A SENSOR-FAULT-TOLERANT DIAGNOSIS TOOL
BASED ON A QUADRATIC PROGRAMMING APPROACH

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ABSTRACT
Kalman filters are widely used in the turbine engine community for health monitoring purpose. This algorithm gives a good estimate of the engine condition provided that the discrepancies between the model prediction and the measurements are zero-mean, white random variables. However, this assumption is not verified when instrumentation (sensor) faults occur. As a result, the identified health parameters tend to diverge from their actual values which strongly deteriorates the diagnosis.

The purpose of this contribution is to blend robustness against sensor faults into a tool for performance monitoring of jet engines. To this end, a robust estimation approach is considered and a Sensor Fault Detection and Isolation module is derived. It relies on a quadratic program to estimate the sensor faults and is integrated easily with the original diagnosis tool. The improvements brought by this robust estimation approach are highlighted through a series of typical test-cases that may be encountered on current turbine engines.

NOMENCLATURE
\( \hat{a} \) estimation of an unknown variable \( a \)
\( A8IMP \) nozzle exit area (nominal value: 1.4147 m\(^2\))
\( b_k \) the sensor fault vector
DEKF Dual Estimation Kalman Filter
hpc high pressure compressor
hpt high pressure turbine
\( k \) discrete time index
\( \sigma \) vector of the standard deviations of the sensors
\( \mathcal{N}(m, R) \) a Gaussian probability density function with mean \( m \) and covariance matrix \( R \)

INTRODUCTION
In the last four decades, many research efforts have been conducted to develop efficient fault detection and isolation techniques for gas turbine engines. Generating a precise information about the health condition of the engine leads to improved safety and reliability while reducing operating costs.
The diagnosis tool considered herein is a gas path analysis method whose purpose is to assess the changes in engine module performance, described by so-called health parameters, on the basis of measurements collected along the gas path of the engine [1]. Typically, the health parameters are correcting factors on the efficiency and the flow capacity of the components (fan, lpc, hpc, hpt, lpt, nozzle) while the measurements are inter-component temperatures, pressures and shaft speeds.

Besides component faults, sensor (instrumentation) faults may occur. Generally speaking, a sensor fault is a data generated by a sensor whose behaviour does no longer respect the manufacturer characteristics. Instrumentation faults can be classified as systematic errors, such as biases and drifts, or as impulsive noise which are random “spikes” in the measured data.

These instrumentation faults can spoil the estimation of the engine condition. It is therefore mandatory to bring robustness against sensor faults in diagnosis tools, which has been the subject of an increasing number of contributions. A short, non exhaustive review of various techniques investigated in the jet engine community is given below:

1. data cleaning / filtering: it is actually a pre-processing of the measurements, the purpose of which is to remove aberrant values from the samples before they are used in the monitoring algorithm [2, 3]. While very simple to understand, such a technique may be difficult to implement in a real-time environment to process transient data.

2. instrumental variables: this second solution consists in treating sensor faults symmetrically to component faults. To this end, parameters intended to model sensor faults are introduced in the diagnosis problem as additional unknowns to be estimated together with the health parameters [1, 4]. This technique however makes the estimation problem under-determined and achieves a poor sensor fault isolation.

3. banks of Kalman filters have also been applied to cope with sensor faults: each filter uses all sensors but one to estimate the health parameters. The filter that does not rely on the faulty sensor is the only achieving an accurate estimation [5, 6]. The major drawback of this approach resides in its combinatorial nature, allowing the isolation of a predefined set of fault events.

4. robust estimation techniques: the concept is to include robustness against sensor faults within the estimation algorithm itself. The robustness is obtained by replacing the least-square criterion by another one (to be defined later), less sensitive to outliers [7–9]. In short, an outlier can be defined as an observation that lies outside the overall pattern of a given distribution.

In the present contribution, the development of a new algorithm for performance monitoring based on robust estimation is reported. The innovative aspect is that the robust estimation problem, which is basically a non-linear one, can be transformed into a Quadratic Programming problem [11] for which efficient solvers are available. The benefit in terms of stability and accuracy brought by the robust diagnosis tool is illustrated for several sensor faults that may be encountered on a jet engine.

