Robust Fault-Tolerant Control approach for a Takagi-Sugeno-Linear Parameter Varying System applied to Aircraft Variable Geometries Systems

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ABSTRACT

In this paper we propose a Robust Fault-Tolerant Control approach, based on Takagi-Sugeno-Linear Parameter system formalism. The proposed FTC approach is applied to Aircraft Variable Geometries (AVG) to ensure a permanent availability of control signals in spite of occurrence of an unexpected fault or complete loss of the sensor during the operation, by designing a virtual sensor based on robust online estimation. The AVG-FTC is based on a hierarchical cascade scheme where offline closed-loop identification is first used to elaborate local linear state space models, after that a multi-model observer is used to build a virtual sensor. Finally, a Neural Extended Kalman Filter (NEKF) is added to circumvent online model accuracy problems. The validation proposed in this paper is done through performance and stability analysis of the AVG-FTC approach and it is applied to two linear parameter varying subsystems: Variable Stator Vane (VSV) and Fuel Metering Valve (FMV). The proposed method is based on Lyapunov theory and LMI optimization approach. Simulations on a certificate flight engine simulator, describing the overall behaviour of jet engine system for a given flight envelope point are presented.

1. INTRODUCTION

In the modern industrial process, costs reductions receive a great interest during the designing phases. Indeed, the current highly competitive economic context prompts the industrials to make more effort, and carry out researches in this path. The Aircraft industry and more particular the Jet Engine industry has already integrated the idea of low-cost during the design, whether it is for production, maintenance or operation costs. One way is to reduce the physical redundancy of some sensors and design new control architecture with sensors containing one single-channel of measurement.

The challenge addressed in the control architecture using sensors containing one single-channel of measurement is to guarantee the availability of the measurement in case of partial or total loss of the sensor during the operation. We propose in this paper a Fault Tolerant Control (FTC) strategy based on an analytical redundancy.

FTC attends to be an integral part of any Prognostic and Health Management (PHM) applications. FTC has the following characteristics: (i) the ability to accommodate automatically faults in components, actuators and sensors, (ii) the ability to keep the overall system stable and acceptable performance in the case of failure. Hence the main task to be tackled in achieving fault-tolerance is the design of a controller with a suitable structure to maintain the overall system stability and acceptable performance. FTC may be called upon to improve the system reliability, maintainability and survivability. Nowadays, FTC has gained in popularity among industrial and academic researchers. (Blanke et al. 2001; Mahmoud et al. 2003; Naik et al. 2012; Nazari et al. 2013; Patton et al. 1989; Patton 1997; Zhang and Jiang 2002; Zhang and Jiang 2008; Zhou and Frank 1998)

The AVG-FTC approach proposed by (Souami et al. 2014b; Souami et al. 2014a) is applied to the Variable Geometries’ closed-loop actuations of a jet engine: Variable Stator Vane (VSV) and Fuel Metering Valve (FMV). It aims at ensuring the availability of the Variable Geometries’ sensor feedback
signal in spite of occurrence of faults or total loss of the sensor signal during the operation.

The VSV is a subsystem controlling the amount of airflow through the High Pressure Compressor (HPC), allowing optimum compressor performance. This control of airflow prevents the engine from stalling. The FMV subsystem aims at controlling the fuel flow, providing the relevant fuel to the combustion chamber, and also but also to actuate the other variable geometries.

This FTC approach, depicted in Figure 1, is built according to the following hierarchical cascaded algorithms: (i) The systems FMV and VSV are locally identified using closed loop identification methods (Bloc a of the Figure 1). These identifications provide local LTI models. From these local LTI models, we use LPV framework and Takagi-Sugeno formalism to approximate the non-linear behaviour of the FMV and VSV systems in different operation and flight envelope points. (ii) Knowing the non-linear model of the FMV and VSV systems, we build a virtual sensor for LPV systems to compensate the fault sensor (Figure 1d) based on Takagi-Sugeno-LPV observer (Bloc c of the Figure 1). (iii) An NEKF is added to circumvent online model accuracy problems (Bloc e of the Figure 1).

In this paper, we propose to use a mathematical framework for the validation of the AVG-FTC approach in terms of achievement of the performance and stability goals required in the specification in both transient and steady conditions. The proposed method is based on Lyapunov theory and LMI optimization approach. To show its effectiveness, simulations on an actual flight engine simulator have been conducted and results in the case of a total loss of the sensor signal are presented.

