Fleet-wide Diagnostic and Prognostic Assessment

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ABSTRACT

In order to anticipate failures and reduce downtime, "predictive diagnostic" aims not only at warning about the failure events before they occur but also at identifying the causes of degradation leading to such detections. Then, based on the results of predictive diagnostic, "prognostic" aims at estimating the remaining useful life in order to plan a maintenance action before unit performances are affected. However, these are complex tasks. To overcome these difficulties, the notion of fleet may be very useful. In the present paper a fleet is composed of heterogeneous units (mainly components but could be systems or sub-systems) that are grouped together considering some similarities. The fleet can provide capitalized data and information coming from other members of the fleet for the improvement/development of the diagnostic/prognostic models. In order to achieve PHM with a fleet-wide dimension, it is thus necessary to manage relevant knowledge arising from the fleet taking into account heterogeneities and similarities amongst components, operational context, behaviours, etc. This paper will focus mainly in the formalization of a data-driven prognostic model considering a fleet-wide approach. The model is based on a prognostic approach of the system health using Relevant Vector Machine. The proposed model is based on historical data coming from similar units of a fleet. The heterogeneity of the monitored data is treated by assessing a global health index of the units. The proposed approach is shown on a case study. This case study illustrates how the fleet dimension facilitates predictive diagnostic and the definition of the prognostic model in the marine domain.

1. INTRODUCTION

PHM involves the following processes: monitoring the process variables of a current situation, assessing the health of the system, prognosticating the Remaining Useful Life (RUL) of the system and making decision for maintenance action. In that sense, the data coming from the different variables of the process is also used for evaluating and monitoring a global indicator representative of the health state of a unit. The health state allows to supervise easily the degradation behaviour and to detect early enough drifts in operations (Rizzolo et al., 2011). If the health state is not satisfying, then predictive diagnostic could be performed. This process allows to identify the causes of a degradation before a failure occurs. Based on the potential degradation modes producing a drift in operation, the representative variables of this degraded component are used to predict the degradation trajectory and to assess the remaining time to reach a threshold, for instance a specified performance loss level. This time is called Remaining Useful Life. Finally the results are used for decision-making in order to select the maintenance actions to be performed in order to solve the drift.

Implementing a PHM 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) whose behaviour can vary all along the different phases of their lifecycle (Bonissone and Varma, 2005). Moreover, for predictive diagnostic (i.e. diagnostic of drift before failure occurs), maintenance operators/engineers need to analyze the alarms and the symptoms behavior/evolution to understand which components may have caused the symptoms and the reasons for the abnormal behavior of the component. This analysis needs to consider the operational context of the symptoms in order to understand the abnormal situation since it influences the component behavior. Finally, prognostic requires some specific model for each degradation, each operational condition, and each material part. Such number of dimension implies that the efforts (according to the type of model, number of data, laboratory tests…) needed for the definition of the model have to be important. Moreover, prognostic deals with the estimation of the future and thus uncertainty appears. However uncertainty could be reduced when more efforts are made (Pecht, 2010).

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 prognostic models (Medina-Oliva et al., 2013).

A fleet shall be viewed as a set of systems, sub-systems and equipment. In this paper, the naval domain is addressed but the proposed approach can be broadened to other domains. 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 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 prognostic. To take advantage of the individual knowledge at the fleet level, a semantic model is used 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, prognostic process could benefit from more contextual information.

2. Problem statement

Prognostic process aims at determining the Remaining Useful Life (RUL) of a unit on which a degradation is running. Some literature review, such as (Byington et al., 2002; Jardine et al., 2006; Heng et al., 2009), propose an overview of this domain and consider classification among the prognostic models. (Byington et al., 2002) propose the first classification and classify the prognostic model into three categories:

- Model based approach issued from physical laws of the degradation,
- Data based approach issued from data or indicator monitored on the system,
- Experience based approach mainly issued from reliability model.

In this paper the aim is to benefit from the knowledge acquired during the operation of every unit of the fleet, i.e. events that occurred and have been solved, in order to solve the event occurring on the present unit (Medina-Oliva et al., 2012b). The objective to benefit from the stored knowledge is subject to these constraints:

- Units are heterogeneous (e.g. technically, structure, mission, environment…) since in the naval domain every ship is highly customized. Moreover, even if units are of the same kind (same technical features), the mission they have to fulfil as well as the environment in which they are evolving have a significant impact on the degradation behaviour.
- Signals are heterogeneous. Indeed, signals are heterogeneous in two ways. The first one is for the same kind of unit, since they are evolving in different environment, with different mission… monitored signals show some significant variations. The second deals with the technical differences among units. In that sense, units could have different number of sensors since they are not technically identical. For instance, if engines have different number of cylinders hence, the monitoring of cylinder temperature means that the number of signals is also different.
- Knowledge about degradation is application/technical oriented since it is mainly supported by FMECA/HAZOP. Hence in the corresponding monitoring databases, the structure of the fault/degradation tree might show some differences.
- The current situation to be prognosticated is partially defined. Indeed, predictive diagnosis aims at finding the running degradation at its early stage. Hence only partial knowledge is available and based on symptoms.

Moreover, in order to benefit from the latest information, since units are on-line monitored the proposed approach aims at integrating all the available information as soon as it is available through its integration at the fleet level. Such integration can be performed almost "on-line" through communication channel such as satellite or with some delay through USB hard disk for instance.

