Robust Passive Fault Tolerant Control Applied to Jet Engine Equipment

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ABSTRACT

In order to minimize the occurrence of unexpected costly flight failures modern aircraft engines industry focuses especially on increasing product's availability. In this work, we propose to monitor the health of a Variable Stator Vane (VSV), 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 proposed methodology is based on an original approach for real time on-board Passive Fault Tolerant Control (PFTC). The objective of the proposed PFTC is to provide acceptable performance and preserve stability when faults occur. The method relies on the design of a specific Robust Virtual Sensor in a Linear Parameter Variable (LPV) polytopic framework. The robustness to model uncertainties is ensured by a Neural Extended Kalman Filter (NEKF) accommodating, in real time, the model prediction. In the proposed methodology, an off-line closed-loop identification scheme is first used to elaborate a multi local linear state space models, after that a multi-model observer based on Linear Matrix Inequalities (LMI) optimization is used to build the virtual sensor. The NEKF is added to circumvent online model accuracy problems. The efficiency and limit of the approach are shown and discussed through simulations on a complete numerical engine test bench.

1. INTRODUCTION

Over the past decades, dependability has gradually become one of the key challenges for the aeronautical industry. The concept of dependability was introduced in the mid-80s by Laprie. (1985). According to his concept, dependability encompasses two features: threats and means. In aeronautics, threats are events that can affect dependability, such as faults and failures. Means are ways to increase dependability, namely removal, prevention, tolerance and forecasting.

During the last 30 years, System Health Monitoring (SHM) has emerged and has been extensively developed in order to improve the system dependability. SHM gives the system the capability to prevent, detect, diagnosis, respond to, and recover from conditions that may interfere with the nominal system operation. In this work, we are interested in developing SHM for a key subsystem of the aircraft engines, namely the Variable Stator Vane (VSV).

The purpose of the VSV system is to control the amount of airflow through the High Pressure Compressor to provide the optimum compressor performance. The control of airflow is aimed to prevent the engine from stalling. The actuators work in pairs as part of a closed-loop electro-hydraulic system to constantly adjust the position of the first stages of the VSV. The off-line closed loop VSV actuation composed of a servovalve, a cylinder and a LVDT (Linear Variable Differential Transformer) sensor. The LVDT is connected to the controller through harnesses which are subject to vibrations. Consequently, this can engender sensor failures and jeopardize the availability of the VSV position, thereby threatening the stability and degrading the performance of the jet engine.

In the current economic context, a material redundancy is used to ensure the availability of measures. This solution no longer profitable, therefore, we would like to implement an original architecture control by replacing the material redundancy by an analytical one, but in our context this is not straight. For this, we propose a Fault Tolerant Control approach aiming to simplify the complexity of the control architecture by reducing the material redundancy while maintaining the reliability, dependability and performance of the nominal operation.

2. PROBLEM STATEMENT

Fault Tolerant Control (FTC) attends to be an integral part of any SHM 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. An FTC system is a control system able to accommodate automatically for system failures. 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. FTC systems have appeared since the early 1980s. Nowadays, FTC has gained in popularity among industrial and academic researchers. Several survey paper and books have appeared (Patton 1997), (Blanke, Staroswiecki *et al*. 2001), (Zhang *et al* 2008). Generally speaking, FTC systems can be classified in two types: *passive* (PFTCS) and *active* (AFTCS).

The *passive* methods, or *reliable control*, aim to achieve the insensitivity to some specific anticipated faults by making the system robust with respect to them. The controller is fixed and requires neither Fault Detection nor Diagnosis schemes (FDD) nor controller reconfiguration. In this approach, often fault-tolerance is achieved by considering faults as uncertainties that the controller can deal with. Hence, we assume that the faults occur in a predefined subset, and the controller should be designed to optimize the worst fault performed (Liao *et al*. 2002; Yang *et al*. 2010)).

In the aeronautical context, PFTC is increasingly introduced in control architectures *et al*. 2012; Richter *et al*. 2011) in order to optimize the Time Between Overhaul (TBO) and consequently, to reduce the Delays and Cancellations (D&C) which have a significant economic impact.

It is important to highlight that our PFTC approach is applied to control a closed-loop actuation Variable Stator Vane which returns a servo-actuator position. The physical non-linear equations describing the operation of the servo-actuator VSV depend on non-measurable variables. Moreover, the complexity of these equations makes them non-embeddable for a real time computation of a VSV position.

In this paper, a real time on-board PFTC approach is proposed to control closed-loop actuation in spite of faulty sensor. The main purpose of the PFTC approach is to ensure availability of a feedback signal, while maintaining the performance of the nominal operation (De Oca *et al* 2010) without retuning on-line the parameters of the controller. The reconfiguration bloc contains a virtual sensor that estimates in real time the system's perturbations and compensates them.

