Decision Versus Identification Issues in Fault Detection/Isolation for Predictive Maintenance

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Abstract. The purpose of this paper is to emphasize the key role of *decision issues* and their connection with *identification issues* in statistical methods for fault detection and diagnosis (or isolation). We first describe a general approach to the design of statistical decision rules for fault detection and isolation in industrial plants, starting from a parametric characterization of the plant. We then report the main performances of the resulting algorithms for two applications: vibration monitoring for mechanical structures or machines, monitoring the combustion chambers in power plant gas turbines. Finally we discuss decision versus identification issues. We outline why fault detection cannot be reduced neither to repeated identification of the parameters nor to innovation monitoring. We explain how to decide that the discrepancy between the identified parameter values and the reference ones is significant, especially in the presence of noises and disturbances on the system. We also outline that the early warning and isolation of small faults can be obtained even with biased identified parametric models.

Key Words. Identification, fault detection, fault isolation, diagnosis

1 Introduction

These last twenty years, there has been a wide variety of theoretical and practical investigations about fault detection and isolation (diagnosis), as reflected in the references [1, 3, 9, 10, 11, 13, 14] and the literature cited therein. In this framework, an increasing interest in condition-based maintenance has appeared in a large number of industrial applications. The key idea is to replace periodic systematic inspections by condition-based inspections, i.e. inspections decided from the continuous monitoring of the considered machine or structure or process, hereafter called *plant*. For this purpose, advanced multi-sensors signal processing methods are necessary in order to get accurate information regarding the time variation of the plant and decide inspections only when necessary. The problem is then:

1. to extract, from the measurements, features characteristic of the plant and appropriate for monitoring;
2. to design decision rules for detecting and diagnosing damage and abnormal situations, while preserving sufficient robustness with respect to changes in functioning modes;
3. to derive quantitative criteria for selecting sensor location or measurement selection relevant for monitoring purposes;
4. to merge judiciously such condensed information with other types of information (for example symbolic, historical, ...) which are also available and useful for fault detection.

In this framework, a possible and successful solution has been shown to consist in the early detection of slight deviations with respect to a characterization of the plant in usual working conditions (without artificial excitation, speeding down, or stop). From now on, we call *signature* any parametric characterization of the plant, should it be a model or a network, based on the physics or not. When considering a parameterized network, we refer to a finite-dimensional neural or wavelet network [12]. This modelling issue is discussed further in section 2.

The purpose of this paper is to outline the key role of decision versus identification issues for such problems. The paper is organized as follows. We first describe, in section 2, a general statistical approach for designing such parametric fault detection and diagnosis algorithms. It should be noted that, when a model is used (and not a network), this approach allows us to design algorithms for fault isolation in the physical domain *even* if the identified parametric model is different from (and generally of much smaller dimension

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than) the underlying physical model. The relevance of this approach is supported by multi-years investigations and experimental results concerning two different types of applications: vibration monitoring for mechanical structures in usual working conditions, and isolation of faulty combustion chambers in power plant gas turbines. In section 3, we comment on the performances of the resulting algorithms in these two applications, where the involved models are linear and dynamic for the first one, and nonlinear and static for the second. Especially we report how the proposed methods are sufficiently sensitive to *small* faults whereas keeping robust with respect to the high nonstationarities in the excitation for mechanical stuctures, and to hard changes in functioning modes for power gas turbines. Finally in section 4 we discuss decision versus identification issues, and emphasize the key role of decision issues in fault detection/diagnosis problems. Basically we claim that fault detection/isolation cannot be reduced to repeated identification of parameters from time to time. The key issue is how to measure the discrepancy between the identified parameter values and the reference ones, and how to decide that this deviation is *significant*, especially in the presence of noises and disturbances on the system. Moreover it is also outlined that, in a wide class of fault detection problems, innovation monitoring is *not* the right way of designing an efficient fault detection algorithm. We also explain how the early warning and isolation of small faults can be obtained even with *biased* identified parametric models.

