Towards multi-model approaches to predictive maintenance: A systematic literature survey on diagnostics and prognostics

Juan José Montero Jimenez[a,b,*], Sébastien Schwartz[a,c], Rob Vingerhoeds[a], Bernard Grabot[d], Michel Salaün[a]

[a] ISAE-SUPAERO, Université de Toulouse, 10 Avenue Edouard Belin, 31400, Toulouse, France
[b] TEC-Tecnológico de Costa Rica, Calle 15, Avenida 14, 1 km Sur de la Basílica de los Ángeles, Provincia de Cartago, Cartago, 30101, Costa Rica
[c] Capgemini DEMS, R&D Dpt., Aeropark, 3 Chemin de Laporte, 31100, Toulouse, France
[d] ENIT- INP Toulouse, 47, avenue d'Azereix, BP 1629, 65016, Tarbes, France

Keywords:
Predictive maintenance
Systematic literature review
Diagnostics
Prognostics
Single-model approaches
Multi-model approaches

A B S T R A C T

The use of a modern technological system requires a good engineering approach, optimized operations, and proper maintenance in order to keep the system in an optimal state. Predictive maintenance focuses on the organization of maintenance actions according to the actual health state of the system, aiming at giving a precise indication of when a maintenance intervention will be necessary. Predictive maintenance is normally implemented by means of specialized computational systems that incorporate one of several models to fulfil diagnostics and prognostics tasks. As complexity of technological systems increases over time, single-model approaches hardly fulfil all functions and objectives for predictive maintenance systems. It is increasingly common to find research studies that combine different models in multi-model approaches to overcome complexity of predictive maintenance tasks, considering the advantages and disadvantages of each single model and trying to combine the best of them. These multi-model approaches have not been extensively addressed by previous review studies on predictive maintenance. Besides, many of the possible combinations for multi-model approaches remain unexplored in predictive maintenance applications; this offers a vast field of opportunities when architecting new predictive maintenance systems. This systematic survey aims at presenting the current trends in diagnostics and prognostics giving special attention to multi-model approaches and summarizing the current challenges and research opportunities.

1. Introduction

The use of a modern multi-technological system requires a good engineering approach, optimized operations, and proper maintenance in order to keep the system in an optimal state of operation. Predictive maintenance focuses on the organization of maintenance actions according to the actual health state of the system, aiming at giving a more precise indication of when a maintenance intervention will be necessary. This is performed by using specialized models and techniques that make possible to perform diagnostics and prognostics over the multi-technological system health state.

Predictive maintenance research has a lot of attention in industry and academy due to its potential benefits in terms of reliability, safety and maintenance costs among many other benefits. As explained by [1], predictive maintenance might reduce maintenance costs by 25 %–35 %, eliminate breakdowns by 70 %–75 %, reduce breakdown time by 35 %–45 %, and increase production from 25 %–35 %. These percentages do not consider important aspects such as system safety and company image.

This article aims at performing a systematic literature review on predictive maintenance, the state of the art on the models used for diagnostics and prognostics, the current challenges, and new potential opportunities of research. Fast expanding trends such as Industry 4.0 boost the use of predictive maintenance, and the interest on the topic remains increasing. Recent reviews mainly focus on a limited scope: prognostics and data-driven models, as for example [2–4]. This motivates an update of the reviews as every year hundreds of publications related to the topic are published.

The methodology to perform the literature review is based on [5] and concerns a systematic literature review methodology that aims at summarizing the existing work of a specific topic. The systematic literature review helps to carry out the literature review process in a

* Corresponding author at: 10 Avenue Edouard Belin, 31400, Toulouse, France.
E-mail addresses: juan.montero@itcr.ac.cr, juan-jose.montero-jimenez@isae-supaero.fr (J.J. Montero Jimenez).

https://doi.org/10.1016/j.jmsy.2020.07.008

structured manner so to obtain a better overview of the subject under study. The systematic literature review protocol includes four main parts: research questions definition, search strategy, study selection, and data synthesis. The research questions are:

- RQ1: What are the current trends in diagnostics and prognostics for predictive maintenance?
- RQ2: What kinds of models, techniques or methods are used to address diagnosis and prognosis in predictive maintenance?
- RQ3: What are the current challenges facing predictive maintenance in diagnostics and prognostics?

The search was divided into two steps; the first one was aimed to check the previous literature reviews on predictive maintenance so to understand the evolution of the topic over the last years. This first search step also helped to identify the model types used for diagnostics and prognostics: knowledge-based, data-driven, physics –based and multi-model approaches. The second search step is based on trial searches using various combinations of search terms derived from the research questions so to identify the main trends in the different models for diagnostics and prognostics. Special attention is given to multi-model approaches, as these models present a promising opportunity to overcome current challenges in predictive maintenance applications. For example, more than one model could be used to address different sources of heterogeneous data, complementary models could be used to reduce uncertainty and improve accuracy on diagnostics and prognostics (see Sections 6 and 7). For both search steps, four sources were consulted: IEEE Xplore, ScienceDirect, Springer and Web of Science. The selection of studies was performed accordingly to the research questions. An assessment on each publication was performed considering the clearness of research objectives, the explanation of proposed model results and the case studies completeness. Appendix A offers further explanation of the structured literature review process followed for this survey.

The rest of the paper is organized as follow: Section 2 introduces predictive maintenance. Section 3 shows some statistics from the systematic literature review. Section 4 shows the findings of the first search step on previews reviews of the topic. Section 5 explains the main single-model approaches identified in the current literature review. Section 6 addresses the multi-model approaches. Section 7 summarizes the identified challenges for predictive maintenance as potential opportunities for future research. Section 8 concludes the current systematic literature review.

