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A short review on the integration of Expert Knowledge in prognostics for PHM in industrial applications

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Abstract—Optimizing maintenance is essential for industrials to stay competitive, and the development of appropriate predictive maintenance is necessary to achieve this objective. To this extent, the Prognostics and Health Management (PHM) paradigm is well established. One of the key steps of PHM is the prognostics of health states of the system. Various state-of-the-art approaches exist for prognostics, with an emerging orientation towards data-driven methods. Indeed, they have lot of potential for Industry 4.0 applications with high amount of data from sensors and control equipment. However, labelled data (i.e., failures of systems) is not always available on real-life applications where preventive maintenance is often already applied. Thus, the learning databases can be unbalanced, with few learning examples, consequently reducing the learning capacities of algorithms, as well as their generalization. One way to optimize learning on such applications is then to use Expert Knowledge, which can provide additional information on the system and its operating model. A challenging issue is herein the development of a general methodology to integrate the Expert Knowledge into data-driven methods.

To face this challenge, this paper aims to propose a categorization of Expert Knowledge based on existing works to identify adapted methods that can help to integrate efficiently the available Knowledge into relevant prognostics algorithms. The proposed categorization will allow and facilitate the review and comparison of approaches and methodologies introduced in the literature and in further research. Finally, the proposed classification will be illustrated on a real case of prognostics for a hydraulic circuit from an ArcelorMittal plant.

Keywords—Prognostics, PHM, Expert Knowledge, Industrial data.

I. INTRODUCTION

In the applications of industrial system's health management and monitoring for condition based maintenance, the PHM paradigm has proven to be efficient [1]. The PHM process is divided in successive steps leading from data acquisition to decision-making. Those steps are data acquisition, data processing, condition assessment, diagnostic, prognostics and decision-making [2] (Fig. 1).

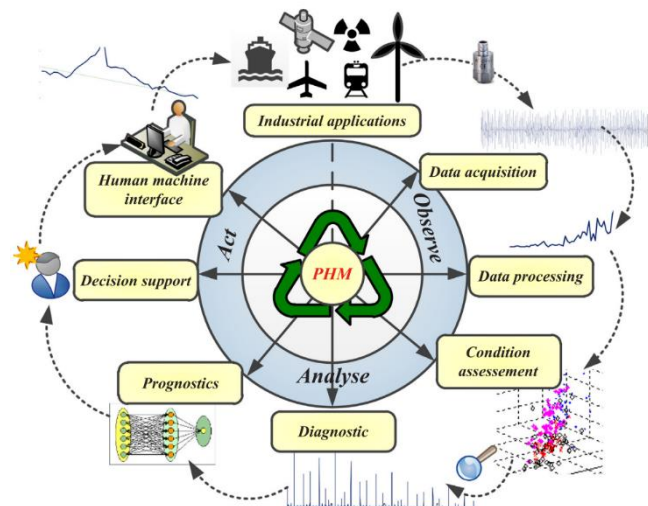


Fig. 1. PHM steps as presented in [3]

Among these steps, prognostics is primordial as it consists in predicting the Remaining Useful Lifetime (RUL) of the monitored system or component, by exploiting available data and current health state of the system, evaluated in the diagnostic step. Prognostics methods in the literature are classified in three main categories [4]: physics-based, data-driven and hybrid models. Physics-based models use physic laws to predict the behavior and future evolution of the system, while data-based methods use historical data to learn the behavior of the system to predict the RUL. Hybrid methods combine both approaches.

Nowadays, as legacy industrial systems evolved with the implementation of Industry 4.0 technologies, data-driven approaches might get more and more pertinent as those technologies increase the availability of informational representations of systems and processes (data providing through digitalization capacities; Cyber-Physical System).

The choice of appropriate best data-driven prognostics approaches for a specific situation is still an open issue [5]. Indeed, it depends on various factors such as data availability, diversity, quality (level of noise, ...) and the availability of

labeled data, i.e., examples of known degradation trajectory until the failures.

Most of data-driven methods require a high quality of data for obtaining good performances. It consists mainly of a low level of noise, enough examples of labels (known failures), representation of each functioning mode and working condition.

However, real industrial data only meets partially these requirements. Indeed, even if a large amount of data is available, measurements are often unequally distributed among components, and they may include high level of noise due to industrial context. Moreover, usually only (very) few examples of (known) failures or degraded health conditions are available because preventive maintenance strategies are already implemented and prevent the system from reaching an unwanted state, whereas they are necessary for data-driven approaches.

To face those data limitations, Expert Knowledge is crucial. It is emphasized that Expert Knowledge can bring additional information to data-driven approaches to compensate the lack of information in available data and improve the performances of data-driven prognostics [6].

