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A Methodology for the Design of Automated Gas Turbine Diagnostic Systems

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ABSTRACT

A methodology for the design of automated diagnostic systems for Gas Turbines is presented. The first stage of the proposed methodology consists in an initial selection of instruments and measuring positions on the engine, based on a basic knowledge of the engine itself and previous experience, as well as modelling capabilities of the phenomena happening in it. It is followed by a stage of "learning" experiments. One purpose of these experiments is to provide measurement data, on which a final selection of instruments will be based. The instruments most suitable for the fault cases of interest are selected, according to the diagnostic potential they offer. Another purpose is to develop procedures of automated fault diagnosis. The necessary background information for the later exploitation of the system is also established. The applicability of the entire methodology is demonstrated for the case of designing a blade fault diagnostic system for an Industrial Gas Turbine.

1. INTRODUCTION

The development and implementation of Engine Condition Monitoring and Fault Diagnosis methodologies for Gas Turbines has received a continuous effort in recent years. The benefits from a successful application of such a methodology have been noted by many authors. It has been recognized that approaches based on different kinds of measurements are essential, in order to cover the full range of expected malfunctions of an Engine. Lifshits et al, (1986), Baines (1987). Meher-Homji and Cullen. (1992). Lifson et al. (1988), Lifson et al, (1990), have presented overviews of the various techniques in use and commented on their suitability for assessment of the condition of parts of a Gas Turbine as well as for identification of different possible malfunctions.

When the implementation of an Engine Condition Monitoring system is considered, a set of requirements for its successful operation arise. Briefly speaking, the techniques employed must cover a range of problems as wide as possible, using as little measurement data as possible, while they should provide reliable information on problem identification. They should also be characterized by as high automation and "intelligence" as possible. The selection of the quantities to be measured, as to their kind and location on an engine, and the processing of the collected data, has to be effected in such a way that these requirements are fulfilled. It must be remembered that it is desirable to employ as few instruments as possible, because instrumentation is costly, its installation is not easy in many cases and instruments must be carefully maintained.

These problems have been dealt with to some extent in methods employing aerothermodynamic data, and methods for optimizing measurement and health parameters selection have been proposed. For example, Stamatis et al, (1992), have proposed such a method, which they tested on steady operation data. Merrington et al, (1990), have introduced a technique for transient operation data, in order to reply to the fact that certain aircraft engines rarely operate in steady conditions. Doel, (1991), has discussed the philosophy for designing monitoring systems so that they reply to the need of deriving maintenance decisions.

The above problems have not received the same kind of attention, when dynamic measurements are concerned. Although such measurements have been widely employed for monitoring, especially under the form of vibration data, their location selection until now is mainly performed empirically (see Lifson et al, 1988). The processing of collected data, and the parameters on which the diagnosis is based, are empirically selected as well. This does not ensure that the most appropriate

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selections are done. Also, even though these empirical selections may be successful in some cases, there is no guarantee that they will be successful in the general case, if application to other engines and faults is required. Some quantitative methods for dealing with these problems have been introduced by Loukis et al, (1992b), in the frame of a proposed automated fault classification method. A method for the selection of relative shaft or bearing pedestal vibration for monitoring has been derived through an analytical study by Rihak and Schmidt, (1992), while aspects related to system identification have been discussed by Stein and Park, (1988).

The present paper addresses these problems by presenting a systematic examination of the requirements for an efficient diagnostic system and a design methodology for fulfilling them. Stages to be followed in order to set up a system are described, as well as methods for building up related background information and methods for achieving a maximum effectiveness during exploitation. Although the presented methodology addresses mainly dynamic measurements, its structure is such that it can also be adapted for use with steady state measurements. An application of the methodology, for the development of the background of a blading faults diagnostic system for an industrial Gas Turbine, is also presented, from which its applicability and its capabilities for realistic cases are demonstrated.

2. DESIRED FEATURES OF AN EFFECTIVE DIAGNOSTIC SYSTEM

A system which performs successfully the task of Engine Condition Monitoring and Fault Diagnosis must possess the following features:

-Cover a wide range of possible malfunctions and faults. All faults which are expected to occur in a particular engine should be identifiable by the system. Additionally, it should be adaptable to add other newly discovered faults, which have not been included in the initial repertory of the system.

-Cover faults of different magnitude. While faults which have a significant effect on engine performance should be identifiable, this should extend to faults of small magnitude not significantly influencing engine performance. Some small faults, even though not directly influencing performance, might be important to identify, because they could rapidly evolve to catastrophic failures. An example of such faults are the ones associated with geometry changes of turbomachinery components blades of an engine.

-Employ as few instruments are possible. The instrumentation should be kept as simple as possible and include the minimum number of instruments. The measurements should be the least intrusive possible, preferring measurements which require the minimum intervention with an engine. Also, the most suitable quantities must be selected for measurement, namely the ones which exhibit differentiations highly correlated to faults of interest and have a minimum content of information irrelevant to the faults. On the other hand keeping the number of instruments low not only keeps the cost low, but also reduces problems which can occur with maintaining the instrumentation itself.

-Produce no false alarms. When an indication of a fault is provided, this should be accompanied with the highest level of confidence possible. Also the most appropriate processing software should be developed, to exploit as much as possible the diagnostic information contained in the measurements.

-Have a high degree of automation. It should include automated procedures for both fault diagnosis during exploitation and its design and tuning. This feature is desired because it minimizes the need for specialized personnel, while it reduces the time of interpretation and therefore decisions can be made quickly.

- Provide diagnostic information with the highest possible detail, about the nature, the location and the severity of a fault. Additionally, it should attach a confidence level to the decisions.

In order to produce a system which possesses these features, appropriate action has to be taken in building all the parts of the system. The main parts into which such a system can be subdivided are as follows:

(a) instrumentation and related hardware
(b) data processing and data reduction module
(c) decision making module.