This paper is organized as follows: First the AVG-FTC is briefly introduced. Then a mathematical formalism is proposed to analyze the validation of this approach. Finally a series of simulations are displayed in order to show the stability, the robustness and the performance of the approach in transient and steady conditions, running throughout several operating points for a given flight envelope point, according to specification requirements.

2. A VALIDATION OF AVG-FTC APPROACH

In a jet engine, there are Variable Geometries, which affect each other. After an influence study, we selected a VBV position (Variable Bleed Valve) reflecting the opening of a valve to remove the excess of the air between the Low and High compressor, which can be the origin of stalling and thus a serious damage of the Low compressor blades. We have exploited these couplings between these Variable Geometries in order to build a multi-model state observer of MIMO systems: VSV-VBV and FMV-VBV (Bloc b of the Figure 1).

Let us consider for example the FMV-VBV MIMO state space representation:

$$\begin{align*}
\dot{x}_{\text{MIMO}}(k+1) &= A_{\text{MIMO}}x_{\text{MIMO}}(k) + B_{\text{MIMO}}u_{\text{MIMO}}(k) \\
y_{\text{MIMO}}(k) &= C_{\text{MIMO}}x_{\text{MIMO}}(k) + D_{\text{MIMO}}u_{\text{MIMO}}(k)
\end{align*}$$

where:

$$x_{\text{MIMO}}(k) = \begin{bmatrix} X_1 \ X_2 \ X_3 \end{bmatrix}_R \in \mathbb{R}^3$$

is the state vector,

$$y_{\text{MIMO}}(k) = \begin{bmatrix} X_{\text{FMV}} \ X_{\text{VBV}} \end{bmatrix}_R \in \mathbb{R}^2$$

is the output vector, where, $X_{\text{FMV}}$ and $X_{\text{VBV}}$ are respectively the FMV and the VBV position and $u_{\text{MIMO}}(k) = (U_{\text{FMV}} \ U_{\text{VBV}})_R \in \mathbb{R}^2$ is the control input where $U_{\text{FMV}}$ and $U_{\text{VBV}}$ are respectively the FMV and the VBV control current.

The off-line identification of (1) allows to bring out the matrix $A_{\text{MIMO}}, B_{\text{MIMO}}, C_{\text{MIMO}}, D_{\text{MIMO}}$ using the Prediction error Method Algorithm (PEM).

In parallel, we build the same way the VSV-VBV MIMO model.

It is to be noticed that the Variable Geometries systems are time varying systems that depend on two varying parameters: the first parameters is the position of the throttle, $\theta(s)$, which determines the operating point; the second parameters is a time varying flight parameter vector $\theta(k)$ including the aircraft velocity and altitude. This flight parameter vector determines the envelope flight point.

To cope with this characteristic, we have developed a double time varying modeling where a first model based on Takagi-Sugeno will deal with the variation of the $\theta(s)$ and a second using a classical LPV model for the time varying vector $\theta(k)$.

Let us consider the preceding Variable Geometries systems for a given flight envelope point. In order to model it we use here, a Takagi-Sugeno formalism which is an interpolation of local linear subsystem using a convex transformation. There exists extensive literature that deals with Takagi-Sugeno formalism and its applications: (i) model and design diagnostic strategy (Akhenak 2004), (ii) develop control’s laws, (iii) study the stability of non-linear systems (Bezzaoucha et al. 2013a).

From the local linear subsystem identified for each operating point, we write the overall non-linear system describing the behaviour of the FMV and VSV for a set of operating point:
\[
\begin{aligned}
\chi(k + 1) &= \sum_{i=1}^{n} \sigma_i(\xi(k)) \left( A_i \chi(k) + B_i u(k) \right) \\
y(k) &= \sum_{i=1}^{n} \sigma_i(\xi(k)) \left( C_i \chi(k) + D_i u(k) \right)
\end{aligned}
\]

with:
\[
\begin{aligned}
\sum_{i=1}^{n} \sigma_i(\xi(k)) &= 1 \\
0 &\leq \sigma_i(\xi(k)) \leq 1 \quad i = 1 \ldots n
\end{aligned}
\]

where:
\( \chi(k) \in \mathbb{R}^3 \) is the overall system state vector, \( y(k) \in \mathbb{R} \) is the overall system output and \( u(k) \in \mathbb{R} \) the control input, and \( n \) number of local subsystems.

