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Diagnosis of Defects by Principal Component Analysis a Gas Turbine

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***Abstract*— The fault detection and isolation have a great practical importance in engineering system. Early detection of the fault occurrence is critical in avoiding product deterioration, performance degradation, major equipment damage and human harm health. The aim of this work is to study the fault detection using linear principal component analysis (PCA) which can be applied to the complex industrial processes. In the first step, we study the fundamental principles of linear PCA are presented, the PCA is used to model normal processes behaviour. In the second time, we study different detection methods have been discussed. Finally, we do the application of this study concern the fault detection an electric power production process.**

***Keywords*— Process monitoring; fault detection; linear principal component; electric power production process**

I. Introduction

In all industrial systems, breakdowns cause considerable economic losses, it is therefore essential to implement monitoring and diagnostic systems to avoid unexpected shutdowns and then increase reliability and ensure the safety of the systems. The industrial diagnosis whose primary function is the detection and localization of system failures, the detection relates to the detection of events that affect the evolution of a system, so to assess then consists in comparing the actual functioning of the system. System with what it should be under the assumption of normal operation. Originally, the diagnosis was limited to high-risk industrial applications for the community such as nuclear or aviation [1] [2], as well as advanced industries such as, industry armament or aerospace. Since the last three decades, the diagnosis has attracted increasing interest both in the industrial world and in scientific research.

In the field of diagnostics, methods based on the concept of redundancy of information have been developed. Their principle is generally based on a consistency test between an observed behavior of the process provided by sensors and an expected behavior provided by a mathematical representation of the process. Analytical redundancy methods therefore require a model of the system to be monitored. This model includes a number of parameters whose values are assumed to be known during normal operation. The comparison between the actual behavior of the system and the expected behavior given by the model provides a quantity, called residue, which will be used to determine whether the system is in a failed state or not.

Multi-variable statistical methods are the most effective for treating the generation of residues. Among them, methods based on Principal Component Analysis (PCA), are very effective for highlighting significant linear correlations between the variables of the process without explicitly formulating the model of the system. Thus, all the correlations between the different variables are taken into account in the PCA model. In this paper we will study this particular model for diagnosed (detection equipment or subassembly fault by precision) a very complicated system of a gas turbine.

II. Principal Component Analysis

Principal Component Analysis (PCA) is part of the group of multidimensional descriptive methods called factorial methods. These methods, which appeared in the early 1930s, were mainly developed in France in the 1960s, in particular by Jean-Paul Benzécri, who made extensive use of geometric aspects and graphic representations.

It has been adapted to the detection and isolation of faults that can be manifested at the system level, it is an analysis technique for multi-variable data [3].

This technique is based solely on the use and operation of the input and output measurements of a system. A data matrix is then constructed from these measurements. By a decomposition into singular values of the matrix of the data, the PCA splits this matrix in two parts, one containing the dominant singular values, representing the useful data, and the other the remainder of the singular values supposed to be negligible and representing the noises. [4]

Several studies have recently appeared in the literature dealing with the use of PCA in the field of defect detection [5, 6, 7, 8, and 9].

In Fig. 1. We present the PCA algorithm that illustrates the principle of principal component analysis.

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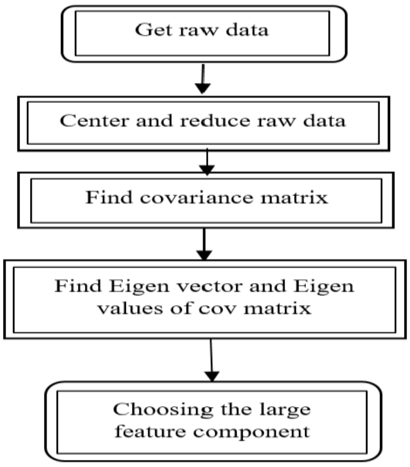

Fig. 1. PCA algorithme.

To find a model based on the linear PCA one needs a database contains variables to monitor for a set of measurements made on the normal operation of the system. Generally, the procedure of model identification consists, after the normalization of the data matrix, to estimate the parameters of the model then to choose a fixed structure and finally to validate this model.

