Prognostics Assessment Using Fleet-wide Ontology

Gabriela Medina-Oliva[1], Alexandre Voisin[1],
Maxime Monnin[2], Flavien Peysson[2], Jean-Baptiste Leger[2]

[1] *Centre de Recherche en Automatique de Nancy (CRAN), Université de Lorraine, UMR 7039 CNRS-UHP-INPL, Faculté des Sciences-1er Cycle - BP239, 54506 Vandoeuvre-Les-Nancy Cedex – France*

gabriela.medina-oliva@univ-lorraine.fr
alexandre.voisin@univ-lorraine.fr

[2] *PREDICT 19, Avenue de la Forêt de Haye, CS 10508, 54519 Vandoeuvre-Lès-Nancy, FRANCE*

maxime.monnin@predict.fr
flavien.peysson@predict.fr
jean-baptiste.leger@predict.fr

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 operating systems such as a fleet, mission readiness and maintenance management issues are raised. PHM (Prognostics and Health Management) plays a key role in controlling the performance level of such systems, at least on the basis of adapted PHM strategies and system developments. Moreover considering a fleet implies to provide managers and engineers a relevant synthesis of information and to keep this information updated in terms of the global health of the fleet as well as the current status of their maintenance efforts. 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. In that way, this paper presents a knowledge structuring scheme based on ontologies for fleet PHM management applied to marine domain, with emphasis on prognostics modeling.

1. INTRODUCTION

Nowadays, due to the high competitiveness, industrial enterprises need to aim at higher performances, i.e. higher quality of products/services, lower costs, sustainability, etc. (Kleindorfer et al., 2005). In that way, the importance of maintenance has increased due to its key role on improving system availability, performance efficiency, products quality, etc. (Alsyouf, 2007). 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. Despite this proactive approach, failures still occur. This could be explained since prognostics involved the prediction of the future which is uncertain (Provan, 2003). Furthermore the whole acquisition and treatment algorithms could fail leading sometimes to some errors such as false alarms or non-detections (Barros et al., 2006).

Implementing a proactive approach at a system level requires the consideration of failure rates of different equipment built on different technologies (mechanical, electrical, electronic or software natures) (Verma et al., 2010) whosebehaviour can vary all along the different phases of their lifecycle (Bonissone and Varma, 2005). However 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 knowledge and data to improve diagnostic and prognostics models.

A fleet shall be viewed as a set of systems, sub-systems and equipment. In this paper, the naval domain is addressed. Hence, in the following an unit of a fleet will be considered as a system (e.g. ship), a sub-system (e.g. propulsion or electric power generation) or equipment (e.g. diesel engine, shaft...) depending on the nature of the study. 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 in order to improve PHM activities such as prognostics. To take advantage of the individual knowledge at the fleet level, a semantic model is proposed for the PHM activities in the naval domain. Such a semantic model enables to reuse particular data, such as maintenance history, reliability analysis, failure analysis, data analysis at a fleet level in order to provide knowledge. As data become available, prognostics models could benefit from more contextual information.

2. PHM AT EQUIPMENT AND SYSTEM LEVEL

PHM activities can give warning about failure events before they occur, reduce the life cycle cost of a product by decreasing inspection costs, downtime and inventory (Pecht, 2008), (Vichare and Pecht, 2006).

The prognostics process consists on treating, via algorithms, a set of input information to produce a future estimation. Mathematical models are used for the extrapolation of value of the degradation indicator. These mathematical models need as an input (Voisin et al., 2010):

- 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 to identify the characteristics and parameters of the prognostics model.
- Current data: on-line data in order to provide the values in real-time of the monitored indicators (variables). This data is captured and must be treated and analyzed. This data warn maintenance engineers about the current state of the unit and it should be used to feed/adjust the current prognostics model.
- Future data: information and/or hypothesis about the future usage of the unit should be provided such as the missions, the operational context, future maintenance interventions, etc. As mentioned in (Peysson et al., 2009) the prognostics of a complex systems (S) is described by three levels (1):

  $$S = \langle \mathrm{M}, \mathrm{E}, \mathrm{P} \rangle \qquad (1)$$

  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 different resources that are monitored.

  This set of information/data allows to refine the evolution of degradation indicators in different situations and simulations.

While analyzing these inputs, different sources of uncertainty will appear such as measurement and sensor errors, future load and usage uncertainty, prediction under conditions that are different from training data and so on. However uncertainty could be reduced when more data becomes available (Pecht, 2008). In these cases the notion of fleet becomes very interesting. It can provide more capitalized data and information coming from other members of the fleet. for the improvement/development of the prognostics models

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 a gathering of 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 designs a set of assets or production lines. In general, a fleet refers to the whole assets of an owner’s systems. Hence, the fleet here is only an abstract 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, systems themselves (Bonissone and Varma, 2005), (Patrick et al., 2010), subsystems or equipment (Umiliacchi et al., 2011). In the following, systems, sub-systems or equipment constituting the fleet, according to the study purpose, will be referred to as units.