DESCRIPTION OF THE METHOD

The scope of this section is to provide a short description of our diagnosis tool (see [10] for more details), to derive the Sensor Fault Detection and Isolation (SFDI) module and to present its integration within the existing diagnosis algorithm.

The Diagnosis Tool

As part of model-based techniques, our diagnosis tool requires a simulation model of the turbine engine. In the framework of gas path analysis, these are basically nonlinear aerothermodynamic models based on mass, energy and momentum conservation laws applied to the engine.

The diagnosis tool is able to process transient data. Given the nonlinearity of the system model, the Extended Kalman filter [12] is used instead of the generic, linear Kalman filter. The simulation model of the engine is written in the state-space form, namely:

\[ x_k = f(u_k, v_k, w_k, x_{k-1}) + \nu_k \]  
\[ y_k = g(u_k, v_k, w_k, x_k) + \epsilon_k \]

where \( k \) is a discrete time index, \( u_k \) are the command parameters (e.g. fuel flow), \( v_k \) are measurable exogenous inputs (e.g. ambient temperature and pressure, Mach number), \( w_k \) are the aforementioned health parameters and \( x_k \) are the state variables. The state variables are associated to the transient phenomena taking place in the gas path of the engine. Generally speaking, three types of transient effects are distinguished: the heat transfers between the gas path and the components of the engine, the shaft inertia and the fluid transport delays.

Equation (1) is named the state transition equation and gathers the deterministic model of the engine dynamics \( f(\cdot) \) and a random variable \( \nu_k \) which represents model inaccuracies. Similarly, equation (2) is called the measurement equation and gathers the deterministic simulation model \( g(\cdot) \) and a random variable \( \epsilon_k \) which represents sensor inaccuracies. To complete the description of the system, a third equation describing the temporal evolution of the health parameters must be supplied. A random walk model is generally adopted (see [13] for further details).

Both \( \nu_k \) and \( \epsilon_k \) are assumed to be zero-mean, white and Gaussian random variables\(^1\) which is denoted by:

\[ \epsilon_k \sim \mathcal{N}(0, R_y) \quad \text{and} \quad \nu_k \sim \mathcal{N}(0, R_x) \]  

\(^1\)In addition, \( \nu_k \) and \( \epsilon_k \) are assumed uncorrelated.
The state variables are either measured, thus noisy, or non measurable. Hence, they must be estimated together with the health parameters from the same sequence of measurements \( y_k \). A marginal estimation approach is selected to solve this dual estimation problem. The marginal estimation approach is presented in [14] and basically relies on two Extended Kalman filters running concurrently, one for the health parameters and the other one for the state variables. Once the former filter has updated the health parameters, the current value is used by the latter to update the corresponding state variables. So, the state variable estimation improves as the identified health parameters are getting closer to their actual values.

Provided that a prior value for the health parameters and the state variables is available, the basic step consists in observing the discrepancies between the model outputs, denoted \( \hat{y}_k \), and the observed measurements \( y_k \). These discrepancies, also called residuals and denoted \( r_k \), are processed by the marginal estimation Kalman filter which recursively updates the health parameters and the state variables so that the residuals are driven to zero on average.

Figure 1. HEALTH PARAMETER AND STATE VARIABLE UPDATE MECHANISM USING A DUAL ESTIMATION KALMAN FILTER

For sake of brevity, elements of the estimation technique are recalled for the health parameter identification side of the dual estimation problem. All developments may be transposed to the state variable estimation problem by making the adequate substitutions.

The Kalman filter can be seen as a recursive maximum a posteriori approach to parameter identification. Both the health parameters and the measurements are considered as random variables following a normal distribution. Within this framework, the estimated health parameters are obtained by minimising the following objective function:

\[
J(w_k) = \frac{1}{2} (w_k - \hat{w}_k)^T \left( P_{w,k} \right)^{-1} (w_k - \hat{w}_k) + \frac{1}{2} r_k^T R_y^{-1} r_k \quad (4)
\]

The first term in the right hand side of equation (4) forces the identified health parameters to lie in a neighbourhood of the prior value \( \hat{w}_k \). The prior covariance matrix \( P_{w,k} \) specifies the shape of this region and summarises the information contained in the measurement sequence up to time \( k-1 \). The second term reflects the weighted least square criterion. The interested reader may consult reference [13] for an extensive derivation.