In an industrial process, especially jet engine industry, the parameters of the controller are tuned off-line for the nominal operation. Changing them on-board with the occurrence of the fault is not allowed, this is why the PFTC approach is chosen in expense of the Active Fault Tolerant Control (AFTC) approach (Stubberud 2006), where the parameters of the controller are re-tuned in real time in order to adapt the controller.

Several approaches have been proposed to deal with PFTC in case of occurrence of partial sensor failure, which means that the sensor is available but provides a wrong feedback signal to the controller (De Oca 2010; De Oca *et al*. 2012; Richter *et al*. 2011). In this paper, we propose a new approach of PFTC for a total sensor failure, where total loss of feedback VSV position signal occurs, and this for a nonlinear system approximated by a multi-model system. In case of a total loss of the sensor, we ensure the availability of the feedback VSV position signal by a Multi-Input Multi-Output (MIMO) estimation of lost signal. At this stage, we consider the inaccuracy of the MIMO estimation as a sensor fault, which is compensated by the virtual sensor bloc reconfiguration.

The multi-model representation allows transforming non-linear sub-systems in a set of linear sub-systems in which theories of linear systems are applicable, while guaranteeing the stability of the overall system during the transition from an operating point to another one.

In order to construct our multi-model, we propose an off-line closed-loop identification that will be performed at several points of interest covering the entire operating domain. This is a specific method for system, such as a jet engine, that cannot be disconnected from the controller for economic and safety raisons. The purpose of this stage is to obtain a local linear state representation applicable for an operating point of the servo-actuator VSV.

In this paper, we propose two kinds of identifications. The first identification Single-Input Single-Output (SISO) aims to bring out the state space representation of VSV behavior.

The second one MIMO aims to get MIMO state space representation using a heterogeneous state vector, which is a concatenation of VSV position and other variable geometry's measures affecting the VSV position.

These two states space representations are used for the synthesis of a multi-model observer based on LMIs optimization. The observer built with the MIMO state space representation allows getting a MIMO VSV position estimation, which is used as an input signal for the virtual sensor. The second observer built with the SISO state space representation aims to estimate the sensor fault through the virtual sensor.

The LPV system receives a great interest in the nonlinear modelling literature (Bezzaoucha, *et al*. 2013, De Oca 2010, De Oca *et al*. 2012, Richter, et al. 2011, Bezzaoucha 2013). Indeed, the LPV framework can be seen as a "middle ground" between linear and non-linear dynamics. It concerns linear dynamical systems state-space representations of which depend on exogenous non-stationary parameters. LPV model consists of an indexed

collection of linear systems, in which the indexing parameter is *exogenous*, *i.e.* independent of the state.
On the other hand, the LPV framework allows us to extrapolate the identification from multitude local linear sub-systems, to the overall non-linear system. Thereby, from a mapping of the identified linear local sub-systems for several operation points we obtain one identified overall system describing the behavior of the servo-actuator for all operating phases. .
Moreover, sub-systems identified from simulations on a complete numerical engine test bench are subject to uncertainties. This could degrades the accuracy of the estimator used in the virtual sensor, and consequently, can jeopardize the stability of the overall system VSV. To circumvent this problem, we propose a Neural Extended Kalman Filter, which compensates the lack of information given by the state-space representation resulting from the experimental identification. We find in the literature some works (Kramer *et al*.2008, Owen *et al*. 2003, Stubberud (2006), Lobbia *et al*. 1995) dealing with the robust estimation using NEKF. Otherwise, NEKF is used to adapt in real-time the prediction model of the reference input signal.
This paper is structured as follows: First, we present VSV system and a closed-loop identification method of the VSV. After a synthesis of an observer for a LPV multi-model system is proposed. These results are used for the PFTC approach trough the virtual sensor, and finally, the robustness is addressed through the NEKF (Figure 1).