Parts (b) and (c) can have the form of dedicated processors, but the tendency is to employ independent computers to perform the task by means of appropriate software. Apart from the processing performed in (b) and (c), there is one more piece of information needed: data about the "healthy" condition of the machine and the "signatures" of the faults. In a computerized system these data can be contained in one or more relevant data bases (see for example the discussion of Hewitt and Bosmans,1991).

Building a diagnostic system consists in setting up parts (a), (b) and (c). In the following paragraphs a methodology for materializing this task, in such a way that the resulting system exhibits the previously discussed features, is presented.

3. BASIC STRUCTURE OF THE METHODOLOGY

The proposed design methodology consists of five stages, shown in fig.1. An initial stage of design is carried out for a primary determination of the physical quantities expected to possess diagnostic capabilities. It is based on physical knowledge of the installation of interest and results of modelling, wherever this is possible. This stage is termed pre-experimental, since it does not involve execution of measurements on the installation. The second stage includes the acquisition and processing of measurement data from the installation in healthy condition. Its target is to draw some first conclusions about the nature of the measured physical quantities, and to acquire baseline information. It is termed the healthy-condition experimental stage. Next comes the third stage, including acquisition and processing of measurement data

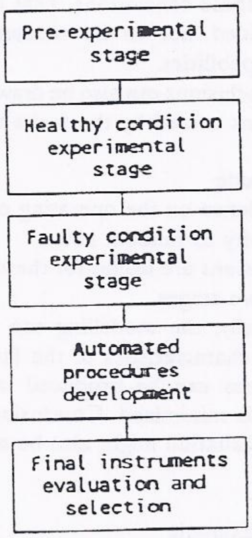

Figure 1: The 5 stages of the design methodology.

from the installation containing faults. Comparison to the corresponding data from the healthy condition gives the diagnostic capabilities of the measured physical quantities as well as information about fault signatures. It is termed the faulty-condition experimental stage.In the fourth stage of the methodology, automated fault diagnosis procedures are built, and their effectiveness is tested using the experimental data. In the fifth stage, the physical quantities which will be finally measured by the diagnostic system are determined. Their selection is based on a quantitative evaluation of their diagnostic capabilities as well as on the cost and functionality of performing their measurement.

The stages of the methodology are described in detail below. In order to make the presentation clear, for each stage application examples are given. The application examples refer to investigations for the development of a blade fault diagnostic system for an industrial Gas Turbine. This industrial Gas Turbine is the one described by Wood,(1981), and will be referred to as the "test engine" in the applications presented later.

4. PRE-EXPERIMENTAL STAGE OF DESIGN

The first stage of the design of a diagnostic system for a specific installation is carried out before performing measurements and acquiring data from the installation under investigation. It is based on the physical knowledge of the structure of the installation, and the physical phenomena which take place in it. Modelling of these phenomena can also be used, both for healthy and faulty conditions. An outcome of this stage is an initial determination of the physical quantities which will be measured by the diagnostic system. The features and ranges of these quantities are also derived, information which is useful for the design of the subsequent experiments. Knowledge of this information is very important, since the experiments of the following stages can be characterized by long duration and high costs. The steps to be taken for performing this stage of the design are schematically given in fig.2 and are further discussed below.

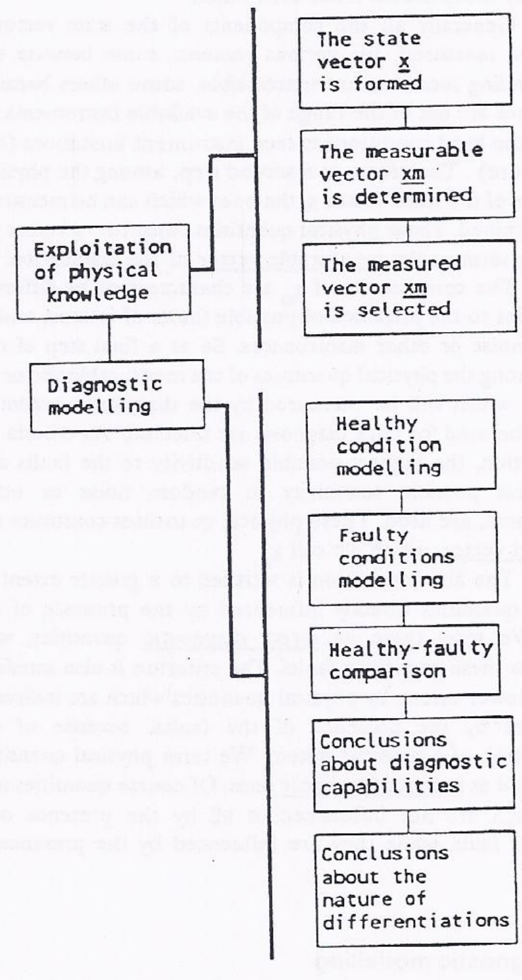

Figure 2: The two-phases of the pre-experimental stage of design

4.1 Exploitation of physical knowledge

The state of an installation can generally be expressed by a set of physical quantities, which may be of many different kinds (e.g. for the case of a Gas Turbine they may be pressures, temperatures, vibration etc.). Their common feature is that each one reflects a particular aspect of engine condition and operation. They can be grouped in a vector $\underline{x}$, which we term the state vector of the installation:

$$\underline{x} = [\, x_1, x_2, \ldots, x_N \,]$$

As a first step the state vector $\underline{x}$ for the installation under investigation is formed. The quantities which constitute its components are selected to fulfil the requirement that they should give the possibility to obtain a full picture of the condition of the installation. For its formulation the knowledge about the structure and the components of the installation, as well as the existing experience about the phenomena which take place in it, are utilized. The components of vector $\underline{x}$ are not necessarily independent from each other.

Generally all the components of the state vector $\underline{x}$ cannot be measured, for various reasons: some because the corresponding locations are inaccessible, some others because their values are out of the range of the available instruments, or because the local conditions exceed instrument limitations (e.g. temperature) . Therefore, as a second step, among the physical quantities of the state vector $\underline{x}$, the ones which can be measured are determined. These physical quantities constitute a vector $\underline{x}_m$, which we term as the measurable vector of the installation.

