Fleet-wide health management architecture

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ABSTRACT

Large complex systems, such as power plants, ships and aircraft, are composed of multiple systems, subsystems and components. When they are considered as embedded in system operating as a fleet, it raises mission readiness and maintenance management issues. PHM (Prognostics and Health Management) plays a key role for controlling the performance level of such systems, at least on the basis of adapted PHM strategies and system developments. However, considering a fleet implies to provide managers and engineers with a relevant synthesis of information and keep it updated regarding both the global health of the fleet and the current status of their maintenance efforts. For achieving PHM at a fleet level, it is thus necessary to manage relevant corresponding knowledge arising both from modeling and monitoring of the fleet. In that way, this paper presents a knowledge structuring scheme for fleet PHM management applied to marine domain.

1. INTRODUCTION

1.1 Context

Large complex systems, such as power plants, ships and aircraft, are composed of multiple systems, subsystems and components built on different technologies (mechanical, electrical, electronic or software natures). These components follow different rates and modes of failures (Verma et al., 2010), for which behaviour can vary all along the different phases of their lifecycle (Bonissone and Varma, 2005), and maintenance actions strongly depends on this context (e.g. failure modes that occur, Cocheteux et al., 2009). When they are considered as embedded in system operating as a fleet, it raises mission readiness and maintenance management issues.

In many cases, a fleet or plant operation is optimized (in terms of production or mission planning), making system availability a primary day to day concern. Thus, PHM plays a key role to ensure system performance and required, most of the time, to move from "fail and fix" maintenance practices to "predict and prevent" strategies (Iung et al., 2003), as promoted by Condition Based Maintenance (CBM)/PHM strategy mainly based on Condition-Monitoring capacities. Nevertheless, even if a condition monitoring program is in operation, failures still occur, defeating the objective for which the investment was made in condition monitoring (Campos, 2009). Moreover, the huge amount of condition monitoring activity, coupled with limitations in setting alarm levels (Emmannouilidis et al., 2010), has led to a problem for maintenance crew coping with the quantity of alarms on a daily basis (Moore and Starr, 2006).

From a practical point of view, predictive diagnosis aims at providing, to maintenance crew, key information about component current state and/or helping to decide the adapted maintenance action to be done, in order to anticipate/avoid failure. However, when considering a fleet of systems in the way to enhance maintenance efforts and facilitate the decision-making process, it is necessary, at the fleet level, to provide managers and engineers with a relevant synthesis of information and keep it updated regarding both the global health of the fleet and the current status of their maintenance efforts on components (Hwang et al., 2007).

Such an issue, at the fleet level, has to be tackled considering an information system enabling to gather/share information from individuals for synthesis,

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case retrieval, engineering purposes. It enables to reuse particular data, such as maintenance history, reliability analysis, failure analysis, data analysis at a fleet level in order to provide knowledge. The reuse of such data requires turning them into information by adding semantic aspect while considered at the fleet level (Umiliacchi et al., 2011).

The semantic perspective at the fleet level allows:

- to unambiguously understand the data,
- to use them for reasoning as far as the reasoning knowledge has been modeled
- to put them in situation in order to enable comparison.

1.2 From collection of PHM systems to fleet integrated PHM system

PHM systems involve the use of multiple methods for acquiring and gathering data, monitoring and assessing the health, diagnosis and prognosis. Numerous approaches have been developed both for the diagnostic and prognostics purpose within system health monitoring. Such approaches are mainly data-driven methods, model-based and even hybrid. Moreover, dealing with systems requires, on the one hand, to consolidate data with for instance data fusion strategies (Roemer et al., 2010, Niu et al., 2010), and on the other hand, to take into account the system environment (Peysson et al., 2008), in order to provide relevant information for supporting diagnosis, prognostics, expertise or reporting processes.

However, most of these approaches cannot be applied in a straight-forward manner because they insufficiently support the multitude of different equipment, sub-system at system/plant-wide and provide only limited automation for failure prediction (Krause et al., 2010).