Nevertheless, Expert Knowledge exists in many forms, and many integration methods are presented in the literature, while selection of adapted methods to integrate a given Knowledge to prognostics has yet not been extensively studied.

In this paper, we ought to propose a classification of Expert Knowledge which helps to identify which kinds of prognostics methods are well adapted for a given application under given available Knowledge.

To achieve this objective, this paper is organized as follow. Section II proposes a classification method for categorizing different types of Expert Knowledge. Section III reviews major prognostics methods/algorithms proposed in the literature. A link with the defined Knowledge categorization is also discussed. Section IV presents an application of the methodology to a real use-case (prognostics at component level) from ArcelorMittal steel industry. Actually, the use-case is a high-pressure water circuit used for scale removal during the hot strip mill process, with many sensors but few failure examples. Finally, Section V concludes on the proposed methodology and discusses perspectives.

II. EXPERT KNOWLEDGE CATEGORIZATION

In order to identify adequate methods for Expert Knowledge integration in prognostics models, we ought to classify Expert Knowledge in relevant categories for which integration methods would be shared in each category. The objective of this categorization is that an application with Expert Knowledge could efficiently identify similar applications and which prognostics methods are adapted to integrate such Knowledge, eventually with available results.

To define these categories, similarly to [7], [8], we define a multi-dimensional space to discriminate and give proper insight about the types of knowledge used in existing works. These dimensions ease the classification of new Expert knowledge's application, which will be located along the defined axes to identify the corresponding category and similar applications.

To be consistent, the definition of the dimensions should follow some specific properties. First, the localization of all included papers must be done without ambiguity and must be distributed along the dimension. Second, under such conditions, Expert Knowledge, within each category, should share some similarities. And third, a rule of non-sparsity could be that no area of the dimensions is left with only few papers, as they would lack representativity and a new application, in this area, would have few comparisons. Following those rules would assure a consistent and efficient categorization.

A. Axes selection methodology

To define this multi-dimensional Expert Knowledge categorization, we must identify then evaluate potential classification dimensions. To do so, we proceeded in the following steps.

Firstly, the selected papers were grouped by the types of Expert Knowledge. Indeed, Expert Knowledge similarity is evaluated based on different aspects such as form, scope, the kind of data concerned, etc. This step was applied to select papers that consider data-based prognostics methods incorporating with Expert Knowledge. In some of them [9], [10], the use of Expert Knowledge might not be explicit. For example, [10] combines multiple data-based methods and the selection is based on the prior knowledge on their data. This step splits the considered papers in seven groups.

The next step is to identify the possible dimensions in the form of criteria, which is achieved by two means. The first comes from the literature, where some papers have already proposed specific classification criteria, see for instance [7], [11]. Secondly, by identifying similarities and oppositions in Expert Knowledge of the papers in the previously formed groups.

Once some dimensions are identified, we evaluate them based on the constraints defined previously. The next subsection provides a synthesis of the most meaningful ones.

B. Descriptions of the elicited dimensions

We applied the methodology above and the obtained results in proposing three dimensions to classify the available Expert Knowledge are the following.

- Nature of the knowledge:
 - Is the Knowledge Quantitative or Qualitative?
- Scope of the knowledge:
 - Does the Knowledge concern the System/Component or the Context / Environment?
- Domain of the knowledge:
 - Does the Knowledge concerns Health Management or not?

1) Nature of the knowledge: *Qualitative – Quantitative*

This dimension should be really helpful for the future methods choice as it is directly linked to the way the Knowledge is available and will be used. It was already proposed in [7], [11], [12].

Knowledge is **quantitative** if it can be written as an equation or is related to data or numbers. Otherwise, it is **qualitative**.

Quantitative knowledge is mostly found in the form of physical models. They can be degradation models like [13] who uses the RUL of similar systems to improve prognostics or [5] who uses models to “infer unobservable model parameters related to a system’s components health”. They can be general physics-based or experienced-based models [14].

Quantitative knowledge can also concern some available experimental results. For instance, [15] uses knowledge from a previous work in determining the tuning parameters of a physics model of a similar system to fine-tune the prognostics model of the system studied.

Qualitative knowledge can concern the nature of the system. In [9], the authors pointed out that “most of the practical application problems use linguistic and ambiguous information, which is fuzzy in nature” and therefore select models adapted to these types of data. In the same fashion, [16] considers the nature of the data, which “have obvious characteristics of nonlinearity, dynamics and time delay” as a discriminator for data processing methods. Such knowledge cannot be written as an explicit equation. Nevertheless, they can bring however useful information about the system and its behavior.

