Monitoring the Combustion Set of a Gas Turbine *

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Abstract. In this paper, we investigate the problem of monitoring the combustion chambers of the gas turbine of an electrical power generator. We describe a general approach for detecting small changes, which can be applied to a wide class of nonlinear systems, can deal with a reduced order and biased signature of the monitored system, and is robust with respect to changes in the functioning mode. We also describe a statistical method for diagnosing the detected changes in the combustion chambers. We report about the processing of a significant amount of real data from two different types of turbines.

Key Words. Failure detection; identification; diagnosis; gas turbines

1 Introduction

These last years, in a great number of industrial applications, an increasing demand appeared for replacing systematic maintenance by conditional maintenance strategies which are based upon the continuous supervision of the considered machine or structure or process. In this framework, it has been shown that a possible solution consists in the early warning of small deviations with respect to a signature of the machine or structure corresponding to its usual working conditions. We have developed an approach for this problem, the so-called asymptotic local approach for change detection [3, 4, 7]. Its original principle consists in characterizing a system via some identified (possibly nonlinear) model, and then to monitor its changes using some data-to-model distance also derived from identification techniques and from the statistical local approach.

In this paper, we discuss the application of this approach to the monitoring of the combustion chambers of the gas turbine of an electrical power generator, using the temperature measurements which are taken at the output of the expansion turbine. We discuss in detail the modeling, identification, failure detection and diagnosis issues. It turns out that the model of interest is a static nonlinear model with noisy inputs and outputs. It is known that the parameters of such a model cannot be identified without a bias [5]. We claim that this bias does not prevent from an accurate monitoring of slight changes in the system parameters [7]. Actually we have shown that model reduction can be enforced; biased identification procedures can be used; and finally one can even get rid of identification for getting the signature, and use instead some much simpler Monte-Carlo estimation technique prior to change detection. In this paper, we show how to implement this extended asymptotic local approach for the monitoring of the combustion chambers, for the detection of both sudden failures and gradual incipient failures. Moreover we describe how to use the so-called min-max robust approach (known for statistical inference in the presence of nuisance parameters) for diagnosing the detected changes.

The paper is organized as follows. In section 2, we describe the thermodynamic model of the combustion chambers of a gas turbine, and we discuss identification issues. In section 3, we describe how to detect small changes in the combustion chambers, while being robust with respect to changes in the functioning mode. In section 4, we describe how to diagnose the failed chamber, assuming that the number of failed chambers is known, and also how to estimate the number of failed chambers. Finally, in section 5, we discuss experimental results on real data.

2 Modeling and identification

In this section, we describe the modeling of a gas turbine, and more precisely of the sub-system composed

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of the combustion chambers and the expansion turbine. We give a relevant thermodynamic model for this combustion set, which turns out to be nonlinear with noisy inputs and outputs. An unbiased parametric signature is thus impossible to get [5]. But we have shown [7] that this bias does not prevent a precise monitoring of small changes in the combustion set.

We are interested in monitoring the 10 combustion chambers and the expansion turbine, using the measurements given by the 18 thermocouples. It is shown in [6] that the temperatures measured by the 18 thermocouples y_j can be expressed in the following way:

$$\begin{aligned} y_j &= \frac{T_s}{T_e}\left(T_e + \frac{T_e - T_2}{C}\sum_{i=0}^{9} a_i g(\phi_j^t - \phi_i^c - d)\right) \\ &+ b\cos(\phi_j^t - \phi^s) + w_j, \quad j = 0, \ldots, 17 \qquad (1) \\ d &= D(T_e, T_s, N) + d_0 + d_6 \sin(\phi_j^t - \phi^s) \end{aligned}$$

where the notations are explained as follows. We use a zero mean function $g(\cdot)$ to express the shape of the temperature profile generated by each combustion chamber and a_i is the scaling factor of the i-th chamber. ϕ_i^c is the angular coordinate of the i-th combustion chamber, and ϕ_j^t is the angular coordinate of the j-th thermocouple. T_e is the mean temperature at the entrance of the turbine, T_2 is the temperature at the output of the compressor and C is a normalization constant. T_s denotes the mean temperature at the exhaust of the expansion turbine, so T_s/T_e is the drop in temperature during the expansion. Besides this drop in temperature, the gas rotates around the axis of the turbine during its expansion. We call this rotation angle *phase shift* and denote it by d. Using prior knowledge, we can compute the phase shift in an approximate way, and this computation is expressed by a known function $D(T_e, T_s, N)$ where N is the rotation speed of the turbine. In view of the approximate feature of $D(T_e, T_s, N)$, we use an additional parameter d_0 to compensate for its error and a corrective term for the dissymetry $d_6 \sin(\phi_j^t - \phi^s)$. The term $b\cos(\phi_j^t - \phi^s)$ takes into account the geometric dissymmetry of the expansion turbine where ϕ^s depends on the direction of the exhauster and b gives a measurement of this dissymmetry. Finally w_j's are noises introduced due to modeling and measurement errors.