2. Predictive maintenance

Within the maintenance strategies to trigger maintenance actions, three terms are commonly applied: corrective maintenance, preventive maintenance and predictive maintenance. Corrective maintenance triggers the maintenance actions once the failure of a component or system has occurred. Preventive maintenance uses intervals of time such as cycles, kilometres, flights, etc. to determine the right moment to trigger the maintenance actions. As explained by [6], the existence of faults is frequently unknown in preventive maintenance. This may lead to replacing components with still remaining useful life, which may be costly. Predictive maintenance can be presented as a maintenance strategy aiming at defining the accurate moment to trigger actual maintenance actions [7]. Too early interventions could represent a waste of resources by changing components with an important Remaining Useful Life (RUL), too late interventions could lead to catastrophic failures. As strategy, predictive maintenance is complementary to corrective and preventive maintenance. Predictive maintenance finds its bases in using specialized techniques and tools to identify the existence of faults on the technical systems and forecast their remaining useful life. A combination of the three mentioned strategies is needed to reach an efficient maintenance management [7].

Predictive maintenance has the goal of improving maintenance activities, performance, safety and reliability [8]. It is a vast topic with two main scopes diagnostic and prognostic. Diagnostics aims at detecting faults, determining their root cause and determining the current health state of the system to prevent unexpected failures. Prognostics are dedicated to predictions of future states of the system and the remaining useful life. Diagnostics and Prognostics can be performed online or off-line. In online applications, data is gathered, processed and analysed in real time to generate alarms or trigger maintenance or adjustment action while the system is running. Off-line applications focus on gathering all operational information to be analysed later (off-line) by the maintenance team. They are not constrained by online real-time limitations [9].

Predictive maintenance is not a new topic. Some studies like [10] state that predictive maintenance already existed in the 1940′s and during the current systematic literature review, publications from the 1970′s were easily found [11]. However, the last 25 years show a growth of interest of the topic year by year. Two extensions of predictive maintenance are found in literature: Condition-Based Maintenance (CBM) and Prognostics and Health Management (PHM). According to [10], CBM was also introduced in the 1940′s while PHM is the most recent term, introduced in the early 2000′s [12]. These terms frequently substitute predictive maintenance in literature and there is no consistency on how these terms are used or how they fit together in

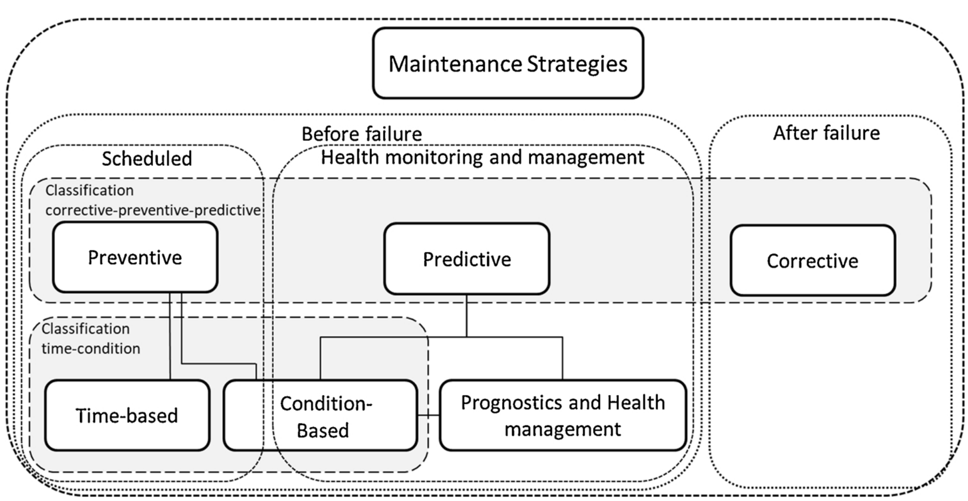

Fig. 1. An overview of Maintenance strategies.

the maintenance field. Over the last years, different contributions are made under different terms and refer to the same field of research. It has an impact on the current review. As result, the three terms were considered for the current review: predictive maintenance, CBM, and PHM. Fig. 1 shows an overview of the maintenance strategies. Predictive maintenance is traditionally grouped along with preventive and corrective maintenance [10,13]. CBM is traditionally shown as a counterpart to time-based maintenance [14]. Besides these traditional classifications, Fig. 1 shows a simple taxonomy which initially classifies the strategies between two categories with regards the maintenance actions triggering: before or after a failure occurs. For the strategies that trigger maintenance actions before failure there is sub-division between strategies with fixed schedule for maintenance actions and strategies that use health monitoring to decide the precise moment to trigger the maintenance actions. This last group includes the chosen strategies for this literature review. It is important to point out that Fig. 1 is not a hierarchical diagram. The lines connecting the different strategies only represent the existence of important commonalities among the connected ones. The clarification of potential confusion in the use of these terms is out of the scope of the current review.

Predictive maintenance is normally implemented through specialized systems which collect data or information from the technical system for diagnostics or prognostics purposes. Norms and standards like OSA-CBM [15,16] offer a list of the traditional functional blocks of these predictive maintenance systems. Fig. 2 shows a functional decomposition of a predictive maintenance system for remaining useful life (RUL) estimation on one machine component subjected to a single failure mode. It shows the traditional functional blocks: collect data (F1), pre-process data (F2), detect and identify faults (F3), assess degradation (F4), compute RUL (F5) and make report (F6). These functional blocks may be present or not in a predictive maintenance system, they could be duplicated or modified depending on the system architecture which relays on the technical system complexity, the requirements for predictive maintenance system and the available knowledge, data and/or information [17]. According to the scope of this literature review, the models used for the functional blocks F3, F4 and F5 are addressed. It is important to point out that one or more models can be used to fulfil one single functional block, see also Section 6.