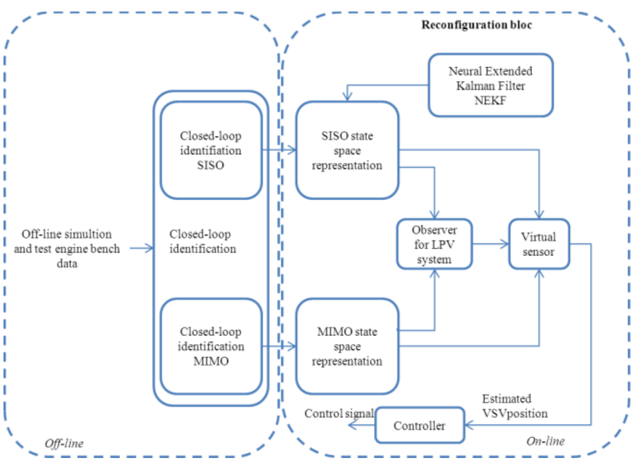

Figure 1: Architecture of a Robust PFTC applied to VSV actuation

3. DESCRIPTION OF THE SERVO-ACTUATOR

3.1. Physical description of the VSV

Before identifying the servo-actuator VSV, it is necessary to bring the physical equation describing the behaviour of the VSV, so that we could determine the order of the system.
The VSV system comprises a servovalve and a cylinder (Figure 2). A servovalve is a device aiming to transform the electric energy to hydraulic one. It is a control interface between the control and the cylinder that provide a suitable fuel flow to the cylinder.
The specifications of the closed-loop servo-actuator VSV impose to choose a three stages architecture, made of two stages servovalve called pilot stage, and a distribution slide. A command current drives the two stages servovalve, providing a fuel flow and a difference of pressure. These are used to actuate the slide distributor which the position is controlled through a spring by a feedback force.
A servovalve comprises a static part and a dynamic part. According to Tafraouti (2006), the dynamic part is represented by a second-order system. And the static part is non-linear function depending on non-measurable variables.
The static part of the servovalve depends on its differential pressure, which is constant for a given operating point. Thus, we assume that non-linear equation describing the static part of the servovalve is a constant. Consequently, we model the behaviour of the servovalve in a given operating point by a second order system.
The servo-actuator comprises a servovalve and a cylinder which can be modelled according to (Tafraouti 2006) by a first order system. Thereby we model the servo-actuator VSV by a third order system.

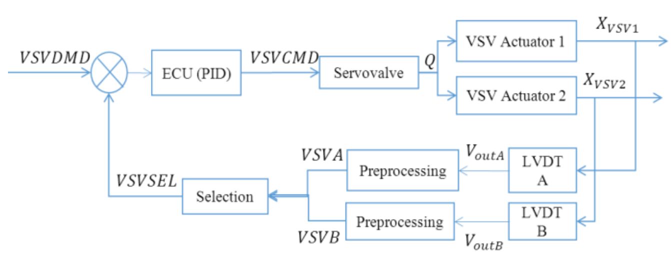

Figure 2: Control architecture of the VSV system

3.2. Identification

In this section, the off-line MIMO and SISO identification are presented
In a jet engine, there are variables geometries, which may affect each other's. We would like to exploit the correlation between these variable geometries to build a multi-model observer. In this work, we bring out the coupling between a VSV position and another variable geometry.
After an influence study, we selected a VBV position (Variable Bleed Valve) (Figure 3) 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.

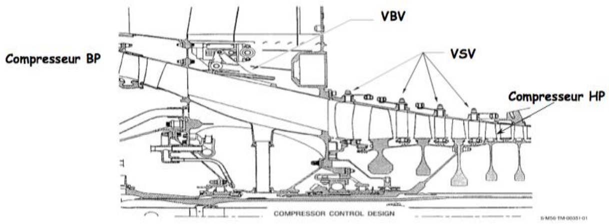

Figure 3: VSV and VBV equipment

Consider the MIMO state space representation:

$$\begin{cases} \begin{pmatrix} X_{VSV} \\ X_{VBV} \end{pmatrix}_{k+1} = A_{MIMO} \begin{pmatrix} X_{VSV} \\ X_{VBV} \end{pmatrix}_k + B_{MIMO} \begin{pmatrix} U_{VSV} \\ U_{VBV} \end{pmatrix}_k \\ X_{VSV} = C_{MIMO} \begin{pmatrix} X_{VSV} \\ X_{VBV} \end{pmatrix}_k + D_{MIMO} \begin{pmatrix} U_{VSV} \\ U_{VBV} \end{pmatrix}_k \end{cases} \quad (1)$$

where:

$\begin{pmatrix} X_{VSV} \\ X_{VBV} \end{pmatrix}$ is the MIMO state vector, X_{VSV} and X_{VBV} are respectively the VSV and the VBV position

$\begin{pmatrix} U_{VSV} \\ U_{VBV} \end{pmatrix}$ is the MIMO control current, U_{VSV} and U_{VBV} are respectively the VSV and the VBV control current.

The off-line MIMO identification (1) allows to bring out the matrix A_{MIMO}, B_{MIMO}, C_{MIMO}, D_{MIMO}, using the Prediction error Method Algorithm.
On the other hand, we use the same method to identify the non-linear behavioral equations of the VSV and VBV by a third order system. This identification aims to obtain, for each operation point, a SISO state space representation, used is LPV Takagi-Sugeno framework.

