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Procedia Manufacturing 19 (2018) 111-118

www.elsevier.com/locate/procedia

6th International Conference on Through-life Engineering Services, TESConf 2017, 7-8 November 2017, Bremen, Germany

Comparison of Different Classification Algorithms for Fault Detection and Fault Isolation in Complex Systems

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Abstract

Due to the lack of sufficient results seen in literature, feature extraction and classification methods of hydraulic systems appears to be somewhat challenging. This paper compares the performance of three classifiers (namely linear support vector machine (SVM), distance-weighted k-nearest neighbor (WKNN), and decision tree (DT) using data from optimized and non-optimized sensor set solutions. The algorithms are trained with known data and then tested with unknown data for different scenarios characterizing faults with different degrees of severity. This investigation is based solely on a data-driven approach and relies on data sets that are taken from experiments on the fuel system. The system that is used throughout this study is a typical fuel delivery system consisting of standard components such as a filter, pump, valve, nozzle, pipes, and two tanks. Running representative tests on a fuel system are problematic because of the time, cost, and reproduction constraints involved in capturing any significant degradation. Simulating significant degradation requires running over a considerable period; this cannot be reproduced quickly and is costly.

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Keywords: Maintenance, Monitoring, Machine Learning

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 $Peer-review \ under \ responsibility \ of \ the \ scientific \ committee \ of \ the \ 6th \ International \ Conference \ on \ Through-life \ Engineering \ Services. \\ 10.1016/j. promfg. 2018.01.016$

1. Introduction

In the past, industries have always focused on quality, efficiency, and cost effectiveness. With technological advancements over the past decade, industries have added one very important aspect to their top priorities: the ability to detect and isolate faults from the onset of evolving. These advancements have made it possible to intelligently measure conditions of equipment, as well as the transport of mediums, in a cost-effective way. Data from sensors placed at specific locations can reveal instrumental information about the health of the system. This information can be of high value to an operator if processed accurately and can lead to actions that ensure processes run smoothly, reduce the risks of unexpected downtime, and deliver expected throughput, maximizing the overall availability of an asset/system/process or a plant. Obtaining real datasets to be used for development and testing of fault detection and fault isolation algorithms is always challenging. Running representative tests on a fuel system are even more problematic because of the time, cost, and reproduction constraints involved in capturing any significant degradation.

Three different approaches to a solution can be taken. Firstly, accelerated testing, which can be achieved by increasing the duty of the components or by manufacturing them using less durable materials. Secondly, by knowing the degradation modes to be investigated, the components can be machined to represent the degraded mode – often referred to as 'seeded fault' testing. The second solution represents only one snapshot in the wear process but can be repeated gradually to increase the effect. Thirdly, by emulating some degradation modes, e.g. a filter replaced by a valve, so that a clogged filter failure mode can be emulated by gradually closing the valve. The latter of these three approaches is adopted in this paper.

Sensor set optimization in the context of fault diagnosis accuracy is a major challenge for specific industry sectors like aerospace as every single additional sensor has an impact on the overall asset availability. A widely-accepted process to identify the minimum number of sensors capable of meeting the fault detection and isolation (FDI) requirements is not available and very often, OEMs ended up developing bespoke processes and tools suitable to specific applications/systems. It was demonstrated, using the same fuel system testbed, how such a process supporting instrumentation optimization can be implemented by using a quantitative model-based approach [1]. This paper continues such work and evaluates the impact on FDI accuracy when using data from optimized vs. non-optimized sensor set solutions.

In general, fault diagnostic approaches in the literature can be categorized into model-based approaches and datadriven approaches, based on the process knowledge that is required a priori [2]. The hierarchy of fault diagnosis approaches is shown in Fig. 1. The model-based approaches depend on a fundamental understanding of the physics of the process. Among thesis model-based approaches are parameter estimation methods [3], parity relation methods [4] and fault tree methods [5].

In data-driven methods, it is given to have a significant amount of available historical process data. In these methods, features can be extracted to present the historical process data as a priori knowledge to a diagnostic system. The feature extraction methods can be divided into qualitative methods, such as expert systems [6] and qualitative trend analysis [7], or quantitative methods. Also, the quantitative feature extraction methods can be categorized into statistical and non-statistical methods. Among the quantitative feature extraction methods are principal component analysis/partial least squares [8], neural network [2], and statistical classifier methods [9].



Fig. 1. Classification of fault diagnosis methods [2].

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