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 (Monnin et al. 2011a). 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, prognostics or maintenance decision making. Common characteristics among units allow to define three types of fleet composition: identical, similar or 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 (Wheeler et al., 2009), (Bonissone and Varma, 2005),(Williams et al., 2008). 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. (Reymonet et al., 2009) propose to apply to the failed system the technical solution corresponding to a similar incident already solved with a comparable asset. (Wang et al., 2008) present a similarity-based approach for estimating the Remaining

Useful Life (RUL) in prognostics using data from a fleet composed by the same type of units. Nevertheless, knowledge derived from the fleet arises from the same kind of units. In a domain where customized units are common, these approaches may give poor results.

- Fleet composed of similar units: the fact of comparing similar units has rarely been addressed as a whole in the literature. In that sense, (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.
- Fleet composed of heterogeneous units: to fully exploit the knowledge issue of the fleet dimension, we propose in this paper to consider the heterogeneous units that compose the fleet level for decision making (e.g. prognostics, maintenance purposes). Situations (i.e. prognostics results, signal evolution) issued from an historical data of a fleet of heterogeneous units are searched based on some similar characteristics to the units in study (e.g. current situation under investigation) (Monnin et al., 2011a), (Monnin et al., 2011b). The originality of the proposed method is to enlarge the search to heterogeneous units (and not identical ones) where the similarity will be defined on-line by the user, according to the results of the search, in order to find relevant information to be reused.

3.2. But how could be used the fleet dimension to improve PHM processes?

One of the industrial realities is the lack of capitalization of knowledge and model reuse which represents high costs and efforts for the enterprises (Weber et al., 2011) (Medina-Oliva et al., 2012). In some fields such as the naval one, units are very customized leading to heterogeneous units. These facts limits mainly:

- Historical data exploitation for identical units. Due to the exposition of industrials systems to different and uncertain missions and environmental conditions.
- Knowledge capitalization about the evolution of the degradation trajectory of an unit under an identical context (identical mission and environment).

To tackle this issue the fleet dimension could provide enough information and data about diagnostic and prognostic models. In that sense, when searching non-identical units but similar ones a higher volume of data becomes available to reduce diagnostic/prognostics models uncertainty. This data could be obtained through the identification of "similar contexts" or "similar individuals". For example, in the naval field, a technical similarity for diesel engines, which are critical equipment for propulsion and power generation, could be the membership to "4-strokes engines" or "high speed engines" features.

The objective of our proposition is to create an iterative investigation process that will allow to define a sub-fleet. The sub-fleet is defined by grouping a set of units (i.e. systems, sub-systems or equipment) based on "similar characteristics". Figure 1 presents the main steps of this process. When prognostics models are implemented on a new unit or when the unit is merged in new operational conditions, the prognostics must be first characterized. Characterization consists on the description of the unit to be pronosticated (e.g. type, age, usage, operating environment) as well as data on which an analysis will be carried out (Figure 1-A). To guide this process, the fleet-wide application proposes different criteria based on the technical features of units as well as on the mission and on the environment description. According to this, a targeted population is defined within the whole fleet (Figure 1-B). Within the targeted population, the potential similar prognostics models and data concerning the evolution of the degradation indicators are investigated in order to complete current knowledge for prognostics (Figure 1-C). In an iterative process of steps B and C, the targeted population can be refined if results (i.e. potential similar degradation indicator data) are too far from the current situation or conversely if targeted fleet points out too many similar situations. Then, the prognosticated unit benefits from the past analysis results (Figure 1-D) for building the corresponding prognostics model. Using this original approach could bring several benefits as presented in (Monnin et al., 2011a), (Monnin et al., 2011b), (Peysson et al., 2012).

Toward this goal, the knowledge corresponding to the fleet domain must be well formalized and structured in order to facilitate the manipulation of the multidimensional aspects of the fleet and the heterogeneous data among all fleet units' databases

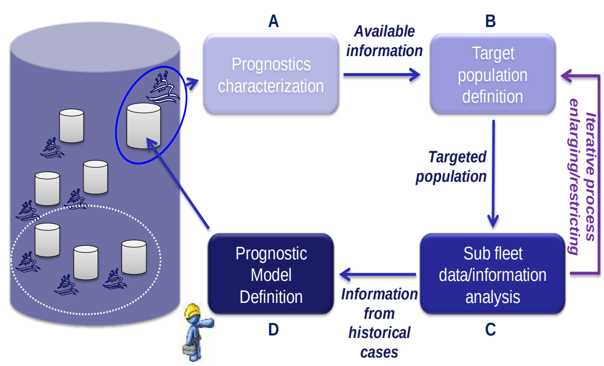

Figure 1. Main steps for fleet case re-use

3.3. Sub-fleet characterization

Nowadays, fleet managers/engineers query separately ship databases for identical units to obtain data/information. However, units (e.g. diesel engine) in the naval domain are very specific and customized. This fact leads to dispose of few identical units. For this reason the proposed methodology leads to search non-identical units but similar ones. Furthermore, another issue emerges. At a fleet level, engineers must treat different databases of different units. These databases might be heterogeneous, in the sense that the database structure might be different, they might have different names for the primary keys and foreign keys, etc.

To tackle these issues, a common semantic becomes necessary (Figure 2). A semantic model provides a high level definition of terms that is common to all databases allowing to query them. It allows to define characteristics of similarities among units and contexts. For instance, to define common characteristics in the technical, operational and contextual domains.

In the following sections a semantic model specifying the similar characteristics necessary to obtain data/information to perform prognostics is presented. The semantic model is specified by means of ontologies.