It is important to note however that some Expert Knowledge can be ambiguous in considering their quantitative or qualitative property. It is the case for instance for knowledge in the form of rules, like in [17] where the knowledge is represented by specific rules in the form of IF ELSE, like “IF (Wavelet Magnitude High) OR (BP Kurtosis High) THEN (Cracked or Broken Teeth High)”. This can be considered as an equation even though it does not directly include mathematical terms since it can be handled with a computer using fuzzy rules for instance.

2) *Scope of the knowledge: System – Context*

The second dimension is whether the knowledge concerns directly the considered system or rather its context/environment. It is close to a “direct/indirect impact” consideration. The border between them can be blur, for instance in the case of the impact of context on a part of the system. Similar discriminant in the form of discrete categories close to system/context has been proposed in [7], [8].

Many papers include Expert Knowledge linked to the **system**. [14] uses “experienced-based information such as legacy failure rates or physical model predictions with signal-based information”. The Expert Knowledge in [18] is about the dynamic behavior of the system, leading them to develop specific health indicators based on this property. In [10], the knowledge of the importance of fuzzy logic and distances-computations leads them to use fuzzy modeling of distances to normality.

Meanwhile, **context and environment** are a source of additional knowledge in many existing works. In [19], the effects of the interaction of context features on machine tools health information is investigated by extracting additional features from the environment and evaluating their impact on the system. Features extraction for prognostics, from the human impact on the system health by human error during maintenance activities as one variable contributing to system failure events, is studied in [20]. In addition, the notion of imperfect maintenance operations could also be considered as context knowledge [21], [22].

Even though it is a discriminant for methods selection, this dimension has the disadvantage of being unbalanced within the considered papers. Indeed, most of the considered works logically focus on the system, as it is the main concern of prognostics and a source of direct information about degradation.

3) *Domain of the knowledge: Health Management – General*

The last proposed dimension is about the application domain of Expert Knowledge, whether it directly concerns health management (failed/degradation state, ...). This differentiation is directly linked to the type of integration approaches used.

This dimension can lead to two types of knowledge but with different types of integration. For instance, both [14] and [23] used external datasets as additional Knowledge. The first one is composed of “experienced-based information such as legacy failure rates” and integrates it directly in the prognostics model. While the second one is composed of similar inputs but other outputs with rich information to enhance the identification accuracy of target domain using transfer learning.

4) *Rejected dimensions*

Other dimensions were also found in the literature, but they are not used because they are not relevant for our approach. For instance, [7], [24] proposed to classify Knowledge between internal or external similarity. It was rejected because it does not provide enough discriminant information on the adapted integration methods.

C. *Conclusion on the proposed dimensions*

Finally, we report in the Table I a summary on the reviewed papers along the three proposed dimensions. This representation shows the classification of Expert Knowledge in the three-dimensional space. The discrimination for each type of Knowledge is quite clear. Eventually, we could ensure that selected papers from each of the initial sub-categories are in the same line of the table. However, these proposed dimensions could still be enhanced by further research. We achieved a first satisfactory classification respecting the initially defined criteria, though it could still be improved. Enhancements could propose new dimensions relevant regarding new applications or merge the proposed dimensions into new hybrid ones.

III. EXPERT KNOWLEDGE INTEGRATION IN PROGNOSTICS METHODS

After having defined a categorization for Expert Knowledge, we ought to identify adapted integration methods for the Knowledge categories.

In that way, the scope is to present prognostics methods proposed in the reviewed papers and to identify which type of Expert Knowledge can be incorporated in, using the proposed three-dimensions classification. Then, the performances are described by using application results as relative measures.

The reviewed methods for data-driven prognostics are grouped in the next sub-sections following the prognostics engineering process, decomposed in three main steps, data processing, model design and finally model training / optimization [25] (Fig. 2).

TABLE I. CLASSIFICATION OF THE REVIEWED PAPERS

Qualitative Quantitative	System Context	Health Management General Knowledge	References
Qualitative	System	Health Management	[17], [40]
Qualitative	System	General Knowledge	[9], [10], [16], [29], [36]–[38], [41]
Qualitative	Context	Health Management	[20]
Qualitative	Context	General Knowledge	[34]
Quantitative	System	Health Management	[13], [14], [18], [41]
Quantitative	System	General Knowledge	[5], [15], [22], [30], [31], [34]
Quantitative	Context	Health Management	[19]
Quantitative	Context	General Knowledge	[23]

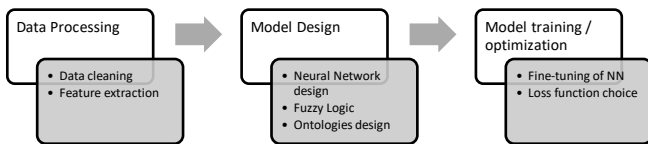


Fig. 2. Engineering process of data-driven prognostics models.