Considering an update mechanism based on an Extended Kalman filter, the residuals are approximated with:

\[
\begin{align*}
    r_k &= y_k - \hat{y}_k \\
    &= y_k - [\hat{y}_k + G_k (w_k - \hat{w}_k)] \\
    &= \hat{r}_k - G_k (w_k - \hat{w}_k)
\end{align*}
\]

(5)

where

\[
\begin{align*}
    \hat{y}_k &= G'(u_k, v_k, \hat{w}_k, \hat{x}_k) \\
    G_k &= \frac{\partial}{\partial w_k} \begin{bmatrix} G'(u_k, v_k, w_k, \hat{x}_k) \end{bmatrix} \bigg|_{w_k = \hat{w}_k}
\end{align*}
\]

are respectively the a priori prediction of the measurements and the Jacobian matrix of the measurement equation around the prior values of the states and health parameters.

Cancelling out the first order derivatives of equation (4) leads to the update relation for the health parameters:

\[
(P_{w,k})^{-1} (w_k - \hat{w}_k) - G_k^T R_y^{-1} r_k = 0
\]

\[
(6)
\]

Making the Algorithm Sensor-Fault Tolerant

As mentioned in the introduction, a sensor fault can be defined as a data generated by a sensor that no longer follows the manufacturer’s characteristics. Mathematically speaking, it means that the measurement noise associated to a faulty sensor cannot be described by a zero-mean Gaussian random variable which is one of the assumptions of the Kalman filter as seen in equation (3). In this section, a robust estimation technique is presented that lowers the sensitivity of the Kalman filter with respect to outliers.

The quadratic penalisation of the residuals in the objective function (4), which derives directly from the assumption of a Gaussian measurement noise, makes the algorithm very sensitive to large residuals. Consequently, even a small amount of outliers can strongly deteriorate the quality of the estimation.
The aim of robust estimation techniques is to lower the sensitivity with respect to large residuals by replacing the Gaussian probability density function by another noise distribution prone to outliers. Among the many candidate distributions, the so-called $\delta$-contaminated function (aka. Huber’s function) has received much attention in the literature and is selected in this contribution. A detailed description of this function is beyond the scope of this paper, but can be found in reference [16]. Basically, Huber’s function consists in a Gaussian random variable contaminated by a fraction $\delta$ of outliers.

Practically, the residuals $r_k$ in equation (6) are replaced with a function $\psi(r_k)$ intended to de-emphasise the influence of large residuals:

$$ (P_{w_k})^{-1}(w_k - \hat{w}_k) - G_k^T R_y^{-1} \psi(r_k) = 0 \quad (7) $$

Huber’s weighting function is represented in figure 2 for a scalar random variable $\varepsilon$. Mathematically, it can be written as:

$$ \psi(\varepsilon) = \max(-\Delta \sigma, \min(\varepsilon, \Delta \sigma)) \quad (8) $$

where $\sigma$ is the standard deviation of the “clean” Gaussian variable and the scalar $\Delta$ is a threshold depending on the contamination level $\delta$ (e.g. $\Delta=1.399$ for $\delta=0.05$).

![Figure 2. HUBER’S WEIGHTING FUNCTION FOR A SCALAR](image)

Adopting Huber’s function as the penalisation function of the residuals leads to robustness against sensor faults, but turns the simple linear function (6) for parameter update into a non-linear one. No explicit update formula can be obtained and relation (7) must be solved numerically, with Newton’s method for instance. This might be cumbersome for on-line applications.

Nonetheless, it is shown in [11] that the non-linear program resulting from the choice of a noise distribution following Huber’s law can be transformed into a quadratic program for which efficient and fast solvers are available [17]. Reported below are the milestones of this transformation.