The proposed approach is dedicated not to work as a single tool but together with some experts of the corresponding field. For instance, in (Medina-Oliva et al., 2013), the authors show how experts can perform predictive diagnosis using the fleet knowledge. For this goal, the experts are using an iterative process in order to select a target sub-fleet that contains the proper information to solve the case under study (Medina-Oliva et al., 2012b).

Furthermore, one has to consider some constraint arising from the industrial context. Those constraints will help in the choice of well-fitted tools to support the fleet wide approach:

- The nature of the monitoring systems embedded in the ships. As for industrial systems, there exist several systems, which do not share a common conceptual data model (Umiliacchi et al., 2011).
- Monitored data is real data. The signal embeds a part of randomness due to, for instance, measurement noise, singular behaviour…
- Due to unique service life of every unit, there exist some heterogeneity between the measured signals. Hence, the sensor signals of a degradation processes can be captured by the probabilistic nature of the prognostic tool.

3. PHM AT THE FLEET LEVEL

For PHM activities, 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., 2012) (Medina-Oliva et al., 2012a). In some fields such as the naval one, units are very customized leading to heterogeneous units. This fact limits mainly data and knowledge capitalization and exploitation.

To tackle this issue the fleet dimension can provide enough information and data to improve/perform PHM activities. In that sense, when searching non-identical but similar units a higher volume of data becomes available to reduce uncertainty (e.g. more confidence on the hypothesis generation about the causes producing a drift or more information about the degradation trajectory of a unit). However, most of the existing fleet-wide approaches treat identical units either for the definition of thresholds based on the data of the fleet (Patrick et al., 2010), technical solution capitalization (Reymonet et al., 2009) or RUL estimation based on a similarity-based approach (Wang et al., 2008). The fact of comparing similar units has rarely been addressed as a whole in the literature. To deal with this issue, this paper is based on a methodology that leads to search non-identical but similar units. To do it, knowledge about different and general characteristics of units was formalized within an ontology (Medina-Oliva et al., 2012b), (Monnin et al., 2011a). This knowledge allows to group heterogeneous units based on shared common characteristics that are relevant for a given situation. Indeed, an expert determines the criteria (i.e. characteristics) to be matched in an iterative process. These criteria depend on the partial knowledge of the current situation, the unit under study, the goal of the expertise (here, predictive diagnosis and prognostic), and the expert itself.

Regarding the prognostic techniques to be used, it has to be defined according the constraints previously defined. First, as the units are on-line monitored, time series data of either sensors or indicators are available for processing. Hence, data-based techniques are well fitted. A review of these techniques has been proposed by (Jardine et al., 2006). Among them, we chose techniques that process the past degradation time series. This choice has been guided since the definition of the unit population used to solve the current case is iterative, i.e. some units are dynamically removed or added. Hence the chosen prognostic model has to be able to integrate quickly new information, in our case time series, to perform its computation. Two example of such techniques are available in (Liu et al., 2007; Wang et al., 2008). (Lui et al., 2007) propose to compute match matrixes that are images of the fitting between the multidimensional time series, the current and the past one, for every past time series. Then, in every image, the best similarity indexes are selected and an Auto Regressive Moving Average model (ARMA) (Box & Jenkins, 1976) predicts the time to failure. Finally, the global RUL is computed by combining the ARMA models according to their degree of similarity. (Wang at al., 2008) propose to compute, first, a health index from the multi dimensional current time series in order to get a mono-dimensional time series. Then, they use Relevance Vector Machine (RVM) and Sparse Bayes Learning (SBL) techniques (Tipping, 2001) in order to synthetize the mono-dimensional signal in a few numbers of kernels. The online prediction process employs the background health information for the health prognostic using the Similarity Based Interpolation (SBI) technique. Moreover, (Wang et al., 2008) mention: "This framework also enables the continuous update of the background health information through offline Sparse Bayes Learning and continuous update of the prognostic results in real-time with new sensory signals through SBI… The SBL process can be carried out individually for different training unit which enables the background health knowledge to be built sequentially without complicated retraining process and updated as more offline training units are gradually available."

Secondly, the online update of the available knowledge can be satisfied. For that purpose, the operator computing the health index has to be determined for every unit in the fleet. Then, once a new event makes new knowledge available, the RVM learning through SBL make knowledge available for prognostic. The resulting information is very sparse and does not require too much space to be stored. Moreover, its use in the on-line phase does not require a huge amount of computing facilities.

Thirdly, since the considered units are heterogeneous, for instance they do not have the same number of cylinder, the monitored signals cannot be handle in the multi-dimensional signal space. Hence, the match matrix cannot handle this aspect. On the contrary, as (Wang et al., 2008) compute a mono-dimensional health index from the multidimensional time series, it is possible to compare the evolution of 2 health indexes even if the underlying units have different number of signals/indicators.