The basic idea of the PCA is to reduce the size of the data matrix. This reduction will only be possible if the initial variables are not independent and have correlation coefficients between them non-zero. These initial variables are transformed into new variables, called principal components. The variance approach of the reconstruction error was chosen to determine the number of principal components to be retained. The variance of the reconstruction error (VNR) can be calculated as follows:

$$u_i = \mathrm{var}\left\{\varepsilon^T (x - x_i)\right\} = \mathrm{var}\{f_i\} = \frac{\tilde{\varepsilon}_i^T \Sigma \tilde{\varepsilon}_i}{(\tilde{\varepsilon}_i^T \tilde{\varepsilon}_i)^2} \tag{1}$$

$$u_i = \frac{\tilde{\varepsilon}_i^T \tilde{\Sigma} \varepsilon_i}{(\tilde{\varepsilon}_i^T \varepsilon_i)^2} = \frac{\left\|\tilde{\varepsilon}_i^o\right\|_{\tilde{\Sigma}}^2}{\left\|\tilde{\varepsilon}_i\right\|^2} \tag{2}$$

Where f_i is an estimate of the magnitude of the defect f which measures the displacement in the direction ε_i, with Σ is the correlation matrix and u_i is the variance of the reconstruction error estimating x^* using x_i. So the PCA is used as a modeling technique of the relationships between the different variables of the process. The estimation of the parameters of the PCA model is performed by estimating the eigenvalues and eigenvectors of the matrix of correlations of the data. However, for the determination of the structure of the model, it is necessary to determine the number of components to retain in this model (number of eigenvectors).

III. Detection By The PCA

The PCA is defined as a linear transformation of the original correlated variables to a set of uncorrelated variables, however, the original variables can be represented by a small number of the main components because of the existing analytic redundancy between the variables, and therefore, instead of analyzing all the variables, the PCA analyzes these components.

The presence of a fault affecting one of the variables causes a change in the correlations between the variables indicating an unusual situation because the relationships between the variables are no longer verified. In this case, the projection of the measurement vector in the residue subspace will increase relative to its value under normal conditions.

To detect such a change in the correlations between the variables, the PCA uses several detection indices that are used for the detection of abnormal operation by the PCA: Hoteling Statistics T^2 and the squared error of prediction SPE.

A. SPE Statistic (Q-Statistic)

A typical statistic for detecting these unnatural conditions is the SPE statistic, also called Q (Squared Prediction Error) which is given by the equation:

$$SPE(k) = e^T(k)e(k) \tag{4}$$

To detect the presence of an anomaly, the SPE must check the following condition:

$$SPE(k) > \delta_\alpha^2 \tag{5}$$

Or δ^2 is the threshold of confidence after Jackson and Mudholkar [10] that develop the expression of the confidence threshold for the SPE.

B. Hotelling T^2 Statistic

The T^2 statistic can be applied, on the first principal components [2], thus one obtains:

$$T^2(k) = \hat{t}^T(k)\Lambda_\ell^{-1}\hat{t}(k) = \sum_{i=1}^{\ell} \frac{t_i^2}{\lambda_i^2} \tag{6}$$

$$\Lambda_\ell = diag(\lambda_1, \lambda_2, \ldots\ldots \lambda_\ell) \tag{7}$$

Or (7) is a diagonal matrix containing the ℓ largest eigenvalues of the correlation matrix, T_o detect the presence of an anomaly the statistic T^2 must check the following condition:

$$T^2(k) > \chi_{\ell,\alpha}^2 \tag{8}$$

Where $\chi_{l,\alpha}^2$ the upper limit for a confidence level α.

We have seen that the use of different tests for detection can affect by the modeling errors that are capable of generating false alarms, the EWMA filter (exponentially weighted moving average) [11] is used to improve the detection.

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IV. APPLICATION OF PCA ON THE GAS TURBINE UNIT.

