Doctoral School on Engineering Sciences
Università Politecnica delle Marche

Extended summary

Data-based design of Fault Detection and Isolation (FDI) Systems

Curriculum: Ingegneria Informatica, Gestionale e dell'Automazione

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Abstract.

The objective of this research is to propose a Fault Detection and Isolation (FDI) system based on data-driven (model-free) approach. The choice of approaching the fault diagnosis problem with a model-free methodology rather than a model-based (like first principle) approach was motivated by the difficulty, experienced at some particular industrial plants, on developing detailed physical models for large scale process (as for example chemical and petro-chemical processes). Furthermore in some particular applications dynamic models are not available or not appropriate for fault detection and isolation purposes.

The proposed innovative FDI system combines Principal Component Analysis (PCA), Cluster Analysis and Pattern Recognition technique. The result is the so called Fuzzy Faults Classifier (FFC). The combination of these techniques allows to automatically detect and isolate single and multiple faults and allows to overcome the growth of the complexity in the analysis of process faults that typically involve many variables. The research is also improved by the use of the adaptive thresholds: the adaptive thresholds scheme follows a classical structure proposed in literature but the parameters used on it have been computed by an innovative approach based on the spectral analysis of the process inputs.

The goodness and the efficiency of the proposed Fault Detection and Isolation system can be appreciate by the inspection of the results obtained in the real process studied: Multishaft Centrifugal Compressor (used for nitrogen compression) and Unmanned Surface Vehicle (developed and exploited by CNR-ISSIA). The results confirm the ability of the system in terms of fault detection and fault isolation and the possibility to extend its use to different real process. The only requirement, not particularly crucial in industrial context, is the presence of good measurement concerning the main process variables.

Keywords. Adaptive Thresholds, Fault Detection and Isolation, Fuzzy Faults Classifier, Multishaft Centrifugal Compressor, Unmanned Surface Vehicle.

1 Problem statement and objectives

The proposed Fault Detection and Isolation (FDI) Systems has been designed and tested on Multishaft Centrifugal Compressor and in Unmanned Surface Vehicle.
In chemical/petrochemical plants and in the oil and gas treatments field exist several processes of various nature such as refinery, natural gas extraction/compression, energy production and gasification. Many of these processes involve the use of centrifugal compressors and their overall efficiency can be greatly influenced by compressors working conditions.
At this regard, in literature many methodologies for control and supervision of these machines have been proposed (see [1], and [2]) where typical problems are speed regulation, power absorption limitation and safe working operational conditions assurance.
Given the importance and the crucial role played by these machines, in the recent years more attention has been given to the prevention of possible frequent malfunctions and potential faults which may cause inactivity of compressor or even its complete break.
The proposed FDI system has been tested in a Multishaft Centrifugal Compressor (see [3]) used for nitrogen compression in the dilution of a particular synthetic gas, called syngas, which is forwarded to a gas turbine. The complex compressor formed by two sections is depicted in the following Figure 1.

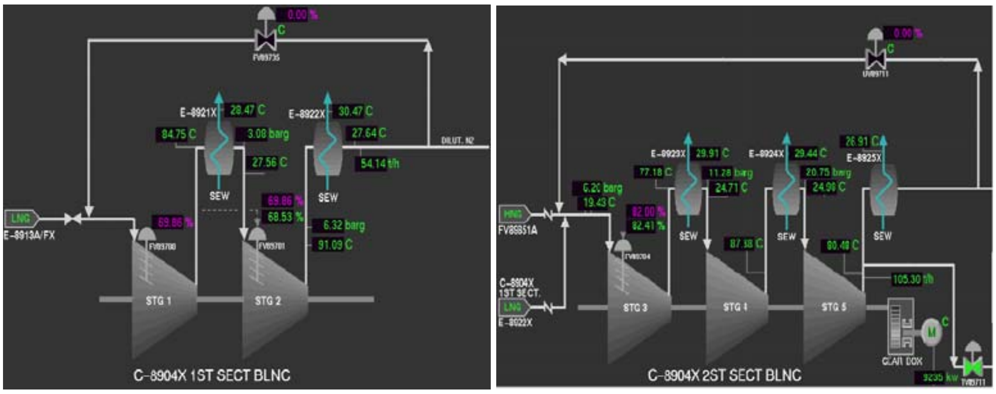


Figure1: The two compressor sections.