The components of $\underline{x}_m$ are characterized by different sensitivities to the presence of possible faults of interest and to random noise or other disturbances. So at a final step of this stage, among the physical quantities of the measurable vector $\underline{x}_m$, the ones which will be measured by the diagnostic system in order to be used for fault diagnosis are selected. As criteria for the selection, the highest possible sensitivity to the faults and the lowest possible sensitivity to random noise or other disturbances, are used. These physical quantities constitute the measured vector, which we call $\underline{x}_\mu$.

The above criterion is satisfied to a greater extent by physical quantities directly influenced by the presence of the faults. We term these as direct diagnostic quantities, with respect to these particular faults. The criterion is also satisfied, but to a lower extent, by physical quantities which are indirectly influenced by the presence of the faults, because of the interposition of a physical system. We term physical quantities of this kind as indirect diagnostic ones. Of course quantities may exist which are not influenced at all by the presence of a particular fault, while they are influenced by the presence of another.

4.2 Diagnostic modelling

The selection of quantities discussed so far has been based only on knowledge of the structure and the phenomena which take place in the installation. After this selection, it is useful to carry out a first examination of their diagnostic capabilities based on modelling. For this purpose models of the installation or its parts are developed and employed for obtaining the values of the physical quantities of interest. These models should cover both the healthy condition and conditions with various faults present. The results of the faulty condition models are then compared with the ones at the healthy condition.

From this comparison, model-based conclusions can be drawn about the differentiations to the components of $\underline{x}_\mu$ caused by the presence of representative faults. Using these conclusions a first examination of their diagnostic capabilities can be done. The initial choice of the components of $\underline{x}_\mu$ might be changed, according to these conclusions. That means that some of them may be decided not to be measured, if they show poor diagnostic capabilities.

Conclusions can also be drawn about the nature of the differentiations caused by the faults to the components of $\underline{x}_\mu$, concerning:

-their magnitude

-their dependence on the operating conditions

-their sensitivity to random noise.

These conclusions are useful for the design of the experiments of the next two stages.

Finally, the modelling can generate very important information: characteristics of the fault signatures. If reliable fault signatures can be produced in this way, the need of experiments is minimized. Conclusions from findings on one particular installation might also be extended to different new applications.

Application Example

The procedure described above has been employed by the present authors in performing the initial design of a Gas Turbine blading faults diagnostic system for the test engine and setting up experiments for this purpose. These investigations have been presented by Mathioudakis et al, (1990, 1991), Loukis et al,(1991). In all these papers the physical reasoning which lead to the choice of the particular instrumentation and its positioning has been explained, based on physical knowledge of the processes taking place in the test engine itself. The measurements which were chosen were: casing internal wall unsteady pressure by means of fast response pressure transducers, casing vibrations, sound and shaft displacement. Out of these quantities, internal wall unsteady pressure is expected to be a direct diagnostic one. It must be commented that although its measurement is feasible, it is not easily implemented, because of the requirement of drilling the compressor casing and the high temperatures at the measurements locations. Casing vibration and emitted sound are expected to be indirect diagnostic quantities, their measurement is however easier in comparison to the previous one. Shaft displacement at the bearings, constitutes a direct diagnostic quantity for certain kinds of faults (e.g. unbalance, misalignment,etc), and it is one of the most usual diagnostic measurements in Gas Turbines.

The diagnostic capabilities of unsteady pressure measurements, which are expected to be the only direct diagnostic ones, among the four selected kinds of measurements , were examined using modelling. The unsteady pressure measured at the inner surface of compressor casing at a location facing a healthy rotor was modelled. The signal is considered to consist of periodic pressure variations, mainly due to the pressure field between rotor blades passing in front of the transducer. The form of the signal of a pressure transducer for a time length corresponding to one full shaft rotation Tr, if the rotor has NB blades, has the form shown in fig. 3.

the blades (namely, the pressure field between two blades adjacent to the missing one comes from a calculation in a cascade with double blade spacing).

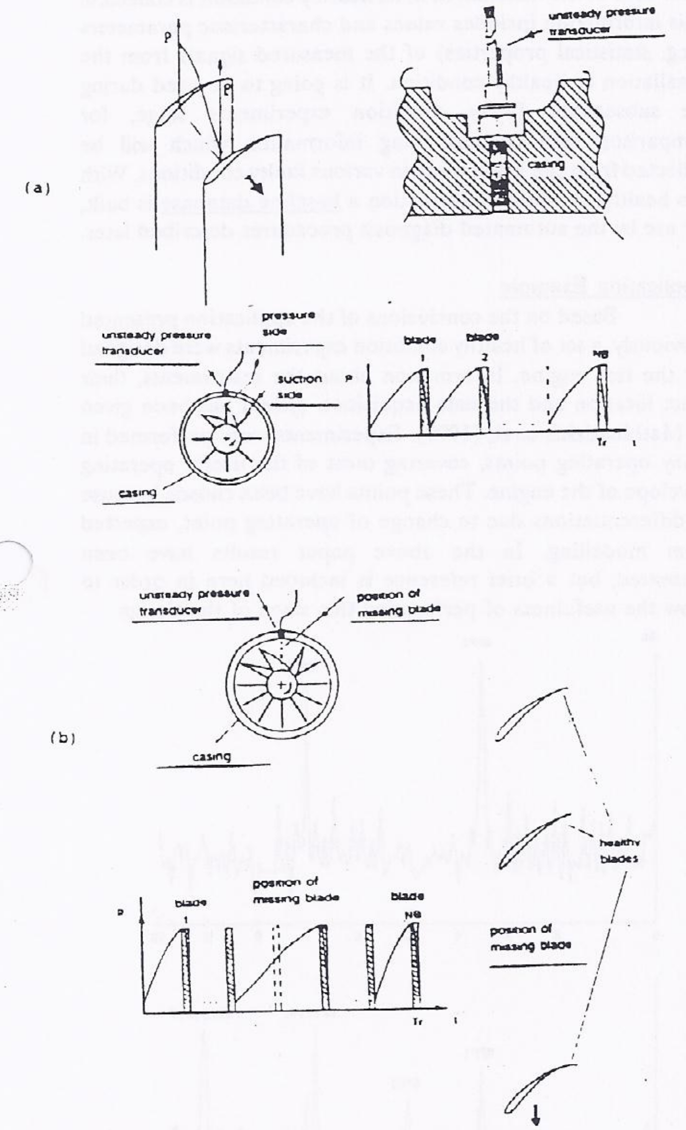

Figure 3: The form of modeled unsteady pressure signals (a) from an intact rotor, (b) from a rotor with one blade missing.