To verify and illustrate the effectiveness of the PCA technique for defect detection, data provided by a real process will be used. This part is dedicated to the application of Linear Principal Component Analysis for the detection of faults in an industrial installation (a single cycle power generation unit (gas turbine)

The group, as it is designed for most installations, consists of a single cycle "single shaft" gas turbine designed for continuous operation and designed to drive an alternator. The combustion of an air-fuel mixture serves to produce the power necessary to drive the compressor shaft, some auxiliaries, and, mainly the alternator.

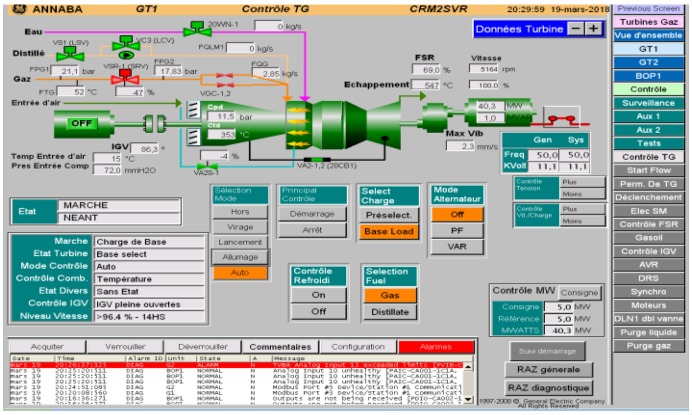

Fig.2. Principle of operation of a gas turbine

V. THE VARIABLES USED TO CONSTRUCT THE LINEAR PCA MODEL

To build the PCA model, we chose 36 essential sensors, measurements are taken during the normal operation of the gas turbine, represented on the table. 1.

TABLE I
DESCRIPTION OF THE VARIABLES OF THE GAS TURBINE

AAT	1	temperature of the air main atomizations
AFPDB	2	compressor inlet pressure
RFA	3	mass flow air intake compressor
BBMAX	4	maximum vibration turbo-alternator
BBMAX GT	5	maximum vibration gas turbine
CMHUM	6	humidity
CPD	7	compressor outlet pressure
CPR	8	compressor compression ratio
CSGV	9	IGV angle in degrees
CDT	10	compressor discharge temperature
CTIM	11	compressor inlet temperature
DF	12	alternator frequency
CFO	13	power factor
DV	14	alternator voltage in%
PSUs	15	reactive power alternator
DVX	16	alternator voltage
DWATT	17	active power alternator
FPG2	18	inter-valve fuel pressure
PCF	19	gas fuel mass flow rate
FTG	20	gas fuel temperature
LTB1D1	21	temperature purge lube oil bearing 1 turbine
LTB2D1	22	temperature purge lubrication oil bearing 2 turbine
LTOT	23	lubricating oil tank temperature
LTTH	24	lubricating oil collector temperature
PAT	25	fuel purge air temperature
GAP2	26	collector pressure lubricating oil
TNH	27	tree rotation speed
TNRCOR	28	velocity shaft rotational%
TTWS1AO1	29	inter-wheel temperature first stage Rear intake turbine
TTWS1FI1	30	inter-wheel temperature first stage before intake turbine
TTWS2FI1	31	inter-wheel temperature second stage before exhaust turbine
TTWS3AO1	32	inter-wheel temperature third stage rear exhaust turbine
TTXM	33	mid turbine exhaust temperature
TTXP1	34	first difference real control combustion
WTAD	35	temperature evacuation cooling water
WTTL1	36	temperature cooling water leg TG

VI. DETERMINATION OF THE OPTIMAL NUMBER OF PRINCIPAL COMPONENTS

To obtain an optimal number of principal components retained in the PCA model, we chose the reconstruction approach, after using this reconstruction method (PCA model structure), Figure (3) presents the evolution of the reconstruction variance depending on the number of principal components, this result indicates that the first seven major components are sufficient to construct the PCA model.