As a first step, the vector $b_k$ is introduced in the measurement equation (2) to model the outliers:

$$ y_k = G(u_k, v_k, w_k, x_k) + b_k + \epsilon_k \quad (9) $$

Then, the objective function of the robust estimation problem becomes:

$$ J(w_k, b_k) = \frac{1}{2}(w_k - \hat{w}_k)^T (P_{w_k})^{-1} (w_k - \hat{w}_k) + \frac{1}{2} r_k^T R_y^{-1} r_k + \Delta^{-1} \sigma^{-T} |b_k| \quad (10) $$

The equivalence between solving equation (7) for $w_k$ with Huber’s $\psi$ function and minimising the objective function (10) with respect to $w_k$ and $b_k$ is established in [11]. It should be pointed out that the criterion (10) is convex and therefore admits a unique optimum. In [18], a robust diagnosis tool for steady-state data is obtained by minimising equation (10) alternatively with respect to $w_k$ and $b_k$.

To transform the objective function (10) into a quadratic program, the quantities $b_k$ and $|b_k|$ are replaced with their positive and negative parts:

$$ \begin{cases} b_k = b_k^+ - b_k^- \quad \text{with} \quad b_k^+ = \max(b_k, 0) \\ |b_k| = b_k^+ + b_k^- \quad \text{with} \quad b_k^- = -\min(b_k, 0) \end{cases} \quad (11) $$

With this change of variables, the objective function writes down:

$$ J(w_k, b_k^+, b_k^-) = \frac{1}{2}(w_k - \hat{w}_k)^T (P_{w_k})^{-1} (w_k - \hat{w}_k) + \frac{1}{2} r_k^T R_y^{-1} r_k + \Delta^{-1} \sigma^{-T} (b_k^+ + b_k^-) \quad (12) $$

At this point, it may be interesting to compare the presented approach and the one based on instrumental variables [1,4]. Both of them introduce a vector of additional unknowns, namely the vector $b_k$, to model the sensor faults. The major difference lies in the fact that the instrumental variable approach treats symmetrically the health parameters and the bias vector $b_k$ while the robust one adds a linear penalising term on $b_k$ – the third term in the right-hand-side of equation (10).

Unlike the Kalman filter, the quadratic programming formulation does not supply an explicit relation for the update of the covariance matrix of the health parameters which is certainly a drawback. Yet, in the realm of performance monitoring, the

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2note that the residuals $r_k$ are also a linear function of $w_k$ and $b_k$
degradation undergone by the engine evolves relatively slowly and is continuously tracked so that the prior value \( \hat{\mathbf{w}}_k \) will generally be close to the true value. Under this assumption, a simplification is applied in the robust estimation problem: the estimations of the bias \( \mathbf{b}_k \) and the health parameters are de-coupled. First, the sensor fault vector is estimated by minimising (10) in which the health parameters are frozen to their prior value. This results in the following quasi-unconstrained quadratic program:

\[
\min_{\mathbf{b}_k^+, \mathbf{b}_k^-} J(\hat{\mathbf{w}}_k^-, \mathbf{b}_k^+, \mathbf{b}_k^-) \quad \text{subject to} \quad \mathbf{b}_k^+ \geq 0 \quad \text{and} \quad \mathbf{b}_k^- \geq 0
\]  

(13)

Secondly, a regular Extended Kalman filter comes into play to update the health parameters and their covariance matrix. The effect of sensor biases is accounted doubly: the residual processed by the Kalman filter is corrected with the vector \( \mathbf{b}_k \) and the covariance matrix of the measurement noise is adapted accordingly:

\[
\mathbf{r}_k = \mathbf{y}_k - \hat{\mathbf{y}}_k \quad \Rightarrow \quad \mathbf{r}_k = \mathbf{y}_k - \hat{\mathbf{y}}_k - \mathbf{b}_k
\]

(14)

\[
\mathbf{R}_y \rightarrow \mathbf{R}_{b,k} = \mathbf{R}_y + \mathbf{b}_k \mathbf{b}_k^T
\]

(15)

From a marginal estimation standpoint, splitting the estimation of the bias and of the health parameters constitutes an advantage given that an objective function analogous to (10) describes the problem of robust state estimation. Yet, with the present technique, only one call to the quadratic programming solver is needed to determine the sensor biases. This is highlighted in the following subsection.

**Modification of the Diagnosis Algorithm**

The block diagram of the modified diagnosis algorithm is shown in figure 3. A short description of the procedure is given in the sequel.