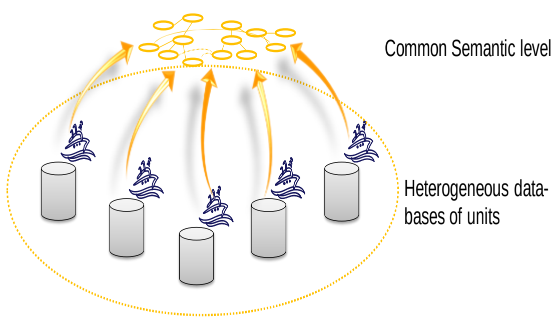

Figure 2. Semantic level to query heterogeneous databases

4. PROPOSITION OF ONTOLOGY FOR FLEET-WIDE SEMANTIC

4.1. Ontology for providing semantic

An ontology explicits formal specifications of knowledge in a domain by defining the terms (vocabulary) and relations among them (Gruber, 2009). To represent knowledge and to explicit semantic (vocabulary and relations), the ontology is coded in Web Ontology Language (OWL) supported by Protégé[*] ontology editor. OWL is composed of classes, properties of the classes and instances. These elements are explained as follow:

- Classes describe concepts in the domain. In PHM domain, an example of classes could be "equipment" or "degradation indicator".
- Properties of the classes describe the attributes of the concepts. For example, the class equipment has a property "is monitored by" the class degradation indicator. The property "is monitored by" link the class "equipment" with the class "degradation indicator".
- Subclasses represent concepts that are more specific than the superclass (mother class). When a superclass has a subclass, it means that they are linked by a subsumption relation, i.e. "is a" relation, allowing a taxonomy to be defined. Hence, a hierarchy of classes is established, from general classes to specific ones.
- Instances are the set of specific individuals of classes. For example, the engine Baudouin 12M26.2P2-002 is a specific individual that is part of the class "equipment".

OWL allows to establish taxonomies. This capability is a useful for example to represent systems, subsystems and equipment. Moreover, OWL provides inference capabilities with plugged reasoners. Inference is based on open-world reasoning. Explicit and manually constructed classes that belong to taxonomy constitute an asserted hierarchy. But thanks to OWL reasoners, an inferred hierarchy is automatically computed allowing to emerge new knowledge. For example if an engine has an internal electrical degradation, the ontology could induce that it is an electrical engine. Moreover, OWL reasoners shall performed consistency checking. Hence, one shall guarantee that the ontology has been built correctly in the sense that no syntactic and inconsistency remain in the ontology. For example, if a fuel-engine is associated to an electrical degradation, an inconsistency will be point out by the reasoner.

Ontologies seem to be a suitable modeling method to provide common semantic and to query heterogeneous databases. Some of the capabilities provided consist on: sharing common understanding of the structure of information among people or software agents, making domain assumptions explicit, defining concepts and knowledge (i.e. a high speed engine 1000rpm, subjectivity is limited) and making domain inferences to obtain non-explicit knowledge (Noy and McGuinness, 2001).

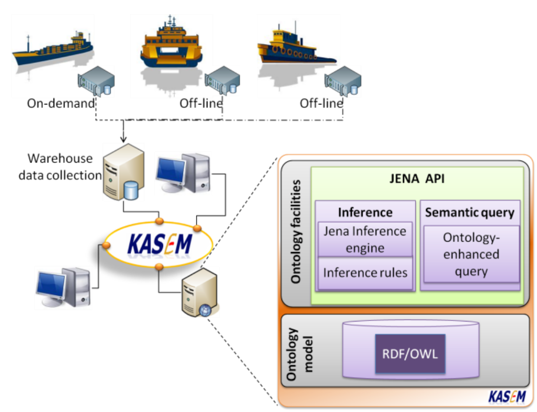

Figure 3: Typical architecture of Fleet-wide PHM system, (Monnin, 2011a)

[*] http://protege.stanford.edu/

The proposed approach based on PHM ontology is not a goal itself. This ontology is a support for PHM software applications through the KASEM software platform (Leger, 2004), (Monnin, 2011c) Figure 3.

In the next section, the formalization of an ontology to support prognostics activities in the naval domain is proposed.

4.2. Ontology-based PHM assessment

Ontology-based fleet-wide PHM

In the section 2.1. key elements to perform prognostics were identified. These elements are technical characteristics of the system/sub-system/equipment, degradation modes, degradation indicators, the mission and the environment.

A semantic model to these elements will be provided in order to obtain formalized knowledge that allows the definition of "similarities" among these units. Based on (Monnin, 2011a) different contexts are defined: a technical context (e.g. characteristics of the system/sub-system/equipment), a dysfunctional context (e.g. degradation modes), an operational context (e.g. mission and environment), a service context (e.g. usage of units) and an application context (e.g. degradation indicators). For a graphical representation of the ontology for these contexts, classes are represented as ovals and relations are represented as links between the classes. Once the ontology model is formalized comparisons of heterogeneous units shall be performed on the basis of context similarity.

Technical context

One might think that the definition of every model of equipment could be enough to take advantage of the fleet dimension. But this modeling choice narrows the manageability to strictly identical units. For this reason, a technical context is proposed. The technical context integrates the technical features and characteristics of the system/sub-system/equipment. This model allows the comparison of heterogeneous units for instance when seeking relevant characteristics such as "4-strokes engines" or "direct injection engines".