4. ROBUST PASSIVE TOLERANT CONTROL

4.1. Multi-model observer

We brought out in the previous section the necessity to use LPV framework to identify the overall non-linear VSV system.
In this work, we introduce a Takagi-Sugeno formalism which is an interpolation of local linear subsystem using a convex transformation (Bezzaoucha *et al*. 2013, Bezzaoucha 2013). Several articles (Akhenak *et al*. 2007, Marx *et al*. 2013, Bezzaoucha 2013) deals with Takagi-Sugeno formalism and use it to: (i) model and design diagnostic strategy, (i) develop control's laws, (iii) study the stability of non-linear systems.
We brought out in the previous section local identified subsystems for each operating point. We use a Takagi-Sugeno formalism to write the overall non-system describing the behaviour of the VSV for a set of operating point.

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{n} \sigma_i\big(\xi(t)\big)\big(A_i x(t) + B_i u(t)\big) \\ y(t) = \sum_{i=1}^{n} \sigma_i\big(\xi(t)\big)\big(C_i x(t) + D_i u(t)\big) \end{cases} \quad (2)$$

where: $x(t) \in \mathbb{R}^{n_x}$ is the overall system state vector, $y(t) \in \mathbb{R}^{n_y}$ is the overall system output and $u(t) \in \mathbb{R}^{n_u}$ in the control input, with n number of 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. $\sigma_i\big(\xi(t)\big)$ $i = 1 \dots n$, satisfying the convex sum property.
The purpose of the Takagi-Sugeno formalism is to use the linear framework for the synthesis of the observer and study the stability and extrapolate to the overall non-linear system using the convex sum. The weighting functions $\sigma_i\big(\xi(t)\big)$ depend on a decision variable $\xi(t)$. In our application, $\xi(t)$ is measurable and allows us to determine the operating point
In this paper, we propose to use the LPV framework to bring out the transition between the sub-systems.
The parameters of the matrix (A_i, B_i, C_i, D_i) of sub-systems vary according to a function $\theta(t)$ dependent on time.
Thus, we obtain Takagi-Sugeno formalism with time varying parameters, which guarantee a smooth transfer from a subsystem to another. This representation has not only the advantage to be mathematically equivalent to the overall non-linear system, but also to be easier to handle.

$$\begin{cases} \dot{x}(t) = \sum_{\theta(t)} \sigma_{\theta(t)}\Big(\xi_{\theta(t)}(t)\Big)\Big(A\big(\theta(t)\big)x(t) + B\big(\theta(t)\big)u(t)\Big) \\ y(t) = \sum_{\theta(t)} \sigma_{\theta(t)}\Big(\xi_{\theta(t)}(t)\Big)\Big(C\big(\theta(t)\big)x(t) + D\big(\theta(t)\big)u(t)\Big) \end{cases} \quad (3)$$

Instead of having an observer and a controller for each subsystem, the LPV Takagi-Sugeno representation defined in Eq. (3) allows to build a common strategy of observation valid for the overall nonlinear system.
The stability analysis and the observer synthesis are based on Lyapunov theory by minimising L_2-gain under LMI constraint

$$\begin{cases} \dot{\hat{x}}(t) = \sum_{i=1}^{n} \sigma_i(\xi(t)) \left(A_i x(t) + B_i u(t) + L\left(y(t) - \hat{y}(t)\right)\right) \\ \hat{y}(t) = \sum_{i=1}^{n} \sigma_i(\xi(t))(C_i x(t) + D_i u(t)) \end{cases} \tag{4}$$

Let us find L a common observer gain for all subsystems such as $\hat{x}(t) \to x(t)$
Let define the error estimation $e(t) = \hat{x}(t) - x(t)$ written in the Takagi-Sugeno formalism:

$$\dot{e}(t) = \sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_i(\xi(t))\sigma_j\left(\xi_j(t)\right)\left(A_i - LC_j\right)e(t) \tag{5}$$

The gain of the multi-model observer L is found such as $\dot{e}(t)$ is stabilized
Let define a Lyapunov function:

Theorem: A system is stable, if there is a positive Lyapunov function such as $\dot{V}(t) < 0$.

$$V(t) = e^T(t)Pe(t) \tag{6}$$

with $P \in \mathbb{R}^{n_x x n_x}$ a positive symmetric matrix.

$$\dot{V}(t) = \sum_{=1}^{n}\sum_{j=1}^{n} \sigma_i(\xi(t))\sigma_j(\xi(t))\, e^T(t)\left(P\left(A_i - LC_j\right) + \left(A_i - LC_j\right)P^T\right)e(t) \tag{7}$$

with:

$$\begin{cases} \sum_{i=1}^{n} \sigma_i(\xi(t)) = 1 \\ 0 \le \sigma_i(\xi(t)) \le 1 \qquad i = 1 \dots . n \end{cases} \tag{8}$$

Knowing that $\sigma_i(\xi(t)) \ge 0$.

$$\dot{V}(t) < 0 \Rightarrow PA_i - PLC_j + A_i^T P - C_j^T L^T P < 0 \quad i,j = 1..n \tag{9}$$

In order to linearize Eq.(9), we define $\overline{L} = PL$. Thereby, we obtain n LMIs

$$\begin{cases} PA_i - \overline{L}C_j + A_i^T P - C_j^T \overline{L}^T < 0 \quad i,j = 1 \dots n \\ P > 0 \end{cases} \tag{10}$$

Finally, we obtain the multi-model $L = P^{-1}L^T$
We use this method to synthetize the two observers introduced above.