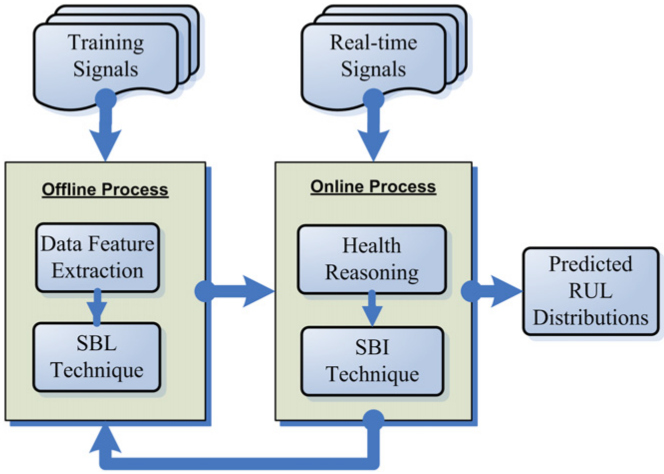

Figure 1. A generic framework for structural health prognostic (Wang et al., 2008)

4. PROPOSED PHM FLEET-WIDE APPROACH

The global fleet-wide approach (Figure 2) is performed in the same way as classical PHM historical based prognostic technics in two stages. The first stage (Figure 2a) consists in determining the hypothetical events causing the deviation (i.e. predictive diagnosis). The result of this first step is a set of solved event that are similar to the actual event under investigation. This set of event is then used in the second stage of the approach (Figure 2b) as historical data in order to performed prognostic.

4.1. Fleet-wide diagnostic approach

The proposed fleet-wide approach allowing case-reuse could bring benefits to almost all PHM activities (Monnin et al., 2011a), (Monnin et al., 2011b), (Medina-Oliva et al., 2012b). Some of them are: PHM solution engineering development/improvement, predictive diagnostic and prognostic model definition.

For the predictive diagnostic, the objective is to identify the causes that produce a drift on operations before failure occurs. To facilitate this task, information/data of past events is capitalized thanks to the semantic model (Monnin et al., 2011b), (Medina-Oliva et al., 2012b). This way it is possible to reuse all the historic data about the real causes producing the abnormal behaviour found among the selected population (Figure 3). As a matter of fact, every time an abnormal situation is studied the experiences such as the alerts detection and the operational context, the real root causes and past maintenance actions, could be capitalized allowing to establish an improvement feedback loop. In that sense feedback about all the individuals composing the selected fleet could be used to obtain more representative statistics based on fleet-wide past experiences, in order to solve a current situation (e.g. alert detection). This approach eases the identification of the real causes and reduces the downtime for a given situation.

Furthermore, historic data about the real causes is used in order to build what we called a “fleet-wide populated causal tree” (Figure 9). This kind of tree shows statistics based on the capitalized data found in the fleet. Moreover, the user is guided by the thickness of the linking-lines to search of the most probable causes that produce an abnormal behaviour (e.g. degradation/deviation). The lines that link one degradation to another are thicker as the number of occurrence of events is higher. This way the user can explore different level of causalities in order to identify the most probable root-cause of an abnormal behaviour before the failure occurs and impacts the systems performances. Once the most probable cause has been identified, it is possible to identify the set of units that have presented this cause in order to reuse this population for prognostic purposes.

4.2. Fleet-wide prognostic approach

The prognostic process conforms to the one proposed by (Wang et al., 2008). We add a selection of the on-line stage using population selection according to the fleet wide approach.

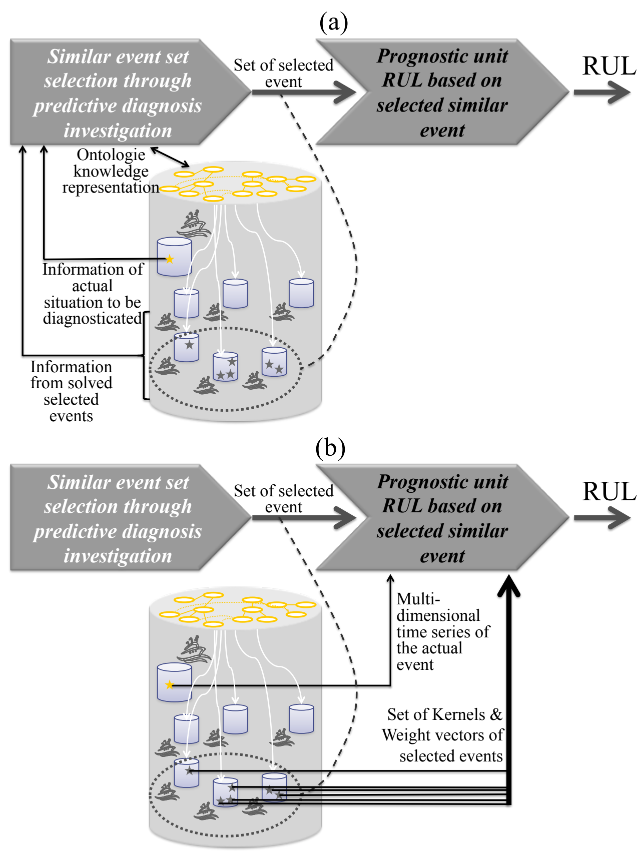

Figure 2. PHM fleet wide diagnostic (a) and prognostic (b) proposed approach process