2 A general approach to monitoring for condition-based maintenance

In this section, we describe a general approach to the design of statistical decision rules for fault detection and isolation in industrial plants, starting from what we call a signature, namely a parametric characterization of the plant, should it be a model or a network, based on the physics or not. When considering a parametric model-based characterization of the plant in usual working conditions, we distinguish between two types of modeling: the *physical modeling* which allows us to explain or even to simulate more or less accurately the phenomena involved in the plant, and the *black-box modeling* which can be used for processing data without considering the physics. In some cases, the two models are identical. When they are different, both of them are of interest for monitoring basically when at least a partial relation between them is available. When considering a parameterized network, we refer to a finite-dimensional neural or wavelet network [12]. In this case, our general approach to the design of decision rules does apply in the same manner, the identified network is then considered as a particular type of parametric model. Of course, the interest of such a parametric signature for physical fault isolation heavily depends upon the existence of a link between the parameters of the network and a possibly partial physical model. Also the choice of the most relevant model for fault detection/isolation, in a given application where the available expert physical knowledge is limited, is an open question. It may very well happen [12] that a parametric network leads to a much better identified model than a simplified physical model (playing then the role of a black-box one); here "better" is in terms of prediction error and/or of simulation performances. Nevertheless this network is not only likely to have little physical meaning, but may very well be of much higher dimension than the simplified model, and of much lower interest as far as the detection performances are concerned.

Our approach is based upon the early detection of slight deviations with respect to such a parametric signature. From now on, we equally use the words deviation, change, failure, and fault, considering that all these events are reflected by a change in the parameters of the model [1, 3] or the network [12]. The approach is summarized in the diagram of figure 1 and consists of the first three steps mentioned in the introduction: identification, detection and isolation, sensor location.

In site identification of the signature: This identification is achieved by learning on data recorded on the plant in usual working conditions. This step is necessary, even when a "design" model is available, for two reasons:

- The model provided by the designer can be non exact in the sense that it does not correctly take into account the phenomena resulting from the actual setting up of the plant. This is the case in vibration monitoring of complex mechanical structures and rotating machines. But the order of magnitude of the deviations which are to be detected is often the same as that of this inaccuracy [7].
- The very principle of monitoring in usual working conditions relies upon the existence of a signature of the plant based on the measurements themselves.

We call it *black-box signature*. However it should be noted that, even when one is unable to obtain a non biased signature (as it is the case for gas turbines combustion chambers for example [15]), we still can perform a continuous monitoring of small changes in the behavior of the plant. We have shown that it is even possible to monitor with the aid of a signature chosen in an approximate manner and not identified. Of course the price to be paid is then a decrease, although not dramatic, in the monitoring performances [15].

Detection: Given such a signature on one hand and new measurements on the other one, the problem is then to decide if these measurements are still conveniently described by this signature or if a significant (but small) change occurred. Two solutions can then be used.

- *Identification of a new signature and comparison between the two signatures* with the aid of a convenient distance [2]. This method is often non appropriate for the following reasons. The first one is that the identification of the signature may be computationally expensive, especially when it cannot be completely achieved automatically and requires human operation. This is the case for complex plants, and in particular in vibration mechanics [7]. The second reason lays in the fact that the success of such a monitoring method crucially depends upon the choice of a relevant distance between the two signatures. Finally, in the case of complex systems, the direct comparison between two signatures can be non sufficient for fault isolation; for example, again in vibration mechanics, it is well known that it is very difficult to match two sets of modal shapes resulting from two successive modal analysis when some of the modes are close to each other.
- *Direct comparison between the new measurements and the available signature.* This is the solution which we propose. We have designed [8, 15] a general method for designing the appropriate indicator. This indicator basically transforms the initial monitoring problem – which can be very complex, even in terms of the black-box model – into a *standard* detection problem: monitoring the mean of a vector Gaussian variable in the independent case. This method allows us to overcome all the drawbacks mentioned above, and provides us with a global alarm of low computational cost and a diagnosis in terms of the black-box signature. Moreover, this method automatically achieves a tradeoff between the magnitude of the detected changes and the precision of the identified signature: the changes which are claimed to be significant are significant with respect to this confidence domain.

Isolation: Given again such a black-box signature (basically from a simple and identifiable model or network), plus a possibly unaccurately known physical model of the plant (generally commplex and non identifiable), and new measurements again, two isolation problems can arise, namely:

- *Diagnosis in terms of the black-box signature*, for example in terms of the modal characteristics in the case of vibration monitoring [4]. Several methods can be used, based upon either a sensitivity technique with respect to a given failure, or a (statistical) method for rejecting the alternative failures. This type of diagnosis brings informations which are interesting in themselves but can be of too complex interpretation: once again, it is well known that two changes very different from a mechanical point of view can lead to similar deviations in the modal signature.
- *Diagnosis in terms of the underlying physical model.* This problem is less simple to solve, because in general the physical model is complex and non identifiable. Our solution [7] circumvents the resolution of the difficult corresponding inverse problem, and relies upon the computation of convenient Jacobian matrices in the change directions which result from the projection of the elementary changes in the physical space onto the space of the black-box signature – in the diagram of figure 1, we call macro-failures these directions – and upon the use of a sensitivity technique. The design of the macro-failures is done once for all when designing the monitoring system. On the other hand, the sensitivity tests are of low computational cost and can be used on-line.

