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Predictive diagnosis based on a fleet-wide ontology approach

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ABSTRACT

Diagnosis is a critical activity in the PHM domain (Prognostics and Health Management) due to its impact on the downtime and on the global performances of a system. This activity becomes complex when dealing with large systems such as power plants, ships, aircrafts, which are composed of multiple systems, sub-systems and components of different technologies, different usages, and different ages. In order to ease diagnosis activities, this paper proposes to use a fleet-wide approach based on ontologies in order to capitalize knowledge and data to help decision makers to identify the causes of abnormal operations. In that sense, taking advantage of a fleet dimension implies to provide managers and engineers more knowledge as well as relevant and synthetized information about the system behavior. In order to achieve PHM at a fleet level, it is thus necessary to manage relevant knowledge arising from both modeling and monitoring of the fleet. This paper presents a knowledge structuring scheme of fleets in the marine domain based on ontologies for diagnostic purposes. The semantic knowledge model formalized with an ontology allowed to retrieve data from a set of heterogeneous units through the identification of common and pertinent points of similarity. Hence, it allows to reuse past feedback experiences to build fleet-wide statistics and to search "deeper" causes producing an operation drift.

1. Introduction

Nowadays, the high competitiveness faced by industrial enterprises requires higher performances, such as higher quality of products/services, lower costs, and sustainability [16]. This way, the importance of maintenance has increased due to its key role in improving system availability, performance efficiency, products quality, etc. [1]. These requirements promote the evolution of maintenance strategies from a "fail and fix" to "predict and prevent" approach. This new vision is supported by condition-based/Prognostics and Health Management (PHM) maintenance strategies [14]. Despite this proactive approach, failures still occur.

To minimize the effects of unexpected system failures, there is an increasing demand for improving fault diagnosis efficiency techniques in industrial machines [18,58]. In that sense, in complex domains such as the naval one, it can be difficult, especially for junior maintainers and even for experts, to generate the required hypotheses about the causes of failures or abnormal behavior (e.g. symptoms occurrence) to resolve the unexpected situation [27]. The resolution of these situations requires knowledge about the degradation mechanisms of different components built on several technologies (mechanical, electrical, electronic or software natures) [47] whose behavior can vary over the different phases of their lifecycle and usage condition [4].

In order to improve PHM processes for large and complex systems such as power plants, ships and aircrafts, one possible approach is to take advantage of the "fleet" dimension. This dimension can provide more knowledge and data to improve diagnostic and prognostic models [24].

A fleet shall be viewed as a set of systems, sub-systems and components. In this paper, the naval domain is addressed. Hence, in the following, a unit of a fleet will be considered as a system (e.g. ship), a sub-system (e.g. propulsion or electric power generation) or component (e.g. diesel engine, shaft, etc.) depending on the target object. To be in accordance with the need of improving PHM at the fleet level, an original methodology is proposed in this paper wherein individual knowledge (of each unit) is capitalized for reuse purpose. The reuse knowledge is used order to improve PHM activities such as predictive diagnosis, which will serve as example in the last part of this article. To take advantage of the individual knowledge at the fleet level, a semantic model is proposed for the PHM activities in the naval domain. The added-value of this paper is to represent and structure in a semantic model the knowledge arising from the different PHM processes as well as from the domain of interest (in this paper the naval domain). Usually,

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applications using ontology in the PHM domain only focus on knowledge of a specific PHM process and for a single component (i.e. knowledge for diagnostic of an electric motor). This way different categories of concepts related to the PHM and system domains, called in our paper contexts, are modeled and relations between these concepts are explicit. Such a semantic model enables to reuse particular data, such as maintenance records, reliability analysis, failure analysis, data analysis at a fleet level in order to provide more knowledge. As data become available, PHM activities could benefit from more contextual information.

2. PHM at component and system level

PHM activities help to reduce the life cycle cost of a product by decreasing inspection costs, downtime and inventory [33,48]. The proposed approach could be performed for any PHM activity but we focus on the diagnosis one in order to exemplify the proposed approach. Lei et al. [18,7] define diagnosis as a process of locating the exact causes of a failure. However, within the PHM activities in order to anticipate failures, "predictive diagnosis" is performed. Predictive diagnosis aims at warning about failure events before they occur and identifying the causes of degradation. For this purpose, features (i.e. variables) of the process and of the components are monitored. Degradation is then identified with the occurrence of at least one abnormal behavior on the process, manifested as symptoms (e.g. an event). Once the event has been detected, the maintenance operator/engineer needs to analyze the symptom behavior/evolution to understand which components may have caused the symptom and the reasons for the abnormal behavior of the component. In that sense, the diagnostic process involves two main sub-processes: generation of hypotheses about what could have been wrong and testing of these hypotheses [30].