In order to model this signal, first the pressure distribution between two compressor rotor-1 blades at the tip was calculated, using a 2-dimensional inviscid aerothermodynamic method, (Katsanis, T., 1965). From this pressure distribution the signal is synthesized and white noise is added, to simulate measurement noise and contributions due to non-periodic flow phenomena.

Then, the unsteady pressure signal was modelled, for various cases of bent or broken blades on the rotor facing the transducer. In all these cases the signal remains the same as the healthy one, and only the pressure distribution between the blades adjacent to the bent or broken one, changes. The form of the signal for the case of one broken blade is shown in fig. 3. The pressure distributions for various cases of broken or bent blades were calculated using the same aerothermodynamic method, and changing only the circumferential spacing between

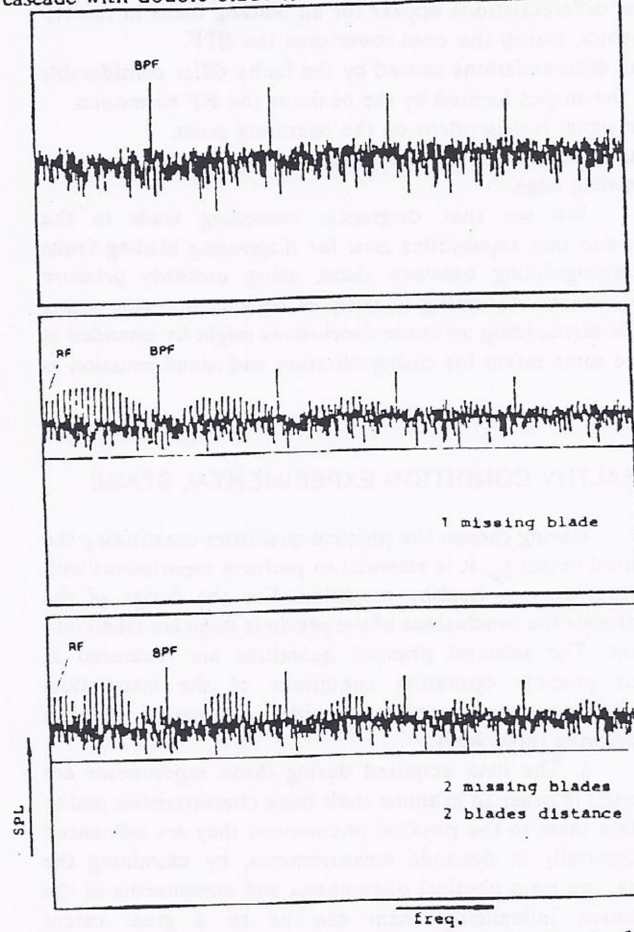

Figure 4: Spectra of modeled unsteady pressure signals, for healthy and faulty rotors

The spectra of the synthesized signals were calculated and are shown in fig. 4. The spectrum from a healthy blading is shown in fig. 4a, while spectra for two cases of faults are shown in figures 4b,c. We can see that in the healthy condition spectrum discrete peaks at the Blade Passing Frequency (BPF) of rotor-1 and its harmonics are present. The spectra for the cases of one and two broken blades have the same basic form, but with some additional peaks at the shaft Rotational Frequency (RF) and its harmonics. Therefore, both these faults cause significant differentiations at the same frequencies (RF harmonics). However, if we examine the shapes formed by the peaks at the RF harmonics for these two faults, we can remark that they differ considerably. (Spectra for a broad set of possible blade faults are given by Loukis, 1993).

From the comparison between the healthy spectrum and the faulty spectra for the examined cases, conclusions relevant to diagnostic possibilities and experimental planning are drawn. Such conclusions for this case are for example the following:

i)All the blading faults cause significant differentiation of the unsteady pressure signal.

ii)Both the signal and the above differentiations show little sensitivity to random noise.

iii)The differentiations appear for all blading faults in the RF harmonics, mainly the ones lower than the BPF.

iv)The differentiations caused by the faults differ considerably as to the shapes formed by the peaks at the RF harmonics.

v)The signal is dependent on the operating point.

vi)The most suitable measurement locations are the ones near the leading edge.

We see that diagnostic modelling leads to the conclusion that capabilities exist for diagnosing blading faults and distinguishing between them, using unsteady pressure measurements. Assuming linearity of both compressor casing and the surrounding air these conclusions might be extended at least to some extent for casing vibration and sound emission as well.

