for both detection filters.

We are looking for a positive definite \( X \) matrix and \( D_{10}, D_{11} \) for which

\[ X > 0 \]

\[ [A_0(\rho) + D_1(\rho) M X + X [A_0(\rho) + D_1(\rho) M] < 0, \quad \forall \rho \in \mathcal{P} \]

(A13)

where \( D_1(\rho) = D_{10} + \rho D_{11} \). It can be proved that for affine LPV systems the LMIs have to be solved only for the vertices of \( \mathcal{P} \). Introducing the new variables

\[ K(\rho) := XD_1(\rho) = XD_{10} + \rho XD_{11} := K_0 + \rho K_1 \]

(A14)

the LMI variables are \( P \), which is symmetric positive definite and \( K = [K_0, K_1] \), which is rectangular. Denote

\[ M(\rho) = \begin{bmatrix} M \\ \rho M \end{bmatrix} \]

(A15)

Now the LMI to be solved is

\[ A^T(\rho) X + X A(\rho) + M^T(\rho) K^T + K M(\rho) < 0 \]

(A16)

for all \( \rho \in \mathcal{P}_0 \), which is a feasibility problem.
From the solution we obtain
\[ D^1_1(\rho) = \begin{bmatrix} 0.5593 \\ -1.0932 \end{bmatrix} + \rho \begin{bmatrix} -1 \\ -1 \end{bmatrix}, \quad D^1_2(\rho) = -1.5 \] (A17)

Having the gains \( D^1_1(\rho), D^1_2(\rho) \) and the matrices \( H_i, P_i \) one can compute the FDI matrices \( N_i, G_i, F_i, i = 1, 2 \). The complete filters in the example are
\[ w_1(t) = \begin{bmatrix} 0.5593 \\ -1.0932 \end{bmatrix} + \rho \begin{bmatrix} -1 \\ -1 \end{bmatrix}, y(t) + \begin{bmatrix} 0 \\ 0 \end{bmatrix} \cdot u(t) \]
\[ r_1(t) = [1 \ 0] \cdot w_1(t) - [1 \ 0] \cdot y(t) \]
\[ w_2(t) = -3.5w_2(t) - [1.5 \ 0] \cdot y(t) + [1 \ 0] \cdot u(t) \]
\[ r_2(t) = w_2(t) - [1 \ 0]y(t) \] (A18)

Appendix B: Example of Nonlinear State Transformation into Affine LPV Model Format

In this Appendix an example of the transformation from a nonlinear state equation to the required affine LPV model is shown in detail. The selected state is the angle of attack and the full nonlinear equation given in Eq. (B1) is obtained from Ref. 20:
\[ \alpha = [1 - (\bar{q}S\bar{c}/2mV^2)(1.45 - 1.8\alpha_0)(\partial C_L/\partial q)]q + \bar{q}(S/mV_T)K_{\alpha}(\partial C_L/\partial \delta_0)\delta_0 + \bar{q}(S/mV_T, S)\gamma \cdot Tn + (1/SV_{TAS})(sx_0 + c_o\delta_0)\bar{g} - \bar{q}(S/mV_{TAS})C_{\alpha,TAS} \] (B1)

We are interested in an affine LPV representation of the state equation with respect to the scheduling variables, \( \rho_i \), and linear on the states, \( x(t) = [\alpha, q, V_T, \theta, \delta] \), and control inputs, \( u(t) = [\delta_0, \delta_3, Tn] \):
\[ \dot{\alpha} = A(\rho)x(t) + B(\rho)u(t) \] (B2)

where \( A(\rho) \) and \( B(\rho) \) are given by Eq. (1).

The requirement of linear dependency on the states and the control inputs is easily verified because Eq. (B1) is already written by grouping terms together based on their linear dependency. It is observed that all equation terms except for the last two fulfill this linear dependency requirement. The easiest approach to solve this problem is to introduce a fictitious input (e.g., \( \delta_{fic} \)) that multiplies the last two terms and enables Eq. (B1) to be rewritten in the format of Eq. (B2). The control input vector is given by \( \vec{u}(t) = [\delta_0, \delta_3, Tn, \delta_{fic}] \). The fictitious input is held constant at 1 rad.

Table B1 provides the minimum and maximum values for the nine scheduling parameters for the longitudinal LPV model of the Boeing 747-100/200 aircraft.

Several assumptions were made after analyzing average values of the equation terms in the face of scheduling parameters, states, and control inputs variations:
\[ a_1 \approx 1 - (\bar{q}S\bar{c}/2mV^2)(1.45 - 1.8\alpha_0)(\partial C_L/\partial q) \]
\[ a_2 \approx -(S/m)K_{\alpha}, \quad a_3 \approx -(4/m)(sx_0 + 0.0436c_o) \]
\[ a_4 \approx (sx_0 + c_o\delta_0)g, \quad a_5 \approx -(S/m) \]
where \( a_i \) represent constants values. Hence, Eq. (B1) is rewritten as an affine LPV model:
\[ \dot{\alpha} = a_1q + a_2p_0\delta_0 + a_3p_3Tn + a_4p_0\delta_0 + a_5p_3\delta_0 \]
\[ = [0 \ 1 \ 0 \ 0 \ 0]x(t) + [a_2p_0 \ 0 \ a_3p_3 \ (a_1p_0 + a_5p_3)]\vec{u}(t) \] (B3)

Table B1: Scheduling parameters table

<table>
<thead>
<tr>
<th>Number</th>
<th>Parameter</th>
<th>Unit</th>
<th>Minimum val.</th>
<th>Maximum val.</th>
</tr>
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<tbody>
<tr>
<td>( \rho_1 )</td>
<td>( \bar{q} )</td>
<td>N/m²</td>
<td>4.1039e+03</td>
<td>4.3577e+04</td>
</tr>
<tr>
<td>( \rho_2 )</td>
<td>( \bar{q} )</td>
<td>N/s³/m</td>
<td>2.7360e+01</td>
<td>1.5563e+02</td>
</tr>
<tr>
<td>( \rho_3 )</td>
<td>( \bar{q} )</td>
<td>s/m</td>
<td>3.5714e-03</td>
<td>6.6667e-03</td>
</tr>
<tr>
<td>( \rho_4 )</td>
<td>( \bar{q} )</td>
<td>rad</td>
<td>-3.4907e-01</td>
<td>3.4907e-01</td>
</tr>
<tr>
<td>( \rho_5 )</td>
<td>( C_{L_{\text{bias}}} )</td>
<td>N/s³/m</td>
<td>5.3889e-01</td>
<td>1.7981e+02</td>
</tr>
<tr>
<td>( \rho_6 )</td>
<td>( \partial C_L/\partial \bar{q} )</td>
<td>N/s³/m</td>
<td>1.9611e-01</td>
<td>4.0034e-01</td>
</tr>
<tr>
<td>( \rho_7 )</td>
<td>( C_{D_{\text{bias}}} )</td>
<td>N/m²</td>
<td>7.3702e+01</td>
<td>1.3503e+03</td>
</tr>
<tr>
<td>( \rho_8 )</td>
<td>( \partial C_D/\partial \bar{q} )</td>
<td>N/m²</td>
<td>-4.4844e+02</td>
<td>-1.1638e+02</td>
</tr>
<tr>
<td>( \rho_9 )</td>
<td>( C_{\text{wind}} )</td>
<td>N/m²</td>
<td>-7.0123e+03</td>
<td>4.3577e+03</td>
</tr>
</tbody>
</table>

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References