PhD Proposal 2017

School: Ecole Centrale de Paris (Centrale Supelec à Gif sur Yvette)	
Laboratory: Laboratoire des Signaux et Systèmes (CNRS-CentraleSupelec-Univ. Paris Sud)	**Web site:** www.l2s.centralesupelec.fr
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Collaboration with other partner during this PhD: **In France:** Prof. D. Diallo in GeePs (Group of Electrical Engineering Paris),	**In China:**

Title: Incipient anomaly detection and estimation for complex system health monitoring	
Scientific field:, Engineering and technology, Electrical, Electronic and Telecommunication Engineering, or Mechanical, Aeronautical & Manufacturing Engineering	
Key words: Fault Diagnosis, estimation, detection, Signal Processing, source separation, information processing	

Details for the subject:

Background, Context:

Nowadays, sensible systems health monitoring is a hot issue in industrial and academic research. Due to increasing safety rules, and in order to avoid systems unwanted stops it is crucial to be able to detect at their early stage failures that will be able to occur disease in a system. Coupled to that, estimating the severity of this failure and sometimes predicting its evolution is necessary. However, the increasing complexity of these systems makes them difficult to be reliably modeled in a sufficiently representative operating range useful in fault diagnosis and prognosis process. Data driven approaches obtained from numerical models or experimental data can then provide additional knowledge and support effective oversight. This latter approach is based on signal processing techniques or statistical analysis linked to estimation and detection theory. Based on these elements, the idea of this work is to enhance the diagnosis performance of incipient fault and reach optimized diagnosis with efficient prognosis. The work proposed here will consist in the development of a methodology for monitoring complex systems for the earliest detection of faults. Based on the idea consisting in judiciously combining data driven approaches, model based ones and advanced signal processing techniques, prognosis solutions will also be studied.

Research subject, work plan:

The last three decades have shown an increased demand for improving the economy and safety of processes. Health monitoring of processes has been widely developed with studies on fault detection and diagnosis. In a wide variety of industrial and on-board applications, the detection and diagnosis of faults are considered essential to ensure high performance level of the plant operation to reduce economic losses and enhance the system security [1, 2, 3].

It has been recognized that statistical-based techniques have many attractive advantages in dealing with large variable sets encountered in complex industrial systems. Among various statistical-based techniques, multivariate projection-based methods are the most popular ones [4]. Principal Component Analysis (PCA) is one of the most often used for multivariate data-driven-based industrial systems health monitoring [5, 6, 7]. Its main interest is the ability to reduce the data dimensional-space by trying to keep the maximum variance information available.

For fault detection purpose, statistical-based criteria in PCA framework have been successfully used. For example T^2, *Q-statistics*, and *f-divergences* techniques have shown their efficiency [6, 7]. Comparing those techniques, J. Harmouche et al [6, 7], have shown that the monitoring strategy with Kullback Leibler Divergences (KLD) using PCA is conceptually more straightforward and also more sensitive for the detection of faults with very low severities namely incipient faults.

In our recent work [9, 10, 11], a PCA-KLD univariate-based approach have been used to detect incipient faults. It has been highlighted that the fault detection threshold, and the performances defined by the Missed Detection Probabilities (P_{MD}) and False Alarm Probabilities (P_{FA}) are strongly related to the Fault to Noise Ratio (FNR). Moreover, the incipient fault detections performances can be degraded by the projection error and the uncorrelated variables that can be yield using PCA. To cope with this problem, in the particular case of incipient fault with nuisance parameters (noise) and increase the fault detection limit, other approaches are necessary for example without using the PCA framework. Moreover our work which is now mainly focused on gain fault detection could be enlarged with other error type modelling and then dedicated to prognosis approaches.

The work proposed here will be to develop a methodology and tools for monitoring complex systems. The main idea is to judiciously combine physical models (analytical and / or numerical) and data driven models issued from signal processing and statistical analysis (methods of data analysis and / or pattern recognition particular core approaches, estimation and detection theory). The work is divided into several stages:

1. Literature review on existing methods in the time domain and / or frequency of representation, classification and discrimination,
2. Analysis of diagnosis methods using model-based approaches,
3. Analysis and design models of representation coupled with physical models
4. Development of a methodology for Fault detection and estimation in diagnosis and prognosis
5. Application of the methodology for electromagnetics systems.

References:

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