Most of the presented methods in the literature are classified as hybrid models, using both data-driven approaches and physics or experiment-based models. Broader reviews of hybrid models already exist such as [26], [27].

A. Data Processing (Feature extraction)

Feature extraction consists in combining available input data to forge new inputs, bringing knowledge because of their relations with the expected outputs. Examples of feature extractions are the computation of unobservable variables from sensor data or extraction of indicators from Fourier and Wavelet transforms to provide more pertinent inputs [28]. Also, [29] considers features extraction from Fourier Transform applied on the input Time Series data because it is known that vibrations and frequencies are key elements of the use-case.

Within the reviewed articles, feature extraction is particularly used with **quantitative** Knowledge concerning the **system**. This category of Knowledge often takes the form of physics-based equation, linking input data. For instance, [30] added new unobservable variables to input data by combining available measurements. As a result, the proposed hybrid framework outperforms purely data-driven approaches by extending the prediction horizon by nearly 127%.

The paper [31] presented the case where the available physical model is used to predict the RUL. Then, a data-driven model (using Neural Network) takes the predicted RUL as an input to compute an enhanced-RUL. This allows improving the physics-based prediction with surrounding data.

The paper [15] used an experience-based tuning of a physic model parameters as Expert Knowledge. The prognostics model is optimized with an interpolation method chosen based on existing information from other related works

about their system. They use tuning of this physical model [32]. Similar approaches use Transfer Learning to exploit data and experience from other similar systems [23].

B. Model Design

Expert Knowledge is often used during the model design step by either guiding through the choice of an adapted model, either through the development of specific models or modification of existing models. The next sub-sections present some examples of model selection based on knowledge and model modification in the reviewed papers.

1) Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) are recurrent neural networks suited for time-dependent input data. It is used in [33] to adapt to chaotic Time Series, where evolution over time of correlations are essential for efficient predictions. This knowledge is **qualitative**, concerns the nature of the **system** and is used to select adequate models.

2) Specific evolution operators for Genetic Algorithms

The reference [9] used knowledge about the expected shape of data to customize a Genetic Algorithm (GA) used for feature extractions. Indeed, to handle the characteristics of data, such as nonlinear, dynamic and time lag, which is **qualitative system** knowledge, they include “domain knowledge” into the framework by defining original evolution operators for the Genetic Algorithms based on those characteristics. As consequence, this leads to an improvement of the Mean Squared Error (MSE) of approximately 25%.

3) Ontologies & Graph-based approaches

The exploitation of **context-based** knowledge can lead to the use of graphs to represent the relations between components, sensors, data and external causes. They are then exploited by graph-based Machine Learning methods. More precisely, system components, sensor data and interactions are represented and analyzed as a graph [34].

This approach is generalized in the ontology field. Indeed, ontologies consist in graph-based representation of information. They are defined as frameworks providing relationships between components, properties and

specifications. It is a promising tool to formalize the knowledge into mathematical models [35]. Ontologies can combine both **system** and **context-based** knowledge in a unique mathematical representation.

It is important to note that ontologies have already been proposed for PHM applications [36]–[38]. They can be based on existing frameworks, such as in [37] where an ontology is proposed based on the OSA/CBM MIMOSA standard [39].

4) Fuzzy Logic

Fuzzy logic allows the handling of imperfect knowledge for instance in like IF-THEN rules or fuzzy numbers (i.e. possibility distribution). It eases the formalization of **qualitative** knowledge available on an industrial system based on experience, and it is an efficient method to integrate Expert Knowledge in prognostics models. For instance, [16] proposed a modified Neural Network architecture based on fuzzy numbers to integrate its knowledge about the uncertainty of their use-case. Neurons of the network are replaced by fuzzy ones, with fuzzy inputs, outputs and weights. This approach improves by a factor of 7 the Mean Squared Error (MSE) on predictions. On the other hand, [17] used a set of rules based on fuzzy data as inputs and outputs to train a Neural Network for practical applications of those rules in investigated systems.

C. Model Training (Fine tuning of Neural Networks)

The last step of the engineering process for data-driven prognostics is learning phase that consists in tuning the model weights to fit available dataset. This step is essential and in the case of Machine Learning (including Neural Networks), it needs then particular attention.