Isolation of single and multiple faults which may cause errors in the sensors reading and/or in the actuators used in the compression process, as well as the detection of the main process faults is a very important and crucial task that may increase the availability of the machine and improve plant safety while achieving functioning costs reduction as well. In order to enhance the efficiency level and the profitability of oil refineries as well as the commitment to meet precise production standards, an increasing level of system automation is required. Furthermore the existence of rigorous environmental standards together with the need to operate in high safety conditions contribute to the implementation of automatic systems of rising complexity devoted to supervision, control and prevention of possible frequent malfunctions and potential faults.

In literature different works have been presented to diagnose possible faults on centrifugal compressor ([4] and [5]); other discussion on fault diagnosis system applied on industrial plant and in particular on rotary machine can be found in [6].
The objectives of the proposed work concerning the fault detection and isolation of the most critical faults of multishaft centrifugal compressor. Beside the not crucial single faults (regarding sensors and actuators), an analysis of historical data revealed two different compressor process faults. These faults are particularly critical because they strongly influence several variables and their identification result more difficult. Fouling (dirtiness) of compression stages and breaks of thrust bearing resulted to be the most frequent causes of faults. If these faults are not identified rapidly, a decrease in the compression efficiency will result that may cause an increase of horizontal and vertical shaft vibrations and an increase in the temperature of thrust bearing.
Visual inspection of critical compressor signal is regularly performed at the scope to detect anomalous system behaviors and warn for possible faults. Nevertheless it is not always simple to associate symptoms to the correct fault. Thus the proposed automatic fault detection and isolation system can largely improve the maintenance operations (see [7] and [8]).

Unmanned Surface Vehicles (USVs, for short) play a key role in improving networking of teams of heterogeneous vehicles executing large scale surveys and supporting Rapid Environmental Assessment (REA). Indeed, due to their position at the air-sea interface, USVs can support the relaying of radio frequency transmissions in air and acoustic transmissions undersea, as proposed, for instance, in the EC funded ASIMOV project [9], and the monitoring of ocean and atmosphere dynamics as well as surface and underwater intrusions.
In the marine environment, installation of a proper structure to cope with unexpected situations is essential for unmanned vehicles to carry out their mission out of human reach. Over the past decade, much attention has been paid to the problem of fault detection and diagnosis in marine systems. This is because these systems have much advanced in functionalities and now there is an increasing demand for high reliability in many applications. A further step on the improvement on autonomy, reliability and safety of marine vehicles is the development of accommodation paradigms that involves the reconfiguration capability of the vehicle or of the mission.
Many methods have been developed for performing fault diagnosis and one of the main distinctions is between model-free and model-based techniques. In the field of marine systems the far more common approach is the model-based one. In particular, it can be further stated that much of the published literature on the underwater field focus on the control system, and how to detect and accommodate actuator faults (see [10]). If in many cases, a mathematical model of the system is at disposal, finding good parameter values is nevertheless a non-trivial task. This motivates the development of FDI solutions based on model-free techniques. In [11] a Principal Components Analysis is proposed for the detection of faults in a vehicle propulsion system and tested on simulation results.
In this work the PCA technique is used to formulate the fault diagnosis system for detection and the isolation of common faults due to environment and occurring during field missions that affect the manoeuvring capabilities of the vehicle. The proposed approach has been preliminary tested on telemetry data acquired during field operations of Charlie USV, developed and exploited by CNR-ISSIA [12] (see Figure 2).

Figure2: Charlie USV during trials.

Charlie USV is a small catamaran–like shape prototype vehicle originally developed by CNR-ISSIA for the sampling of the sea surface microlayer and immediate subsurface for the study of the sea–air interaction. Charlie is 2.40 m long, 1.70 m wide and weighs about 300 kg in air.
As discussed, in order to detect and isolate common faults that occur during field mission, the proposed FDI system has been preliminary tested on telemetry data acquired during field operations.

2 Research planning and activities

2.1 Fault Detection and Isolation with PCA

Principal Component Analysis (PCA) is defined as mathematical procedure that transforms a number of possibly correlated variables of the process into a smaller number of uncorrelated variables, called Principal Components (PCs). The author proposes the use of PCA for fault detection and isolation purposes: particular signals (called residuals) able to detect possible faults (**fault detection**) are computed and, to perform the isolation of these faults (**fault isolation**), the residuals values are compared to a threshold. One the main contributes proposed in this Thesis is the design of adaptive thresholds used to detect and isolate possible faults. Different approaches to design adaptive thresholds have been introduced (see [13] and [14]). The proposed adaptive threshold scheme provides the use of a gain proportional to the amplitude of the input signals and of a constant term for a tight tuning (see Figure 3).