Since a machine has many components and is highly complex, diagnosis of a machine failure/degradation usually requires technical skill and experience [18]. It also requires understanding the machine's structure and operation. To better understand machine operation, the first step is to perform a functional analysis about the normal functioning of the system. Once functioning knowledge is formalized, abnormal situations are studied. Abnormal situations are studied through dysfunctional analysis (such as Failure Mode, Effects and Criticality Analysis (FMECA) and Hazard and Operability Study (HAZOP)) where degradation modes at different abstraction levels are identified [28]. Moreover, the causes and consequences of the degradations modes have to be identified in order to define the underlying causality chain and to reach the system level. This causality chain helps to identify the link between the monitored variables and the degradation mode that is monitored in order to locate easily the abnormal behavior.

Moreover it also requires knowledge about the context such as the operational conditions of the machine. In that sense, according to Cinar and Kayakutlu [5] some of the input information valuable for diagnostic is:

- Current data: on-line data in order to provide the values in real-time of the monitored indicators (variables). Data is captured and must be treated and analyzed. This data provides information to maintenance engineers about the current state of the unit. It should be used to compare the evolution of the current situation with similar situations (e.g. similar case retrieval).
- Past data: feedback about past failures on the system, as well as historic data about the evolution of degradation indicators under different circumstances (mission, environment, etc.). This data allows comparisons among the current and the past behaviors. Moreover past events could be used to make statistics that could ease the hypothesis generation process about the causes of degradations.

Additionally as mentioned in Peysson et al. [35] the health of a complex systems (S) depends mainly on three factors (1):

$$S = \langle \mathrm{M}, \mathrm{E}, \mathrm{P} \rangle \tag{1}$$

where M is the Mission that defines the use of the system during a time period; E is the Environment that represents the area where the mission is accomplished and where the process evolves and P is the process that gives the necessary means to accomplish the mission. The process is decomposed according to the different resources that are monitored during the mission.

Such a model shows that the contextualization of the information according to the operational conditions and the usage of the machine is of great importance [36,37,50]. For diagnosis purpose, experts could use this set of contextual knowledge in order to make hypothesis about the possible explanations of abnormal operation. Indeed, contextual knowledge allows a refinement on data analysis (facilitating the selection of relevant information for hypothesis reasoning).

While analyzing this knowledge, several sources of uncertainty may appear such as measurement and sensor errors, future load and usage uncertainty and so on. However uncertainty could be reduced when more data becomes available [33]. In these cases the notion of fleet becomes very interesting since it can provide more capitalized data and information coming from other members of the fleet for improving the efficiency on the solution of a problem (e.g. diagnosis).

The following section presents a review about the use of the fleet notion in the PHM domain.

3. PHM vs. fleet-wide approach

3.1. Fleet integrated PHM review

A fleet generally refers to gathering ships into a group of ships and the term is extended also to any kind of vehicle (e.g. trains, aircrafts, or cars). For industrial systems, the term fleet refers to a set of assets or production lines that may share some common components. In this paper, the fleet is considered as an abstract point of view to define a set of objects for a specific purpose (e.g. a unit maintenance planning) and for a given time (e.g. before the end of the current mission) that share some common "properties".

The fleet can be viewed as a population consisting of a finite set of objects (individuals) on which a study is ongoing. In this context, a fleet is generally a subset of the real fleet under consideration, i.e. a sub-fleet related to the aim of the study. Individuals composing the fleet/sub-fleet may be, as needed, systems themselves [4,32], sub-systems or components [44]. In the following, systems, sub-systems or components constituting the fleet, will be referred to as units.

In fact, fleet's units must share some characteristics that enable to group them together according to a considered purpose. These common characteristics may be technical, operational or contextual [25]. Such consideration allows to put data or information related to the whole selected fleet of units on the same benchmark in order to bring out pertinent results for the PHM activities. Common characteristics among units allow the definition of three types of fleet composition: identical, similar and heterogeneous fleets.

Based on these three types of fleet, some relevant works are reviewed below:

- Fleet composed of identical units: when considering maintenance operator's point of view, fleet management aims at making decisions that affect asset life extension and performance, operational costs and future planning [55,4,56]. In Patrick et al. [32], the authors notice that condition monitoring