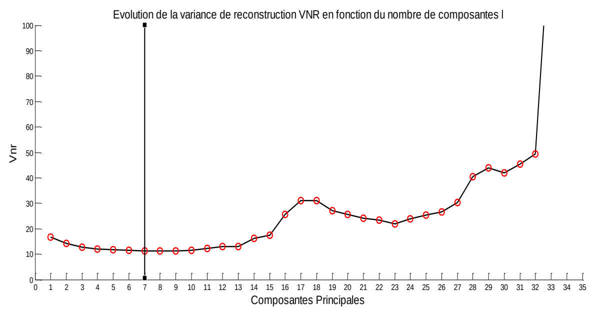

Fig.3. Evolution of non-reconstruct variance VNR as a function of number of components.

VII. DETERMINATION WITH THE PCA EVOLUTION OF THE VARIABLES AND THEIR MODELS

The six figures (4), (5) and (6) show, respectively, the measurements and their estimates of : compressor inlet pressure, humidity and compressor compression ratio by using the already obtained PCA model.

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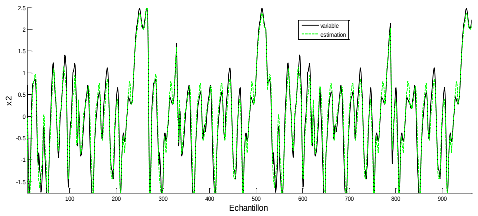

Fig.4. Evolution of X 2 and its estimate.

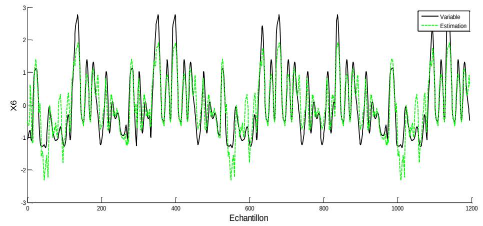

Fig.5. Evolution of X 6 and its estimate.

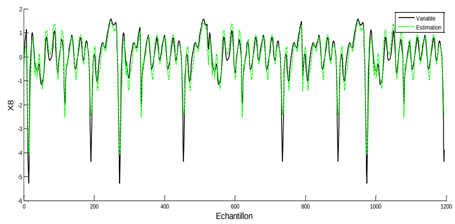

Fig.6. Evolution of X 8 and its estimate.

VIII. The Evolution of Detection Index Case Without Defect

Figures (7), (8) and (9) illustrate the evolution of the three statistical tests; SPE, SPE filtered and T^2, respectively, from data representing normal operation, they are adapted to choose the detection thresholds for each test (red lines).

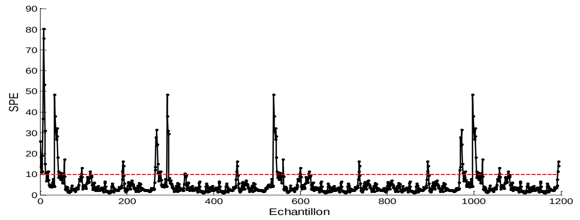

Fig.7. Evolution of SPE "faultless case".

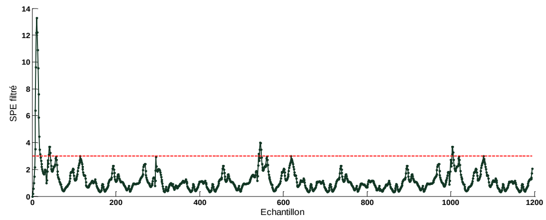

Fig.8. Evolution of SPE filtered "faultless case".

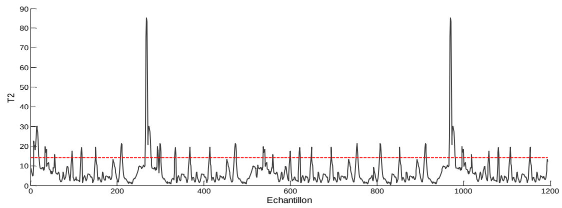

Fig.9. Evolution of T^2 "faultless case".

IX Fault Detection with Linear PCA

To test and verify the effectiveness of the PCA model obtained for detection from defects, we collected a database with four real defects of the gas turbine.

Based on the model PCA already obtained, they are four figures (10), (11), (12), (13) have, respectively, the evolution of the PES detection index filtered in the presence of the four scenarios of defects:

- Triggering of the gas turbine by lower pressure gas (fuel),
- Tripping of the electric default gas turbine (maximum current 51TP),
- Tripping of the gas turbine default of the group circuit breaker synchronous coupler,
- Triggering the gas turbine default gas compressor.