The overall non-linear system is an aggregation of the local linear subsystems by a weighting sum. Thereby, the linearity is transferred from the subsystems to the weighting functions. \( \sigma_i(\xi(k)) \) \( i = 1 \ldots n \), satisfying the convex sum property.

The purpose of the Takagi-Sugeno formalism is to use the linear framework to extrapolate the overall non-linear system using the convex sum (3). The weighting functions \( \sigma_i(\xi(k)) \) depend on a decision variable \( \xi(k) \). In our application, \( \xi(k) \) allows us to determine the operating point.

We obtain a Takagi-Sugeno representation that guarantees a smooth transfer from a local subsystem to another (Akhmen et al. 2007; Bezzaoucha et al. 2013b). This representation has not only the advantage to be mathematically equivalent to the overall non-linear system, but also to be easier to handle, with a set of \( \{A_i, B_i, C_i, D_i\} \) representing the \( i \)-th LTI constant parameters model.

Now for the entire envelope flight, we vary the parameter \( \theta(k) \) and therefore the previous LTI model \( \{A_i, B_i, C_i, D_i\} \) becomes LPV \( \{A_i(\theta(k)), B_i(\theta(k)), C_i(\theta(k)), D_i(\theta(k))\} \) depending on time varying flight parameter vector \( \theta \).

The system (2) becomes for the entire envelope flight as follow:
\[
\begin{aligned}
\chi(k + 1) &= \sum_{i=1}^{n} \sigma_i(\xi(k)) \left( \xi(\theta(k)) \right) \left( A_i(\theta(k)) \chi(k) + B_i(\theta(k)) u(k) \right) \\
y(k) &= \sum_{i=1}^{n} \sigma_i(\xi(k)) \left( \xi(\theta(k)) \right) \left( C_i(\theta(k)) \chi(k) + D_i(\theta(k)) u(k) \right)
\end{aligned}
\]

with:
\[
\sum_{i=1}^{n} \sigma_i(\xi(k)) = 1
\]

Equation (4) shows that the non-linearity of the overall system is transferred into the weighting function \( \sigma \) and the non-linear time varying function \( \theta \) representing the variation of the velocity and the altitude of the aircraft.

(Fujimori and Ljung 2006) propose a method to identify an aircraft system, modeled by a LPV system. This method is based on a polytopic model that approximates the LPV system, where the parameter function \( \theta(k) \) is assumed to be known. Let us consider the Takagi-Sugeno-LPV system (4).

We propose a weighting function respecting the condition (5)
\[
\sigma_i(\xi(\theta(k))) = \frac{\omega_i(\xi(\theta(k)))}{\sum_{i=1}^{n} \omega_i(\xi(\theta(k)))}
\]

with:
\[
\omega_i(\xi(\theta(k))) = \exp \left( -\frac{\|\xi(\theta(k)) - \beta_i(\theta(k))\|^2}{a_i(\theta(k))} \right)
\]

Thereby we obtain a Multi-model-Takagi-Sugeno-LPV representation approximating the non-linear system of the FMV and VSV for the entire flight envelope.

We need now to identify the parameters \( \sigma_i(\theta), \beta_i(\theta) \) to build the multi-model system. Thereby, we introduce \( \delta_{\theta_i} = [\beta_i(\theta) \ \sigma_i(\theta)]^T \) the parameter vector to be identified \( \theta(k) \).

To identify the parameter \( \delta \), we solve an optimization problem minimizing the function cost \( J_n(\delta) \) defined by a quadratic criterion
\[
J_n(\delta) = \frac{\sum_{i=1}^{n} \gamma_{\text{meas}}(k) - \gamma_{\text{est}}(k))^2}{\sum_{i=1}^{n} \gamma_{\text{est}}(k) ^2}
\]

with \( \gamma_{\text{meas}}(k) \) output of a healthy sensor and \( \gamma_{\text{est}}(k) \) the output of the following system
\[
\begin{aligned}
\dot{\hat{\chi}}_i(k + 1) &= \sigma_i(\xi(\theta(k))) \left( A_i(\theta(k)) \hat{\chi}_i(k) + B_i(\theta(k)) u(k) \right) \\
\end{aligned}
\]

where \( \hat{\chi}_i(k) \) is the off-line local estimated state using a Luenberger observer.