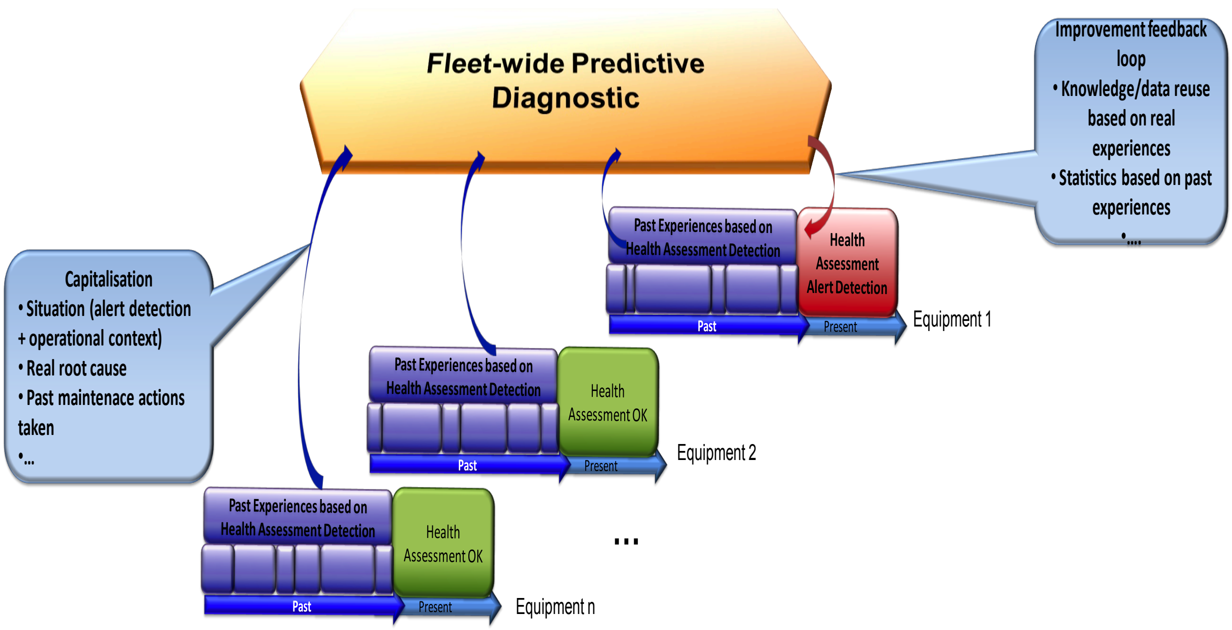

Figure 3. PHM Monitoring and Fleet-wide Diagnostic simplified process

4.2.1. Off line stage

The off line stage is composed (Figure 4) of (a) the determination of the aggregation function for health index and of (b) Sparse Bayes Learning (SBL) for health time series.

(a) Health Index computation

Wang et al. use a linear data transformation matrix T such that:

$$T = (Q^T Q)^{-1} Q S_H \tag{1}$$

Where, Q is composed of both faulty (degraded) and nominal multi-dimensional signals and SH is a {0,1} matrix corresponding to every element of Q according to its state, i.e. 0 for degraded and 1 for healthy. T is able to transform any set of multi-dimensional signal into a mono dimensional signal of health index.

For the purpose of our approach, T has to be determined for every unit, event type and operating condition. On one hand, the computation of the matrix is not time consuming neither required complex data selection (2 sets of data: normal and degraded). On the other hand, this job has to be performed for every unit and every event type since degradation signals changes according to these 2 features. Both of them are easily identifiable. Moreover, operational conditions mode are influencing degradation signals as well, but are more hardly identifiable. Hence, some work is required for such a purpose. Then, normal and degraded signal are extracted as well as operational mode identification, and T matrixes are computed.

(b) off training scheme with SBL

For the sake of conciseness, we do not present the SBL. For more details, one can refer to (Wang et al. 2008) or to the original paper of Tipping (2001). The SBL is a generalized linear model in a Bayesian form and it shares the same functional form of the Support Vector Machine (SVM). Tipping has formulated this generalized linear model in a Bayesian form, named the Relevant Vector Machine (RVM). It achieves comparable machine learning accuracy to the SVM but provides a full predictive distribution with substantially fewer kernel functions.

The RVM is a special case of a sparse linear model:

$$h(t) = \sum_{i=1}^{N} \omega_i \phi(t, t_i) + \varepsilon(t) \tag{2}$$

where $\varepsilon(t)$ is the measurement noise, $\omega = [\omega_1, \omega_2, \cdots, \omega_N]$ a weight vector and basis functions are formed of kernel functions $\phi(t, t_i)$ centered at the training point t_i. The sparseness property enables the automatic selection of a proper kernel at each location by pruning all irrelevant kernels. A sparse weight prior distribution can be assigned, in such a way that a different variance parameter is assigned to each weight. Moreover, SBL allows to integrate the uncertainty contained in the health index time series by using the statistics of the coefficients ω of the RVs.

In the fleet repository, the degradation time series, associated to a solved event, are summarized by the Gaussian kernels and the weight vectors (mean and covariance matrix). It represents available knowledge for prognostic purpose. SBL performed every time new event has been solved and a degradation time series has to be integrated.