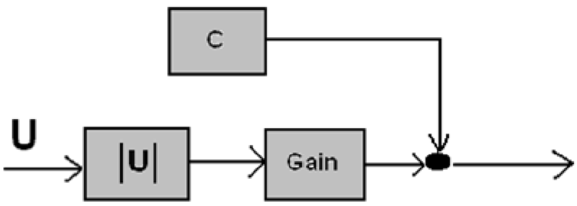


Figure 3: The adaptive threshold scheme adopted in the analysis.

The gains presented in the previous scheme have been computed by taking into account the input variables that actually contribute to the generation of residuals. The choice of gains has been conducted by performing a frequency analysis of the input signals.
A key issue in developing a PCA model is to choose an adequate number of principal components to represent the process in a "optimal" way. If fewer principal components are selected than required, a poor model will be obtained which has an incomplete representation of the process. On the contrary, if more principal components than necessary are selected, the model will be over-parameterized and will include a significant amount of noise.
To cope with these problems, several methods for selecting the optimum number of PCs have been proposed in the literature; although the PCA method is widely applied, some of the these methods are rather subjective, other methods do not offer the possibility to work with both correlation and covariance matrix of the data. To overcome these difficulties a new approach, based on the statistical Test ANOVA (ANalysis Of VAriance) has been proposed in this Thesis [15]. In the present context, in order to determine if additional information is gathered by adding a new eigenvalue, ANOVA's Test is used. Two hypotheses about the parameters of the model, in particular about the number of eigenvalues of the correlation matrix, are proposed and tested:

1) the added eigenvalue can be neglected
2) the added eigenvalue is necessary to the model

While the hypothesis 1) holds false, the dimension of the Principal Components space is increased.

2.2 Fuzzy Fault Classifier

The main problem encountered in process faults isolation with PCA techniques is related to the high number of residual signals that have to be investigated. This is particularly verified in case of process faults that involve many variables. Furthermore some of the variables involved in the considered process faults may exhibit a slightly different behaviour from the training case due to different environmental and/or operative conditions. To solve this problem an automatic procedure for the inspection of all the residuals, the Fuzzy Fault Classifier (FFC), has been developed.
The system, based on Cluster Analysis and Pattern Recognition of fuzzified residuals values, suggests the most likely faults within a record of known faults. Historical data concerning known system faulty/unfaulty operative conditions are processed offline and proper fault prototypes are generated.

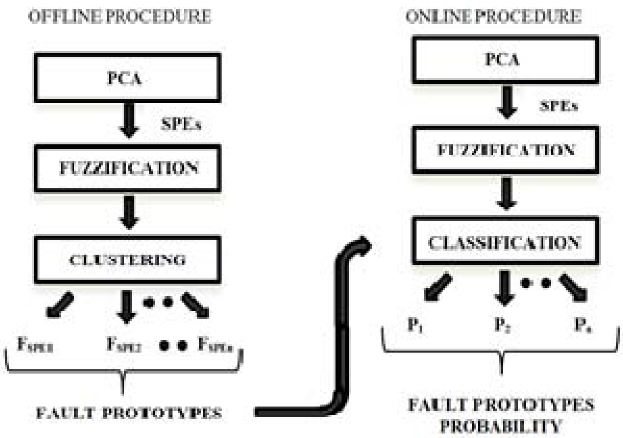


Figure 4: Offline and online FDI procedure.

As depicted in Figure 4 the offline procedure is based on three main preliminary steps:

- computation of the residuals (called SPE – Square Prediction Error) which is performed by the PCA algorithm;
- fuzzification of the SPE values;
- construction of the faults prototype vectors performed by the Cluster Analysis.

The fault prototypes generation is based on Cluster Analysis. The author proposes to use of the well-known Fuzzy C-Means (FCM) algorithm to perform the prototypes generation and the adoption of the Jeffrey-Matusita distance as metric for the validation of the clustering procedure.
Online the fuzzification of the currently computed SPEs values is performed by the Fuzzy Faults Classifier and the fuzzy value of the computed SPEs, is computed.
To accomplish the classification task a distance between the computed SPE configuration and the stored SPE configurations is computed. The author propose the use of Mahalanobis distance (respect other non-statistical metric, like Euclidean distance) to cope this problem (see [16] and [17]).
Finally, based on the computed distance, the current probability of each fault prototype is given as output. More specifically the highest probability is associated to the minimal distance (see Figure 5).