4.2. Virtual sensor

In this subsection, we propose a PFTC strategy based on virtual sensor (Figure 4). This contains a multi-model LPV observer based on LMIs constrains, aiming to estimate in real time, faults of a VSV estimation based on MIMO identification.
Moreover, virtual sensor contains a bloc reconfiguration which is used to compensate the faults estimated the multi-model LPV observer. (De Oca 2010, De Oca *et al*. 2012, Nazari *et al*. 2013, Richter *et al*. 2011) propose a PFTC for LPV system.
In this paper, we propose an original method of reconfiguration without on-line re-tuning the parameters of the controller.
In general, PFTC approach supposes that the measure is available. Here in this work, we treat a case of a complete loss of the VSV sensor. Up to our knowledge (De Oca 2010, De Oca *et al*. 2012), the PFTC has not been used for thiscase. We ensure the availability of the input signal of the virtual sensor through MIMO VSV estimation.
This MIMO VSV estimation has the inconvenient to be inaccurate in the transient phases. This can have a negative effect for the stability of the overall VSV system. That is why we use a virtual sensor to estimate and compensate these inaccuracies that we consider as sensor fault.
We consider a following subsystem with a faulty sensor for a given operating point:

$$\begin{cases} \dot{x}(t) = A_i(\theta(t))x(t) + B_i(\theta(t))u(t) \\ y(t) = C_{f_i}(\theta(t))x(t) + D_i(\theta(t))u(t) \end{cases} \tag{11}$$

With C_{f_i} output subsystem matrix including the fault
The virtual sensor applied to the polytopic LPV system can be written as following:

$$\begin{cases} \dot{x_v}(t) = \sum_{\theta(t)} \sigma_{\theta(t)}\left(\xi_{\theta(t)}(t)\right)\left(A(\theta(t))x_v(t) + B(\theta(t))u(t) + L_v\left(y_v(t) - y_f(t)\right)\right) \\ y_v(t) = \sum_{\theta(t)} \sigma_{\theta(t)}\left(\xi_{\theta(t)}(t)\right)\left(C_f(\theta(t))x_v(t) + D(\theta(t))u(t)\right) \end{cases} \tag{12}$$

with $x_v(t)$ the state vector of the virtual sensor state space and L_v the multi-model observer gain
de Oca and Puig (2010) brings out a reconfigurabilty condition:

$$Rank\left(C_f(\theta(t))\right) = Rank\begin{pmatrix} C_f(\theta(t)) \\ C(\theta(t)) \end{pmatrix} \tag{13}$$

Consider the coefficient of reconfigurabilty P:

$$P\left(\theta(t)\right) = C\left(\theta(t)\right)C_f\left(\theta(t)\right)^T\left(C_f\left(\theta(t)\right)C_f\left(\theta(t)\right)^T\right)^{-1} \quad (14)$$

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

$$C_\Delta\left(\theta(t)\right) = C\left(\theta(t)\right) - P\left(\theta(t)\right)C_f\left(\theta(t)\right) \quad (15)$$

$$y_\Delta\left(\theta(t)\right) = C_\Delta\left(\theta(t)\right)x_v\left(\theta(t)\right) \quad (16)$$

and thereby, we obtain the corrected output signal

$$y_c(t) = P\left(\theta(t)\right)y_f(t)y_\Delta\left(\theta(t)\right) \quad (17)$$

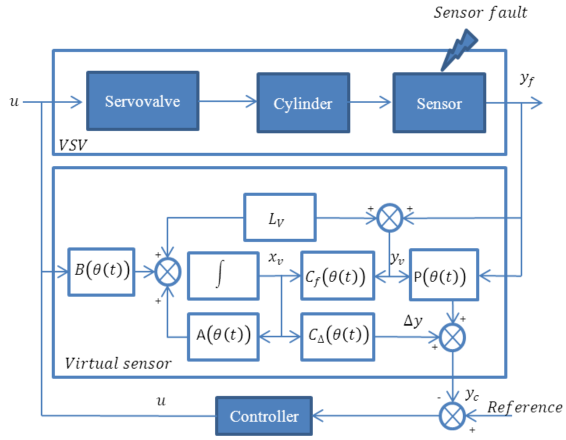

Figure 4: PFTC diagram

4.3. Robustness-Neural Extended Kalman Filter

Kalman filter has received a great attention in aeronautical industry. In this paper, we propose a robust observer for inaccurate state space representation using a Neural Extended Kalman Filter.