To summarize, the parameter vector of the model is written as:

$$\theta = (a_0, \ldots, a_9, b, d_0, d_6)^T$$

and the available observations are:

$$X_k = (T_e(k), T_2(k), T_s(k), N(k), y_0(k), \ldots, y_{17}(k))^T$$

where T_s is a simple average of the 18 thermocouples. Since (1) is a static system and we assume the noise to be white, the sample X is an i.i.d. sequence. We monitor changes in the process using records of X which we denote by $\{X_k\}$.

An identification procedure is proposed in [6] to identify θ using a record $\{X_k\}$. It consists in minimizing the cost function:

$$C(\theta) = \mathbf{E}\{c(\theta, X_k)\} \qquad (2)$$

where :

$$c(\theta, X_k) = \frac{1}{2}\sum_{j=0}^{17}(F_j(\theta, k) - y_j(k))^2 \qquad (3)$$

and $F_j(\theta, k)$ is the value of the measurement predicted by the model (1). A stochastic gradient algorithm of Robbins-Monro type would be of the form:

$$\theta_k = \theta_{k-1} + \gamma_k H(\theta_{k-1}, X_k) \qquad (4)$$

with :

$$H(\theta, X_k) = -\frac{\partial c(\theta, X_k)}{\partial \theta} \qquad (5)$$

but practically cannot be stable and convergent, because of the nonlinearity of the model, and the presence of noise at both the output and *the input* of the considered system. Thus we proposed in [6] an off-line stable identification procedure which separates d_0 and d_6 from the other parameters. But this estimation is known to be biased because of the noisy input [5]. This is not a major drawback for monitoring, since, as we previously discussed, the local approach for change detection can be implemented using biased nominal models.

3 Fault detection

In this section, we describe how to detect small faults and not changes in the functioning mode. In [3, 7], we have shown that the problem of detecting changes in a wide class of nonlinear processes (namely the class of semi-Markov processes) can be reduced to the much simpler problem of detecting a change in the mean of an independent Gaussian random sequence. Moreover, in [7], we have extended this method to the case where it is not possible to get an unbiased estimate of the model parameter. We now recall the main result, and describe the two detection procedures, off-line and on-line respectively for slow and fast changes, together with a modification which enables to detect small faults while keeping robust with respect to changes in the functioning mode.

3.1 Main result

Assume that the model parameter θ can be reached by identification, for example with a recursive algorithm of the form (4). At the corresponding equilibrium point, the mean vector :

$$h(\theta) = \lim_{n \to +\infty} E_\theta H(\theta, X_n)$$

is zero.

As we explain in [3], for detecting and analyzing changes in the true system , we suggest to monitor the deviations, with respect to zero, of the mean value of $H(\theta, X_n)$. The idea is to detect a change in the parameter θ when this function of observations is significantly different from zero. It turns out that there exists a mathematical result which makes this statement have a precise sense. We recall it now.

The two types of change detection problems which we consider are as follows. For the first one, we have a sample of measurements for which we wish to check if it corresponds to the signature; this problem is often called *model validation*. In the second one, we wish to test for the presence of the change inside the sample; this problem is called on-line change detection. These two problems can be stated as hypotheses testing problems for n-size samples in the following manner. For *model validation*, we consider the hypotheses :

$$\begin{aligned} \mathcal{H}_0 : \theta &= \theta_0 \\ \mathcal{H}_1 : \theta &= \theta_0 + \frac{\Upsilon}{\sqrt{n}} \end{aligned} \tag{6}$$

For *on-line detection* , we use the hypotheses :

$$\begin{array}{lcl} \mathcal{H}_0 & : & \theta = \theta_0 \\ \mathcal{H}_1' & : & \exists \tau \in [0,1] \text{ such that} \\ & & \theta = \theta_0 \;\; \text{for } k < \tau n \\ & & \theta = \theta_0 + \dfrac{\Upsilon}{\sqrt{n}} \text{ for } \tau n \leq k \leq n \end{array} \tag{7}$$

In both cases, $\Upsilon \neq 0$ is an unknown change vector.