3. Survey process and some statistical results

The systematic literature review shows that predictive maintenance is gaining importance in the research community, especially over the last 25 years. To illustrate this, Fig. 3 shows the number of publications mentioning the terms "predictive maintenance", "condition based maintenance and "prognostics and health management" over the last 25 years in one of the consulted search sources (ScienceDirect). The tendency on IEEE Xplore, Springer and Web of Science is the same. The topic has a high importance in the research community; hundreds of articles are published every year with new contributions. It is important to mention that not all the papers mentioning the terms of interest are directly related to the scope of the current survey. The articles related to maintenance management practices, maintenance policies, maintenance schedule optimization, are examples of topics discarted in the scrutinity process for this survey as they were out of scope.

During the first search step 23 survey articles were consulted (see Appendix B) to identify the models used for predictive maintenance and the evolution on the trends over the years. The taxonomies used to classify the different models for diagnostics and prognostics in predictive maintenance show slight variations on the terms from one study to another. Two main approaches can be extracted: single-model approaches and multi-model approaches. For single-model approaches there are three model types; for this survey these model types will be named knowledge-based models, data-driven models and physics-based models. Multi-model approaches combine at least two models from the three mentioned models types. Multi-model approaches may have different configurations and sometimes are called hybrid models; however, not all multi-model approaches should be referred to as hybrid (see Section 6).

The identified groups were the basis for the second search step. Following the mentioned taxonomy, Table 1 shows the distribution of consulted articles from 2015 to 2019. The survey also considered studies from previous years; however, due to the scrutiny process recent articles with similar scope and case study substituted older articles. The table shows that recent papers have been consulted to illustrate each category. Further explanation of model types, their current challenges and research opportunities are discussed in Sections 4,5 and 6. Data driven models are divided into three categories to be consistent with the taxonomy shown in Section 5. The three categories are: statistical models, stochastics models and machine learning models.

An important aspect is the distribution of the mentioned models between diagnostics and prognostics as main task for the consulted studies. In the end, out of the consulted articles in the second search step, 48.9 % were dedicated to diagnostics while 51.1 % to prognostics so that it is possible to say that they have equal share. Fig. 4 shows the distribution of the consulted studies between single-model approaches and multi-model approaches for diagnostics (left part of Fig. 4) and prognostics (right part of Fig. 4), for all the consulted articles in the second search step. It is important to point out that diagnostics and prognostics are not always exclusive to each other. To perform prognostics is normal to have a previous diagnostic step to determine the current health state of the technical system to estimate future behaviours of the technical system. The main contribution presented by each consulted study in the second research step was considered to classify the scope between diagnostics and prognostics. For both, diagnostics and prognostics, single-model approaches are more presented than multi-model approaches. For diagnostics, knowledge-based models have a higher importance than for prognostics. Consulted studies on physics-based models were dedicated almost exclusively to prognostics. Data-driven models have the main part of consulted studies for diagnostics and prognostics.

4. Findings on the first search step

The first search step was dedicated to previous reviews on predictive maintenance and it helped to study the commonalities among

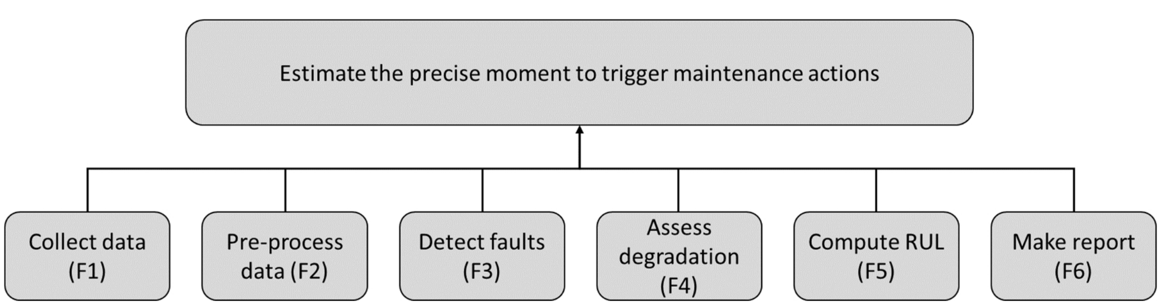

Fig. 2. Functional decomposition for an example of predictive maintenance system, modified from [17].