Neural Extended Kalman Filter (Kramer *et al*. 2008, Stubberud 2006, Stubberud *et al*. 1995) 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 imposed as an embeddability constraint. This simplification may jeopardises the precision of the estimation and consequently affects all applications using the estimation ,like synthesis of observer for diagnostic or reconfiguration, control laws…etc.

In this paper, we propose to use an adaptive robust method, which consist of setting in real time, the parameter of the state-space representation in order to guarantee the robustness of estimation against the inaccuracy engendered by the identified model equations (Figure 5).

Consider a non-linear state space representation:

$$\begin{cases} x_{k+1} = f(x_k, u_k) + r_k \\ y_k = g(x_k, u_k) + q_k \end{cases} \quad (18)$$

where: f and g are nonlinear functions, r_k and q_k are respectively the noise process and the measure noise.

Let remind the extended Kalman filter:

$$\begin{cases} K_k = P_{k|k-1}\frac{\partial g(\hat{x}_{k|k-1})}{\partial \hat{x}_{k|k-1}}^T\left(\frac{\partial g(\hat{x}_{k|k-1})}{\partial \hat{x}_{k|k-1}}P_{k|k-1}\frac{\partial g(\hat{x}_{k|k-1})}{\partial \hat{x}_{k|k-1}}^T + R_k\right)^{-1} \\ \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left(y_k - g(\hat{x}_{k|k-1})\right) \\ P_{k|k} = \left(I - K_k\frac{\partial g(\hat{x}_{k|k-1})}{\partial \hat{x}_{k|k-1}}\right)P_{k|k-1} \\ \hat{x}_{k+1|k} = f(\hat{x}_{k|k}, u_k) \\ y_k = g(\hat{x}_{k+1|k}) \\ P_{k+1|k} = \left(\frac{\partial f(\hat{x}_{k|k}, u_k)}{\partial \hat{x}_{k|k}}\right)P_{k|k}\left(\frac{\partial f(\hat{x}_{k|k}, u_k)}{\partial \hat{x}_{k|k}}\right) + Q_k \end{cases} \quad (19)$$

We assume that the measure and process noises are Gaussian.

where:

x	$\in \mathbb{R}^{n_x}$ state of the system
y	$\in \mathbb{R}^{n_y}$ output of the system
K	Kalman gain
Q	Covariance matrix of the measured noise
R	Covariance matrix of the process noise
P	Covariance matrix of state estimation error
f	Prediction function of the state
g	Output function

In our case, the function f is non-linear and embeddable. Thus, we approximate it by an off-line closed loop identification $\overline{f}$, which is added to an on board learned neural network (Kramer *et al*. 2008, Stubberud 2006, Lobbia *et al*. 1995)

$$f(x_k, u_k) = \overline{f}(x_k, u_k) + NN_f(x_k, \omega_k, u_k) \quad (20)$$

We assume that the function g is linear and we note: $h = \frac{\partial g}{\partial \hat{x}_{k|k-1}}$

$$\begin{cases} K_k = P_{k|k-1} h(\hat{x}_{k|k-1})^T \left(h(\hat{x}_{k|k-1}) P_{k|k-1} h(\hat{x}_{k|k-1})^T + R_k \right)^{-1} \\ \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(y_k - g(\hat{x}_{k|k-1}) \right) \\ P_{k|k} = \left(I - K_k h(\hat{x}_{k|k-1}) \right) P_{k|k-1} \\ \hat{x}_{k+1|k} = \overline{f}(\hat{x}_{k|k}, u_k) + NN_f(\hat{x}_{k|k}, \omega_k, u_k) \\ y_k = g(\hat{x}_{k+1|k}) \\ P_{k+1|k} = \left(\dfrac{\partial f(\hat{x}_{k|k}, u_k)}{\partial \hat{x}_{k|k}} \right) P_{k|k} \left(\dfrac{\partial f(\hat{x}_{k|k}, u_k)}{\partial \hat{x}_{k|k}} \right) + Q_k \end{cases} \tag{21}$$