For $m \leq n$, we introduce the following quantity :

$$\Delta_{n,m}(\theta_0, \Upsilon) = \frac{1}{\sqrt{n}} \sum_{k=1}^{m} \left(H(\theta_0,\ X_k) - h_0 \right)$$

where :

$$h_0 = \mathbf{E}_{\theta_0} H\left(\theta_0, X_k\right) \tag{8}$$

Note that, in principle, h_0 should be zero. But it helps in compensating for slight misfits of θ_0 due to imperfect learning; see the above discussion about biased identification. We define $\Delta_{n,t}$ as the linear piecewise interpolation of $\Delta_{n,m}$ at the points $t = \frac{m}{n}$. Under the hypothesis $\mathcal{H}_1'$ with $\tau \in [0,1]$, the behavior of $\Delta_{n,t}$ when n goes to infinity is governed by the following theorem [3, 4] :

Theorem 1 *Under $\mathcal{H}_1'$, the process ($\Delta_{n,t}$) converges weakly towards the diffusion process (Δ_t) which is solution of the differential equation :*

$$d\Delta_t = -1_{\{t \geq \tau\}} \cdot h'_{\theta_0} \cdot \Upsilon \cdot dt + R^{\frac{1}{2}}(\theta_0)\, dW_t$$

where (W_t) is the standard Brownian motion and :

$$\begin{aligned} R(\theta_0) &= \sum_{i=-\infty}^{+\infty} cov_{\theta_0} \left[H(\theta_0; X_i), H(\theta_0; X_0) \right] \\ h'_{\theta_0} &= \left. \frac{\partial h(\theta)}{\partial \theta} \right|_{\theta=\theta_0} \end{aligned} \tag{9}$$

The behaviors of $\Delta_{n,t}$ under the other hypotheses can be obtained as particular cases of this general theorem : $\mathcal{H}_0$ by letting $\Upsilon = 0$, and $\mathcal{H}_1$ with $\tau = 0$. In other words, this theorem replaces the complex initial problem of detecting a non additive change in a nonlinear process into the much simpler problem of detecting a change in the mean of an independent Gaussian sequence with known and constant covariance matrix. The connection between this local non-likelihood approach and the classical local likelihood approach is discussed in [1].

3.2 Computing the tests

The two quantities $R(\theta_0)$ and h'_{θ_0} of the previous theorem are estimated *on a reference sample* (X_k^0) corresponding to a safe state of the process, with the aid of the following formulas :

$$\begin{aligned} R(\theta_0) &\approx \sum_{i=-\infty}^{+\infty} \frac{1}{n} \sum_{k=1}^{n} \left(H(\theta_0, X_{k+i}^0) - \widehat{h}_0 \right) \\ & \qquad \left(H(\theta_0, X_k^0) - \widehat{h}_0 \right)^T \end{aligned} \tag{10}$$

$$\text{where} \quad \widehat{h}_0 \approx \frac{1}{n} \sum_{k=1}^{n} H(\theta_0, X_k^0) \tag{11}$$

$$h'_{\theta_0} \approx \frac{1}{n} \sum_{k=1}^{n} \left. \frac{\partial H\left(\theta, X_k^0\right)}{\partial \theta} \right|_{\theta=\theta_0} \tag{12}$$

The statistics which is used in all our tests is :

$$\Delta_n \triangleq \frac{1}{\sqrt{n}} \sum_{k=1}^{n} \left(H(\theta_0, X_k) - \widehat{h}_0 \right) \tag{13}$$

where (X_k) is the *new sample* of observations. We apply the above non-likelihood method with the aid of the vector field defined by (5) and (3), where F is the output predicted by the model (1). Note that, because the measurements (X_n) correspond to an independent sequence, this leads to a simplification of the formula (10), because the only non zero term corresponds to $i = 0$.

3.2.1 Model validation

We consider the hypotheses (6). In this case, it results from the above theorem that :

$$\mathcal{H}_0 : \Delta_n \quad \sim \quad \mathcal{N}\left(0;\ R(\theta_0)\right) \tag{14}$$

$$\mathcal{H}_1 : \Delta_n \quad \sim \quad \mathcal{N}\left(-h'_{\theta_0} \cdot \Upsilon;\ R(\theta_0)\right) \qquad (15)$$

The maximization of the log-likelihood ratio leads to the test :

$$\chi_n^2 = \Delta_n^T\, R^{-1}(\theta_0)\, \Delta_n \qquad (16)$$

where Δ_n is defined in (13). $\mathcal{H}_1$ is decided when the quantity χ_n^2 is greater than a threshold.