Hence, a main concern today in single and, even more, in multiple PHM systems design lies in the limitation due to the use of proprietary/closed information system leading to harden the integration of multiple applications. Hence, for instance, the Department of Defense policy community requires the use of open information systems to enable information sharing (Williams et al., 2008). Main standards used in the PHM systems are CBM+, Integrated Vehicle Health Management (IVHM) architecture (Williams et al., 2008), MIMOSA[*]… The two main parts of the later are dedicated to Open System Architecture for Enterprise Application Integration (OSA-EAI) and Open System Architecture for Condition Based Maintenance (OSA-CBM) (Thurston and Lebold, 2001). OSA-CBM improves CBM application by dividing a standard CBM system into seven different layers, with technical modules solution as shown in figure 1. According to the OSA-CBM architecture, the health assessment is based on consumed data issued from different condition monitoring systems or from other health assessment modules. In that way, health assessment can be seen as the first step to manage global health state of complex systems (Gu et al., 2009). It allows to define if the health in the monitored component, sub-system or system has been degraded.

Although the use of standard brings syntaxes to warehouse data collection (Umiliacchi et al., 2011), it lacks semantics to benefit from information/event/decision made upon a component for its reuse on another component at the fleet level. Gebraeel (2010) proposes to consider a fleet of identical systems where each system consists of the same critical equipment. Such an approach is context dependent and provides a low level of reusability but allows, to some extent, comparison.

In a general case, where several different systems are considered as a fleet, several PHM systems and data warehouse coexist. Hence, a straightforward way to bring semantic at a fleet level is to develop and use ontology.

1.3 Fleet integrated PHM review

A fleet generally refers to a gathering of group of ships and by extension the term is also used for any kind of vehicle (e.g. trains, aircrafts, or cars). For industrial systems, the term fleet designs a set of assets or production lines. In general, a fleet refers to the whole of an owner’s systems. In operational context, it refers to a subset of the owner fleet, e.g. a set of ships managed by a superintendant, or assets of a production site. Hence, the fleet here is only an abstraction point of view to consider a set of objects for a specific purpose (e.g. a unit maintenance planning), for a given time (e.g. before the end of the current mission). Indeed, 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 making up the fleet/sub fleet may be, as needed, the systems themselves (Bonissone and Varma, 2005), (Patrick et al., 2010). When specific subsystems are under investigation, a fleet of all similar subsystems or installations is considered. Finally, a set of equipment may be also considered when a fleet is fitted (Umiliacchi et al., 2011). In the following, systems, sub-systems or equipments constituting the fleet, according to the study purpose, will be referred to as units.

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In fact, fleet's units must share some characteristics that enable to group them together according to a specific purpose. These common characteristics may be of technical, operational or contextual nature. They allow to put data or information related to all the fleet units on the same benchmark in order to bring out pertinent results for monitoring, diagnostics or maintenance decision making.

Both fleet assignment and fleet maintenance scheduling problems have been studied mainly focusing on an optimization purpose (e.g. (Charles-Owaba et al., 2008), (Patrick et al., 2010)). Fleet management aims at maximizing adaptability, availability and mission success while minimizing costs and resources usage. 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 (Wheeler et al., 2009), (Bonissone and Varma, 2005),(Williams et al., 2008).

Nevertheless, fleet's predictive maintenance, i.e the fact of monitoring units' behaviors regarding the comparable behavior within the fleet, has rarely been addressed as a whole in the literature. (Umiliacchi et al., 2011) show the importance of having a standard format for the diagnostic data in order to facilitate their understanding across several subsystems and trains within a railway fleet. In (Patrick et al., 2010), the authors notice that thresholds indicative of condition indicators limits could be derived from statistical studies of fleet wide behaviors and known cases of faults. A more direct and less expensive maintenance technique is mentioned in (Reymonet et al., 2009). It consists in applying to the failed system the technical solution corresponding to a similar incident already solved with a comparable asset. Nevertheless, knowledge derived from the fleet in (Patrick et al., 2010) and (Reymonet et al., 2009) which arises from the same kind of units, in a domain where customized units are common, may give poor results.