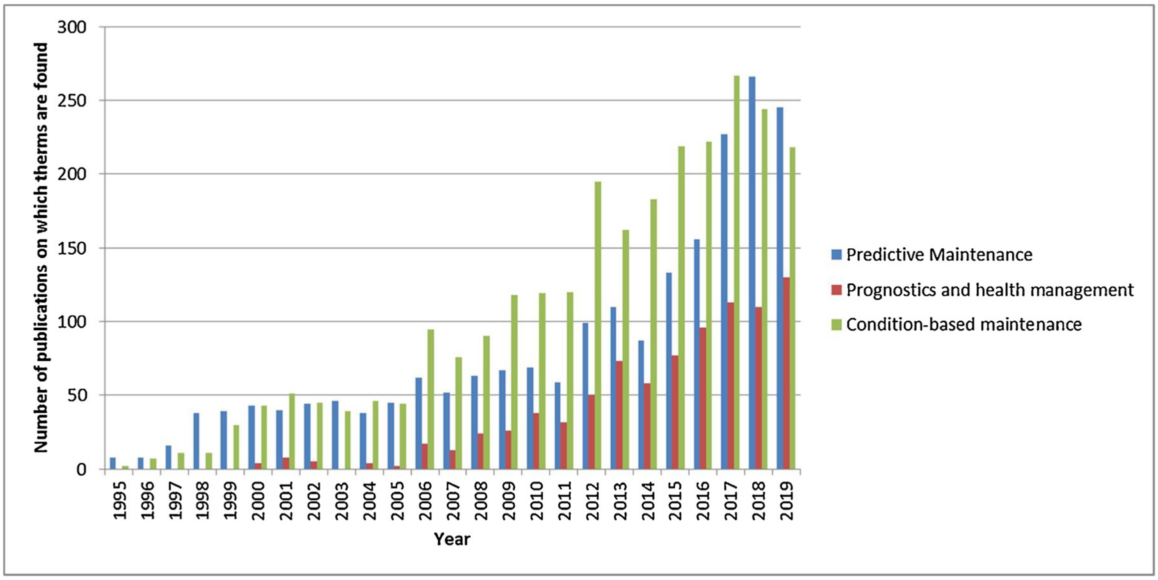

Fig. 3. Number of publications over the last 25 years related to prognostics and diagnostics in maintenance using three search terms in ScienceDirect.

Table 1
Distribution of publications per model from 2015 to 2019 in the systematic literature review on Predictive maintenance.

Approach	Model type	Models	2015	2016	2017	2018	2019
Single-model approaches	Knowledge-based models	Rule-based, Case-based, and fuzzy models	[18–20]	[21]	–	[22–24]	[25–28]
	Data-driven models	Statistical, stochastic and machine learning models	[29–33]	[34–37]	[38–49],	[50–62,7,63–75]	[76–81]
	Physics-based models	Laws of physics governing the degradation of the system.	–	[82]	[83,84]	[85]	[76,78,86]
Multi-model approaches	Different configurations	Combination of two or more models.	–	[87]	[88]	[69]	[76,78,89–94]

the terms “predictive maintenance”, “condition-based maintenance” (CBM) and “prognostics and health management” (PHM). The use of these terms is not homogeneous in literature. Sometimes CBM and PHM are presented as if they were synonyms to predictive maintenance [95,96], while other studies shown CBM and PHM as extensions or subdivisions of predictive maintenance [6,10,97–99]. Opposite statements are also found clustering predictive maintenance as sub-part of CBM [100]. The three terms were developed by different research communities and today many contributions concern similar maintenance activities done under different names. None of the consulted reviews presents an alignment of the three terms in the same study.

Trying to align these terms, this survey adopts predictive maintenance as the first term to refer the maintenance strategy. CBM is suggested as an extended version of predictive maintenance where alarms are added to warn when the system has overpassed predetermined thresholds. CBM has been used as preferred term to describe diagnostics tasks in norms [99,101] and in some referential books such as [102]. Likewise, PHM is suggested as an extension of CBM as an answer to the need to improve on predictability and life cycle management of the assets [100,102,103]. Fig. 5 shows a summary of the evolution on the use of the terms considering the consulted reviews. When performing literature research, it is then worthy to consider the three terms.

Besides a general notion of the terminology, the first search step of the current survey allowed the study of evolution of the research trends on the topic. Out of the 22 consulted reviews, the first one dates from

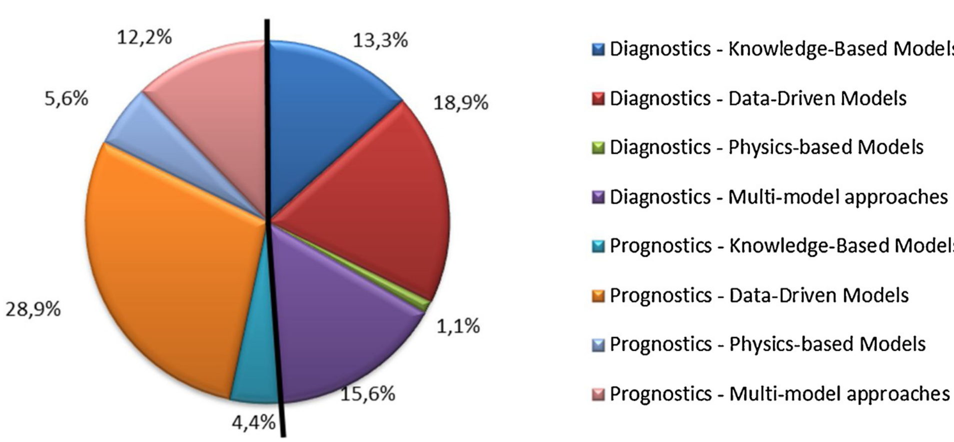

Fig. 4. Studies distribution for diagnostics and prognostics considering the consulted papers for the second search step.

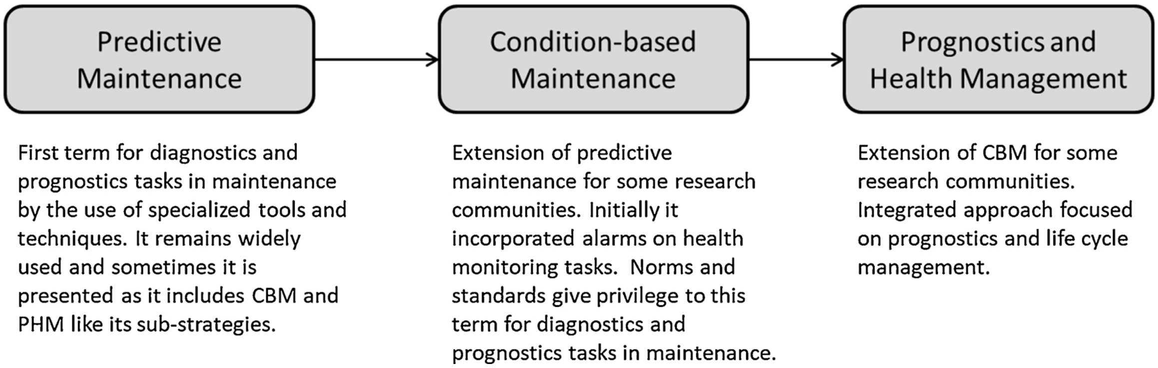

Fig. 5. Relationship among Predictive Maintenance, CBM and PHM.