3.2.2 On-line detection

We now consider the hypotheses (7), and we denote by r the discrete change time. In this case, it results from the previous theorem that we can work as if the increments of the cumulative sum Δ were independent with distribution :

$$\begin{array}{lcl} \mathcal{H}_0 : H(\theta_0, X_k) - h_0 & \sim & \mathcal{N}(0\,;\ R(\theta_0)) \\ \mathcal{H}_1 : H(\theta_0, X_k) - h_0 & \sim & \mathcal{N}\left(-h'_{\theta_0} \cdot \Upsilon\,;\ R(\theta_0)\right) \end{array}$$

Note that we could have used this formulation for the model validation problem, but it would have led to exactly the same test as in (16).

In the present on-line situation, the corresponding test is based upon the stopping rule:

$$t_a = \min\{n \geq 1, g_n \geq \lambda\}$$

$$g_n = \max_{1 \leq j \leq n} (\chi_j^n)^2$$

where :

$$(\chi_j^n)^2 = (\Delta_j^n)^T\, R^{-1}(\theta_0)\, \Delta_j^n \qquad (17)$$

and :

$$\Delta_j^n = \frac{1}{\sqrt{n-j+1}} \sum_{k=j}^{n} \left(H(\theta_0, X_k) - \widehat{h}_0\right)$$

In order to reduce the cost of the search for the maximum in j of $(\chi_j^n)^2$, we constrain this search inside a window $\mathcal{M}$ with fixed length $L = n_1 - n_0 + 1$:

$$\begin{array}{rcll} \mathcal{M} & = & \{(n - n_1), \ldots, (n - n_0)\} & (18) \\ g_n & = & \max_{j \in \mathcal{M}} (\chi_j^n)^2 & (19) \\ \hat{r} & = & \arg\max_{j \in \mathcal{M}} (\chi_j^{t_a})^2 & (20) \end{array}$$

3.3 Refinement

Preliminary experiments with the aid of real data have shown that, even under $\mathcal{H}_0$, *the values of* χ_n^2 *(16) are large*, which can be explained by the nonstationarity induced by the changes in the functioning mode of the turbine itself.

In order to increase the robustness of the detection algorithm with respect to this practically important nonstationarity, we modify the algorithm in such a way to allow the measurements to deviate a little bit from the nominal model. For simplicity, we now discuss only model validation problems. Actually the detection of the changes in the mean of Δ_n - remember (14)-(15) - can then be achieved through the following way [1]. It consists in distinguishing between two new hypotheses :

$$\begin{array}{l} \mathcal{H}_0 :\ \left(h'_{\theta_0} \cdot \widetilde{\theta}\right)^T R^{-1}(\theta_0) \left(h'_{\theta_0} \cdot \widetilde{\theta}\right) \leq r_0^2 \\ \mathcal{H}_1 :\ \left(h'_{\theta_0} \cdot \widetilde{\theta}\right)^T R^{-1}(\theta_0) \left(h'_{\theta_0} \cdot \widetilde{\theta}\right) \geq r_1^2 \end{array}$$

where r_0^2 and r_1^2 are two thresholds to be chosen. The introduction of r_0^2 allows the robustness with respect to nonstationarities. The maximization of the log-likelihood ratio between these two hypotheses leads to [1] :

$$\frac{1}{n} S_n = \begin{cases} -(\tilde{\chi}_n - r_1)^2 & \text{for } \tilde{\chi}_n \leq r_0 \\ -(\tilde{\chi}_n - r_1)^2 + (\tilde{\chi}_n - r_0)^2 & \\ \quad \text{for } r_0 \leq \tilde{\chi}_n \leq r_1 & \\ +(\tilde{\chi}_n - r_0)^2 & \text{for } \tilde{\chi}_n \geq r_1 \end{cases} \qquad (21)$$

where :

$$\tilde{\chi}_n = \frac{1}{\sqrt{n}} \chi_n$$

and where χ_n is given in (16). We decide $\mathcal{H}_1$ when S_n is greater than a threshold.

Similarly an on-line decision procedure can be built in the same way [1], using the decision rules given in the subsection 3.2.2 and replacing $(\chi_j^n)^2$ by S_j^n. The behavior of this on-line decision function on some real data is shown in the figures 1 and 2, corresponding respectively to no change, and to a decrease of 20 K in the first thermocouple.