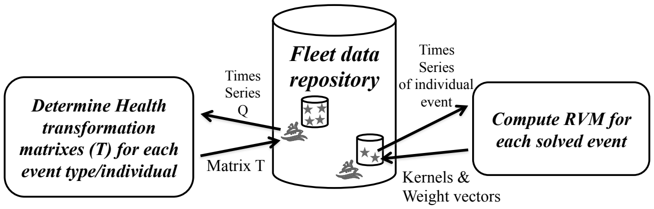

Figure 4. Off line stages of prognostics process

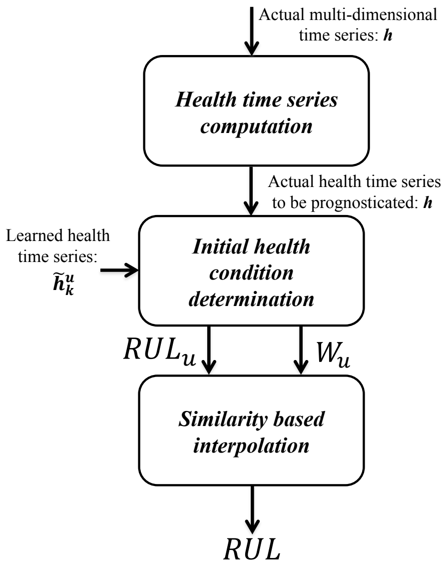

Figure 5. On line stages of prognostics process for one learned time series

4.2.2. On-line stage

The on line stage (Figure 5) is split into 3 steps: (a) Actual health time series computation, (b) initial health condition and (c) Similarity Based Interpolation

(a) Actual health time series computation

Based on the transformation matrix T (see eq. 1), the actual multi-dimensional time series is transformed into mono-dimension health time series h.

(b) Initial health condition determination

Lets consider $\tilde{h}$ a time series of health degradation from learned units with a length of $\tilde{l}$. $\tilde{h}$ and h the current one transformed using T with a length of l. Then, if both series represents the same degradation, first $l < \tilde{l}$ and second we supposed that h can be found in $\tilde{h}$. Indeed, as (Wang et al. 2008) explained h and $\tilde{h}$ may have different initial health index at the beginning of the time series due for instance to manufacturing variability or different service life. Hence the RUL estimation (see Figure 6), according to that single $\tilde{h}$, is:

$$RUL = \tilde{l} - l - T_0 \qquad (3)$$

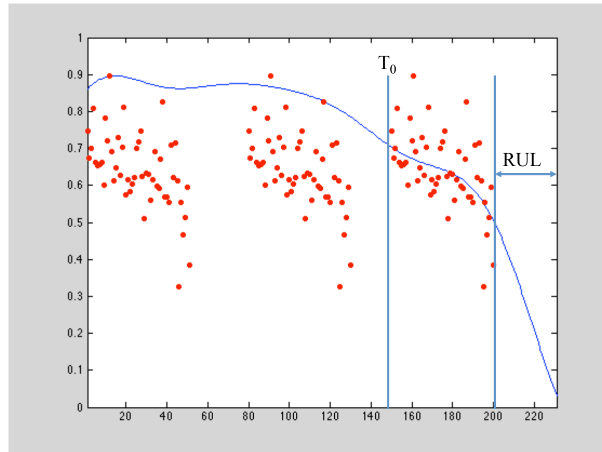

Figure 6. Initial health condition determination

with T_0 the initial time of matching between h and $\tilde{h}$ determined as:

$$T_0 = min_{T_0 \in [0, \tilde{l}-l]} \sum_{i=1}^{l} \left(h(t_i) - \tilde{h}(T_0 + t_i) \right)^2 \qquad (4)$$

(c) Similarity based interpolation

Indeed, the computation of the RUL using step (a) is performed for every degradation time series selected using the fleet wide capability, i.e. $\tilde{h}^u$. Similarity based interpolation aims at combining these several RULs. Obviously, h does not match every $\tilde{h}^u$ with the same level of similarity. Hence, the combination of the RUL depends on the degree of matching. For a single unit u, its weight is issued from the matching step:

$$W_u = \left[\sum_{i=1}^{l} \left(h(t_i) - \tilde{h}(T_0^u + t_i) \right)^2 \right]^{-1} \qquad (5)$$

The final RUL is computed as:

$$RUL = \frac{1}{W} \sum_u (W_u RUL_u) \quad where\ W = \sum_u W_u \qquad (6)$$

4.2.3. Uncertainty management

As explained earlier, the RVM approach allows to capture uncertainty contained in the data by means of the vector ω and the associated covariance matrix. Hence, for every unit u, instead of having only one $\tilde{h}^u$, for instance the mean curve, one has several $\tilde{h}_k^u$ corresponding to random realization of the weight ω^u. Hence eqs. (3) and (4) have to be computed for all the random realizations of the weight ω^u.

Finally, eq. (6) is re-written as:

$$RUL = \frac{1}{W} \sum_u \left(\frac{1}{W_u} \sum_k (W_k^u RUL_k^u) \right)$$
$$where\ W = \sum_u W_u\, , and\ W_u = \sum_k W_k^u \qquad (7)$$

5. CASE-STUDY

To illustrate the feasibility of the proposed approach as well as the added-value, a scenario was developed. This scenario shows how the fleet-wide approach is useful for experts during the decision making process for diagnosis and prognostic purposes. The scenario is developed using an ontology-based fleet-wide software application (Medina-Oliva et al., 2012 & 2013) and KASEM® (Knowledge and Advanced Service for E-Monitoring) e-maintenance software platform.