1.4 Industrial Challenge

Behind the need of fleet PHM management stand an industrial demand. On one hand, the users of PHM system are fleet owners as well as fleet maintainers. Fleet owners aim at operating their fleet using indicators regarding not only single system but (sub) sets of systems as well. It requires being able to handle several indicators coming from several PHM systems in a common way in order to make easier data fusion/aggregation/synthesis, Human-Machine Interface (HMI) and their interpretation. Fleet maintainers would like to take benefit from event/decision already made in order to facilitate, enhance and/or confirm them. On the other hand, PHM system developers would like to decrease their development time and cost. All the previous requirements could be done through the reuse of parts of PHM system already existing on similar systems.

From the operational point of view, efficient maintenance decision needs to analyze complex and numerous interrelated symptoms in order to identify the real (health) problem. The diagnostic process requires comparison between information coming from several subsystems. Moreover, diagnostics tasks are today still under the supervision of human experts, who can take advantage of their wide and long-term experience allowing appropriate actions to be taken (Umiliacchi et al., 2011). Such practical consideration raises limitations due to time consuming, repeatability of results, storage and transfer of knowledge.

For achieving PHM at a fleet level, it is necessary to manage relevant corresponding knowledge arising both from modeling and monitoring of the fleet. That leads to increasingly consider environment and condition of usage within the PHM main processes (Patrick et al., 2010) in order to allow monitored data and corresponding health to be analyzed by means of comparison from different points of view (for instance regarding the level considered or the operating condition). Indeed, monitored data and elaborated Health indicators strongly depends on the usage of the component. For instance engine cylinder temperatures are related to both the required power output and the cooling system for which inlet air or water depends on the external temperature. It is thus necessary to manage these criteria in order to compare for instance cylinder temperature within similar condition in terms of both power and external temperature in the available fleet-wide data.

The paper focuses on a knowledge structuring scheme for fleet PHM management in the marine domain. The goal of the proposed approach is to allow fleet units to benefit from the predictive maintenance features within a fleet scale. This could be possible by looking at the fleet level for further and complementary knowledge to the unit level. Such knowledge may emerge from similar situations already encountered among fleet units historical data/information. Next section introduces Fleet-wide Knowledge-based model development starting with the issue raised, and then presenting the basis of knowledge domain modeling and finally the fleet-wide expertise retrieval. The last section is dedicated to an illustrative industrial example dealing with fleet of diesel engines.

2. Fleet-wide Knowledge-based model

2.1 Issues

PHM development is a knowledge-intensive process, requiring a processing of expert knowledge together with heterogeneous sources of data (Emmannouilidis et al., 2010). Such issue is strengthened at the fleet level. To support the main PHM processes development and to achieve a better understanding of monitored data, especially for diagnostic and maintenance decision making purposes, the underlying domain knowledge needs to be structured. Such system should enable to:

- Manage condition monitoring activities
- Associate monitored data with component operating condition
- Support diagnostic process with fleet-wide comparison facilities (i.e. benefits in a repeatable way of the fleet-wide expertise)
- Pro-actively anticipate failure (i.e. provide targeted maintenance actions recommendation).

It will ensure consistent information to be used throughout, from raw data acquisition to fleet-wide comparison (Figure 1). The key factor to turn data into such information is to enhance data with semantic context by means of ontology.