4 Diagnosis

After an alarm, it is desirable to decide which part of the machine has failed, namely how many components and which ones. In [3, 2], we describe a *sensitivity* technique for solving this diagnosis problem, in the general case where the physical model in terms of which the diagnosis is desired is of much greater dimension than the parameter θ used as a signature. Here the situation is different in the sense that the parameter θ already contains physical information, and thus the diagnosis in terms of the components of θ themselves is of interest. Here we propose to use the *minmax* robust approach [1] for solving this diagnosis problem. The idea is, for each component (or subset of components) of θ of interest, to build a test which monitors changes in this component, while being insensitive to the other components which are considered as nuisance parameters. It turns out that, assuming that the number of failed components is known, the minmax and sensitivity approaches are connected to each other, as we show now. Then, we describe an algorithm for estimating the number of failed components.

4.1 Minmax and sensitivity approaches

Let Y be a Gaussian random variable $\mathcal{N}(\mu, \Sigma)$, for which we test between the hypotheses $\mathcal{H}_0 \; : \; \mu = 0$ and $\mathcal{H}_1 \; : \; \mu = M\eta = [M_\theta, M_\psi] \begin{bmatrix} \Theta \\ \Psi \end{bmatrix}$, where M is a *full column rank matrix* and Σ is nonsingular. The *minmax approach* for testing a change in Θ while ignoring changes in Ψ consists in building the test which is optimal for the worst nuisance parameter Ψ which minimizes the power of the test. Straightforward but long computations [1] show that the optimal test is quadratic :

$$t_0^* = Y^{*T} \mathcal{J}^{*^{-1}} Y^*$$

The quantities Y^* and $\mathcal{J}^*$ are defined below.

When looking for the *a priori* unknown components which actually changed, it is useful to re-formulate the previous result in terms of a permutation of the components of θ, so as to assume that the monitored components are the first ones. Let σ be a permutation matrix, we define $\eta_\sigma = \sigma\,\eta$ by $\eta_\sigma(i) = \eta(\sigma(i))$ for all i. The minmax test is then :

$$\begin{aligned} t_\sigma^* &= Y_\sigma^{*T} \mathcal{J}_\sigma^{*^{-1}} Y_\sigma^{*T} \\ Y_\sigma^{*T} &= [I, -\mathcal{J}_{\theta_\sigma\,\psi_\sigma} \mathcal{J}^{-1}_{\psi_\sigma\,\psi_\sigma}]\,\sigma\, M^T\, \Sigma^{-1}\, Y \\ \mathcal{J}_\sigma^* &= \mathcal{J}_{\theta_\sigma\,\theta_\sigma} - \mathcal{J}_{\theta_\sigma\,\psi_\sigma} \mathcal{J}^{-1}_{\psi_\sigma\,\psi_\sigma} \mathcal{J}_{\psi_\sigma\,\theta_\sigma} \end{aligned}$$

where :

$$M_\sigma^T \Sigma^{-1} M_\sigma = \begin{bmatrix} \mathcal{J}_{\theta_\sigma\,\theta_\sigma} & \mathcal{J}_{\theta_\sigma\,\psi_\sigma} \\ \mathcal{J}_{\psi_\sigma\,\theta_\sigma} & \mathcal{J}_{\psi_\sigma\,\psi_\sigma} \end{bmatrix}$$

For the gas turbine, we have: $\Sigma = R(\theta_0), M = h'_{\theta_0}, Y = \Delta_n$.

The *sensitivity approach* consists in considering that the nuisance is zero in the alternative hypothesis $\mathcal{H}'_1 \; : \; \mu = M\eta = [M_\theta, M_\psi] \begin{bmatrix} \Theta \\ 0 \end{bmatrix}$, and using the GLR test. The drawback of this approach is that it does not decouple the different faults, whereas the (decoupling) minmax one is known to have a lower detectability. However, we have shown experimentally that, when the number of faults is known, the diagnosis can be achieved through the rule :

$$\hat{\sigma}_i = \arg \min_{\sigma \in G_i} t_\sigma$$

where t_σ is the sensitivity test and G_i the subset of permutations which put i components in first position. The components of the mean vector where the changes occurred are then given by the i last values of y, where $y = \hat{\sigma}_i x$, $x = [1, 2, ..., \ell]^T$ and ℓ is the dimension of the parameter vector θ.