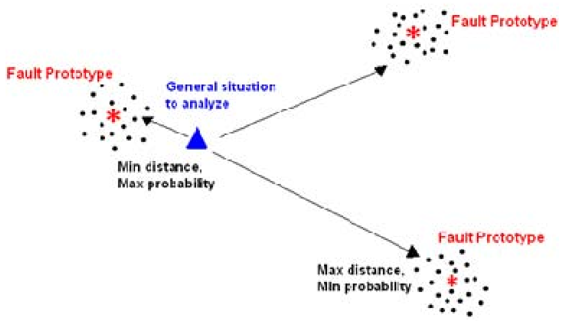


Figure 5: Fault probabilities are inversely proportional to fault prototypes distances.

3 Analysis and discussion of main results

3.1 FDI on Multishaft Centrifugal Compressor (Multiple Fault)

After have defined a process faults database (based on historical data) the proposed FDI systems has been applied to detect and isolate the break of the thrust bearing of the Multishaft Centrifugal Compressor.
The dataset analysed for the FDI system has been chosen to contain twelve variables, concerning sensors, actuators and performance parameters (like polytrophic efficiency). Data are collected from a DCS (Distributed Control System) and sampled at a rate of 10 minutes.
The following Table 1 summarizes the main stored faults in the process faults database.

Table1: Fault prototypes code number and description

FAULT PROTOTYPE CODE	DESCRIPTION
(1)	Absence of faults.
(2)	Breaking of the thrust bearing.
(3)	Single fault (thermocouple)
(4)	Fouling (contamination) of the compressor stage.

The first step of the PCA approach is the selection of the adequate number of the Principal Components; the suitable dimension of the Principal Component subspace has been computed to be five: a good compromise between faithful data reconstruction and fine noise filtering.
On line, after the computation of the fuzzified values, the FFC performs a matching with the stored faulty/unfaulty conditions cluster prototypes described in Table 1. Results of the FFC module when considering the Euclidean distance as metric are shown in Figure 6 and Figure 7.

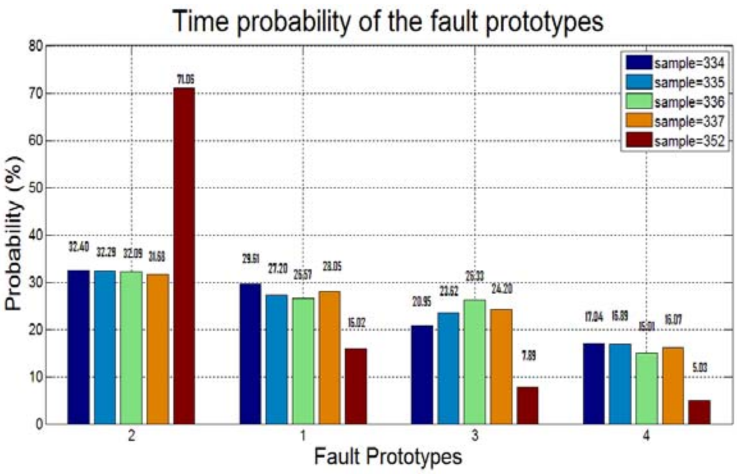


Figure 6: Fault prototypes probabilities histograms when adopting the Euclidean distance metric.

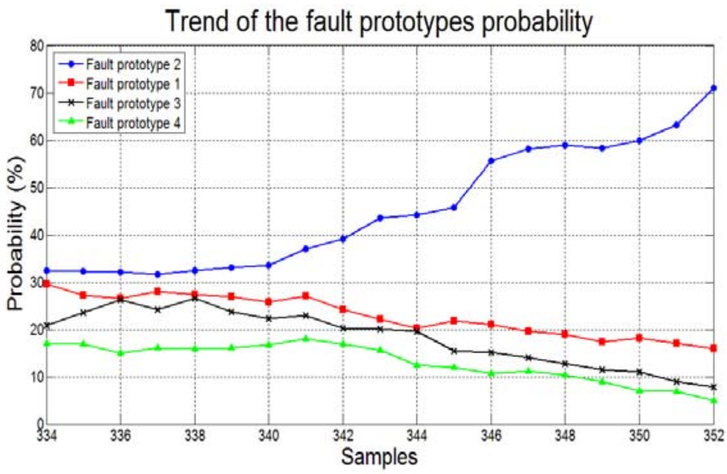


Figure 7: Trend of the Fault prototypes probabilities when adopting the Euclidean distance metric.