Learning can be optimized with Knowledge by integrating it into the loss function. For instance, [31] possessed knowledge in the form of equations between the target and input variables. They include these relations in the loss function as a penalization when the relations are violated. This approach tends to select a function that satisfy the stated relations. These approaches are adapted to **quantitative** Knowledge about **Health Management**.

These loss-tuning approaches can also be used for a second learning phase of Neural Networks to fine-tune the learned weights, see [40]. Their use-case is about shape-finding in images, on which they have a prior knowledge about the expected shapes. They fine-tune the learning of their CNN by optimizing the weights of the network with respect to the prior knowledge loss function including their knowledge-based rule about the expected shape of recognized objects in the pictures.

IV. DESCALING USE-CASE

We ought to apply this methodology to an example from steel industry (ArcelorMittal company) for failure prognostics on a high-pressure water circuit used for scale removal on hot plates. The circuit is composed of standard hydraulic elements (filters, pumps, valves, pipes, and nozzles). The descaling is a key step for steel making, as if the water physic characteristics (e.g., pressure) are not in nominal state, the production must be stopped. So, prognostics of degradation is primordial for keeping performance of the system.

The available data correspond to the mitigated industrial situation presented in the introduction. Firstly, time series

signals are available as sensors (pressure, flow rate, ...) and controllers inner states. They are located all along the circuit, but with variable levels of instrumentation among components. Secondly, even though months of measurements are available, only few failure events are registered and labelled.

These limitations of available data correspond to the initially described constraints on industrial use-cases for prognostics. Therefore, we ought to compensate for them with the integration of Expert Knowledge into prognostics models. Expert Knowledge on the system is available from R&D research and field knowledge.

The first type of Expert Knowledge available is physics-based and experience-based models. According to the categorization, it is a **quantitative** knowledge **about the system**. Based on this classification, similar Knowledge used for feature extractions were studied in [15], [30], [31]. Similarly, we will use those models to extract additional features and improve the input dataset given to prognostics models. For instance, the opening delay of valves will be computed from the pressure measurements.

The second type of Knowledge is empirical knowledge about the standard evolution of some signals. For instance, opening time of valves is always increasing, except after maintenance operations. According to the categorization, it is a **quantitative** knowledge about **health management**. Similar knowledge is found in [31], [40] to adapt optimize the loss function of Machine Learning. It is also used to customize prognostics models as investigated in [9].

The last type of Knowledge is formalized in the form of Failure Mode, Effects & Criticality Analysis (FMECA), which is needed for every failure. It includes details about a past failures, its causes, consequences, measurements and impacts. It also includes links between components behaviors. According to the categorization, it is a **qualitative** knowledge about **health management**, concerning **both system and context**. Regarding to existing works, similar knowledge was not identified in the literature, but the graph-based approaches could fit the system and context property. They allow also exploiting the knowledge about the links between components, causes and consequences.

The categorization of our Knowledges identified methods to integrate it into prognostics, in the form of feature extraction, loss function tuning and graph-based models. Those methods are still general, and more detailed study is needed to evaluate their pertinence and applicability on the application. Actually, the detailed investigation on the use-case is in process, some quantitative results should be available soon.

V. CONCLUSION AND PERSPECTIVES

In this paper, we proposed a classification of Expert Knowledge to identify adapted integration methods of it in data-driven approaches for RUL prognostics.

We proposed a three-dimensional classification defined by the characteristics of Knowledge. The three proposed dimensions are the nature of the knowledge (quantitative or qualitative), its scope (system or its environment/context), and the domain of the knowledge (health management). These dimensions were selected with regards to further selection of integration methods.

Followingly, we identified some groups of methods in the literature. In addition, we presented the corresponding Knowledge and located them along the proposed dimensions. Hence, adapted methods for a given Expert Knowledge can be identified by locating it within the dimensions.

Finally, by applying the proposed methodology to a use-case from the steel industry, we observed that the current classification method identified a type of methods rather than a unique one. Indeed, in the current state of the methodology, the classification of the knowledge is not discriminative enough, resulting in knowledge categories still presenting an important variety. However, this is a first proposal for such methodology, which ought to be furtherly enhanced, by reviewing a larger number of publications and identifying more precise types of knowledge and algorithms.

Our further work will focus on the investigation of the feasibility of the method, its credibility, and on the extension of the classification dimension. Its feasibility could be tested by implementing on the industrial use-case and the identified methods to assess the performance gain. Its credibility could be evaluated by verifying the robustness of the identified methods, i.e., improve the prognostics performances.

Finally, as mentioned earlier, the proposed dimensions do not offer a “fine enough” classification of knowledge, and other future works could focus on identifying additional dimensions or some clusters along the proposed dimensions.

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