5. HEALTHY CONDITION EXPERIMENTAL STAGE

Having chosen the physical quantities constituting the measured vector $\underline{x}_\mu$, it is essential to perform experiments with the installation in healthy condition. For the design of the experiments the conclusions of the previous stage are taken into account. The selected physical quantities are measured at various possible operating conditions of the installation. Acquiring these measurements provides information useful in the following three ways:

a. The data acquired during these experiments are processed in order to examine their basic characteristics and to associate them to the physical phenomena they are influenced by. Especially in dynamic measurements, by examining the spectra, the main physical phenomena and components of the installation influencing them can be to a great extent determined. This is due to the fact that usually different physical phenomena and components generate contributions at different characteristic frequencies (e.g. for a Gas Turbine, each stage of the compressor or the turbine generates contributions at its own Blade Passing Frequency and harmonics. e.t.c.). Therefore it can be determined for each measured quantity whether it is influenced by physical phenomena or components related to the faults of interest. If this happens, it constitutes an indication for diagnostic capabilities, based on experimental data. Modifications in $\underline{x}_\mu$ may be judged necessary from these findings: some of the initially chosen components of $\underline{x}_\mu$ may be discarded, if they are not influenced by physical phenomena or components associated with faults.

b. The dependence of the measured physical quantities on the operating conditions is also examined. This is very important for cases where differentiations of the measured quantities are caused not by the presence of faults but by the change of operating conditions. This dependence on the operating conditions should be known, in order to avoid that such differentiations are attributed to faults and lead to false alarms.

c. Also during this stage, information about the behaviour of the installation in its healthy condition is collected. This information includes values and characteristic parameters (e.g. statistical properties) of the measured signals from the installation in healthy condition. It is going to be used during the subsequent faulty condition experiments stage, for comparison with corresponding information which will be collected from the installation in various faulty conditions. With this healthy condition information a baseline database is built, for use by the automated diagnosis procedures described later.

Application Example

Based on the conclusions of the application presented previously, a set of healthy condition experiments were designed for the test engine. Information about the instruments, their exact location and the data acquisition system has been given by Mathioudakis et al, (1990). Experiments were performed in many operating points, covering most of the useful operating envelope of the engine. These points have been chosen because of differentiations due to change of operating point, expected from modelling. In the above paper results have been presented, but a brief reference is included here in order to show the usefulness of performing this stage of the design.

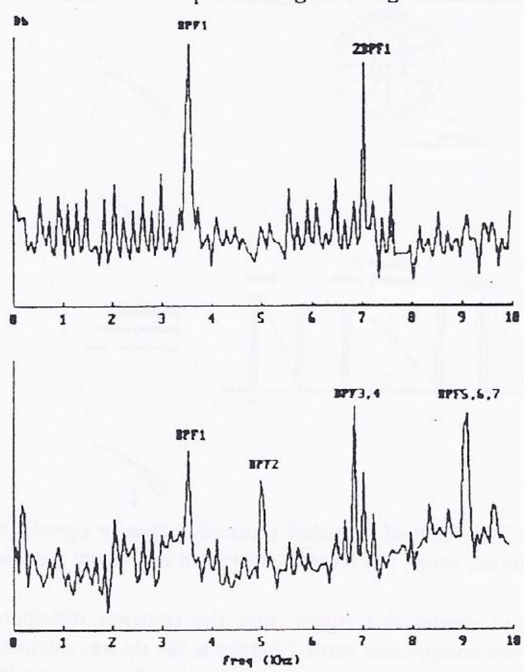

Figure 5: Power spectra from (a) unsteady pressure measurements, (b) casing accelerometer

The spectrum of the unsteady pressure transducer PT2, facing compressor stage-1 rotor, is shown in fig. 5a. We can see that most of the spectrum energy is in the BPF of stage-1 rotor and its harmonics. This shows that PT2 signal is dominated by the influence of the rotor it faces. However, we can see that smaller parts of the spectrum energy are in the he RF harmonics and BPFs of other stages. Similar conclusions hold for the other pressure transducers as well, confirming the corresponding conclusions from diagnostic modelling.

The spectrum of the accelerometer A6 is shown in fig.

5b. We can see that most of the energy is in the BPFs of the first seven stages' rotors and their harmonics. This shows that A6 signal is not influenced dominantly by its nearest stage-5 rotor, but contains influences of comparable magnitude from a number of adjacent rotors as well. The same conclusions hold for the other accelerometers as well as for the microphones.

Examining measurement results in this way, allows the derivation of the conclusion that unsteady pressure, casing vibration and sound emission signals contain significant influences associated with the compressor blade rows and their flow fields. Therefore these signals would be expected to reflect faults related to changes of the geometry of these blades. For this reason it was decided to carry out these measurements during the faulty condition experiments as well.

The dependence of the above signals on the operating point was also examined. It was found that unsteady pressure, casing vibration and sound emission signals are dependent on the operating point (actually confirming the conclusion from the diagnostic modelling). This dependence is mainly upon shaft rotational speed and secondarily upon the delivered power. On the contrary, the signals of shaft displacement at bearings do not show any significant dependence on the operating point.

From the signals acquired during these experiments a baseline database of the test engine was built, with healthy signals of all the instrument at various operating points.

6. FAULTY CONDITION EXPERIMENTAL STAGE

The pre-experimental and the healthy condition experimental stages create all the necessary background for designing and performing a set of experiments in the installation, containing faults. The components of $\underline{x}_{\mu}$, as they have initially been selected during the first stage and modified after the second, are measured. The data are processed and the results are compared to the corresponding ones of the healthy condition.

This comparison can be done first by inspection of the obtained results. It gives some first conclusions about the differentiations caused by the presence of the examined faults to each of the components of $\underline{x}_{\mu}$, and therefore about their diagnostic capabilities. Conclusions about the nature of these differentiations are also drawn (e.g. for dynamic data, whether time or frequency domain data are more sensitive to the faults, e.t.c.).

Although a simple inspection may reveal the desired features, it is in many cases essential to proceed to comparisons and evaluation of differentiations on the basis of quantitative criteria. Using them complete and detailed conclusions about the differentiations caused by the examined faults are derived, while the necessary background for the development of automated diagnosis procedures is established.

In order to develop such criteria first the differentiation between healthy and faulty signals is quantitatively expressed using comparison indices, from which differentiation patterns are formed. Based on the differentiation patterns the following analyses are carried out:

i) Analysis of the capabilities for diagnosing fault presence.

The analysis uses differentiation patterns between faulty and healthy signals on one hand and differentiation patterns between healthy signals on the other. These two categories of differentiation patterns are quantitatively compared as to the level of their components. From the result of this comparison the capabilities for diagnosing fault presence are determined.

ii) Analysis of the capabilities for fault identification.