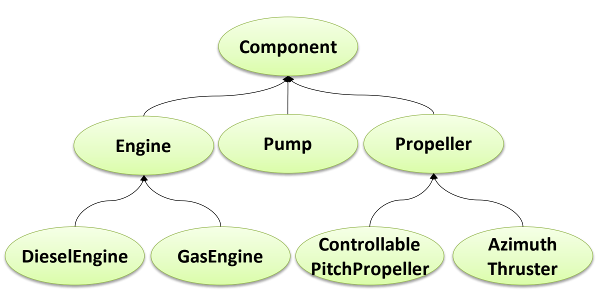

Figure 4: Part of the equipment taxonomy

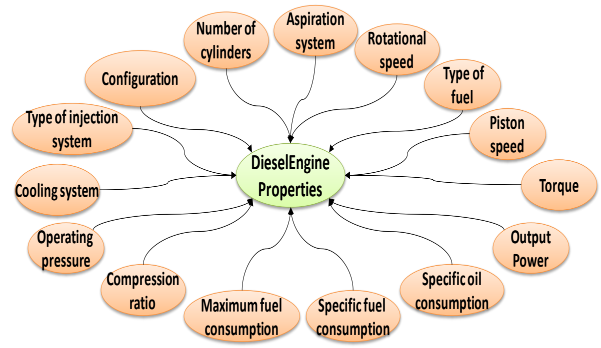

Figure 5: Part of the equipment properties

To model the technical context, "Equipment" (Figure 4) classes are specified as well as "Properties" classes (Figure 5) which define all their features. Hence, units with similar technical properties could be clustered according to their technical properties such as the power output, the rotation speed, the number of cylinders, etc. (Figure 5) in order to retrieve data/information.

Dysfunctional context

The dysfunctional context takes into account the information about the degradation modes on the units. It considers the generic degradation modes. Generic degradation modes are taken from the standard (IEC 60812, 2006). Classes include electrical degradation modes, mechanical degradation modes, hydraulic degradation modes, etc. Degradation modes are linked to units (Figure 6).

Furthermore, in this context, it is considered that one degradation mode could be caused by another degradation mode. In that sense, this context allows to describe information about the causality chain of degradation modes that produced an undesirable event. This knowledge is very valuable to retrieve information/data for troubleshooting and corrective maintenance issues. This modeling choice allows to explore the main causes of similar degradation modes. For example to explore common causes of pumps failures regardless of the use of the pumps.

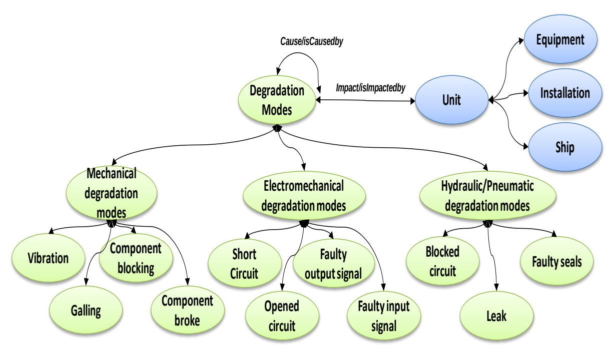

Figure 6: Part of the dysfunctional analysis on units

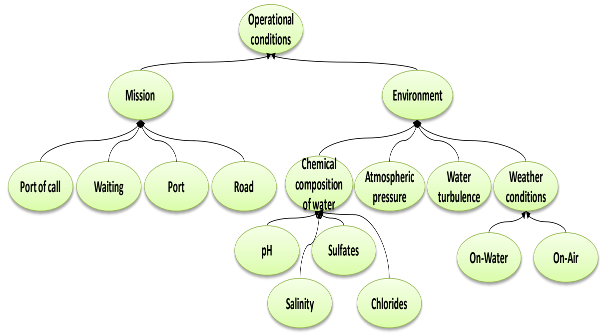

Figure 7: Part of the operational context

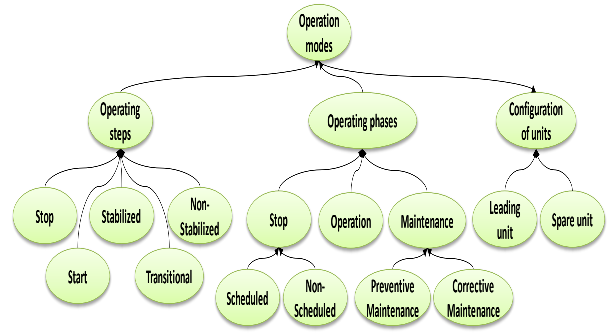

Figure 8: Part of the service context

Operational context

Even if units are identical, the operational conditions lead to different units' behaviors. For this reason, one could need to cluster information/data according the operational and service contexts.

The operational context integrates the operational conditions to which the units are exposed to. As explained in section 2, for prognostics the mission (*M*) and the environment (*E*) are considered. The operational conditions are given by the mission to be performed for units as well as the environment that surround them (Figure 7). In the naval domain, the mission is a sequence of dated tasks in a geographical area (e.g. Port of call mission) (Peysson et al., 2009). Hence, similar missions on similar units could be compared (Figure 7). On the other side, the environment takes into account the weather conditions, the chemical composition of water (pH, salinity…), the pressure, water turbulence, etc. (Figure 7) which might impact degradation mechanisms and units' functioning behavior.