We consider first the predictive diagnosis of Volvo Penta D16 MG diesel engine. This engine presents one symptom: higher temperature of the turbo-compressor exhaust outlet gas. This symptom points out a degradation on the air-intake system.

5.1. Predictive diagnostic of a diesel engine

The air-intake system of this machine is a turbocharged system. A turbo-compressor consists of a turbine and a compressor connected by a shaft. The compressor draws in ambient air and compresses it. The compressor is connected to the turbine by a shaft and its outlet is routed to the engine cylinder air intake. Exhaust gas from the engine cylinders enters the turbine and expands, performing work on the turbine. The turbine spins the shaft connected to the compressor (Figure 7).

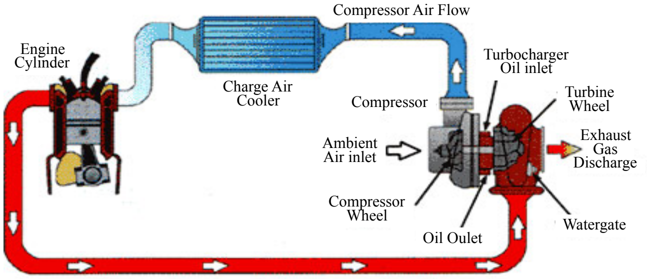

Figure 7. Turbo-charge system

The objective is first to help an expert to extract/retrieve data coming from the fleet in order to solve the diagnostic of this situation. In that sense, the expert should identify which are the most probable root-causes of degradation in the air-intake system (Figure 8) either internal or external causes to the turbo-compressor (Muller et al., 2008).

For the purpose of this example, the fleet is limited to diesel engines. Two hundred eighteen (218) events that occurred on diesel engines (Table 1) are considered. Table 1 presents an extract of the engine units of fleets and their technical features. It is possible to notice that units are heterogeneous, meaning they have different technical features. The ontology-based application aims at helping the expert in the research of similar cases among a heterogeneous fleet of engines that allows the identification of the root-causes. This way, to search the causes of the degradation the application guides the user and proposes different criteria such as the properties or technical features of units. For instance, since there is a degradation on the air-intake system for a turbo-charged engine, the embedded knowledge in the ontology (i.e. classification of engines) allows to select only turbo-charged engines. This criterion is essential to analyze the same type of degradation, for this reason it is necessary to integrate this criterion in the query. This kind of cluster could be relevant for the user since this criterion allows the definition of common and similar characteristics of engines behavior even though they are not identical.

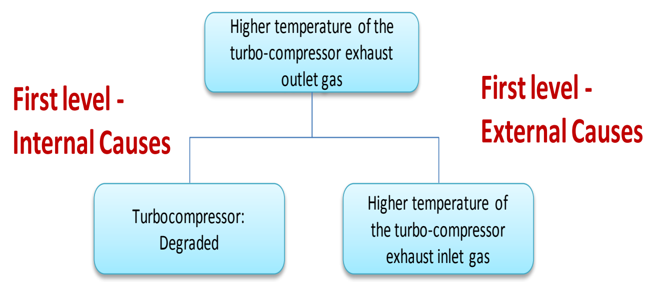

Figure 8. Causality tree about the possible causes of degradation of the air-intake system

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

Engine Ref	Output power (kW)	Nb. of Cylinder	Configuration	Engine Speed (rpm)	Tag related to the ontology	Engine cycle	Air admission	Total	Installation
Wärtsilä 12V38	8700	12	V	600	Fuel engine	4	Turbocharged	2	Propulsion engine
Wärtsilä RT-flex50	13960	8	L	124	Fuel oil	2	Turbocharged	2	Propulsion engine
Wärtsilä RT-FLEX82T	40680	9	L	80	Fuel oil	2	Turbocharged	1	Propulsion engine
Baudouin 12M26P1FR	357,94	12	V	1800	Fuel engine	4	Naturally-Aspirated	5	Generator engine
Wärtsilä 16V38	11600	16	V	600	Fuel engine	4	Turbocharged	3	Propulsion engine
Wärtsilä 9L38	6525	9	L	600	Fuel engine	4	Turbocharged	1	Propulsion engine
Wärtsilä 8L38	5800	8	L	600	Fuel engine	4	Turbocharged	1	Propulsion engine
Volvo Penta D16C – AMG	500	6	Ligne	1800	Fuel engine	4	Turbocharged	2	Generator engine
ABC 12VDZC	2652	12	V	1000	Fuel engine	4	Turbocharged	2	Propulsion engine
Baudouin 6 M26 SR P1	331	6	Ligne	1800	Fuel engine	4	Turbocharged	3	Generator engine
Baudouin 12 M26 SR	662	12	V	1800		4	Turbocharged	2	Propulsion engine

Once an ontology-based query is performed among the fleet, the user might be able to investigate the past events that have occurred in the fleet in order to reuse this information for example for predictive diagnostic purposes.

