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Marine gas turbine monitoring and diagnostics by simulation and pattern recognition

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ABSTRACT

Several techniques have been developed in the last years for energy conversion and aeronautic propulsion plants monitoring and diagnostics, to ensure non-stop availability and safety, mainly based on machine learning and pattern recognition methods, which need large databases of measures. This paper aims to describe a simulation based monitoring and diagnostic method to overcome the lack of data. An application on a gas turbine powered frigate is shown. A MATLAB-SIMULINK® model of the frigate propulsion system has been used to generate a database of different faulty conditions of the plant. A monitoring and diagnostic system, based on Mahalanobis distance and artificial neural networks have been developed. Experimental data measured during the sea trials have been used for model calibration and validation. Test runs of the procedure have been carried out in a number of simulated degradation cases: in all the considered cases, malfunctions have been successfully detected by the developed model.

1. Introduction

Real time operation monitoring and effective fault diagnosis are crucial issues in plant management, in order to increase safety and reliability. High availability, even if a fault occurs, is a desirable feature in almost any engineering application field. Several monitoring and diagnostic techniques have been developed, especially for industrial power plants and aeronautic propulsion systems. The general intent of these techniques is to monitor the plant's operation through a number of measures of an appropriate set of physical and thermodynamic parameters, then to identify one or more diagnostic variables through a model, which can be based on various computing techniques such as simulation, optimization algorithms, expert systems, response surfaces. The presented approach features a large use of simulation techniques, combined with Artificial Neural Networks (ANN) and Mahalanobis distance calculation (Taguchi and Jugulum, 2002), to obtain a fast and effective diagnosis for real-time applications. In the past years the authors gained significant experience in marine propulsion plants simulation (Benvenuto et al., 2000; Benvenuto and Campora, 2005; Campora et al., 2013; Altosole et al., 2014), as well as in the application of ANN based metamodels for ship machinery diagnostics (Campora et al., 2015; Zaccone, 2013; Zaccone et al., 2015).

In these last studies, simulations were performed to generate a large amount of operational data, in order to overcome the lack of experimental measures. In addition, simulation helped to investigate the effects of component degradation, and ANN based metamodels were used in place of simulation to reduce computation time and allow problem inversion. The presented application is focused on the gas turbine-controllable pitch propellers propulsion plant of a frigate: a set of simulations in different working conditions has been carried out in order to obtain an exhaustive description of the plant behavior in all the operating and degradation states. Simulation results have been used to define a reference state of the plant, and Mahalanobis distance has been adopted in order to easily detect abnormal working conditions during plant's operation. In addition, the obtained database has been used to train a diagnostic artificial neural network, which provides the fault coefficients of the different plant components. In order to match the simulation database with the real plant's operation data, a calibration method has been applied.

2. Gas turbines diagnostics: an overview

Several approaches to fault diagnosis have been developed in

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the last 50 years. Gas turbine powered systems diagnostic literature is wide and rich, especially in the aeronautic field. Li (2002) offers a review of the principal state-of-the-art techniques, analyzing a large number of papers by different authors, presenting a classification of the most used diagnostics and monitoring methods. According to Li, the approaches to the diagnostics problem can be divided into the following categories: linear model based methods, nonlinear model based methods, artificial intelligence based methods, fuzzy logic based methods.