From the inspection of Figures 6 and 7, it can be evinced that the FFC properly recognizes the break of the thrust bearing at sample 334 (approximately just after the symptom on the horizontal vibration has appeared) assigning to it a probability of about 32.40%. At sample 352, i.e. three hours later, the probability relative to the correct fault increases up to 71.6%. This result confirm the capability of the FFC in detecting the fault; the efficiency in isolating the true fault is also appreciable but an improvement in the performances may be desirable and it can be achieved by the introduction of the Mahalanobis distance.
Distances of the current SPE configuration at each sample time from each of the four clusters computed considering the Mahalanobis metric are shown in Figure 8 and Figure 9.

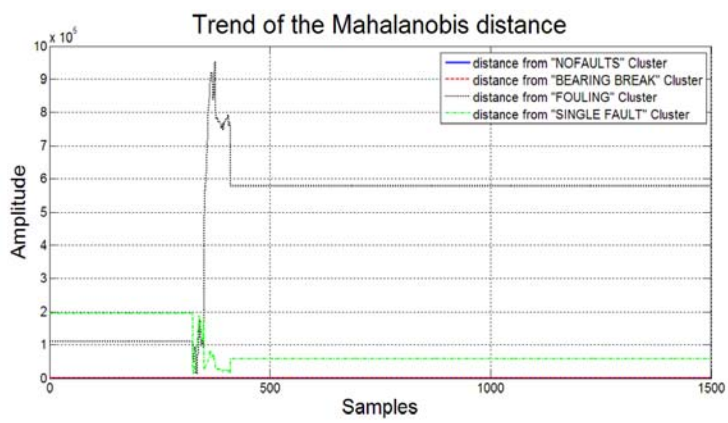


Figure 8: The Mahalanobis distances of the analysed data from the stored fault centroids.

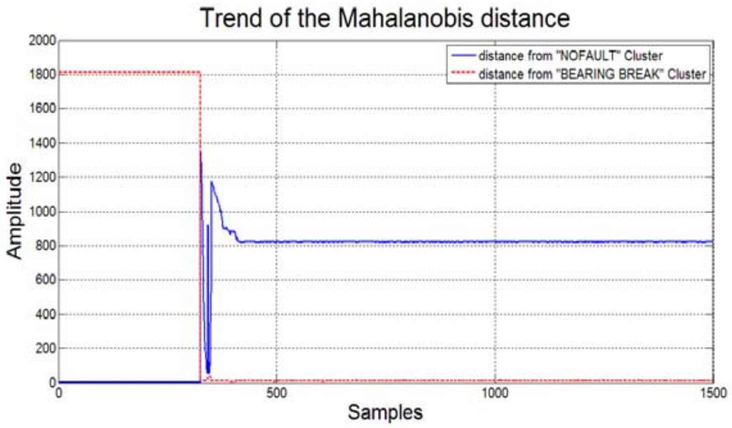


Figure 9: Zoom of the Mahalanobis distances of the analysed data from the stored fault centroids.

At sample 334, when the first symptoms are detected the distance from the cluster associated to the absence of faults increases. Accordingly, the distances from the others centroids decrease and the one relative to the break of thrust bearing results to be the lowest one (see Figure 9). This situation remains unchanged until the end of the faulty dataset.
The output of the FFC when considering the new metric approach is depicted in Figure 10 and 11.

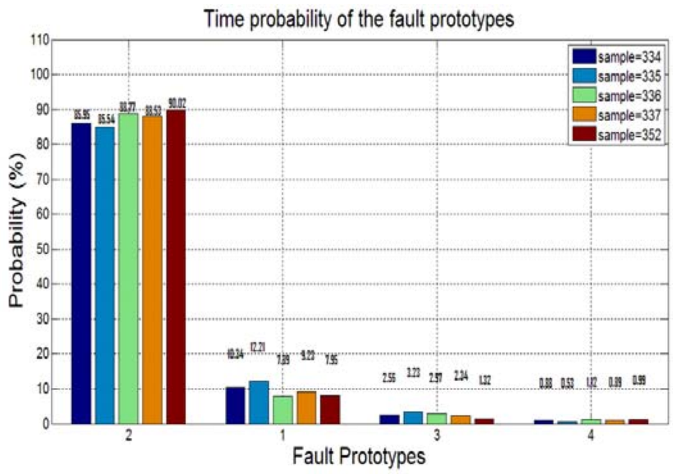


Figure 10: Fault prototypes probabilities histograms when adopting the Mahalanobis distance.