The solution of optimization problem (9) allows us to identify the overall behaviour of the system for several operating points and the entire flight envelope.

From this identification, we are able to build a Takagi-Sugeno-LPV model as written in (4), and therefore propose an FTC strategy based on Multi-Model-Takagi-Sugeno LPV observer.

For certification reasons, we are not allowed to return online the controller. To cope this constraint, we propose a Fault Tolerant Control without changing the controller. (Montes de Oca and Puig 2010; Montes de Oca et al. 2012; Montes de Oca et al. 2008; Nazari et al. 2013; Richter et al. 2011) propose a FTC without changing the controller approach for LPV system based on virtual sensor (Figure 2).

In general, FTC approach using virtual sensor supposes that the measurement is available i.e. it deals only with a partial loss of the sensor. Here in this work, we treat a case of a complete loss of the FMV and VSV sensor. In this work, we
treat the case of total loss of sensor feedback signal. Thus, we propose once a sensor failure detected to switch on an analytical feedback signal provided by the MIMO FMV and VSV model (Figure 2).

This MIMO FMV and VSV model has the inconvenient to be inaccurate in the transient phases. The MIMO modeling uncertainties can have a negative effect on the stability of the overall FMV and VSV systems. To cope with this case, we propose to use a specific virtual sensor which aims at estimating and compensating these uncertainties that we consider here as "sensor fault". Indeed, the virtual sensor contains a Multi-Model observer based on LMIs constrains, aiming to estimate in real time, faults of a FMV and VSV estimation.

Figure 2. Virtual sensor diagram for failed sensor

Let us consider a following subsystem with a faulty sensor for a given operating point (the -th operating point):

\[
\begin{aligned}
\dot{x}_i(k+1) &= A_i(\hat{\theta}(k)) \dot{x}_i(k) + B_i(\hat{\theta}(k)) u(k) \\
y_{f_i}(k) &= C_{f_i}(\hat{\theta}(k)) x_i(t) + D_i(\hat{\theta}(k)) u(k)
\end{aligned}
\]  

(11)

\[\text{with } C_{f_i} \text{ output subsystem matrix including the fault.}\]

The virtual sensor applied to LPV system can be written as following:

\[
\begin{aligned}
\dot{\hat{x}}_i(k+1) &= \sum_{i=1}^{n} \hat{\Delta}_i(\hat{\theta}(k)) \left( A_i(\hat{\theta}(k)) \hat{x}_i(k) + B_i(\hat{\theta}(k)) u(k) \right) \\
+ & B_i(\hat{\theta}(k)) u(k) + L_{v_i}(\hat{\theta}(k)) \left( \hat{y}_v(k) - y_f(k) \right) \\
\hat{y}_v(k) &= \sum_{i=1}^{n} \hat{\Delta}_i(\hat{\theta}(k)) \left( A_i(\hat{\theta}(k)) \hat{x}_i(k) + C_{f_i}(\hat{\theta}(k)) \hat{x}_v(k) + D_i(\hat{\theta}(k)) u(k) \right)
\end{aligned}
\]  

(12)

\[\text{with } x_i(t) \text{ the state vector of the virtual sensor state space and } L_{v_i} \text{ the multi-model Takagi-Sugeno-LPV observer gain for the -th operating point , and } \hat{\Delta}_i(\hat{\theta}(k)) \text{ solution of the optimization problem (9).}\]

De Oca et al. (2010) define the reconfiguration coefficient \( R \):

\[
R(\hat{\theta}(k)) = C_{i}(\hat{\theta}(k)) C_{f_i}(\hat{\theta}(k))^T \left( C_{f_i}(\hat{\theta}(k)) C_{f_i}(\hat{\theta}(k))^T \right)^{-1}
\]  

(13)

Thereby, we obtain the output corrective matrix and output signal:

\[
C_{\Delta_i}(\hat{\theta}(k)) = C_{i}(\hat{\theta}(k)) - R(\hat{\theta}(k)) C_{f_i}(\hat{\theta}(k))
\]  