Linear methods have been introduced by Urban (1969), using Gas Path Analysis (GPA): the purpose of the GPA is to extract information associated with the gas turbine engines via the analysis of the principal physical parameters of the plant, for example, pressures, temperatures, rotation speeds, flow rates, measuring them in different locations on the machinery. The GPA has been the most used approach to gas turbines monitoring and diagnostics in the last decades (Stamatis, 2011; Fentaye et al., 2016). In its most simplified form, the linear GPA, the highly nonlinear relationship between gas turbine dependent and independent parameters is simplified through a linear approximation at a given operating point (such as maximum power, cruise power, etc.). The paper by Verbist et al. (2011) shows an example of the application of linear GPA to a gas turbine engine. In order to overcome the problems due to the non-linear behavior of the gas turbine, nonlinear model based methods have been introduced. These methods are based on an accurate modeling of nonlinear gas turbine performance, combined with optimization techniques: the difference between measured and model predicted engine performance is minimized with an optimization approach in order to find the best set of engine component parameters. The artificial intelligence field is best referred as machine learning, or computational intelligence, with some slight semantic differences, however aims to mathematically reproduce biological systems architectures or behaviors such as neural systems, reproduction, human thinking or learning, in order to solve simpler problems. Artificial intelligence based methods are widely used in diagnostics applications: they are mainly based on genetic algorithms (GA), expert systems (ES), artificial neural networks (ANN), fuzzy logic. GA-based methods are model-based methods, theoretically similar to nonlinear model based. GAs are applied in the optimization phase, in order to identify a set of engine component parameters which produces the set of performance parameters that best matches the measured values. Expert systems are computer programs based on mainly experience knowledge (Bidini et al., 1998): an ES is composed of a knowledge base and an inference engine. The user interacts with the inference engine, which uses the knowledge base in order to solve problems and give advice: the solution of the problem is obtained through a heuristic type analysis. ANNs are based on the mathematical modeling of biological neural systems behavior, in order to store experimental knowledge contained in a database and to make it available for use. A brief description of ANN behavior can be found in a dedicated paragraph. In Palmé et al. (2011a) an ANN based system is used for gas turbine diagnostics: the ANN is trained using the experimental records of the first three months of operation of the plant, in order to obtain a model that can be used as a reference to the correct working condition. Other applications of auto-associative ANN in combination with principal component analysis are shown in Palmé et al. (2011b) and Kramer (1991). In the marine field, the authors presented an application of ANN to simulation and diagnostics of gas turbine and diesel engine powered marine propulsion plants (Campora et al., 2015), while Coraddu et al. (2016) presented an approach to marine gas turbines diagnostics based on statistical learning algorithms.

ANN applications to marine diesel engine diagnostics extensively discussed by Li and Su (2008) and Pawletko (2005), and later in Zaccone et al. (2015).

Fuzzy logic based methods are also popular: fuzzy logic is an extension of the boolean logic theory, based on a 'truth value' between 0 and 1, which must not be confused with probability. Ogaji et al. (2005) show an application to gas turbine diagnostics using a GPA approach. Fuzzy logic can be applied in combination with neural networks, expert systems, genetic algorithms. Neuro-fuzzy approaches to diagnosis are described in Izadi-Zamanabadi et al. (2001) and Li and Su (2008) referring to gas turbines and marine diesel engines respectively. Finally, an effective diagnostic method based on the Mahalanobis - Taguchi system, combined with Bayesian networks and orthogonal arrays is presented in Kumano et al. (2011). The present work is based on this approach as described in the following.

3. Power plant monitoring and diagnostics procedure

The purpose of this paper is to present a procedure suitable for monitoring and diagnostics of energy conversion and propulsion plants. The procedure is structured on two monitoring levels: at a basic level, Mahalanobis distance (MD) is used as an index of abnormality of the system; such parameter is computed from a set of state variables in order to compactly express the state of the system. The advantage of using only one parameter for system monitoring is obvious in terms of ease of representation and threshold setting. The robustness of such parameter to some external influences is shown in the paper. On a deeper monitoring level, if a high MD value is detected, a multi-input multi-output ANN based model is used in order to extract information on the state of each system component from the state variables.

3.1. The Mahalanobis distance

Mahalanobis distance (MD) is a multivariate squared distance that takes in to account the variance and the correlation between the variables. In the framework of the Mahalanobis – Taguchi (MT) method (Taguchi and Jugulum, 2002), MD is used to quantify the abnormality of a generic condition of a multivariate system with respect to the 'normal' or 'healthy' condition, which is represented by a reference set of observations, called Mahalanobis Space (MS). The abnormality is measured by calculating the MD value for the actual condition. The advantage of using the MD instead of a different distance (for example the Euclidean distance) is the possibility to take into account the correlation between the variables.

Suppose the MS composed by n observations of k variables named $X_1, \ldots, X_k$, n sufficiently large; if m_i and s_i are the means and the standard deviations of the variables respectively, C the correlation matrix of the variables, the MD of the j^{th} observation is given by the following expression:

$$MD_j = \left(\frac{1}{k}\right) Z_{ij}^T C^{-1} Z_{ij} \tag{1}$$

Where Z_{ij} is the i^{th} standardized variable for the j^{th} observation:

$$Z_{ij} = \frac{X_{ij} - m_i}{s_i} \tag{2}$$

Note that MD is a dimensionless squared distance. An alternative definition is used in Kumano et al. (2011), where the square root is used in order to eliminate the quadratic dependence. This last definition is used in this work:

$$MD_j = \sqrt{\left(\frac{1}{k}\right) Z_{ij}^T C^{-1} Z_{ij}} \tag{3}$$

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