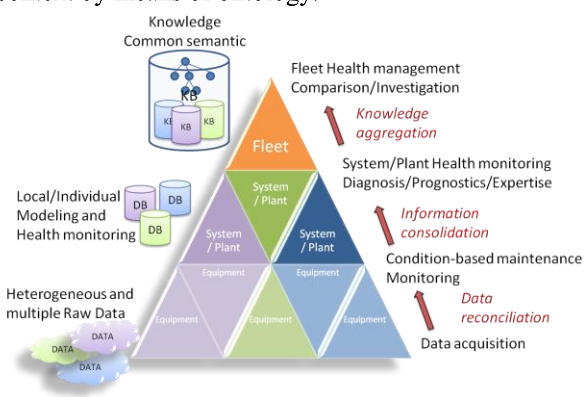

Figure 1: Proactive fleet management hierarchy, (Monnin et al., 2011a)

2.2 Basis of Knowledge modeling

Knowledge domain modeling relies on formal language that allows concepts to be described as well as the relationships that hold between these concepts. Starting from basic concepts, complex concepts can therefore be built up in definitions out of simpler concepts. Recent developments in the semantic modeling, based on information used and its context, have led to techniques using ontology to model complex systems. The ontology stores the relationships between physical components in a system, as well as more abstract concepts about the components and their usage (Figure 2). The key benefit over simple databases is that reasoning can take place to infer the consequences of actions or changes in the ontology instances (Umiliacchi et al. 2011).

Thus, information about the system can be inferred from the contextual information provided by the ontology. For instance, consider a fleet of ships each of them having one or more diesel engines for propulsion and/or electric power generation. With an ontology-based system, both propulsion engine and generator engine can be considered as diesel engine. Thus, the system can handle a generic request for the state of the diesel engine and the corresponding data.

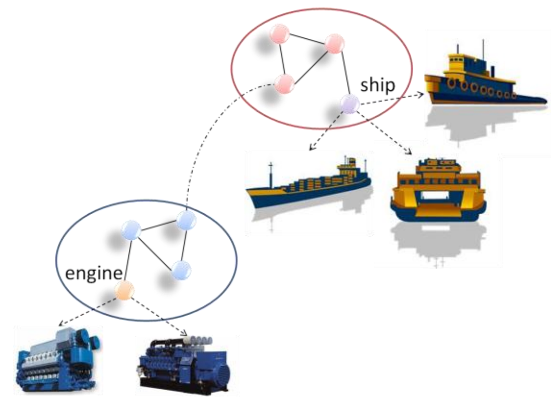

Figure 2: Scheme of concepts relationships

2.3 Fleet-wide expertise retrieval

For both diagnostic comparison and expertise sharing purposes, contextual information from the ontology enables to group component together given a particular context (e.g. component with the same usage). Four levels of context are defined in order to provide comparison facilities:

- Technical context
- Service context
- Operational context
- Performance context

These contexts defined within the ontology allow both to group instance sharing similar properties and to infer information about the system such as health indicators.

The technical context can be seen as the first and obvious level of comparison. It allows the technical features of the components to be described in the ontology. By means of taxonomy of components (Figure 3), it enables to conceptually describe components of a fleet. As a consequence, for instance, two different components (e.g. a propulsion engine and power generator engine) can be considered of the same type if a particular feature is considered (e.g. aspiration system).

However, from a practical point of view, the operating context influences the component behavior. The operating context can be split in service context and operational context.

The service context deals with sub-system for which component, even if similar, undergoes different solicitations. For instance, diesel engines can be both used for propulsion and electric power generation. Both engines are diesel engines and can be compared from technical points of view. However, even if the components belong to the same type, their functioning (i.e. service context) is quite different (e.g. load changes, redundancy). On the other hand, components that belong to different types can be compared in a way, since they operate in the same service context

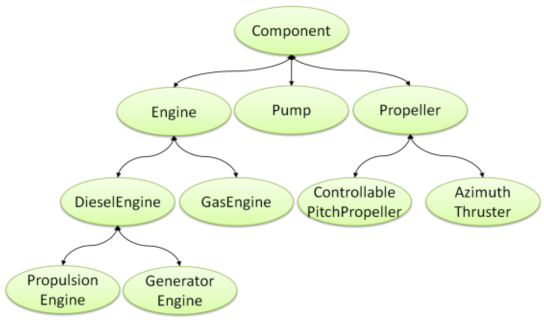

Figure 3: Part of the component ontology

The operational context defines the operating condition of a system (e.g. environment, threats). It provides contextual information according to the system operation. The definition of system taxonomy within the ontology enables to distinguish the operational contexts (e.g. Figure 4). This level describes higher operational requirements that can help the diagnostic process. For instance, abnormal behavior can be caused by the system environment. In that case the contextual information do not only concern technical or service context level.