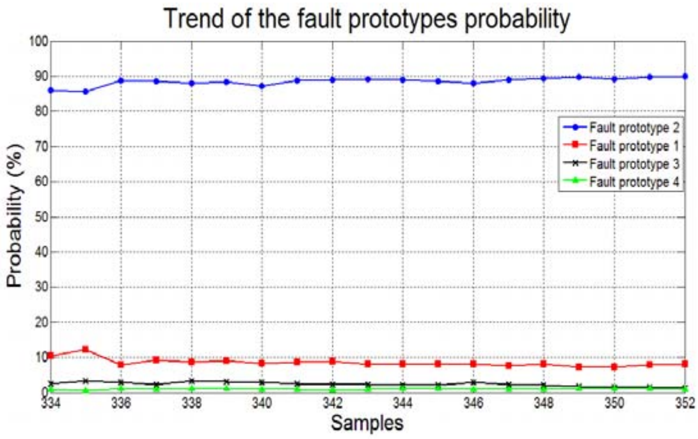


Figure 11: Trend of the fault prototypes probabilities when adopting the Mahalanobis distance.

From an analysis of the results it is possible to conclude that the capability in the faults detection when adopting either of the two metrics is comparable: at the same sample time 334 the faulty situation is detected. On the other hand, considering the ability in the faults isolation, the Mahalanobis distance offers the best results.

3.2 FDI on Unmanned Surface Vehicle

A problem with a submersed wall obstructing Charlie USV path on which the vehicle repeatedly collided was experienced while executing a survey of a coastal archaeological site. Figure 12 illustrates the behaviour of the USV before and after hitting the submersed wall in terms of its position (GPS coordinates) and actuators input voltages.

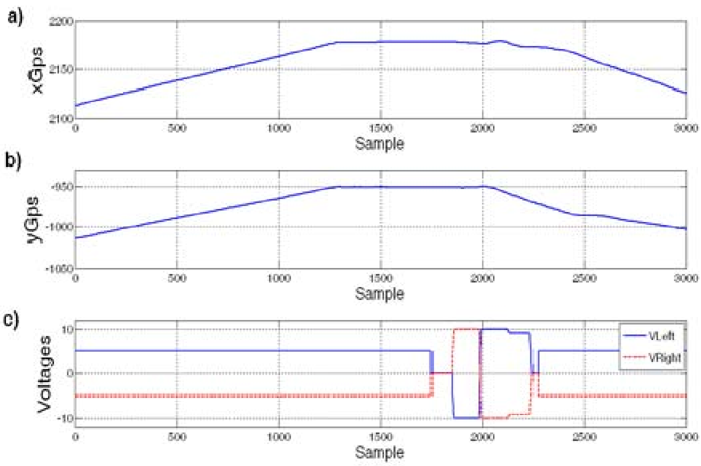
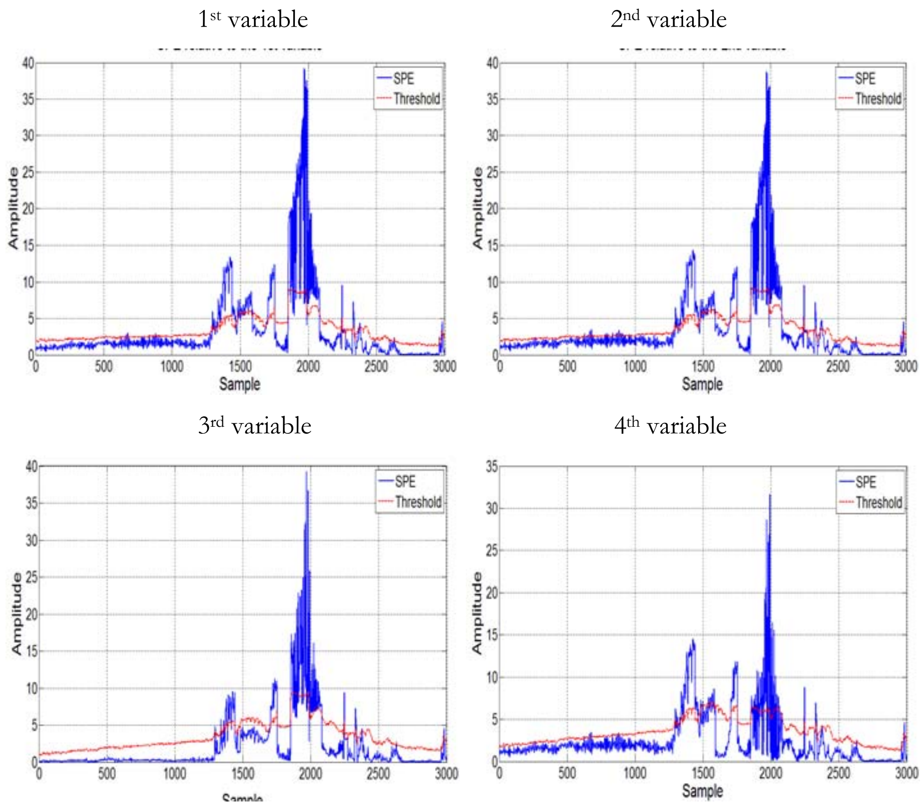