This way, information/data of past events is capitalized. The application allows to reuse all the historic data about the real causes producing the abnormal behavior found among the selected population. Furthermore, historical data about the real causes is used in order to build a “fleet-wide populated causal tree” (Figure 9). When exploring this tree which is based on statistics of fleet-wide past events (not on the signal of the events), it is possible to notice that the most probable cause producing the symptom is a degradation on the poppet valve of the outtake gas, which is delayed to open. Hence, the user can perform a predictive diagnostic guided by an ontology-based application that embeds useful knowledge about the marine domain and that allows the capitalization of data/knowledge within a fleet composed of heterogeneous units.

Then, based on the results of predictive diagnostic, a prognostic will be performed using the health state trajectory of the resulting 74 events that are presenting a problem with the poppet valve. This way it will be possible to estimate the remaining useful life of the Volvo Penta D16 MG diesel engine in order to plan a maintenance action before the engine performances are affected.

The on-line prognostic process in performed on the Volvo Penta D16 MG diesel engine. The first step is to compute the health time series of the engine.

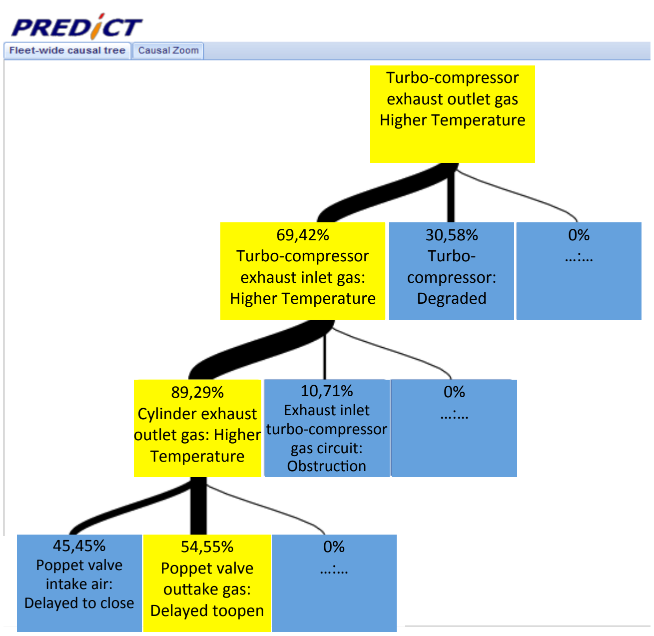

Figure 9. Fleet-wide *populated* causal tree

5.2. Prognostic based on the obtained fleet-wide population

The second step is the computation of the RULs for every event time series. This part requires to get their degradation background knowledge, i.e. kernel vector, weights and covariance matrix. Then, several $\tilde{h}_k^u$ curves are generated. We show some curves in order to show different level of uncertainties capture by the RVs for k in {1…100} (Figure 11).

For every event u and $\tilde{h}_k^u$ curves, a RUL_k^u is computed. Figure 12 shows the histograms RULs for k in {1,…,10000}. One can notice that the relative dispersion of the histograms do not always correspond to a larger uncertainty in $\tilde{h}_k^u$. For instance, for event 41, $\tilde{h}_k^{41}$'s show some uncertainty (Figure 11c) while the RUL_k^{41}'s do not since a single value has been found. In the same way, RUL_k^{26} and RUL_k^{33} (Figure 12b and d) exhibit the same dispersion while $\tilde{h}_k^{26}$ and $\tilde{h}_k^{33}$ (Figure 11 b and d) do not. Moreover, the contribution of every RUL_k^u in the final RUL through the weight W_k^u, eq. (7), allows to draw histograms for every event as well (Figure 13).

Over all the events, only 68 gave a proper result to be used in the computation of the overall RUL. In such application, the computation of a single RUL does not seem of great relevance. Instead, the analysis of the histograms of the RUL^u would give better information. Such analysis could be performed with different number of histogram class (Figure 14). We take 4 numbers of class, N, between 6 and 13. One can notice between only one mode (Figure 14 b) for N=6, three modes ((Figure 14 a and c) for N=8 and 11 or even four modes ((Figure 14d) for N=13. Such differences could be further investigated by going down the cause-tree, investigating the population homogeneity according their service life, mission… and with the help of engine experts.

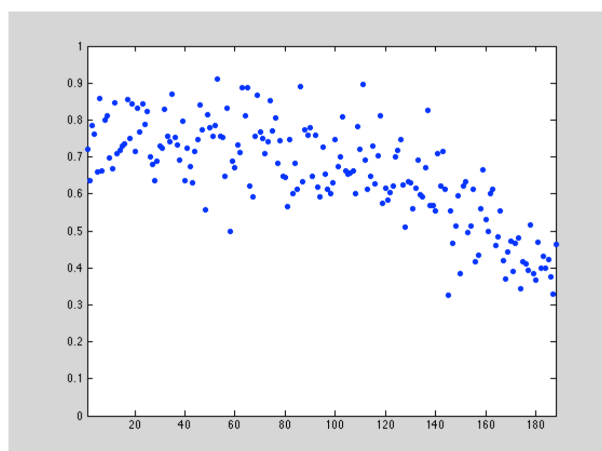

Figure 10: Health time series of the Volvo Penta D16 MG diesel engine with ill-defined running degradation