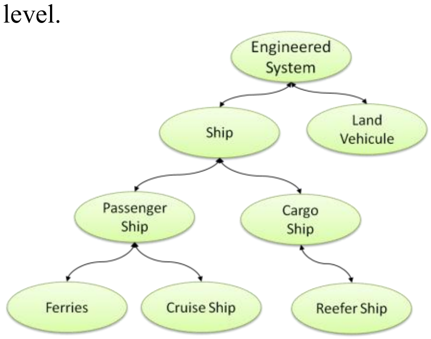

Figure 4: Part of system taxonomy

Finally, the performance context is linked to the key purpose of the fleet and defines, to some extent, the needs of optimization. For instance, a commercial fleet will focus on costs whereas a military application will be focused on availability. From a fleet-wide comparison point of view, the performance context enables large and global consideration to comparatively assess the global health of the fleet.

By means of taxonomies, each context can be described and both similarities and heterogeneities can be considered within the diagnostic process.

Therefore, the contextual information provided by the ontology allows better identification of component operating condition - i.e. component health. It enables to provide the data of the monitored component with the corresponding context defined in the ontology. The significant health indicator can be defined according to the corresponding component and context.

In that way, health condition situation of component can be gathered according to different criteria (i.e. context description). From the diagnosis point view, abnormal behaviors, which are depicted through the health condition, can be defined by symptom indicators. The relationship between symptoms and faults is also considered in order to make available a certain understanding (i.e diagnosis) of the corresponding health condition (Figure 5).

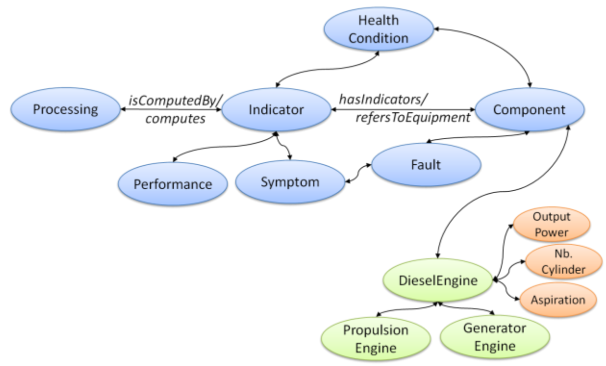

Figure 5: Part of the PHM ontology

Coupling with the data of monitored component, the abnormal behavior can be early detected. The corresponding indicators (performance, symptom…) allow early diagnostic and enable failure anticipation leading to plan adapted maintenance actions. The fleet-wide knowledge-based model, supported by means of ontology enables efficient predictive diagnosis and failure anticipation. The contextual information structured and stored within the ontology makes fleet-wide comparison easier. The fleet-wide expertise can be gathered, analyzed and reused, in a repeatable way.

The next section provides a case study of the fleet-wide knowledge-based model within an industrial PHM platform.

3. Industrial application

The industrial application demonstrates how the preceding concepts are embedded in a commercial application (Leger, 2004, Monnin, 2011b) developed by PREDICT. The example presents abnormal situation analysis helping using similar case retrieval within the fleet. The aim of the analysis is to anticipate failure, i.e. to perform predictive diagnosis. First we present the case under consideration, second the fleet wide knowledge platform, and finally situation monitoring and analysis.

3.1 Case Description

Diesel engines are critical onboard component of ship. In many cases they provide both propulsion of the ship and electrical power within many possible configurations. Avoiding blackout is of primary concerns and marine diesel engine monitoring and maintenance tend to benefit from advanced technology. Indeed, because embedded maintenance facilities are limited, a better knowledge of the engine health condition will allow to better drive maintenance actions needed when ships are in port.