Sensor location: The investigation of the sensor pools and of their optimal location for monitoring is also achieved at the stage of the design of the monitoring system. We propose a quantitative criterion, based upon the power of the statistical tests [5, 7], which allows us to assess the quality of a given sensor location for monitoring and diagnosis purposes. This criterion can be used in two manners: for a given sensor pool location (it is not always possible to choose!), find the failures which are detectable and diagnosable; for one given (set of) fault(s), find the sensor pools and locations (possibly a simple selection of the available measurements) which will allow us to detect and diagnose them.

3 Two examples

In this section, we report about the main performances of the algorithms corresponding to this general approach in two different types of applications: vibration mechanics and combustion set of power gas turbines.

Vibration monitoring The above general approach has been developed as an extension of the approach developed at IRISA for monitoring, in usual working conditions, the vibrations of offshore platforms and turbo-alternators of electricity power plants, in cooperation with IFREMER and EDF, respectively. The problem is to separate, in the multidimensional measurements, the high nonstationarities in the excitation (of no interest for monitoring) from the slight nonstationarities in the vibrating behavior of the structure or the machine. The basic idea is to consider that the proposed method is accurate enough for the identification of the signature to "take advantage of any excitation" (for example, turbulences caused by the steam inside the turbine of the alternator), and to be achieved on observations covering the maximum number of possible excitations and functioning modes. In this example, the black-box model to be identified and monitored is a linear dynamic model, namely the AR part of a multivariable ARMA model, which MA part is nonstationary. The use of this type of black-box model is justified by the fact that it results directly from the fundamental law of mechanics [7, 4, 5]. Thus in this case we have a direct link between the physical and black-box models, although this link implicitly involves a drastic reduction in dimension, basically because a very small number of sensors is usually available whereas the number of degrees of freedom of the finite elements model is about several hundreds if not thousands.

The main features of the condensed information brought by our detection/isolation algorithms in this domain are the following:

- It is possible to detect and diagnose *small* changes – typically 1% – in eigenfrequencies, provided that the modes are only slightly damped (which is the case in the considered applications) and that the record length is large enough (typically, several thousands sample points). It should be clear that such changes are not necessarily visible in the plot of the corresponding spectral density.
- It is even possible to detect modal changes corresponding to zero change in the eigenfrequencies, but only to changes in the geometry of the modal shapes. It should be clear that such changes cannot be detected when using a componentwise Fourier analysis of the signals.
- Rather than ultimate decisions regarding safety and maintenance, the algorithm provides *accurate* likelihoods of various failures. Moreover it automatically achieves a tradeoff between the magnitude of the detected changes and the precision of the identified signature: the changes which are claimed to be significant are significant with respect to this confidence domain, and also with respect to the noise level. This is a great advantage with respect to more classical model updating methods in mechanical engineering, where no tool is available for assessing the *significance* of the observed modal deviations.
- The physical diagnosis method is not always able to recognize the physical nature of the change – namely mass versus stiffness or volumic mass versus Young modulus – but rather provides us with a relevant localization of the change in the structure or the machine.

Finally, it should be noted that these algorithms concern *eigenstructure analysis, monitoring and diagnosis* in general, of which vibration analysis is only one typical application.

Monitoring the combustion set of a gas turbine The extended approach has been then investigated for its application to the monitoring of the combustion chambers of gas turbines, in cooperation with ALCATEL-ALSTHOM-RECHERCHE (Marcoussis) and EUROPEAN-GAS-TURBINES (Belfort). In this thermodynamical problem, the two (black-box and physical) models which are used are identical, namely we consider a nonlinear static model representing the combustion and diffusion phenomena in a simplified manner [15]. Preliminary experiments on real data have shown that, even when no fault occurs, the values of the global test are large, which can be explained by the nonstationarity induced by 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. More precisely, we introduce a confidence ellipsoïd around the signature, and a minimum magnitude of change to be detected.