The mission and the environment could affect equipment, sub-system and system performances. For this reason the mission was formalized at different abstraction levels (system, sub-system, equipment).

Service context

The service context deals with the usage of units. Even when units are similar they are exposed to different usages according to the corresponding mission tasks. Hence a service context is formalized in order to differentiate behaviors of the evolution of degradation indicators. In that sense, usage could be divided according to the operating steps, operating phases and the configuration of units (Figure 8).

In order words, degradation behavior can be analyzed according to different abstraction levels.

Application context

The application context is related to the needs of PHM optimization. Within the application context, the optimization aims the capitalization of knowledge to perform health assessment. Health assessment deals with the definition of indicators such as functional, dysfunctional and environmental indicators at different levels as well as the treatment (processing) of these indicators, etc (Figure 9). This context enables data/model retrieval of the monitored unit with its corresponding context defined in the ontology.

The ontology-based knowledge formalization provides the basis to capitalize knowledge with contextual information. In that sense, one might define similar units, i.e. high speed engines with similar missions and under similar context in order to compare signal evolution of indicators. The next section illustrates the benefits of the proposed methodology within the PHM context.

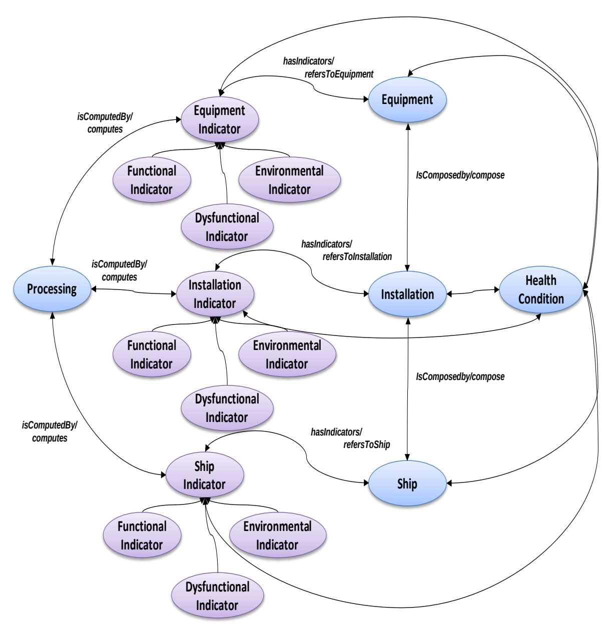

Figure 9: Part of the application context

ID	Engine Ref	Output power (kW)	Nb. of Cylinder	Confi-guration	Engine Speed (rpm)	Type of cooling system	Engine cycle	Tag related to the ontology
Eqpt1	Wärtsilä 12V38	8 700	12	V	600	Dry water cooling system	Four-stroke engine	Fuel engine
Eqpt2	Wärtsilä 12V38	8 700	12	V	600	Dry water cooling system	Four-stroke engine	Fuel engine
Eqpt3	Baudouin 6M26SRP1	331	6	L	1800	Sea water cooling	Four-stroke engine	Fuel engine
Eqpt4	Man V8-1200	883	8	V	2300	Desalination systems	Four-stroke engine	Fuel engine
Eqpt5	Man V8-1200	883	8	V	2300	Desalination systems	Four-stroke engine	Fuel engine
Eqpt6	Wärtsilä RT-flex50	13 960	8	L	124	Sea water cooling system	Two-stroke engine	Fuel engine
Eqpt7	Wärtsilä RT-FLEX82T	40 680	9	L	80	Sea water cooling system	Two-stroke engine	Fuel engine
Eqpt8	Wärtsilä 12V64	23280	12	V	400	High and low temperature separated circuits	Four-stroke engine	Fuel engine
Eqpt9	ISOTTA vl1716hpcr	2750	16	V	2100	High and low temperature separated circuits	Four-stroke engine	Fuel engine
Eqpt10	Baudoin 12M26P1FR	357.94	12	V	1800	High and low temperature separated circuits	Four-stroke engine	Fuel engine

Table 1: Extract of engine fleet technical features stored in the data bases

Prognostic-model retrieval from fleets composed of heterogeneous units

The proposed approach could be very useful for PHM processes for new units. In the case of new equipment there's neither degradation indicators defined nor historical data about their evolution. But when disposing of an ontology-based approach, knowledge and data could be gathered from heterogeneous units and contexts. To illustrate the proposed methodology, To tackle the fleet dimension three possibilities are shown:

1. *Consideration of identical fuel engines to the Baudouin 8M26SRP engine*
2. *Consideration of all fuel engines composing the fleet*
3. *Consideration of the heterogeneous units composing the fleet using the ontology-based approach*

1. *Consideration of identical fuel engines to Baudouin 8M26SRP*

The first step to capitalize data from the fleet dimension would be to consider identical units to Baudouin 8M26SRP. Nevertheless, if the same kind of units is considered, then any unit would match to the results as shown in Table 1. For these reason, other approaches should be investigated.