The analysis uses differentiation patterns between fault and healthy signals. The similarity level between such differentiation patterns corresponding to a particular fault, is quantitatively compared with the similarity level between differentiation patterns corresponding to different faults. From the result of this comparison the capabilities for fault identification are determined.

Also with this faulty conditions' information a faults' signatures database is built for use by the automated diagnosis procedures described next.

Application example

The faulty condition experiments, which were performed in the test engine are described by Mathioudakis et al (1991) and by Loukis et al (1991). A full set of results of the qualitative comparison between faulty and healthy signals is given for all the measured physical quantities of $\underline{x}_{\mu}$ in the same papers. In fig. 6b the spectrum of the unsteady pressure transducer PT2 is shown for the case of a fault consisting of one twisted blade on the rotor the transducer faces. By comparing to the corresponding healthy spectrum of fig. 6a we remark that this fault causes the appearance of peaks at the RF and its harmonics. This confirms the corresponding conclusions drawn from application of the diagnostic modelling presented above.

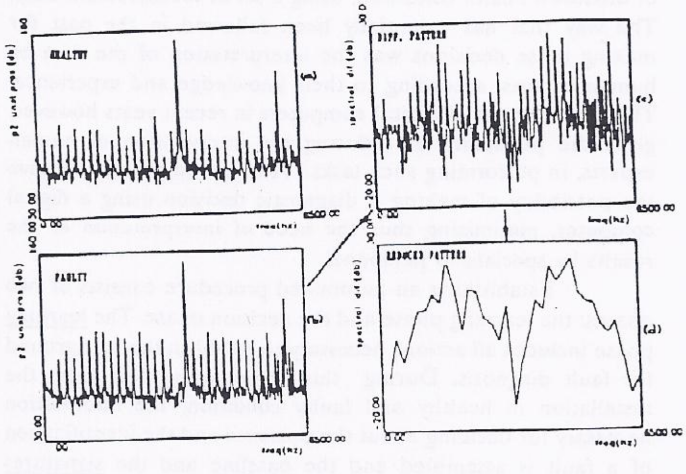

Figure 6: Unsteady pressure signals power spectra for healthy rotor, rotor with one twisted blade and difference patterns

Also quantitative comparison criteria and analysis procedures of the capabilities for diagnosing fault presence and for fault identification have been developed. They are extensively described and discussed by Loukis et al, (1992a). A full set of results of the quantitative comparison using these criteria and the analyses procedures based on them are given in the same paper. In fig. 6c we can see the spectral difference pattern (an exact definition of it is given by Loukis E. et al 1992a, and Loukis 1993) between the spectra of the two signals of PT2, one from a healthy rotor-1 and one with one blade of the same rotor twisted. Also the same spectral difference pattern, but considered only in the RF harmonics, where most of the differentiation appears, is shown in fig. 6d.

The main conclusions drawn as to the diagnostic capabilities of the measured physical quantities of x_μ are:

i) The unsteady pressures show significant capabilities for diagnosing faults of the rotor in front of the transducer. They also show some capabilities for diagnosing faults of adjacent rotors and stators.

ii) The casing vibration show significant capabilities for diagnosing faults of adjacent stators, and also some capabilities for diagnosing faults for adjacent rotors.

iii) The microphones show significant capabilities for diagnosing stator faults. They also show lower capabilities for diagnosing severe faults of adjacent rotors.

iv) The shaft displacement at the inlet bearing shows only some capabilities of diagnosing faults of the first stages' stators.

Also from the signals acquired during these experiments a faults' signature database was built.

7. DEVELOPMENT OF AUTOMATED FAULT DIAGNOSIS PROCEDURES

Once the data from the previous two stages are available, the next task is to develop procedures for deciding about the presence and identification of a fault in an installation of unknown health condition, using a set of measurement data. The way that has essentially been followed in the past for making these decisions was the interpretation of the data by human experts, according to their knowledge and experience. The development of digital computers in recent years however, gives the possibility of reducing the intervention of human experts, in performing such tasks . Automated procedures give the possibility of making a diagnostic decision using a digital computer, minimizing thus the need of interpretation of the results by specialized personnel.

Establishing an automated procedure consists of two phases: the learning phase and the decision phase. The learning phase includes all actions necessary to establish the background for fault diagnosis. During this phase, using data from the installation in healthy and faulty condition, the information necessary for deciding about the presence and the identification of a fault is assembled and the baseline and the signatures databases are finalized. The learning phase is usually performed during the initial set-up of the automated procedure. However a versatile diagnostic system should have the possibility of "further learning" (in the sense of extending the repertory of faults and conditions identifiable) during the course of its exploitation. Therefore the learning phase should actually be continued during exploitation.

Establishing the decision phase consists in setting up the software and the procedure to be followed in order to make diagnostic decisions. These decisions can be of different levels, starting from the decision about the presence of a fault and going as far as possible about the kind and the location of the fault. The relevant software should include:

(a) All the modules necessary for calculating fault indices and diagnostic parameters corresponding to measurement data from the installation under examination. This software has already been developed during the learning phase, in order to produce the contents of the data base.

(b) Software including all the modules for decision making.

The decision software in order to be functional in its application to realistic cases should take into account:

(i) The statistical properties of the faults signatures,
(ii) The costs of the various maintenance actions,
(iii) Existing experience about the probabilities of the faults.

The decision software is used during system exploitation. During the initial system set-up, it is tested on the data obtained from the experimental stages.

During the design of the above automated procedures, it is essential to take into account the nature of the specific diagnostic problem, in selecting the appropriate diagnostic parameters. For this purpose it is useful to develop procedures of their systematic selection. They offer the flexibility to define the optimal diagnostic parameters, which fulfil predefined discrimination criteria, increasing in this way the efficiency and the reliability of the diagnosis. This systematic selection enables the adaptation of the identification procedure in accordance with the peculiarities of the specific problem, instead of a priori choosing diagnostic parameters intuitively and finding after whether they are effective or not. On the other hand this procedure offers the possibility to redefine the diagnostic parameters when new data are available or new faults have to be introduced. This means that when new faults have to be added, the procedure can be adapted to the new data, ensuring that discrimination capabilities will still be optimal.