For the purpose of this example, the fleet is limited to diesel engines. Seven engines are considered and briefly presented in Table 1. In this table an extract of the technical features of the engines are given as well as their use (i.e. propulsion, electric power generation and auxiliary).

Engine Ref	Output power (kW)	Nb. of Cylinder	…	Use
Wärtsilä 12V38	8 700	12V		ElectricPower
Wärtsilä 12V38	8 700	12V		ElectricPower
Baudouin6M26SRP1	331	6L		Auxiliary
Man V8-1200	883	8V		ElectricPower
Man V8-1200	883	8V		Propulsion
Wärtsilä 16V38	11600	16V		ElectricPower
Wärtsilä 12V38	8 700	12V		Propulsion

Table 1: Extract of engine fleet technical features

3.2 Fleet-wide knowledge-based platform

The ontology model is coded in OWL (Ontology Web Language) which is a formal ontology language, using the †Protégé ontology editor. The Protégé platform supports the modeling of ontologies. The ontologies can be exported into several formats including Resource Description Framework (RDF) and OWL.

For the purpose of the underlying software application, the ontology model is integrated by means of an SQL-backed storage and the java framework JENA‡ is used for ontology exploitation through the KASEM platform. It provides the user with a web portal that allows benefiting of the fleet-wide expertise. The JENA inference engine allows semantic queries and inference rules to be solved within the platform. Relevant contextual information can be retrieved and gathered for the purpose of, for instance, failure anticipation, investigation or expertise sharing.

The underlying monitoring data are collected by means of a data warehouse (MIMOSA compliant). The platform integrates the ontology model on top of the warehouse data collection. Given an application, the data can be made available on-line, off-line or even on-demand. A typical architecture is given Figure 6.

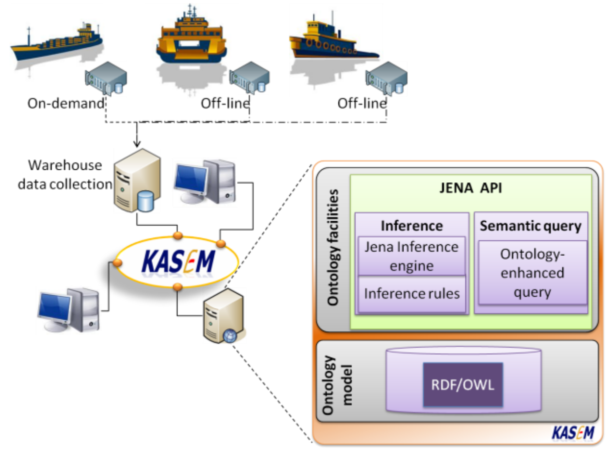

Figure 6: Typical architecture of Fleet-wide PHM system

3.3 Abnormal behavior Monitoring and Predictive Diagnosis

The diesel engine under consideration within the fleet includes regulatory sensor measurement as well as alarm monitoring system for the purpose of certification. Moreover further sensor measurements are also available for the engine operation. Some of commonly used sensor measurement are Cylinder temperature, Oil temperature, Oil pressure, SeaWater Temperature, SeaWater Pressure, FreshWater, Temperature, FreshWater Pressure, Turbocharger temperature, Speed, Power output.

From a predictive diagnosis point of view existing alarm monitoring systems are not sufficient since they do not allow failure to be anticipated. Once the alarm occurs, the remaining time to failure is too short for preventing it. Moreover, the cause identification of such alarms must be analyzed subsequently.

Abnormal behavior can be monitored by means of specific indicators such as symptoms and analyzed within their contexts (i.e. technical, service, operational and performance). For the sake of illustration, we consider cylinder temperatures for diesel engines. In normal conditions the cylinders temperatures are changing in a similar way. Thus, a health indicator of abnormal behavior shall be built by detecting any evolution of one of the temperatures disconnected from the rest of the set of temperatures. Figure 7 illustrates temperatures measurement evolution of a diesel engine. Two behaviors are highlighted on the graph. The first behavior, labeled A, shows a normal situation where the temperatures are correlated despite one of them is a

† http://protege.stanford.edu/
‡ http://jena.sourceforge.net/index.html

couple of degrees below. The second behavior, labeled B, shows a decorrelation of the lowest signal.