2006 and is frequently cited by others [104]. This first survey dedicates a different section for diagnostics a prognostics, summarizing the most important techniques for each approach (only single-model approaches). Other survey articles have more specific subtopics that where addressed: RUL estimation through vibration data analysis on bearings and gears [105]; prognostics with a bound scope on data-driven or physics based models [106]; or on bibliometric indicators for predictive maintenance [107]. More general overviews on predictive maintenance models were covered by conference papers [97,108]. These conference articles have a limited scope to only few models and examples.

The most complete reviews are [2] and [3], from 2017 and 2018 respectively. These two reviews gave privilege to the term PHM to address the topic and offer an overview from the data collection to the decision making process (all functional blocks mentioned in Section 2); however, their main scope is on predictability and remaining useful life (RUL) estimation. They both respect the taxonomy of four model types (with slight differences in the naming): knowledge-based, data-driven, physics-based and hybrid (partially addressed). These two articles update and extend the work done by previous survey studies on prognostics and RUL estimation [109–111]. The latest consulted survey is from 2019 and is exclusively dedicated to data-driven methods for prognostics tasks, especially those related to machine learning and deep learning [4]. A summary of the previous reviews could be found in Appendix 2.

The consulted reviews on predictive maintenance are mainly focusing on single-model approaches, data-driven models and prognostics. The second search step covers these gaps giving special attention to the use of multi-model approaches in both diagnostics and prognostics. The following Sections (5, 6 and 7) cover the findings of the second search step based on a complementary point of view to recent reviews to cover the mentioned gaps.

5. Single-model approaches for predictive maintenance

This section briefly introduces to single-model approaches used for diagnostics or prognostics, their strengths and weaknesses and how recent studies already implement complementary models to fulfil the intended tasks in predictive maintenance systems and overcome complexity. It is a complementary point of view to recent and complete review that have extensively covered single-model approaches. The models in this section are divided into three model types: knowledge-based models, data-driven models and physics-based model.

5.1. Knowledge-based models

Knowledge-based models build upon experiences. Experience can be represented by rules, facts or cases that have been gathered over the years of operation and maintenance of the technical system [9,112,113]. Experience can be used to identify faults, describe the degradation and forecast a potential failure of components or systems. These rules, facts or cases, can be used in computational intelligence techniques to automate the inference on diagnostics and prognostics for maintenance purposes. It was the state of the art of maintenance in the early 1990′s. Publications such as [9,114,115] describe how knowledge based models were used to perform diagnostics in technical systems. Knowledge based models remain an important field of research for maintenance purposes and three main topics were identified in the systematic literature review: rule-based models, case-based models and fuzzy knowledge-based models.

Rule-based models are knowledge-based models in which the knowledge is represented by rules in the format “IF-THEN”, allowing to perform an inference supposed to simulate a simplified reasoning mechanisms of human experts [112]. Rule-based systems consist of a knowledge base gathering all the rules, a fact base and an inference engine. The inference using rules is an iterative process. Initial “facts” are used as inputs. The inference engine compares these inputs with the set of rules contained in the knowledge base and produces conclusions as outputs. The inference engine uses these conclusions as new facts to be compared again with the set of rules so that new conclusions are obtained. This process is repeated depending on the inference engine design until the reasoning process comes to an end. Fig. 6 shows a simplified generic model of a rule-based system for diagnostics and prognostics.

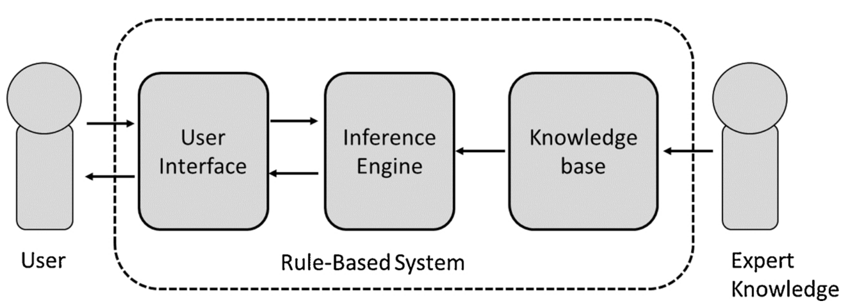

Fig. 6. Basic RBS inspired on [18].