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 [6]. The main features of the condensed information brought by our detection/isolation algorithms in this domain are the following:

- It is possible to detect faults of *small* magnitudes with respect to the nonstationarities due to hard changes in functioning modes.
- The tuning of the parameters – size of the confidence ellipsoïd, minimum magnitude of change, threshold – can be achieved in an automatic manner by "learning" on the available data.
- In the case of single faults, it is possible to isolate the failed combustion chamber with probability around 0.98. In case of *multiple* faults, we can estimate the number of failed chambers and isolate them.

4 Detection versus identification issues

We now emphasize what are, in our mind, the key roles of decision and identification issues in fault detection and isolation. These conclusions are based on the above mentioned investigations.

- Fault detection/isolation cannot be reduced to repeated identification of parameters from time to time. The key issue is how to measure the discrepancy between the identified parameter values and the reference ones, and how to decide that this deviation is *significant*, especially in the presence of noises and disturbances on the system. A poor distance measure at this step may very well destroy the accuracy of the identification procedure. Moreover, it should be clear that the relevance of a parametric model crucially depends on the use of the model which is to be performed – here fault detection – and that the criterion for validating the identified signature at the end of the identification step should be of the *same* nature as the criterion used at the detection step for deciding if a deviation is significant [6].
- In a wide class of fault detection problems, innovation monitoring is *not* the right way of designing an efficient fault detection algorithm. Actually the innovation is basically a sufficient sytatistics only for *additive* faults, namely changes in the mean value of the observed signals, and not for changes in the correlations, in the spectrum, in the transfer function, ... For these type of faults – often called *multiplicative* faults – a function of the signature and the signal which is different from the innovation should be computed and monitored [3].
- The early warning and isolation of small faults can be obtained even with *biased* identified parametric models [15]. Of course this bias decreases – but does not annihilate – the performance of the detection procedure.

REFERENCES

[1] M. BASSEVILLE: Detecting changes in signals and systems – A survey. *Automatica*, vol.24, no 3, May 1988, pp.309-326.

[2] M. BASSEVILLE: Distance measures for signal processing and pattern recognition. *Signal Processing*, vol.18, no 4, Dec.1989, pp.349-369.

[3] M. BASSEVILLE, I. NIKIFOROV: *Detection of Abrupt Changes - Theory and Applications*. Prentice Hall Information and System Sciences Serie (T.Kailath, ed). Apr.1993.

[4] M. BASSEVILLE, A. BENVENISTE, G. MOUSTAKIDES, A. ROUGÉE: Detection and diagnosis of changes in the eigenstructure of nonstationary multivariable systems. *Automatica*, vol.23, no 4, July 1987, pp.479-489.

[5] M. BASSEVILLE, A. BENVENISTE, G. MOUSTAKIDES, A. ROUGÉE: Optimal sensor location for detecting changes in dynamical behavior. *IEEE Trans. on Automatic Control*, vol.AC-32, no 12, Dec.1987, pp.1067-1075.

[6] M. BASSEVILLE, A. BENVENISTE, G. MATHIS, Q. ZHANG: Monitoring the combustion set of a gas turbine. *Proc. Safeprocess'94*, Helsinki, Finland, June 13-16, 1994.

[7] M. BASSEVILLE, A. BENVENISTE, B. GACH-DEVAUCHELLE, M. GOURSAT, D. BONNECASE, P. DOREY, M. PREVOSTO, M. OLAGNON: Damage monitoring in vibration mechanics: issues in diagnostics and predictive maintenance. *Mechanical Systems and Signal Processing*, vol.7, no 5, Sept. 1993, pp.401-423.

[8] A. BENVENISTE, M. BASSEVILLE, G. MOUSTAKIDES: The asymptotic local approach to change detection and model validation. *IEEE Trans. on Automatic Control*, vol.AC-32, no 7, July 1987, pp.583-592.

[9] J.J. GERTLER: Survey of model-based failure detection and isolation in complex plants. *IEEE Control Systems Magazine*, vol.8, no 6, 1988, pp.3-11.

[10] R. ISERMANN: Process fault detection based on modeling and estimation - A survey, *Automatica*, vol.20, 1984, pp.387-404.

[11] R. ISERMANN: Fault diagnosis of machines via parameter estimation and knowledge processing - Tutorial paper, *Automatica*, vol.29, 1993, pp.815-836.

[12] A. JUDITSKY, Q. ZHANG, B. DELYON, P-Y. GLORENNEC, A. BENVENISTE: Wavelets in identification. Tutorial, *These Proceedings*.

[13] R.J. PATTON, P.M. FRANK and R.N. CLARK (eds): *Fault Diagnosis in Dynamic Systems : Theory and Application*. Prentice Hall International (UK), 1989.