Similarly to the original procedure detailed in figure 1, the previous estimates of the state variables \( \hat{\mathbf{x}}_{k-1} \) and health parameters \( \hat{\mathbf{w}}_{k-1} \) are used together with the current inputs \( \mathbf{u}_k \) and \( \mathbf{v}_k \) by the engine performance model to generate an a priori estimation of the measurements. The a priori residuals between the measurements and their estimation are input to the SFDI module which computes the sensor fault vector \( \mathbf{b}_k \) by solving (13). The residual \( \mathbf{r}_k \) is formed by subtracting the sensor fault vector \( \mathbf{b}_k \) to the a priori residuals and is fed into the original DEKF. The covariance matrix of the measurement noise \( \mathbf{R}_y \) is replaced with \( \mathbf{R}_{b,k} \) further to lower the contribution of the faulty sensor to the state and parameter updates.

A further operation which is not sketched in figure 3 has been implemented in the robust diagnosis tool. Besides its direct use in equations (14-15), the sensor fault vector \( \mathbf{b}_k \) is also processed with an Exponentially Weighted Moving Average filter. As soon as one of the components of the filtered \( \mathbf{b}_k \) exceeds a predefined threshold, the related sensor is discarded in the DEKF. In that way, the DEKF becomes totally immunised against a detected sensor bias or drift by processing an incomplete residual vector. Reference [15] explains the modifications to apply to the Kalman filter in that case.

The impact of the SFDI module on the global computational burden is very limited (less than 10 % increase) due to the existence of very efficient solvers for quasi-unconstrained quadratic problems. Moreover, most of the CPU time is spent in the computation of the Jacobian matrices needed by the Extended Kalman filters.

**APPLICATION OF THE METHOD**

**Engine Layout**

The application used as a test case is a large bypass ratio mixed-flow turbofan. Due to non-availability of real data, the robust diagnosis tool has been tested on simulated data only. The engine performance model has been developed in the frame of the OBIDICOTE project and is detailed in [19]. A schematic of the engine is sketched in figure 4 where the location of the eleven health parameters and the station numbering are also indicated. One command variable, which is the fuel flow rate fed in the combustor, is considered in the following.

A dynamic model is available in the state-space form specified by relations (1-2). The modelled engine dynamics account for the shaft inertia and for the heat transfers in the hpc, the combustor and the hpt which results in the set of seven state variables listed in table 1.

The sensor suite selected for tracking the performance degradation is representative of the instrumentation available onboard contemporary turbofan engines and is detailed in table 2.
In the present application, the redundancy is extended by taking into account the fact that, on modern engines, the instrumentation is generally "dual-channeled": each of the eight probes is connected to two independent lanes (sensing element and signal processing hardware). As a result, 16 measurements are available which provides the necessary redundancy to perform the robust estimation problem. It must be pointed out that this trick does not modify the observability of the health parameters, which is linked to the variety in the sensor suite.

Definition of the Test-Cases

A series of test-cases has been designed to assess the efficiency of the new robust estimation technique. The operating conditions are set to sea-level static, standard day conditions. The evolution of the fuel flow versus time is open-loop scheduled as depicted in figure 5. The sequence is 800 seconds long and is made of two successive power sweeps between ground idle and max-continuous regimes, followed by a slam between ground idle and take-off ratings.

The engine wear is simulated from the component fault case proposed in [20]. It consists in a drift of nearly all health parameters, starting from a healthy engine (all parameters at their nominal values) at t=0 s and with the following degradation at the end of the sequence (t=800 s): −0.5% on SW12R, −0.5% on SE12, −0.4% on SW2R, −0.5% on SE2, −1.0% on SW26R, −0.7% on SE26, +0.4% on SW41R, −0.8% on SE41, −0.5% on SE49.

Gaussian noise, whose magnitude is specified in table 2 is added to the clean simulated measurements in order to make them closer to real ones. The data is processed at a sampling frequency of 50 Hertz, which is a sufficient value to capture the aforementioned engine dynamics.