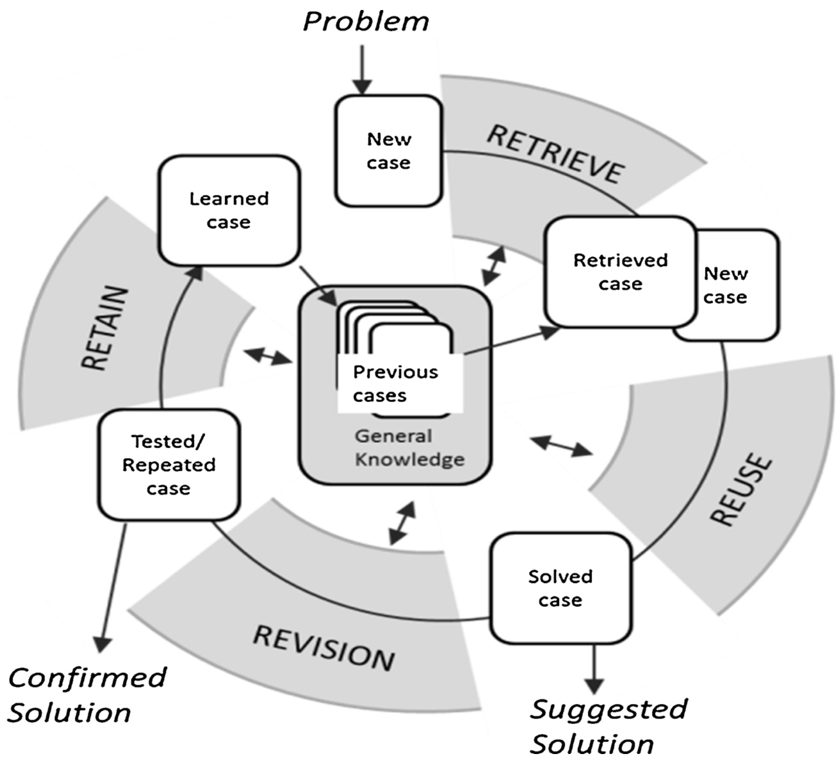

Fig. 7. The Case-based reasoning cycle [116].

Case-based models are knowledge-based models whose knowledge representation is through cases, obtained from previously experienced, concrete problem situations [116]. Cases are normally represented by a paired knowledge, like for example (problem, solution), in a case base. When facing a new problem, the most similar case is retrieved from the case base. Once a similar case has been identified, its "solution" is reused to adapt the solution for the new. There is a revision to confirm if the suggested solution solves the new problem. If the solution is confirmed, the new case can be retained as learnt knowledge in the case base. Fig. 7 shows the standard case-based reasoning cycle. Unlike rule-based reasoning, case-based reasoning can be used when the relations between facts cannot be declared explicitly [9]. A case is described by a set of attributes that could be numeric data and/or text-based data. Finding the relevant attributes to describe the cases is a difficult task when developing case-based systems.

Fuzzy knowledge-based models use basically the same format of rules IF-THEN as rule-based systems but the statements use intentionally fuzzy logic [110]. Unlike Boolean logic in which a proposition can only be true or false, in fuzzy logic there are intermediate values to describe the level of truth or falsehood of a statement [117]. Fuzzy logic is strongly related with human perceptions. Symbolic linguistic terms such as 'hot', 'cold', 'small', 'large', etc., are frequently used. This characteristic makes fuzzy logic an important tool for uncertainty management. Fuzzy logic can be also used in case-based reasoning and other data-driven models.

Knowledge-based models find limitations for prognostics as it is very difficult to obtain accurate knowledge for predictability purposes from experience. The identified examples in the current literature review are more related to diagnostic tasks and those which are intended for prognostics also include complementary models to estimate remaining useful life. Another drawback of knowledge-based models is the limited access to experts or knowledge sources to build the systems. Current trends in knowledge-based models use data mining techniques to extract the required knowledge from databases. [118,119] are examples for rules extraction while [22,120] aim at extracting cases from databases. One strong point of knowledge-based models forms the explicative results they offer [101]. It is possible to explain each reasoning step these models perform, it makes easier to justify their implementation against authority regulations for safety-critical systems, such as aircraft or nuclear power plants. Table 2 shows a summary of the identified applications of knowledge-based models in the current systematic literature review.

5.2. Data-driven models

Data-driven models have gained a lot of importance in recent years thanks to the improved availability of computational power and the production of large amounts of data coming every day from technical systems. Modern technical systems include an important number of operational parameters constantly measured and recorded. The resulting high volume of data can be used explicitly or implicitly for many purposes, including maintenance. Information obtained from data can be used to study the degradation of components, the current health state of the system or its remaining useful life. Fig. 8 shows an example of jet-engines degradation assessment based on trend analysis of measured data [7]. For the current survey, data-driven models are classified in three groups: statistical models, stochastic models and machine learning models.

One of the main challenges for data-driven models is the management of uncertainty coming from data [3,104,108,127]. Probability theory plays a vital role in data-driven models, as it is the most common way to manage uncertainty. Other studies use Dempster–Shafer models [31,40] (evidence theory), fuzzy logic [128] or possibility theory to manage data uncertainty.

5.2.1. Statistical models

Statistical models aim at analysing the behaviour of random variables based on recorded data. For predictive maintenance, statistical models are used to determine the current degradation and the expected remaining life of the technical systems. This is performed by comparing their current behaviour of measured random variables against known behaviours represented by series of data. Normalization and data cleaning are common preliminary tasks performed on data series to obtain the distribution function before the trend analysis. This prevents from outliers, constants, binary or any other variable that is not useful for degradation analysis.

For degradation analysis, the trend analysis of random variables is vital. The random variables must show a correlation with operational time or any other non-random variables that describe the lifecycle of the technical system. This correlation will show the evolution of degradation along the life cycle. For instance [129], used correlation to select the variables to describe the degradation on jet engines data. Covariance evaluations are frequently performed when the degradation is described by several variables [30]. Statistical models are also used for prognostics. Regression analysis will help to determine the relationship between the random variables and the life cycle of the technical systems so that a computation of future behaviours is possible.

Besides regression analysis there are two other statistical approaches that stand out: Autoregressive models and Bayesian models. Autoregressive-moving average models (ARMA) are statistical models for which a future value of a random variable is assumed to be a linear function of past observations and random errors [110]. ARMA models and their variants [50,130–133] are used to forecast future values of data series. Autoregressive-models have the advantage of simplicity in their computation. However, as they rely on statistical degradation trends, their accuracy could be affected when assessing new degradation trends where no previous information was available [3].

Bayesian models are those which apply Bayesian theorem [108], a statistical inference method to estimate conditional probability. It computes the probability of an hypothesis based on the prior (initial) probabilities of events that are related to the hypothesis [134]. Finding these prior probabilities poses the main problem for Bayesian theorem application. For predictive maintenance purposes, Bayesian models can be applied when data including anticipated failures with their corresponding symptoms and life expectancy is available [96,108]. Bayesian models play an important role on data-driven models for predictive maintenance, specially combined with other data-driven models to manage uncertainty [36,53,54,135]. Table 3 presents a summary of the applications of these two statistical approaches identified in this literature review.