4.2 Estimating the number of faults

When the number of failed components is unknown, the problem is that, even if only i chambers failed, there can exist a higher sensitivity test monitoring $(i+1)$ components. But, it turns out that the minmax and sensitivity approaches are related through a Pythagorean relation : the global test is the sum of any sensitivity test and the minmax test monitoring the complement set of components. We thus propose to estimate the number of faults in the following manner :

1. Let i be the number of assumed failed components; begin with $i = 1$;
2. For each set of i components, compute the sensitivity test; select the set with the greatest one;
3. For this set, compute the minmax test monitoring its complement. If this test is greater than a threshold, set $i = i + 1$, and go to 2. If not, stop; and the failed components are those of the last selected set.

In practice, we also use robustness parameters for computing the minmax test, namely we use the formula (21) in which :

$$\tilde{\chi}_n = \frac{1}{\sqrt{n}} (t_0 - t_{\hat{\sigma}_i})^{\frac{1}{2}}$$

and $t_{\hat{\sigma}_i}$ is the highest sensitivity test monitoring i components.

5 Experimental results

The proposed algorithms have been run on a significant amount of real data measured on two different types of turbines (different numbers of chambers and thermocouples, and different shape of the output diffuser). It is important to note that the identification, detection and diagnosis algorithms have been designed in such a way that the tuning of their parameters is either not necessary – they are all pre-tuned – or achieved in an automatic manner by “learning" on the available data. More precisely, for the detection, the key “robustness" values r_0, r_1 in (21) are learned by re-processing the real data used for the identification in such a way to estimate the size r_0 of the confidence ellipsoïd around the signature θ_0, and the minimum magnitude of change r_1 to be detected.

We now show some typical results of the diagnosis algorithm. As we have never registered any data with actual fault of the gas turbine system, we simulated faults, by modifying the signature θ_0 and running the tests on the (assumed) safe data. Here we show only results of the off-line diagnosis. We took 176 samples of 2000 real measurement points X_k. For each sample we simulated a change of 20K of temperature in each of the 10 combustion chambers, so we did in total 176×10 simulations. The diagnosis was performed on each of these samples of 2000 measurement points with simulated faults. The algorithm successfully determined that the number of faults was 1 in all these simulations. The rates of success in the isolation of the faults are shown in table 1. For some chambers the right isolation was 100%. The lowest rate 97.7% was obtained for the 9th chamber.

6 Conclusion

We reported our results on the application of statistical methods on change detection to the monitoring and diagnosis of gas turbine systems. A large amount of real data were processed, and the results are encouraging.

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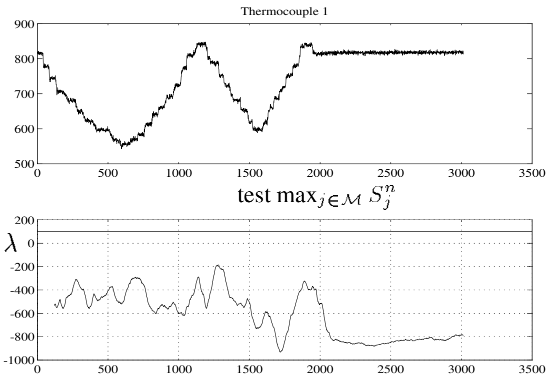

Fig 1: Behavior of the test when NO failure occurs - Note the robustness with respect to the nonstationarity due to the changes in the functioning mode : the test statistics remains negative and does not cross the positive threshold.

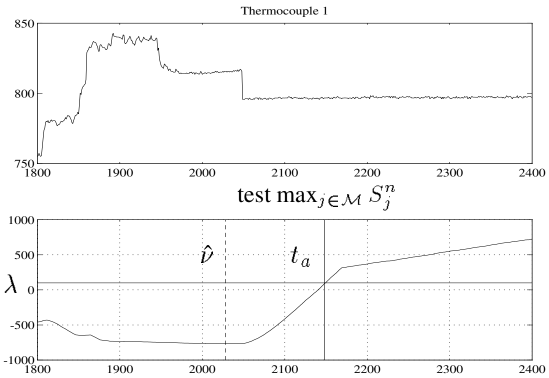

Fig 2: Detection of an abnormal decrease of 20 K in the first thermocouple at time 2050 - Note that the magnitude of the change is *small* with respect to the nonstationarities.

Comb. chamber number	1	2	3	4	5	6	7	8	9	10
Nb. of mis-isolations	0	0	1	0	0	0	1	2	4	1
Rate of success (%)	100	100	99.4	100	100	100	99.4	98.9	97.7	99.4

Tab 1: Rate of successful fault isolations