(14)

\[
y_{\Delta_i}(\hat{\theta}(k)) = C_{\Delta_i}(\hat{\theta}(k)) \hat{x}_v(k)
\]  

(15)

Thereby, the corrected output signal is defined as:

\[
y_v(k) = P(\hat{\theta}(k)) y_f(k) + y_{\Delta_i}(\hat{\theta}(k))
\]  

(16)

From what has been presented above, it's evident that robustness against modelling errors and disturbances will be a crucial issue. Therefore, we propose here to use a Neural Extended Kalman Filter (NEKF) to circumvent these modelling errors that results from model inaccuracy (Souami et al. 2014b; Souami et al. 2014a). Neural Extended Kalman Filter (Kramer and Stubberud 2008; Stubberud et al. 1995; Stubberud 2006) is a robust and adaptive state estimator, with an approximate knowledge of the state space representation, or the physical equations describing the behaviour of the system. This robust estimation method is often used for the complex system where a simplification is due to the embeddability constraint.

We propose to use an adaptive robust method, which consist of readjusting, in real time, the parameter of the state-space representation in order to guarantee the robustness of estimation against modelling errors (Figure 3).

Let us consider our non-linear state space representation:

\[
\begin{aligned}
\dot{x}_v(k+1) &= \tilde{f}(\hat{\theta}(k), \hat{x}_v(k), u(k)) + r(k) \\
y_f(k) &= C_{f_i}(\hat{\theta}(k)) \hat{x}_v(k) + q(k)
\end{aligned}
\]  

(17)

\[\tilde{f}(\hat{\theta}(k))\] is a nonlinear function representing the real system in operation for the -th operating point. It depends on the flight envelope parameter \(\hat{\theta}(k)\). This function is not available to be embedded, moreover, the complexity of the real system make it non-embeddable for a real time application. Thus, we approximate it by an off-line closed loop experimental identification providing a linear function \( \hat{f}(\hat{\theta}(k)) \), which is added to an on board learned neural network to compensate the approximation errors that results from the closed loop experimental identification, approaching thereby the physical behaviour of the system during the operation (Kramer and Stubberud 2008; Stubberud et al. 1995; Stubberud 2006).

We consider the approximation errors as model uncertainties.

Let us consider the system in the -th operating point, modeled by the -th LPV local subsystems \( \{A_i(\hat{\theta}(k)), B_i(\hat{\theta}(k)), C_{f_i}(\hat{\theta}(k)), D_i(\hat{\theta}(k))\} \), with \( D_i(\hat{\theta}(k)) \) a null matrix.
\[
\mathbf{f}(\mathbf{x}_k) = f(\mathbf{x}_k, u_k) + \mathbf{NN}(\mathbf{x}_k, \mathbf{u}_k, \mathbf{y}_k, \mathbf{u}_k)
\]
\[
K_i = P(k|k-1)C_{r_i} (\mathbf{h}(k))
\]
\[
\hat{x}_i(k|k-1) = \hat{x}_i(k|k-1) + K_i(k) (y_f(k) - C_{r_i} (\mathbf{h}(k)) \hat{x}_i(k|k-1))
\]
\[
P(k|k) = \left( I - K_i(k) C_{r_i}(\mathbf{h}(k)) \right) P(k|k-1)
\]
\[
\hat{x}_i(k+1|k) = \mathbf{f}(\mathbf{h}(k), u(k))
\]
\[
\hat{y}_f(k) = C_{r_i}(\mathbf{h}(k)) \hat{x}_i(k+1|k)
\]
\[
P(k+1|k) = \left( \frac{\partial \mathbf{f}(\mathbf{h}(k))}{\partial \hat{x}_i(k|k)} \right) P(k|k) + Q(k)
\]

where: \(K_i\) is the Kalman filter gain, \(Q\) is the covariance matrix of the measurement noise, \(R\) is the covariance matrix of the process noise, \(P\) is the covariance matrix of state estimation error, \(\mathbf{f}(\mathbf{h}(k), \mathbf{u}(k))\) is the prediction function of the state, \(L_{r_i}\) is the gain for the stability multi-observer Takagi-Sugeno-LPV.