Figure 12: X and Y GPS coordinates and left and right actuators input voltages before and after hitting the wall.

From inspection of Figure 12 it can be seen that for more than 90 sec the vehicle is stuck in the same position (X and Y position data remain constant). In particular, it can be observed that, for about one minute, from sample #1284 to sample #1750 the vehicle is not moving even if forward propulsion is active as voltage signal shows.
At field, Charlie USV operator could detect that something was going wrong thanks to direct observation of the vehicle. Thus, he started to manoeuvre in order to refloat the vessel from a probable underwater obstacle. At sample #1750, the actuators are stopped and after twelve seconds a backward manoeuvre is undertaken. At sample #2017, i.e. twenty one seconds after, Charlie is able to continue its mission.
In order to apply the fault diagnoser, from the mission log file eight variables have been selected: the vehicle GPS position coordinates, its computed speed, roll and pitch angles, the commanded rudder position and input voltage to the left actuator.
The first step is the choice of the Principal Components retained in the model. The ANOVA test proposed by the author suggests retaining four PCs: this choice turns out to be a good compromise between the fulfilments of adequate reconstruction of the original data while preventing negative effects due to overfitting.
As a second step in the PCA procedure, SPE signals are computed so that detection and isolation of the fault under study (hitting of the wall) can be performed. In Figure 13, the SPEs computed for the all variables are shown.



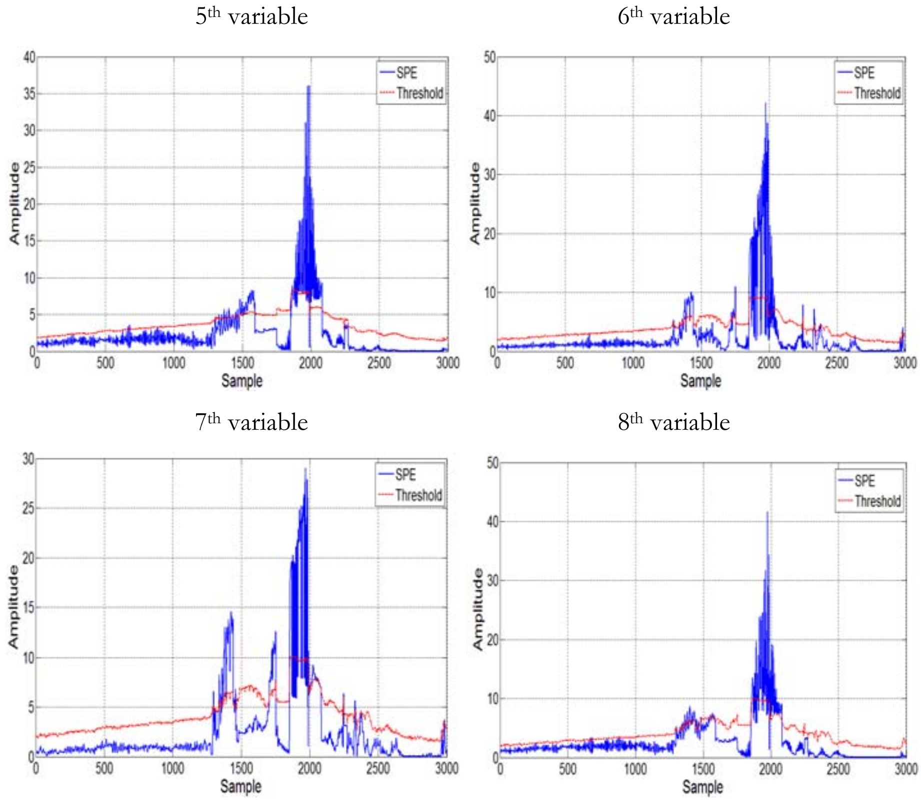


Figure 13: Square Prediction Error (SPE) (blue) computed on a single direction and their adaptive threshold (red).