Three types of sensor faults are investigated in the test-cases: impulsive noise, sensor bias and sensor drift. The sign of the sensor fault must also be accounted for, this results in six types of sensor faults which are described in table 3.
Table 3. DESCRIPTION OF THE SENSOR FAULTS

<table>
<thead>
<tr>
<th>Case</th>
<th>Description</th>
<th>Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>5% impulsive noise</td>
<td>+10 σ</td>
</tr>
<tr>
<td>b</td>
<td>5% impulsive noise</td>
<td>-10 σ</td>
</tr>
<tr>
<td>c</td>
<td>sensor bias</td>
<td>+5 σ</td>
</tr>
<tr>
<td>d</td>
<td>sensor bias</td>
<td>-5 σ</td>
</tr>
<tr>
<td>e</td>
<td>sensor drift</td>
<td>+10 σ</td>
</tr>
<tr>
<td>f</td>
<td>sensor drift</td>
<td>-10 σ</td>
</tr>
</tbody>
</table>

The level of impulsive noise per sensor is set to 5%; it means that on average, 5 out of 100 samples are aberrant. The magnitude is set to ±10 times the standard deviation. For the biases, only one sensor is simulated faulty at a time. The bias starts at t=100 s and does not evolve till the end of the sequence. Considering the drifts, only one sensor is simulated faulty at a time as well. The drift starts at time t=100 s with a magnitude of zero and reaches a magnitude of ±10 standard deviation at t=800 s. The magnitudes of the sensor faults have been selected according to contributions from members of the OBIDICOTE project.

Definition of a Figure of Merit

The efficiency of the estimation performed by the original diagnosis tool and the robust one is assessed in terms of the maximum root mean square error (RMSE) over the whole sequence:

$$e_{RMS} = \max \left( \frac{1}{n} \sum_{k=1}^{n} \left( \frac{w_k - \hat{w}_k}{w^{\text{hl}}} \right)^2 \right)$$  (16)

where \(w^{\text{hl}}\) are the nominal values of the health parameters.

Given the stochastic character of the measurement noise, each test-case has been run twenty times and the RMSEs reported in tables 4-6 are the average over the twenty runs in order to guarantee that they are statistically representative. A test-case characterised by an averaged maximum RMSE below 0.25% is declared as successful which is indicated by a checkmark. This threshold corresponds to three times the standard deviation of the identified health parameters (i.e. the square root of the diagonal terms of the covariance matrix \(P_{w,k}\)).

Results – Impulsive Noise

Table 4 reports the figure of merit defined above for the test-cases involving no sensor fault (i.e. Gaussian noise only) and impulsive noise (fault types a and b). It can be seen that the robust DEKF achieves the same efficiency in the estimation of the health parameters as the regular DEKF when no sensor fault is present. The figure of merit obtained by the standard DEKF when facing impulsive noise underlines the pronounced sensitivity of the Kalman filter with respect to outliers. On the contrary, the robust DEKF keeps the same level of accuracy when processing data contaminated with “spikes”.

Table 4. Comparison of the estimation errors obtained with the original and with the robust diagnosis tool in the case of no sensor fault (nosf) and impulsive noise

<table>
<thead>
<tr>
<th>Fault case</th>
<th>Regular DEKF</th>
<th>Robust DEKF</th>
</tr>
</thead>
<tbody>
<tr>
<td>nosf</td>
<td>0.07 %</td>
<td>✓</td>
</tr>
<tr>
<td>a</td>
<td>0.67 %</td>
<td>✓</td>
</tr>
<tr>
<td>b</td>
<td>0.68 %</td>
<td>✓</td>
</tr>
</tbody>
</table>

Results – Sensor Biases

The scores obtained by both diagnosis tools in the case of one biased sensor are given in table 5. Whatever the faulty sensor and the sign of the bias, the basic DEKF provides a spoiled diagnosis of the engine condition. It can be concluded that only one measurement out of 16 violating the zero-mean Gaussian assumption suffices to put the Kalman filter into trouble. This is another proof of the high sensitivity of least-square based methods to outliers. As far as the robust DEKF is concerned, it seems to be simply unaffected by the sensor bias as the figure of merit is roughly the same as for the no-sensor-fault case.