Now, we have to pay attention to the stability of the overall system in transient and steady conditions:

We define a new state vector, which a concatenation of state vector of the system and the adjustable parameters of the neural network and we note \(A_i(\mathbf{h}(k)) = \frac{\partial \mathbf{f}(\mathbf{h}(k), \mathbf{x}_k, \mathbf{u}_k, \mathbf{y}_k, \mathbf{u}_k)}{\partial \hat{x}_i(k|k)}\)

\[
\mathbf{\bar{x}}(k) = \begin{pmatrix} \mathbf{x}_k(k) \\ \omega_k(k) \end{pmatrix}
\]
\[
\mathbf{\hat{x}}(k+1|k) = \begin{pmatrix} \hat{x}_i(k+1|k) \\ \hat{\omega}_i(k+1|k) \end{pmatrix} = \begin{pmatrix} A_i(\mathbf{h}(k)) + \frac{\partial \mathbf{NN}}{\partial \hat{x}_i(k|k)} \left( \frac{\partial \mathbf{NN}}{\partial \omega_i(k|k)} \right) \hat{x}_i(k|k) \\ L_{r_i}(\mathbf{h}(k)) \end{pmatrix}
\]

\[
\text{(21)}
\]

\[
\mathbf{y}_f(k) - C_{r_i} (\mathbf{h}(k)) \hat{x}_i(k|k)
\]

\[
\text{(22)}
\]

\[
\text{Figure 3. Virtual sensor with NEKF diagram for failed sensor}
\]

The NEKF as presented above has three advantages: (i) Adaptability to the real context during operation. (ii) Robustness to modelling uncertainties. (iii) Stability guarantee. Indeed, the adaptability and the robustness are ensured by: the adaptive matrix \(A_i(\mathbf{h}(k))\) which is adjusted in real time by the partial differential of the neural network on the state vector and the on board up-date of the adjustable parameters of neural network. The stability analysis and the observer synthesis are based on Lyapunov theory by minimising \(L_2\)-gain under LMI constraints.
The stability of \( e(k) \) depends on the choice of the gain observer \( L_{vi}(\hat{\theta}(k)) \). Therefore, the system is stable, if there is a positive definite Lyapunov function such as \( V(k+1) - V(k) < 0 \).

We apply a flight maneuverer corresponding to different throttle level positions imposed by the pilot during the flight, with a given environment condition defining a given point in the flight envelope. Each throttle level position in a given flight envelope point defines an operating point, which corresponds to a target value of a fuel quantity.

The target value of a fuel quantity is the reference of the closed loop engine control, aiming at reaching a given velocity of the high pressure compressor velocity, and thereby a given velocity of the low pressure compressor, and consequently a positioning of the Variable Geometries in a given configuration.

To test the robustness of the AVG-FTCV approach, we add uncertainties to the SISO identified state space matrix:

\[
\begin{align*}
A_{i_{\text{real}}} &= A_{i_{\text{id}}} + \Delta A_i \\
B_{i_{\text{real}}} &= B_{i_{\text{id}}} + \Delta B_i
\end{align*}
\]

where:

\[
\begin{align*}
\Delta A_i &= \varepsilon_A A_{i_{\text{id}}} \omega_A \\
\Delta B_i &= \varepsilon_B B_{i_{\text{id}}} \omega_B
\end{align*}
\]

with: \( \omega_A, \omega_B \) are uniform distributions over the intervalle \([-1,1] \), \( |\varepsilon_A| < 1 \) and \( |\varepsilon_B| < 1 \).

We replace the identified matrix in AVG-FTC algorithm by the matrix defined in equations (28).

We assume in this paper that the controller parameters are chosen to stabilize the FMV and VSV systems. Moreover, for a given operating point and a given point of the flight envelope, the FMV and VSV systems are linear. Consequently, for a given operating point and a given point of the flight envelope, the overall system stability depends only on the stability of the observer and is guaranteed by the gain (27).