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 $A = \frac{\partial \overline{f}(x_{k|k})}{\partial x_{k|k}}$

$$\overline{X}_k = \begin{pmatrix} x_k \\ \omega_k \end{pmatrix} \tag{22}$$

$$\overline{X}_{k+1|k} = \begin{pmatrix} x_{k+1|k} \\ \omega_{k+1|k} \end{pmatrix} = \begin{pmatrix} \frac{\partial \overline{f}(x_{k|k})}{\partial x_{k|k}} + \frac{\partial NN_f}{\partial x_{k|k}} & \frac{\partial NN_f}{\partial \omega_k} \\ O & I_d \end{pmatrix} \begin{pmatrix} x_{k|k} \\ \omega_{k|k} \end{pmatrix} \tag{23}$$

$$\bar{x}_{k+1|k} = \underbrace{\left(A + \frac{\partial NN_f}{\partial x_{k|k}} \right)}_{\overline{A}} x_{k|k} + \frac{\partial NN_f}{\partial \omega_k} \omega_{k|k} \tag{24}$$

According to the Eq. (22) the matrix $\overline{A}$ is adjusted in real time by the partial differential of the neural network on the state vector.

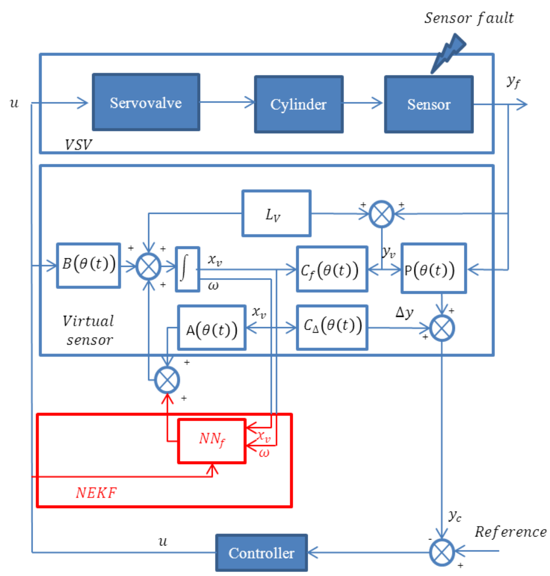

Figure 5: Robust PFTC diagram

5. SIMULATION RESULTS

We use a jet engine simulator to simulate a flight scenario defined by a set of operation points. For this, we apply a flight maneuverer equivalent to what imposes the pilot through the control yoke during a flight. Indeed, each control yoke position determines target value of a fuel quantity which induces high pressure compressor's speed and thus low pressure compressor's speed and a certain configuration of variables geometries such as VSV position.

Consider a flight maneuverer in which we include a VSV sensor failure.

In Figure 7, we simulate a maneuver with a faulty VSV sensor shown in Figure 6.

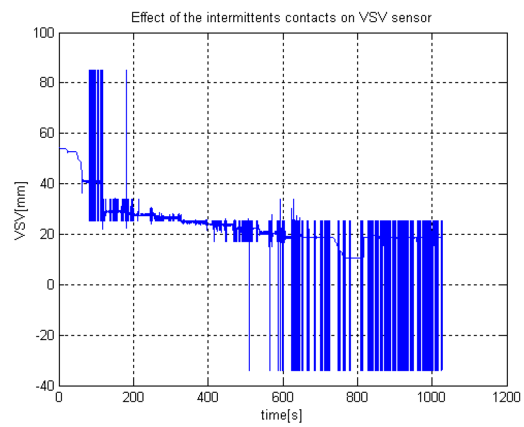

Figure 6 : Effect of the intermittent contacts on VSV sensor

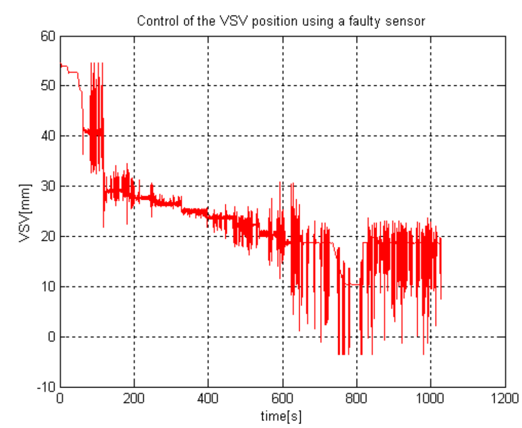

Figure 7 : Control of the VSV position using a faulty sensor

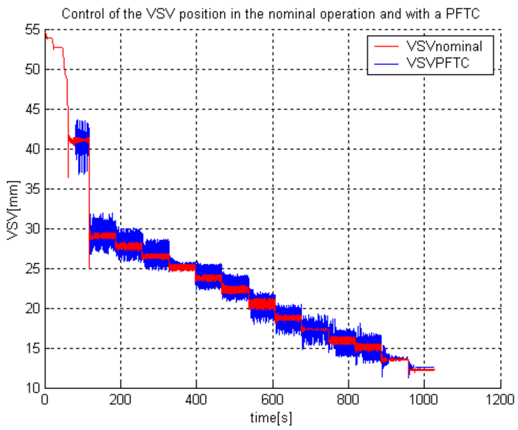

Figure 8: Control of the VSV position in the nominal operation and with a PFTC

Figure 7, shows the effect of a periodic random switch in the electric input of the VSV sensor, which provide intermittent contact of the VSV sensor feedback signal. This kind of failure is the most probable to occur during a flight, and it may jeopardize the stability of the close-loop VSV actuation, and consequently engender irreversible damage in high pressure compressor.