Table 5. Comparison of the estimation errors obtained with the original and with the robust diagnosis tool in the case of sensor biases

<table>
<thead>
<tr>
<th></th>
<th>Regular DEKF</th>
<th>Robust DEKF</th>
</tr>
</thead>
<tbody>
<tr>
<td>(p_{13})</td>
<td>0.78 %</td>
<td>0.08 %</td>
</tr>
<tr>
<td>(p_{26})</td>
<td>1.14 %</td>
<td>0.07 %</td>
</tr>
<tr>
<td>(\tau_{26})</td>
<td>3.95 %</td>
<td>0.08 %</td>
</tr>
<tr>
<td>(p_{58})</td>
<td>0.42 %</td>
<td>0.08 %</td>
</tr>
<tr>
<td>(\tau_{57})</td>
<td>0.57 %</td>
<td>0.07 %</td>
</tr>
<tr>
<td>(N_{1\text{p}})</td>
<td>0.47 %</td>
<td>0.07 %</td>
</tr>
<tr>
<td>(N_{\text{hp}})</td>
<td>0.35 %</td>
<td>0.07 %</td>
</tr>
<tr>
<td>(\tau_{6\text{p}})</td>
<td>0.29 %</td>
<td>0.06 %</td>
</tr>
</tbody>
</table>

For illustrative purpose, figure 6 depicts the estimation made by the SFDI module of a bias affecting one of the hpc discharge pressure channels.
The bias is introduced at t=100 s and nearly immediately detected by the SFDI module. This rather fast detection of the sensor fault is due to the classification nature of the algorithm supporting the SFDI task (basically relying on Huber’s weighting function (8)). It can be seen that a fair estimation of the magnitude of the sensor fault is achieved. Note that analogous comments apply to the other fault cases involving a sensor bias.

Results – Sensor Drifts

The performance of the diagnosis tools when the data is contaminated with a drifting reading on one sensor is summarised in table 6. As for the sensor bias case, the regular DEKF is unable to cope with the sensor drift and generates a very poor information about the engine condition. In most cases, the robust DEKF manages to capture the instrumentation fault and to keep an accurate tracking of the engine wear.

Table 6. Comparison of the estimation errors obtained with the original and with the robust diagnosis tool in the case of sensor drifts

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Regular DEKF</th>
<th>Robust DEKF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>case e</td>
<td>case f</td>
</tr>
<tr>
<td>$p_{13}^0$</td>
<td>1.13 %</td>
<td>3.21 %</td>
</tr>
<tr>
<td>$p_{26}^0$</td>
<td>1.67 %</td>
<td>1.64 %</td>
</tr>
<tr>
<td>$T_{26}^0$</td>
<td>5.82 %</td>
<td>6.37 %</td>
</tr>
<tr>
<td>$p_{13}^0$</td>
<td>0.58 %</td>
<td>0.67 %</td>
</tr>
<tr>
<td>$T_{31}^0$</td>
<td>0.74 %</td>
<td>0.80 %</td>
</tr>
<tr>
<td>$N_{lp}$</td>
<td>0.61 %</td>
<td>0.74 %</td>
</tr>
<tr>
<td>$N_{hp}$</td>
<td>0.41 %</td>
<td>0.51 %</td>
</tr>
<tr>
<td>$T_6^0$</td>
<td>0.34 %</td>
<td>0.43 %</td>
</tr>
</tbody>
</table>

Nonetheless, it can be seen in table 6 that the robust estimation algorithm is not able to deal with a positive drift on the hp spool speed and with a negative drift on $T_6^0$. A drift (positive or negative) on the hpc inlet temperature leads to a higher RMSE too, which is highlighted by bold values in table 6. Two of these cases are studied deeper hereafter.

First, the case of a positive drift on $T_{26}^0$ is investigated. In figure 7, the identification of the sensor fault is plotted. The upper figure indicates the status of the considered sensor; 1 being healthy and 0, faulty. It can be seen that the sensor is really declared faulty from $t=250$ s whereas the drift begins at $t=100$ s. Between $t=100$ s and $t=200$ s, the sensor is seen as healthy by the SFDI module and between $t=200$ s and $t=250$ s, the algorithm hesitates about the status of the sensor.