As expected, since hitting the wall involves more than one variable, all the SPEs shown in Figure 13 exceed their adaptive threshold.
Diversely, the only SPE that remains under the threshold is the one that is associated with the pair variables {5,6} involved in the faulty behaviour i.e. the commanded rudder position DeltaRef and the computed speed speedGps (Figure 14).

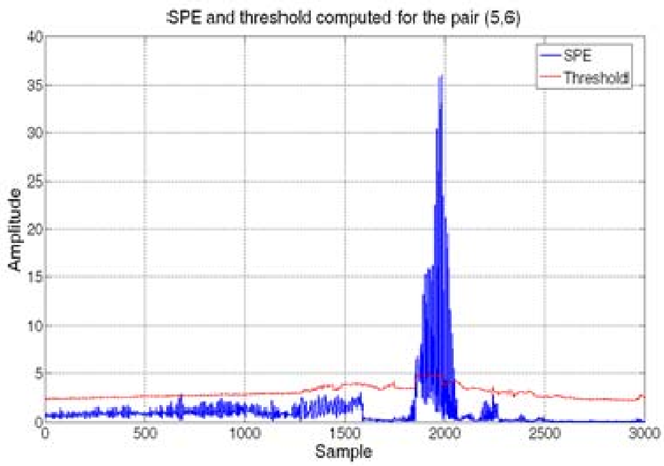


Figure 14: SPE and the relative threshold computed considering the pair {5,6}.

The system at sample #1296 correctly isolates the occurred hitting of the submersed wall, indicating the presence of a multiple fault on the 5th and 6th variable.
The Time-to-alarm, that is the time elapsed between the occurrence of the fault and the warning of the condition is less than one and a half second (from sample 1284 when Charlie hits the wall to sample #1296 where the SPEs firstly overcomes their threshold), confirming the efficiency of the FDI system in detecting and isolating the real fault [18].

4 Conclusions

This thesis proposes a new Fault Detection and Isolation (FDI) system based on data-driven, model-free approach. The system combines the Principal Component Analysis (PCA) approach, Cluster Analysis and Pattern Recognition techniques; the FDI system (called FFC – Fuzzy Faults Classifier) is structured through an offline and online procedures.
From experimental results on data concerning the process studied (the Multishaft Centrifugal Compressor and the Unmanned Surface Vehicle) the effectiveness and efficiency of the propose FDI could be proven as well as and its validity on enhancing process safety and achieving reduction of plant functioning costs.
Summarizing the major contributions of this research can be stated as:

- Implement a rigorous way to determine the dimension of the PC subspace when approaching fault diagnosis problems with PCA techniques in real contexts such refinery plants. The proposed Principal Component (PC) selection method is based on the statistical test ANalysis Of VAriance (ANOVA); its major benefits can be stated to be its reliability, its objectiveness and the uniqueness of the proposed solution.
- Provide adaptive thresholds used to identify a fault condition. The scheme adopted for the adaptive thresholds follows a classical structure proposed in literature but some coefficients used inside them have been estimated by an innovative procedure based on the power spectrum of the input signals.
- Combine the Cluster Analysis and Patter Recognition to develop an automatic procedure, implemented in the Fuzzy Fault Classifier, useful to recognize the known faults of the process. The system allows to overcome to the growth of complexity in the analysis of process faults that typically involve many variables; in this way an automatic procedure for the isolation of the principal known faults of the system under study has been accomplished.
- Perform the classification of the most probable faults of the system by the use of the well-known Mahalanobis distance. The main benefit of this metric is the possibility of taking into account the correlation between the data and this sensitively increases the performances of the overall system. The improvements are mainly associated to the faster response for the true fault isolation with respect to the use of some other non-statistical based distance into the FFC module.
- Propose the use of the Jeffrey-Matusita distance for the optimal generation of the process fault prototypes. The main advantages of using the Jeffreys-Matusita distance concerning the possibility of applying this metric to distributions with nonidentical dispersion and it does not require distributions to be normal.

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