2. *Consideration of all fuel engines composing the fleet*

Another approach to take advantage of the fleet dimension would be to consider all the fuel engines composing the fleet. This approach allows the capitalization of data. However, the fleet is composed of a wide variety of different engines. If one take a look to Table 1, it is possible to notice the fleet is composed let's consider finding a prognostics model for the degradation trajectory of a diesel engine within a costal surveillance mission in the south Atlantic for a new ship. In this example, we suppose the new ship is propelled by a diesel engine Baudouin 8M26SRP.

For the purpose of this example, the fleet is limited to diesel engines. Ten engines are considered and briefly presented in Table 1. The table shows an extract of the technical features of the engines.

of big size, high power, two-stroke engines such as the. Wärtsilä RT-FLEX82T engine and of other engines with lower output power and four-stroke cycles such as the Wärtsilä 12V38 engine. These units are very different and thus their degradation behavior is very different as well. For this reason considering all the fuel engines might not be appropriated to study the degradation behavior of the Baudouin 8M26SRP engine.

3. *Consideration of the heterogeneous units composing the fleet using the ontology-based approach*

As mentioned previously, the developed application based on ontologies guides the definition of "similar characteristics" in order to define the sub-fleet of units to be used for prognostics purposes (Figure 1-A). To guide the sub-fleet definition some questions will be asked, automatically by the application, based on the relations between the different contexts defined in the ontology. One question concerns the *application context*, if one seeks a degradation indicator, a treatment or mainly a prognostics model. For this example, a prognostics model is searched. Then another question deals with the *technical context*. The application poses questions about the type of unit (i.e. engine, thruster, pump…), the application domain (i.e. marine, land, aeronautics, etc.) and the subsystem (i.e.

propulsion and power generation). For this example, an engine located on a ship (marine) for propulsion purposes is sought.

In the ontology the definition and relations of prognostics have been established. For this reason, another question is asked about the mission and the environment of the engine (*operational context*). The mission in this example is costal surveillance mission (Figure 1-B). One can start searching data found in the sub-fleet definition (Figure 1-C).

Afterward, the application proposes to keep finding other similarities criteria for example those related to the geographical area (Figure 1-A). It proposes several choices such as the south Atlantic, north Atlantic, Indian, south Pacific oceans, etc. For this example the environment is located in the south Atlantic. The sub-fleet evolves automatically when other criteria are chosen.

The ontology embeds that hot oceans impact the performances of the cooling systems. For this reason, another question is asked about the type of cooling system such as high and low temperature separated circuits, sea water cooling, dry water cooling system or desalination systems (*technical context*). The answer, in this case, for the Baudouin 8M26SRP engine is a high and low temperature separated circuits. The sub-fleet is shown automatically. Three similar equipment with similar contexts are found: Baudouin 12M26P1FR, Wärtsilä 12V64 engine and ISOTTA vl1716hpcr (Figure 1-D).

Figure 10 shows the updated degradation prognostics models of these three engines. The time horizon represents the mission that the engines have already experienced. Capitalizing this information allows to build a prognostics model for the Baudouin 8M26SRP engine (Figure 13-orange line). To build the estimated degradation trajectory, histograms for each monitored time issues from retrieved trajectories are built. Then the estimated trajectory is computed as the mean on each of the histograms. The orange line shows the estimate of the degradation trajectory of the Baudouin 8M26SRP engine for the given mission. However, more sophisticated methods could be used to estimate the degradation trajectory such as proposed by (Liu et al., 2007) and (Wang et al., 2012).

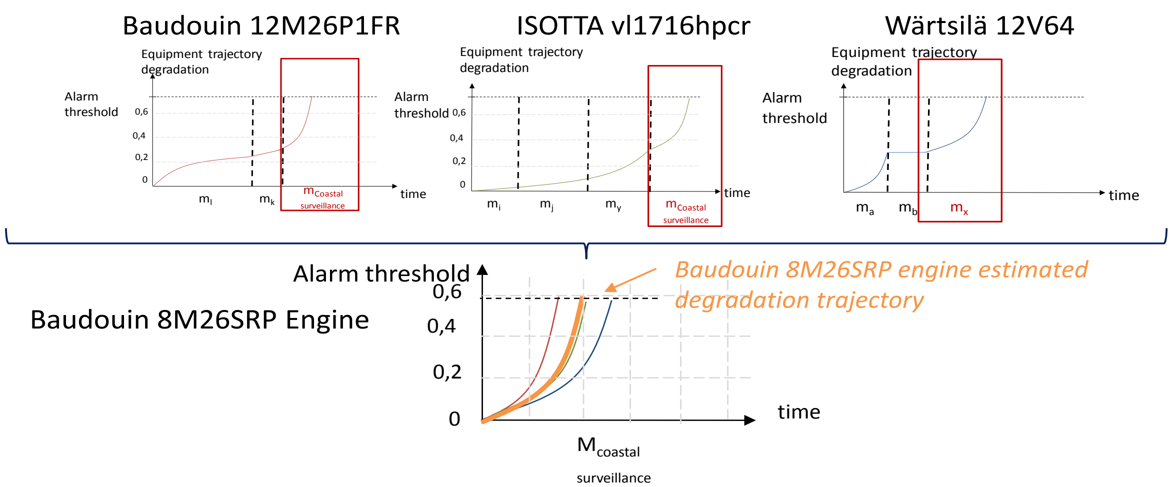

Figure 10. Degradation trajectory estimation for the Baudouin 8M26SRP engine based on similar units behaviors for a costal surveillance mission

5. Conclusion

Fleet-wide PHM requires knowledge-based system that is able to handle contextual information. Prognosis 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 based on ontologies is proposed. Contextual information is structured by means of specific contexts. These contexts allow to consider fleet unit similarities and heterogeneities. Data of the monitored unit are considered within their context and enhance the identification of the corresponding health condition.