Statistical models offer an important number of potential solutions to fulfil diagnostic and prognostic tasks. The main drawbacks of statistical models concern the need of enough previous data to build a reliable model and uncertainty management. For predictive maintenance systems, statistical models are often implemented in multi-model approaches.

5.2.2. *Stochastic models*

Stochastic models are probability models aiming at the study of the evolution of random variables over time [134]. The building blocks of stochastic models are stochastic processes. In the literature review, three main stochastic processes were identified for diagnostics and prognostics: Gaussian processes, Markov processes and Levy processes.

- A *Gaussian process* is a collection of random variables or any finite variable number of which have a joint Gaussian distribution [137]. Gaussian processes can be used for non-linear regression [138]. This property has motivated the use of Gaussian processes for diagnostics and prognostics in the maintenance field. According to [139] Gaussian processes are flexible models to work with small or large-dimensional datasets for prognostics purposes. However, it requires a high computational power to perform the predictive tasks.
- *Markov chains* are part of a bigger family of stochastic tools called Markov processes [140]. Markov chains suppose that given a process in its present state, the future depends on the present state independently of the past of the process. According to [110] the main shortcomings of Markov models for predictive maintenance are: 1) the need of large volume of data for training, 2) the impossibility to

Table 2
Summary of identified applications for knowledge-based models in this systematic literature review.

Model	References	Tasks	Case Studies	Complementary models
Rule-based models	[18,19,21,26,118,121,122]	Fault diagnostic, root cause analysis, RUL estimation (along with complementary techniques)	Power circuit breakers, overhead cranes, mining excavators, lubricant pipe abrasion, high voltage circuits, xenon lamps, oil pipe lines	Markov models, Grey theory, Bayesian model, data mining models.
Case-based models	[20,9,120,123,124]	Fault diagnostic, RUL estimation (limited number of applications)	Induction motors, power equipment, railway systems, simulated jet-engines data	Rule-based systems, data mining models.
Fuzzy knowledge-based models	[23,24,125,126]	Fault identification, uncertainty management	Grinding wheels, oil pumps, rolling bearings, simulated jet-engines data.	Data mining models.

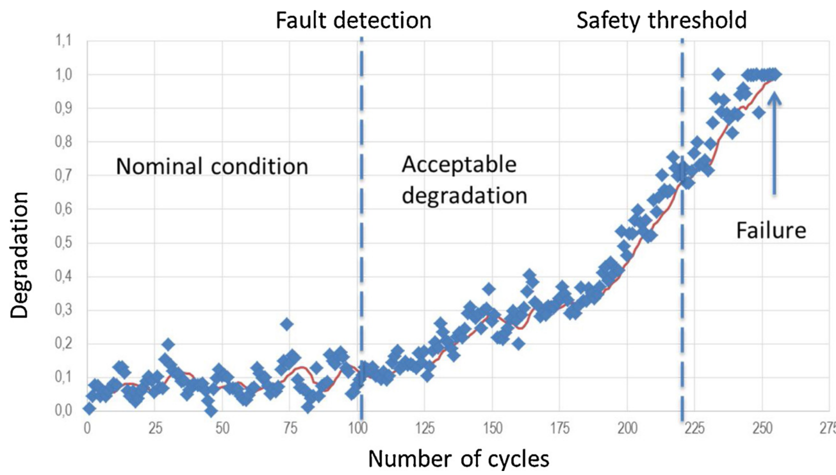

Fig. 8. An example of degradation analysis based on series of data [7].

model different degradation stages, and 3) the impossibility to model unanticipated failures or faults. As these models cannot be used to model different degradation stages, they are not suitable for reparable components that have been partially restored. It should be noted that the model complexity increases when the degradation does not follow an exponential trend [3].

- Lévy *processes* are stochastic processes within the family of Markov processes [141]. These processes represent the motion of random variables whose displacements are independent and stationary within time intervals of the same length [142]. Weiner processes, Gamma processes and Poisson processes belong to the category of Lévy processes used for predictive maintenance. Extensive reviews in Lévy processes for predictive maintenance can be found in [59,60]. Lévy share the general limitations of Markov processes. In prognostics, Lévy processes are bound to monotonic degradation processes [3,110].

Table 4 presents a summary of the stochastic models addressed in this literature review. It can be seen that this type of models is more suitable for degradation modelling and RUL estimation because of their regression capabilities. These models have many drawbacks in common, such as for example high computational power requirements, advanced mathematical knowledge to be implemented and uncertainty management. Complementary techniques or models are often used along stochastic models.

5.2.3. Machine learning models

Machine learning is a branch of artificial intelligence [96] that uses specialized learning algorithms to build models from data. These models are capable of dealing with and capturing complex relationships among data, difficult to obtain using physics-based, statistical or stochastic models. One key point of machine learning models is their learning process and depends on the application, goal and the available data for the system [146].

- *Supervised learning* is preferred when the expected outcomes of the model and data under study are known. Its training is an iterative process assessing the output error against the expected one. The training finishes when an “acceptable” level of error is reached.
- *Unsupervised learning* is used when no preliminary outcomes are known. No error levels are measured to assess or to end the training process. These algorithms use other criteria to end the training process, such the number of training iterations or the progress of a convergence indicator over time [147]. Clustering is an example of tasks performed by unsupervised learning algorithms.
- *Reinforcement learning* aims to train a model by experience instead of examples [148]. The model “interacts” with an environment and receives a “reward” depending on the interaction. This reward is linked to a performance indicator that the learning algorithm tries to optimize. The final outcomes of the learning are not known.