[14] A.S. WILLSKY: A survey of design methods for failure detection in dynamic systems, *Automatica*, vol.12, 1976, pp.601-611.

[15] Q. ZHANG, M. BASSEVILLE, A. BENVENISTE: Early warning of slight changes in systems and plants with application to condition based maintenance, *Automatica - Special Issue on Statistical Methods in Signal Processing and Control*, vol.30, no 1, Jan.1994, pp.95-114.

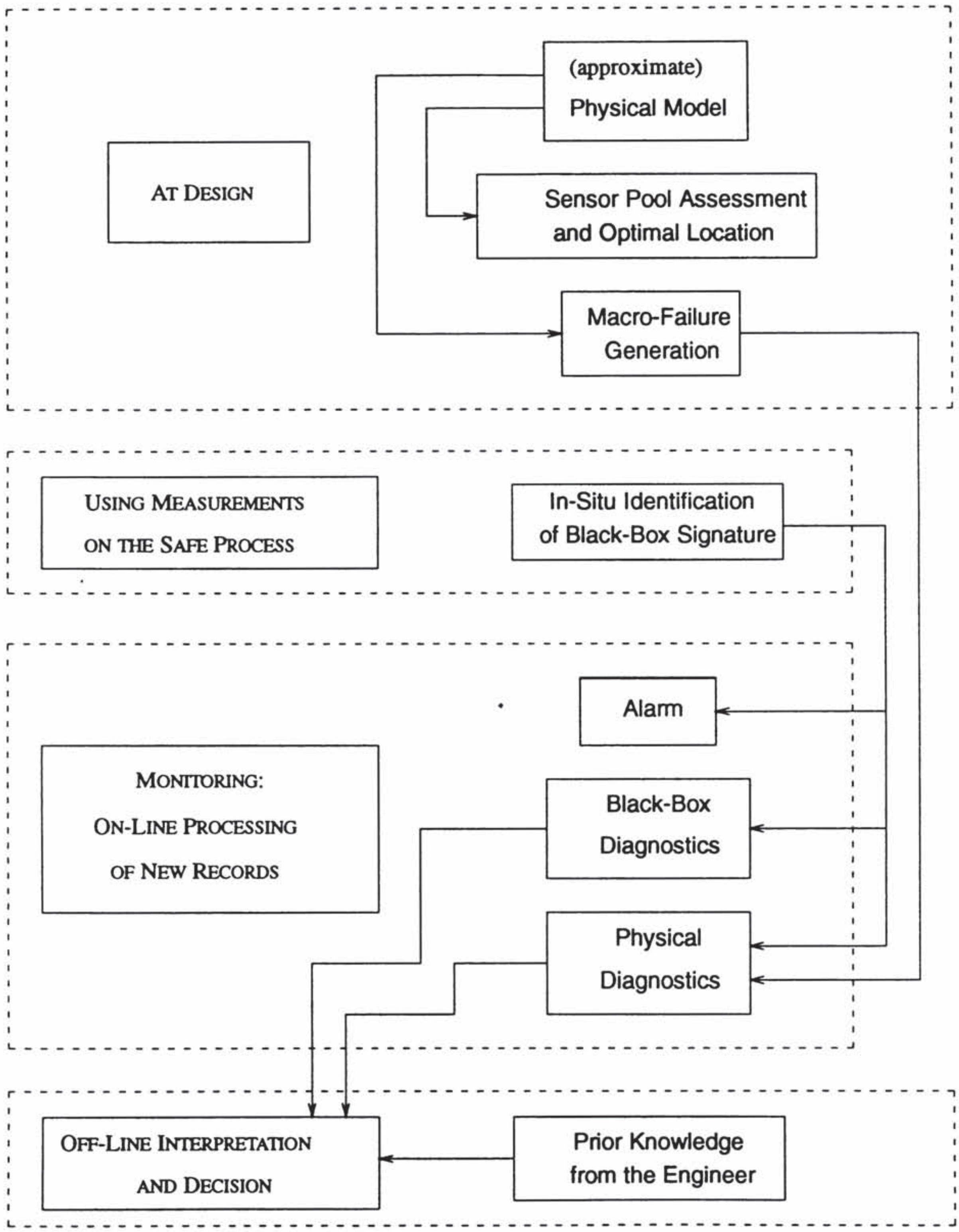

Fig 1. Synoptic of the proposed approach to monitoring.