This fuzzy behaviour can be explained by the very nature of the implemented sensor fault. Indeed, the drift starts with a zero magnitude and linearly increases up to +10 times the standard deviation as can be seen in the bottom figure. Hence, in the first dozens of seconds after its appearance, the drift has on average a lower magnitude than the threshold used by the SFDI module to classify the sensor fault (which is, as a reminder, $\Delta \sigma$). Superimposed to the low magnitude of the drift, the Gaussian noise makes the fault detection even more tough.

The evolution of the identified health parameters is depicted in figure 8. If attention is only paid to the estimated values in the last part of the test, the accuracy is of good quality. When looking overall, this statement must be qualified however. Indeed, the estimation of the health parameters related to the turbines and the nozzle is fairly good throughout the sequence. A similar comment applies to the identified values for the fan and the hpc. On the contrary, the evolution of the health parameters associated to the lpc, namely SW2R and SE2, exhibits a bump which extends roughly between $t=100$ s and $t=400$ s, reaching its maximum around $t=250$ s. This hump, responsible for the increase in the RMSE (see table 6) is directly linked to the aforementioned difficulty for the SFDI module to capture a rising drift.

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The bump goes down as soon as the sensor is declared faulty, the rate of decrease being controlled by the covariance of the health parameters $P_{w,k}$.

The second detailed investigation is carried for the case of a negative drift on $T_6^0$ (Exhaust Gas Temperature). Figure 9 sketches the information generated by the SFDI module for both EGT channels. The fault is actually implemented on channel one as shown in the left graph, but the SFDI module assigns the fault, after some 250 s, to channel 2 as is indicated in the two pictures. Clearly, in this case, the sensor fault is wrongly diagnosed and this translates into a totally spoiled estimation of the engine condition.

To prove this statement, the identified health parameters are plotted versus time in figure 10. Up to $t=250$ s, the robust DEKF is able to track accurately the engine degradation because the magnitude of the sensor drift is too small to perturb the estimator. Afterwards, the SFDI module diagnoses the wrong EGT channel as faulty and discards its use by the DEKF. The health parameters are then adapted to catch not only the engine wear, but also the drift on the remaining EGT channel (which is believed non-faulty by the algorithm). This leads to an erratic estimation of the engine condition. The health parameters that are the most affected by the wrong sensor are SW2R, SW26R, SW41R and SW49R with up to 2% variation for the hpt capacity at the end of the sequence. This is not surprising as it is known that measurements are more sensitive to flow capacity corrections than to efficiency corrections [21].

**DISCUSSION**

To complete the analysis of the results, some issues that may lead to further developments of the proposed methodology are discussed in the following.

The first question is related to the rejection of sensor biases. The SFDI module has managed to detect a bias with a magnitude of $+5$ times the standard deviation. It is clear that a higher sensor bias will also be correctly diagnosed by the classification logic, but the determination of the lowest bias for each sensor that can be caught by the SFDI module may be of practical interest.

A second interesting axis of research consists in making the present robust DEKF, which is primarily dedicated to performance monitoring, capable to track abrupt variation of the engine condition (due for instance to foreign object damage). This problem is quite challenging since the abrupt component fault may be interpreted by the robust diagnosis tool as sensor faults.

Finally, in the light of the quadratic programming approach presented herein, the application of Moving Horizon Estimation techniques to the problem of robust estimation may be tempting. Indeed, MHE possesses some very appealing features such as the recursive minimisation of a quadratic objective function over a finite time interval or the natural inclusion of constraints on the estimated variables [22].
CONCLUSION

In this contribution, a sensor-fault-tolerant tool for performance monitoring has been developed in the framework of robust estimation. The advantages of this approach such as direct integration in the estimation procedure of the robustness issue or ability to handle a variety of fault scenarios have been pointed out. The improvements in the accuracy of the estimation of the engine condition achieved by the robust diagnosis tool with respect to the classical one are demonstrated for typical sensor fault cases that may occur on a turbofan engine.

The robust estimation tool can cope correctly with impulsive noise and sensor biases. Considering the estimation of sensor drifts, which is by far more complicated than the two other types, promising results are obtained. They tend to show that protection against sensor drifts may be achieved at the price of a relatively high hardware redundancy (variety of the on-board instrumentation).

REFERENCES