3. SIMULATION: ROBUSTNESS, STABILITY AND PERFORMANCE ANALYSIS

We use a jet engine Snecma simulator (MMR: Modèle Moteur régulé) to simulate a flight scenario defined by a set of operating points. The MMR is a simulation platform which is used by Snecma to validate the control laws according to the specification requirements such as: performance, stability in both steady and transient conditions.
In this paper we simulate flight maneuvers in steady and transient conditions using the MMR. The maneuvers include several operating points, for one point in the flight envelope corresponding to condition of stationary aircraft on the ground (velocity null and altitude null). Through these flight maneuvers, the performance of the AVG-FTC are discussed such as the stability of the multi-observer Takagi-Sugeno-LPV, the convergence of the AVG-FTC approach, the parameters variation influence of the NEKF. Moreover, the robustness of the AVG-FTC approach is discussed by adding noises in the identified state local matrix. These noises are the modelling uncertainties which represent the distance of the identified system from the real system in operation. The AVG-FTC approach is said convergent, if for all operating point, the virtual sensor error is less than the specified failure threshold.

We simulate flight maneuvers in which we include respectively a FMV and VSV sensor failure from time $t_f$. Figure 4 represents the comparison between the positions of the VSV a healthy and a failed one using the AVG-FTC approach. Whereas, the Figure 5 represents the comparison between the positions of the FMV with a healthy FMV sensor and a failed using the AVG-FTC approach. In these figures, the convergence of the AVG-FTC approached using both failed VSV sensor and failed FMV sensor is verified. The thrust allows us to evaluate the performance of the jet engine. Figure 6 represents the comparison between the thrust of the jet engine with health VSV sensor and faulty using the AVG-FTC approach. Figure 7 represents the comparison between the thrust of the jet engine with health FMV sensor and faulty using the AVG-FTC approach for four operating points which represent flight phases in a given point of the flight envelope (We choose Ground as a the first point of the flight envelope). That means that the performance requirements are respected in transient and steady conditions. Indeed, by computing the loss of thrust, this does not exceed 0.9% in case of faulty FMV sensor and 1.2% in case of faulty VSV sensor. Moreover, the superposition of the curve of the FMV and VSV position in case of failed and healthy FMV and VSV. Figure 4 and Figure 5 show that the stability is guaranteed in transient and steady conditions.

Let us define the AVG-FTC errors as the difference between the VSV position using healthy VSV sensor and using the AVG-FTC with a faulty VSV sensor (respectively FMV). The AVG-FTC error belongs to specified fault tolerant interval in both transient and steady conditions. That means that the precision of the AVG-FTC approach is acceptable according to specified requirements for Ground flight envelope. (2.9 mm for the VSV and 1.3 mm for the FMV).

In this paper, we have varied $R$ the covariance matrix of the measurement noise and $Q$ the covariance matrix of the process noise of the NEKF in order to show the influence of the variation of these parameters on the performance of the AVG-FTC approach.

4. CONCLUSIONS

In this paper, we proposed a validation of the AVG-FTC approach applied to monitor the Variable Stator Vane and Fuel Metering Valve of a jet Engine, for both partial and total loss of the LVDT sensor. The validation was proposed for four operating points representing different flight phases in a given flight envelope (Stationary aircraft on the ground).

The AVG-FTC approach was applied to two Jet Engine Variable Geometries control systems controlling the airflow in the HP compressor and the amount of fuel, with a strong constraint of non-modification on line of the controller parameters and the maintaining of the operability satisfactory performance of the jet engine. In the current architecture of the Variable Geometries control systems the LVDT sensors are redundant, guaranteeing thereby the availability of the measurement during the operation. These LVDT sensors are subject to faults known as intermittent contacts and failures with adverse consequences on the operability and performance of jet engine.

The results obtained for this configuration are satisfactory. Indeed, they respect the specified requirements in terms of
stability and performance in both transient and steady conditions. Moreover, the results are encouraging to extend the approach for the whole flight envelope. However, The AVG-FTC approach is based on off-line identified models, and off-line trained neural network, using simulation data. A study in progress use test bench data, and operation data for the identification of the embedded models and the training of the neural network. The NEKF ensure the robustness of the AVG-FTC approach provided that the identified models are close to the real system in operation. Moreover, the AVG-FTC as presented does not take into account the aging of the jet engine which contributing to the distance between the identified models and neural network system and the real system in operation. We propose in a work in progress an embedded identification algorithm for the models and an embedded training algorithm for the neural network. Thereby the AVG-FTC approach will be more representative of the real operations and can be embedded in the Jet engine control unit.

REFERENCES