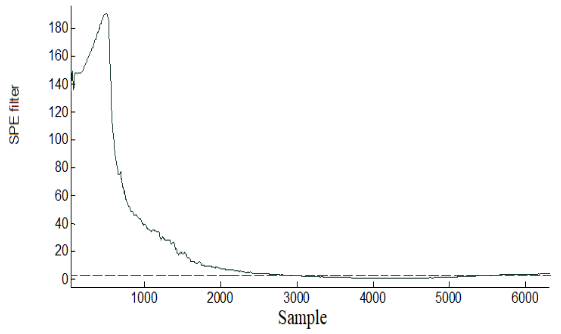

Fig.10. Detection defect lowering gas pressure by PCA.

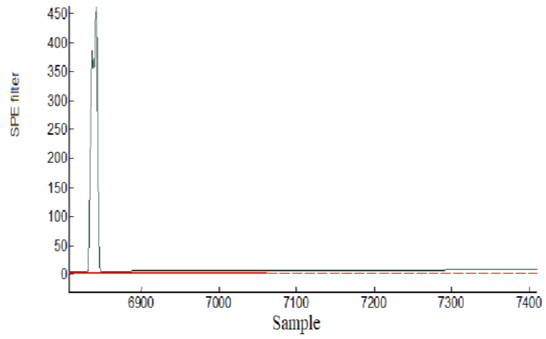

Fig.11. Electrical type fault detection by PCA.

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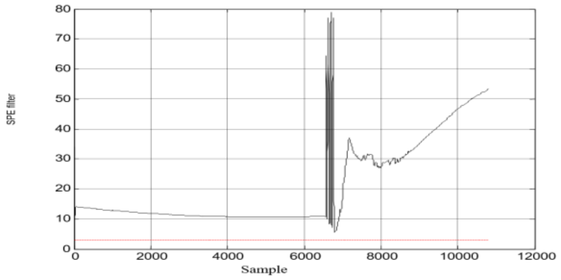

Fig.12. PCA synchrocoupler fault detection.

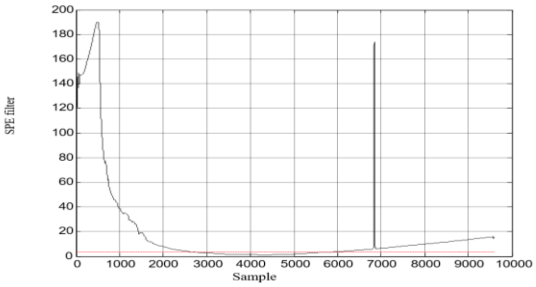

Fig.13. Gas compressor fault detection by PCA.

According to the above figures, it is noted that the detection index (black curve) has a large excess relative to the detection threshold (red line) calculated by the PCA model for proper functioning, thereby conclude an unusual operating condition of the turbine has occurred.

X. CONCLUSION

The work presented in this paper focuses on the diagnosis of PCAL based systems, which is used as a modeling technique for relations between different process variables. The estimation of the parameters of the linear PCA model is performed by estimating the eigenvalues and eigenvectors of the matrix of correlations of the data. However, for the determination of the structure of the model, it is necessary to determine the number of components to retain in this model (number of eigenvectors).

Once the model is identified, the defect detection procedure can be performed by generating the defect indicators (residuals) by comparing the observed behavior of the process given by the measured variables and the expected behavior given by the PCA model. Most PCA-based detection methods use the SPE (squared error) statistic for defect detection, and the T^2 statistic of Hoteling. Thus, we used the EWMA filter to improve detection, but with die delay detection.

Finally, we presented the application of the model PCAL for the detection of defects of a production process electric energy based on a gas turbine, to complete this work we recommend to use the data of this memory in the study of fault localization methods. As we used in this work the PCAL model that seeks to identify the linear relationships between process variables. Another recommendation is to study nonlinear PCAs that extract both linear and nonlinear relationships.

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