From a prognosis point of view, the analysis of a degradation variable evolution could improve the prognostics model and precision can be improved through the capitalized data.

The fleet knowledge model has been structured for a marine application. The resulting ontology has been integrated in the KASEM industrial PHM platform. Some experimentation has already been done however; other experimentations should be tested to show the feasibility and the added value of this methodology. This paper arises some perspectives related to the manipulation of the uncertainty of prognosis (Petch, 2008), as well as the definition of the trajectory model based on retrieved models (Liu et al., 2007) and (Wang et al., 2012).

REFERENCES

Alsyouf, I. (2007). The role of maintenance in improving companies' productivity and profitability. International Journal of Production Economics, 105, 70–78.

Azam M., Tu F. and Pattipati, K. R. (2002) "Condition Based Predictive Maintenance of Industrial Power Systems", SPIE conference on Fault Diagnosis, Prognosis and System Health Management, Orlando, April 2002.

Barros A., Bérenguer C., Grall A. (2009). A maintenance policy for two-unit parallel systems based on imperfect monitoring information. Reliability Engineering and System Safety 91 (2006) 131–136.

Bonissone, P.P., Varma, A. (2005). Predicting the Best Unit within a Fleet: Prognostics Capabilities Enabled by Peer Learning, Fuzzy Similarity, and Evolutionary Design Process. In Proceedings of the 14th IEEE International Conference on Fuzzy Systems, IEEE, pp. 312-318.

Gruber, T. (2009), Ontology. In: the Encyclopedia of Database Systems, Ling Liu and M. Tamer Özsu (Eds.), Springer-Verlag.

IEC 60812. Analysis techniques for system reliability – Procedure for failure mode and effects analysis (FMEA). 2006

ISO 13381-1:2004. Condition monitoring and diagnostics of machines- Prognostics- Part 1: General guidelines

Kleindorfer PR, Singhal K, Van Wassenhove LN. (2005). Sustainable operations management. Production and Operations Management; winter, 14(4):482–492.

Léger J-B. (2004). A case study of remote diagnosis and e-maintenance information system, Keynote speech of IMS'2004, International Conference on Intelligent Maintenance Systems, Arles, France.

Liu J., Djurdjanovic D., Ni J., Casoetto N., Lee J. (2007). Similarity based method for manufacturing process performance prediction and diagnosis. Computer in Industry 58, Pages 558-566.

Medina-Oliva G., Weber P., Levrat E., Iung B. (2012) Using probabilistic relational models for knowledge representation of production systems: A new approach to assessing maintenance strategies. CIRP Annals - Manufacturing Technology. in press. DOI: 10.1016/j.cirp.2012.03.059

Monnin M., Abichou B., Voisin A., Mozzati C. (2011b). Fleet historical cases for predictive maintenance. The International Conference Surveillance 6. October 25-26. Compiègne, France.

Monnin M., Voisin A., Leger JB., Iung B. (2011a). Fleet-wide health management architecture. Annual Conference of the Prognostics and Health Management Society. Montreal, Quebec, Canada.

Monnin, M, Leger, J-B., Morel, D. (2011c). KASEM®: e-Maintenance SOA Platform, in Proceedings of 24th International Congress on Condition Monitoring and Diagnostics Engineering Management, 29th May – 1st June, Stavanger, Norway.

Noy N. F. and McGuinness D. L. (2001). Ontology development 101: A guide to creating your first ontology. Technical Report SMI-2001-0880, Stanford Medical Informatics.

Patrick, R., Smith, M J., Byington, C S., Vachtsevanos, G J., Tom, K., Ly, C. (2010). Integrated Software Platform for Fleet Data Analysis, Enhanced Diagnostics, and Safe Transition to Prognostics for Helicopter Component CBM, in Proceedings of Annual Conference of the Prognostics and Health Management Society, October 10-16, Portland, Oregon.

Pecht, M. (2010). A prognostics and health management roadmap for information and electronics-rich systems, IEICE Fundamentals Review, vol. 3, no. 4, pp. 25 – 32.

Peysson F, Ouladsine M, Outbib R, Leger JB, Myx O, Allemand C (2009). "A generic prognostics methodology using damage trajectory models." IEEE Trans. Reliab., 58(2) (277 - 285), June.

Peysson F., Léger J-B., Allemand C., Ouladsine M., Iung B. (2012) New approaches for ships fleet-wide management and naval mission prognostics. MFTP 2012: The Prognostics and Health Management Solutions Conference. April 24-26. Dayton, Ohio, USA.

Provan, G., (2003). Prognosis and Condition-Based Monitoring: an open systems architecture. 5th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, 57--62, Washington, USA.

Rajkumar and Bardina. Training data requirement for a neural network to predict aerodynamic coefficients. Proceedings of SPIE, 2003.