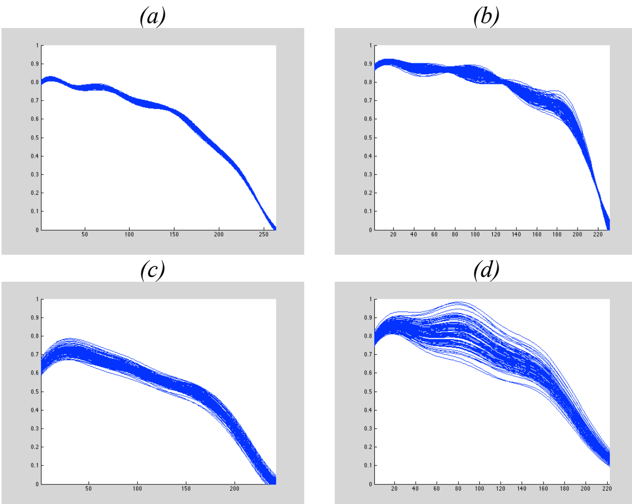

Figure 11: Several health curves for event 74 (a), 26 (b), 41 (c), 33 (d).

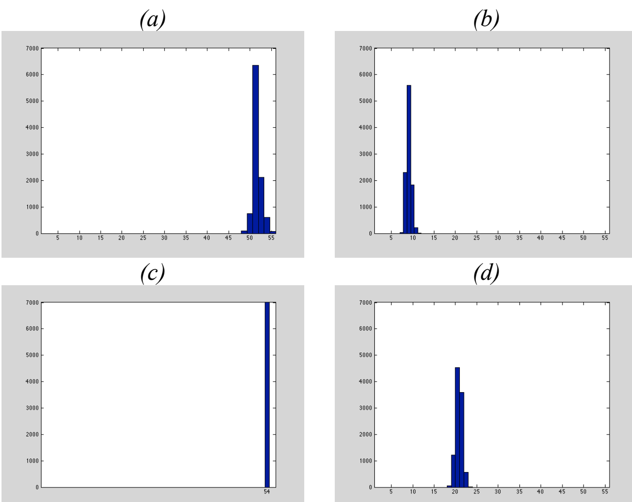

Figure 12: Histograms of RUL_k^u for the event 74 (a), 26 (b), 41 (c), 33 (d).

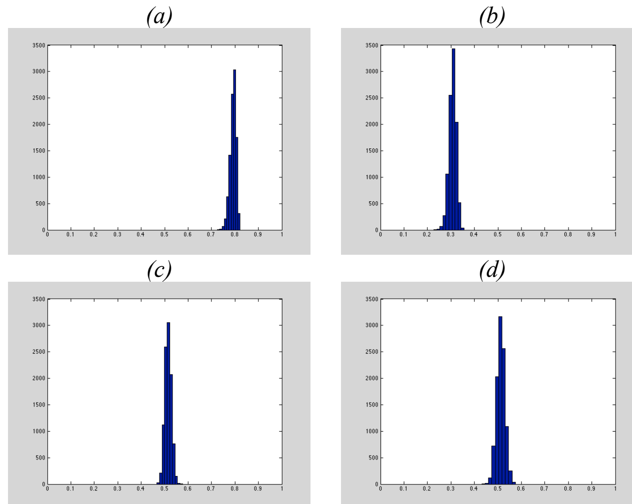

Figure 13: Histograms of W_k^u for the event 74 (a), 26 (b), 41 (c), 33 (d).

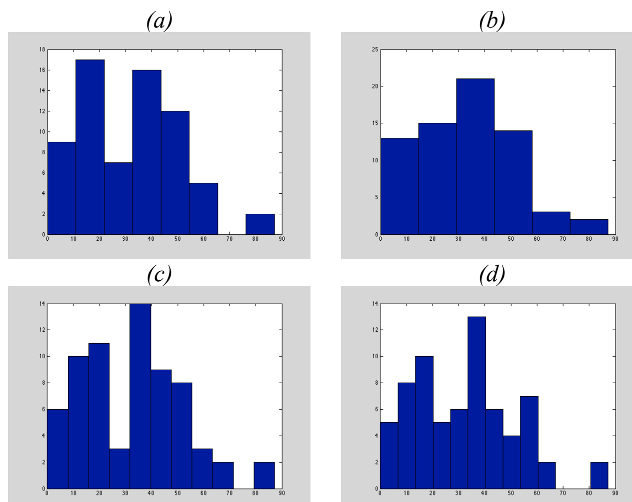

Figure 14: Histogram of the RUL^u of the Volvo Penta D16 MG diesel engine with ill-defined running degradation with different numbers of class: 8 (a), 6 (b), 11 (c) and 13 (d).

6. CONCLUSION

In this paper we proposed an approach taking advantage of all available knowledge at a fleet level for predictive diagnosis and prognosis. The originality of this work lies in the ability to make prognosis even if the degradation occurring is ill-defined, i.e. only partial knowledge about the degradation is available. Obviously, such a tool is clearly not self-sufficient. It is meant to work with experts whose knowledge helps to focus on how to solve a situation.

Despite the presented case study belongs to the naval domain, the proposed approach is general and can be applied to fields such as wind turbine farms, vehicle fleets… The presented work is a first step in that direction. Further steps can improve the usefulness of the proposed approach in several directions such as the computation of the units health which has to be homogenous over the entire fleet. An investigation on the operators to be used could be performed. The computation of the histograms of the RUL^u could be performed at every stage of the cause-tree.

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