In the Figure 8, we simulate the same maneuver, but we replace the faulty sensor by the model using a Robust Passive fault Tolerant Control approach.

We use a PFTC approach as soon as sensor failure is detected. Figure 8 shows the control of VSV actuation using an analytical VSV model as feedback signal, with a PFTC approach described below.

We notice in the Figure 8, oscillations. These are due to the inaccuracies of the analytical VSV model feedback signal. Indeed, the controller is tuned for the nominal operation, and it is not designed to reject model inaccuracies. Consequently, we tune controller off-line taking into account these model inaccuracies, not only in order to reject oscillations but also to reach performance requirements imposed in the specifications. Once tuned off-line, controller is unchanged on-line during the operation, respecting thereby the constraints which led us to choose the PFTC approach instead of the AFTC approach.

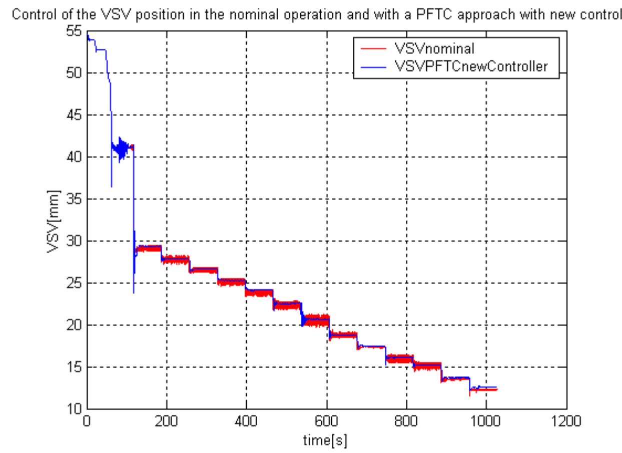

Figure 9: Control of the VSV position in the nominal operation and with a PFTC approach with new controller

Figure 9 shows the control of the VSV position using the PFTC with the new adjusted controller rejecting thereby the oscillations engendered by the analytical VSV model inaccuracies.

To test the robustness of the PFTC approach using the NEKF, we add uncertainties to the SISO identified state space matrix:

$$\begin{cases} A_{real} = A_{identified} \pm \delta A \\ B_{real} = B_{identified} \pm \delta B \\ C_{real} = C_{identified} \pm \delta C \end{cases} \tag{25}$$

where, δB , δC are additive uncertainties modeled by Gaussian noise.

We replace the identified matrix in PFTC algorithm by the matrix defined in Eq.(25).

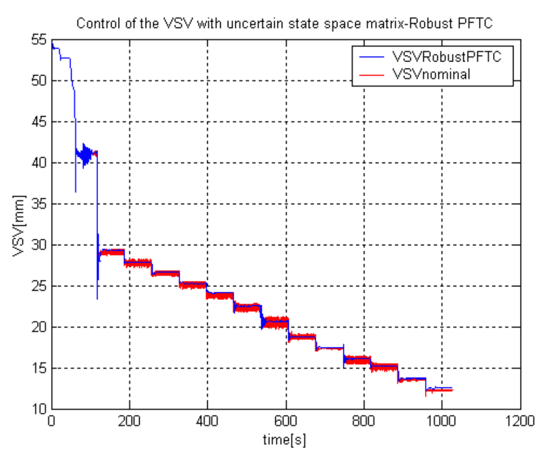

Figure 10: Control of the VSV with uncertain state space matrix-Robust PFTC

Figure 10 shows the rejection of state space matrix uncertainties using NEFK. Indeed, in spite of adding uncertainties to state space matrix, we obtain an analytical VSV model with an acceptable accuracy.

6. CONCLUSION

In this present paper, a Robust Passive Fault Tolerant Control approach was proposed in a LPV framework using LPV Takagi-Sugeno formalism. This approach is applied to jet engine equipment, a Variable Stator Vane actuation which is subject to sensor failure on-board. That may jeopardize the stability of the closed-loop actuation, affecting thereby the performance and the operability of the jet engine.

The work proposed in this paper, allows guaranteeing the availability of the feedback information to VSV position, with acceptable performance and operability of the jet engine, in spite of the inaccurate VSV model.

In a jet engine, there are several systems of closed-loop actuation with sensors subject to failure. We will propose in a future paper an extension of the work for the VBV

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