Reymonet, A., Thomas, J., Aussenac-Gilles, N. (2009). Ontology Based Information Retrieval: an application to automotive diagnosis, in Proceedings of International Workshop on Principles of Diagnosis, June 14-17, Stockholm, Sweden, pp. 9-14.

Umiliacchi, P., Lane, D., Romano, F. (2011). Predictive Maintenance of railway subsystems using an Ontology based modelling approach, in Proceedings of 9th world Conference on Railway Research, May 22-26, Lille, France.

Verma, A. K. and Srividya, A. and Ramesh, P. (2010). A systemic approach to integrated E-maintenance of large engineering plants, International Journal of Automation and Computing, vol. 7, pp. 173-179.

Voisin, A., Levrat, E., Cocheteux, P., & Iung, B. (2010). Generic prognosis model for proactive maintenance decision support: Application to pre-industrial e-Maintenance test bed. Journal of Intelligent Manufacturing. 21 (2): 177-193.

Wang P., Youn B., Byeng D. A generic probabilistic framework for structural health prognostics and uncertainty management. Mechanical Systems and Signal Processing. 28, Pages 622–637

Wang T., Yu J., Siegel D., Lee J. (2008). A similarity-based prognostics approach for Remaining Useful Life estimation of engineered systems. International Conference on Prognostics and Health Management. Denver, USA.

Weber P., Medina-Oliva G., Simon C., Iung B. (2012). Overview on Bayesian networks Applications for Dependability, Risk Analysis and Maintenance areas. Engineering Applications of Artificial Intelligence, vol. 25 (4), (671-682).

Wheeler, K., Kurtoglu, T., Poll, S.D. (2009). A survey of health management user objectives related to diagnostic and prognostics metrics, in Proceedings of International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, August 30–September 2, San Diego, California, USA.

Williams, Z., Gilbertson, D. & Sheffield, G., (2008). Fleet analysis and planning using CBM+ open architecture, in Proceedings of IEEE International Conference on Prognostics and Health Management, Denver, CO.

BIOGRAPHIES

D**r Gabriela MEDINA-OLIVA** is a Research Engineer at CRAN. She received his PhD from the University of Nancy and her M.S. in Reliability and Risk Analysis from the University of Las Palmas Gran Canarias in Spain. She has experience in maintenance within the oil industry. Moreover, she has worked in the formalization of knowledge with probabilistic tools for maintenance strategies assessment. Her current work focuses on fleet-wide health management. He is member of the French DIAG 21 Association (www.diag21.com) and of the PHM Society.

Dr Alexandre VOISIN was born in Metz, France, in 1969. He obtained an engineering degree in Electrical Engineering form the EFREI in 1992 and he received his Ph. D degree in Electrical Engineering from the Université de Lorraine. He is currently assistant professor at the Université de Lorraine. His primary research were in the field of fuzzy logic and information processing where he applied these techniques to subjective evaluation in the area of car seat comfort. Since 2003 he is involved in e-maintenance research project. His research deals with dependability, maintenance decision in a proactive maintenance strategy, prognostics and monitoring. He is member of French and International projects/groups on e-maintenance such as the CNRS MACOD working group (Modeling and Optimization of Distributed vs. Collaborative Maintenance), the French scientific interest group 3SGS on “Dependability of Complex Systems” in the project DEPRADEM (Degradation and Prognosis Modeling for Maintenance Decision Making), the European Integrated Project DYNAMITE (Dynamic Decision in Maintenance), and the international project DEPEN-IMPRO (Modeling Policies for the improvement of Production Systems’ Dependability). He is involved in industrial projects with EDF, DCNS, ALSTOM. He is member of the French DIAG 21 Association (www.diag21.com) and of the PHM Society.

Dr. Maxime MONNIN is a Research Engineer at PREDICT Company where he is responsible of the R&D Team. In 2007, he received his PhD from the University of Valenciennes. This research founded by the French Procurement Agency (DGA), was conducted in collaboration with NEXTER and the Nancy Research Center for Automatic Control (CRAN), and addressed system of systems availability modelling and simulation. His research interests focus on fleet-wide health management. He is member of the French DIAG 21 Association (www.diag21.com) and of the PHM Society.

Dr Flavien PEYSSON is a Research Engineer at PREDICT company, France, with the experience in the development of Diagnostic/Prognostic strategies for PHM systems. He received his M.S. in Industrial Engineering from the Marseilles University Polytechnic School, and earned his PhD, in 2009, from the Aix-Marseilles University, France. His current work is on the development of a Prognostic Framework based on experience and data analysis. He is member of the French DIAG 21 Association (www.diag21.com) and of the PHM Society.

Dr. Jean-Baptiste LEGER is CEO and co-founder, in 1999, of the PREDICT company, France. He is graduated from Nancy University, France and his PhD thesis, presented in 1999, was on Formal Modelling Framework for Proactive Maintenance Systems mainly based on Monitoring, Predictive Diagnosis and Prognosis. He has more than 17 years of experience on CBM and PHM systems. His experience includes fault detection and isolation, condition monitoring, fault tolerant control, prognostic, health management, intelligent maintenance and e-maintenance. He is currently working on formal approach of CBM, PHM and Therapy Systems. He is member of the management board of the French DIAG 21 Association (www.diag21.com) and of the PHM Society.