Application Example

Procedures for automated diagnosis of Gas Turbine blade faults, from fast response measurement data, have been introduced by the present authors (Loukis et al, 1992a,b, 1993) and applied to the test engine. In particular, procedures have been developed for:

a) Diagnosing the presence of a fault.
b) Identification of the fault, among a set of possible faults. This procedure is based on statistical pattern recognition and possesses the desired features (i) to (iii), mentioned above.
c) Locating damaged blades.

Results from performing this stage on the test engine have been presented by Loukis et al, (1992a,b), while some additional ones, for the first time presented here, are given below.

An example of applying the first procedure is shown in fig. 7, where we can see the percentage of correct decisions made about the presence of a fault, from a number of data sets of each fault (totally four faults were examined for the test engine). We remark that these percentages are high.

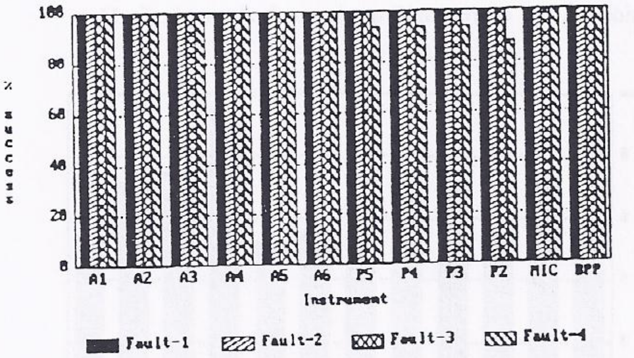

Figure 7: Percentage of correct decisions about the presence of a fault, for four different faults and various measuring instruments

In fig. 8 we can see the percentage of correct decisions about fault identification. We remark that for most instruments the success is absolute (100 %), while for the others it is also quite high.

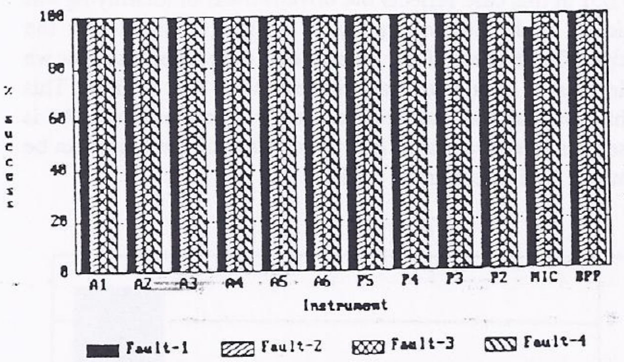

Figure 8: Percentage of correct decisions for fault identification, for four different faults and various measuring instruments

An example of damaged blades location from data of the unsteady pressure transducer PT2 is shown in fig 9. In the vertical axis we can see the values of a Blade Fault Parameter (BFP) (more details about it are given by Loukis, 1993), while in the horizontal axis is the blade number. These values are from both healthy and faulty experimental data signals. We remark that values corresponding to damaged blades are higher than the ones corresponding to healthy ones, therefore damaged blades can be located.

Also a procedure for optimizing the above automated fault identification procedure by systematically selecting the diagnostic parameters has been proposed by the present authors. Using this procedure, parameters which are optimal with respect to a specific diagnostic problem, for each instrument, can be selected. They thus enable maximum exploitation of the diagnostic information contained in the signals from the instrument, processing them with a chosen processing method. This procedure has been successfully applied to the test engine (Loukis et al, 1992b).

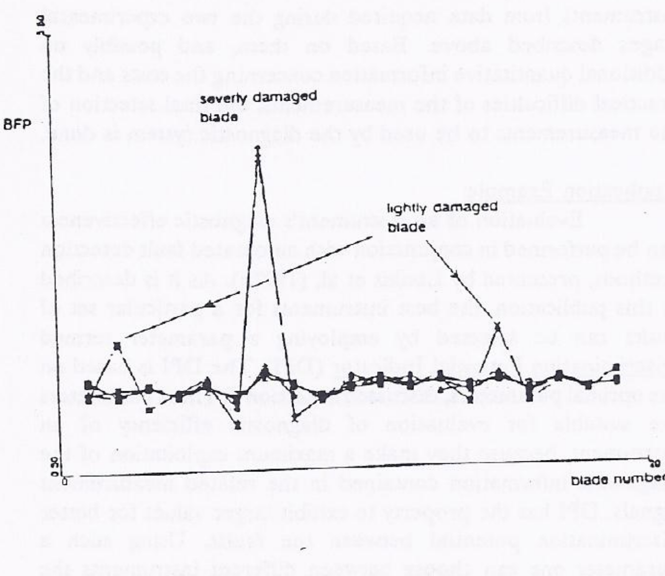

Figure 9: Blade fault parameter for signals from a healthy rotor and rotors with faults

8. FINAL EVALUATION

A significant feature of this methodology is the possibility to assess the diagnostic effectiveness of the measuring instruments in conjunction with the processing methods employed. This feature is very important because it enables the final selection of the minimal and most appropriate instrument set, for the diagnosis of the faults of interest.

While information about effective data processing can be found in many sources, the same is not true for evaluating diagnostic effectiveness of instruments. An obvious way to achieve this target is of course an a-posteriori evaluation of a number of cases encountered in field operation. It is nevertheless desired to be able to derive such information during the design of the diagnostic system, from the data obtained in the experimental stages described above.

The quantitative assessment of the diagnostic effectiveness should include the development of parameters quantifying the diagnostic capabilities we are interested in for the designed diagnostic system. For example, the interest may lie in fault identification and distinguishing between a number of possible faults. In another diagnostic system one fault may be of special interest, if it is expected to occur more frequently or it is of vital importance for the specific installation. In such a case, the capability of identifying this particular fault is of significant interest to the user. Also when one instrument is known to be available or easy for implementation, it is desired to know how effective it is for identifying particular faults. On the other hand, before proceeding to installation of an instrument which is not easy or is costly, similar information should be available. These specific interests and requirements have to be taken into account in developing the above parameters.