Such data trend analysis, even if coupled with a detection process, will not allow to anticipate failure. Whereas the abnormal behavior is highlighted, contextual information that enable the understanding (i.e. diagnostic) of the behavior are missing. Retrieving similar situation and comparing it is almost not possible.

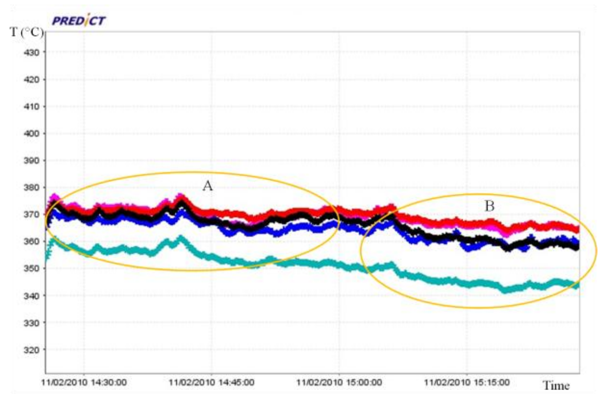

Figure 7: Zoom over a one-hour period of cylinder temperature measurement, zone A shows a normal behavior, while zone B an abnormal situation.

The knowledge-based model proposed allows providing such monitoring data with the corresponding context at different levels. Thus, fleet-wide comparison of the cylinder temperature evolution is enabled according to criteria such as technical context (e.g. same number of cylinders), service context (e.g. propulsion vs. electric power generation). If the corresponding fault has been identified and linked to the health condition situation (Figure 5), the underlying expertise can be retrieved.

Figure 8 presents an example of fleet-wide expertise retrieval results. For the given engines of the fleet (Table 1), some diagnostic results are proposed and summarized. With such a system, the expert, in face with a particular situation, can make any association to find out the closest cases with the case to solve and shall concentrate on the most frequent degradation modes already observed. From the different contextual information available, the system helps understanding the behavior without hiding its complexity with too simplistic rules.

4. CONCLUSION

Fleet-wide PHM requires knowledge-based system that is able to handle contextual information. Diagnosis and maintenance decision making processes are improved by means of semantic modeling that deals with concepts definition and description. In this paper, a knowledge model is proposed. Contextual information is structured by means of specific contexts. These contexts allow considering fleet component similarities and heterogeneities. Data of the monitored component are considered within their context and enhance the identification of the corresponding health condition.

From a diagnosis point of view, the analysis of abnormal health condition leads to link the description of such behavior with the corresponding diagnosis and maintenance decision. Thus, the expertise becomes available within the fleet.

The fleet knowledge model has been done according to a marine application. The resulting ontology has been integrated in the KASEM industrial PHM platform and an example of use and results have been shown.

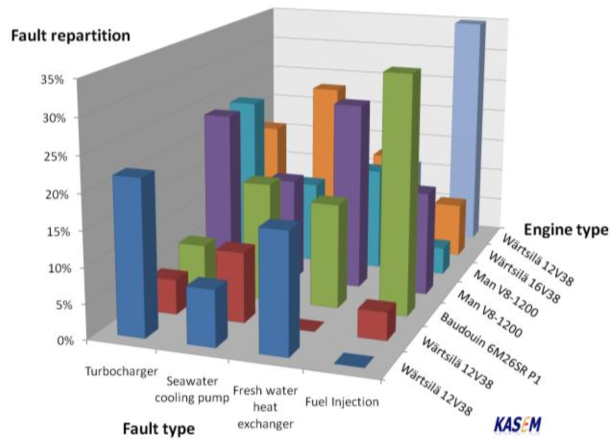

Figure 8: Sample of results for a fleet-wide cases retrieval visualization

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