These parameters are then calculated for all the instruments from data acquired during the two experimental stages described above. Based on them, and possibly on additional quantitative information concerning the costs and the practical difficulties of the measurements, the final selection of the measurements to be used by the diagnostic system is done.

Application Example

Evaluation of an instrument's diagnostic effectiveness can be performed in conjunction with automated fault detection methods, presented by Loukis et al, (1992b). As it is described in this publication, the best instruments for a particular set of faults can be selected by employing a parameter termed Discrimination Potential Indicator (DPI). The DPI is based on the optimal parameters, discussed in section 7. These parameters are suitable for evaluation of diagnostic efficiency of an instrument, because they make a maximum exploitation of the diagnostic information contained in the related measurement signals. DPI has the property to exhibit larger values for better discrimination potential between the faults. Using such a parameter one can choose between different instruments the most suitable ones for fault identification.The above evaluation procedure has been successfully applied to experimental data from the test engine.

Another more sophisticated procedure for the evaluation of an instrument's diagnostic effectiveness is presented by Loukis, (1993) and applied for the test engine. It is based on another parameter, termed Identifiabity Index (IDI), which can focus not only on the whole set of faults covered, but also on subsets of them. IDI is also based on the optimal parameters. The IDI values for all the four blading faults examined, calculated from experimental data from the test engine is shown in figure 10, for all the instruments.

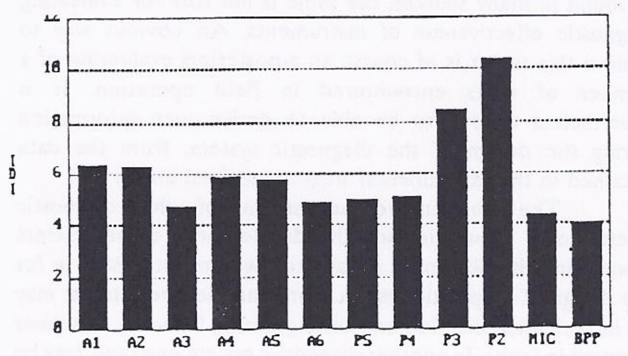

Figure 10: Identifiability Index for a set of four blade faults and different measuring instruments

We remark that some instruments have higher IDI values than others, indicating better discrimination capabilities. Pressure transducer PT2 is characterised by the maximum IDI from all the instruments, so it is the most appropriate of them. If now one particular fault, among the four examined ones, is considered, the corresponding picture is shown in fig 11.

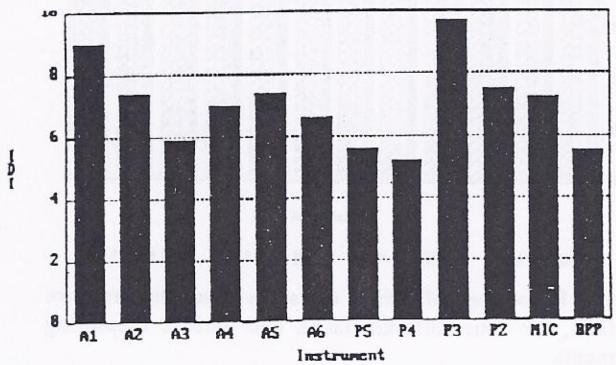

Figure 11: Identifiability Index for one blade fault and different measuring instruments

The IDI in this case reflects the effectiveness of identifying this particular fault. Comparing fig.10 to fig. 11, shows that the relative effectiveness of the instruments differ, because now we are interested in only one fault instead of all four of them. This might influence the final choice. Finally if accelerometer A1 is chosen, its effectiveness in identifying each of the faults can be examined by inspection of fig 12.

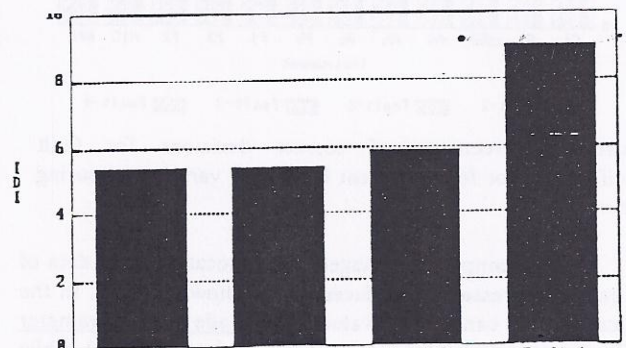

Figure 12: Identifiability Index of accelerometer A1, for a set of four blade faults

The results shown from this case of application (presented here for the first time) show that multiple different aspects of diagnostic effectiveness may be considered in designing a diagnostic system for a specific installation. Also it is obvious that other practical or economical factors will have to be taken into account before taking the final decision as well.

9. DISCUSSION - CONCLUSIONS

The methodology presented in the previous sections can be used for the design of diagnostic systems for the general case of an installation to be monitored. The application examples presented refer to a particular Gas Turbine, for which an investigation was carried out using fast response measurements. The described procedure is not restricted to this kind of measurements, however. Other measurements, such aerothermodynamic and engine performance measurements can be handled. The difference is that the software and processing employed will have to be suitable for such measurements. From this point of view, the procedure proposed by Stamatis et al, (1992), can be incorporated in the present methodology.

Very significant for the methodology is the execution of experiments on the installation of interest. Such experiments can be performed on a test bed, but on engines operating in the field as well. For the faulty condition, the faults can be implanted during the initial setup (as is the case of the application examples presented), but it is possible that data from engines in the field are used, when malfunctions occur. Data from the occurrence of faults initially unforseen can be used for further extension of the possibilities of the system.

Finally, it should be noticed that the proposed methodology possesses features which are required for its application in realistic cases and is quite suitable for present day systems employing digital computers.

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