Within the identified machine learning models for predictive maintenance applications, artificial neural networks are computational models inspired by biological neural networks in an attempt to mimic their unique processing capabilities [149]. They consist of elementary units called “neurons”, usually represented graphically as nodes in a graph. Neurons are processing units which receive several inputs and produce one or multiple outputs that may be the input for other neurons. A neuron’s output is equal to the weighted sum of its inputs values by means of an activation function. The learning process of the neural network aims at choosing and adjusting the weights of the neurons’ inputs. Neurons are organized into layers. These layers can be organized in different configurations (architectures). For predictive maintenance the most used configurations are multi-layer perceptron neural networks, recurrent neural networks (including long-short term memory neural networks), convolutional neural networks, self-organizing maps and support vector machines with different variants. An extensive explanation of these models can be found in the reviews [3] and [4].

The learning process used to train the neural-network will depend on its architecture and the available data, information or knowledge for training. As [99] suggests, artificial neural networks do not need in-depth knowledge of dysfunctions of the technical system which makes artificial neural networks a strong tool to get implicit knowledge from the data.

Table 5 summarizes some applications of machine learning models identified in this literature review. Opposite to other predictive maintenance models, machine learning approaches might not include all the functional blocks F3, F4 and F5 mentioned in Section 2 (see Fig. 2). Some neural network applications with several internal layers of neurons (Deep Learning) aim at letting the algorithm learn from raw data to obtain directly the desired outcome, whether it is diagnostic or prognostic. Even when good results are already obtained, a comprehensive explanation of the trained algorithm behaviour is even more difficult to be justified against regulations on safety-critical systems, such as aircraft or nuclear power plants. Once the model has been trained, it is difficult to explain how it works, what is reasoning behind in the model. Explaining the reasoning inside a trained machine learning model is a promising opportunity of research for the coming years. Even when publications are found in this area (e.g. [150]), they do not cover predictive maintenance applications.

Table 3
Summary of identified applications of statistical models in predictive maintenance.

Model	References	Tasks	Case Studies	Complementary models
Regression analysis	[34,38,39,76,129,136,75]	RUL estimation, fault diagnostics, health assessment	Power transformer, electric cooling fan, simulated jet engine data, air compressor, aluminium plates, lithium-ion batteries, bearings	Other statistical models, physics-based models
ARMA	[50,131–133]	RUL estimation	Bearings, aircraft generators, structural damage, semiconductors switches	Other statistical models, Neural Networks
Bayesian models	[36,41,53,135,33]	Stochastic degradation parameter identification and update. Fault diagnostics	Laser machines, sensors, high power circuits, circuit boards.	Stochastic models, other statistical models, Monte-Carlo simulation.

Table 4
Summary of identified studies applying stochastic models for predictive maintenance.

Model	References	Task	Case Study	Complementary models
Gaussian Process	[77,143]	Fault diagnostics, RUL prediction	Wind Turbines, slow speed bearings	For signal processing
Markov Chains and Hidden Markov chains	[36,52,56,57,122,144]	Produce stationary distribution for RUL computation, Degradation simulation	Milling machines, simulated jet-engine data, semiconductor manufacturer machine, continuous stirred tank reactor, asphalt roads	Bayesian model, genetic algorithm, belief rule-based model, Monte Carlo.
Levy process	[43,58,145]	RUL computation, Degradation Modelling	Simulated jet-engine data, high-power white LEDs, automotive engine cranking	Proportional hazard model, combination of different stochastic models

Table 5
Summary of identified applications for machine learning models.

Model	Reference	Task	Learning process	Case Study	Complementary models
MLP	[44,45,63,64]	Fault identification	Supervised	Wind turbine gear boxes, combustion engines, nuclear power plants, rotary machines	Signal processing models, radial basis function network, multiple NN
RNN	[148,46,47,66,74]	Fault diagnostic, RUL estimation	Supervised, reinforcement	Gear boxes, jet engines, mill fans, rolling bearings	Different NN
CNN	[67,73,79,80]	Fault diagnostics, RUL estimation	Supervised	Jet engines, gear boxes, bearings.	Statistical models, Extreme learning machine, autoencoder
SOM	[2,32,68,94,127],	Degradation modelling, fault detection	Unsupervised	Jet Engines, Cyber-physical systems, railway point machines	Statistical models
SVM, SVR	[34,37,70–72,81,151]	Health assessment, fault detection, prognostics	Supervised, Unsupervised	Battery cells, metal-mechanics equipment, electrical equipment, chemical industry, chillers, Tennessee Eastman process, industrial simulated data	Statistical models, RNN (LSTM)

NN: Neural Network. MLP: Multi-layer Perceptron. RNN: Recurrent Neural Network. CNN: Convolutional Neural Network. SOM: Self-Organizing Maps. SVM: Support Vector Machines. SVR: Support Vector Regression. LSTM: Long-short memory Neural Network.

5.3. Physics-based models

Physics-based models use the laws of physics to assess the degradation of components. They demand high skills on mathematics and physics of the phenomena for the application. This kind of mathematical model remains an important topic of research with interest for many disciplines. With an accurate model of the physical behaviour of a system it is possible to perform accurate simulations to study the degradation behaviour on a specific component or a system. Within the identified studies of physics-based models there are fatigue and crack propagation models for mechanical and structural components [102,152]. With the computational power rising over the last decades, the use of finite element methods has increased for damage propagation and failure prediction, some identified examples are [83] on a rotor cage and [85] on solenoid valves. Other physics based model have been used to study the tube erosion of boiler head exchangers [86], clogging prognostics on filters of fluids [82], degradation evaluation of industrial robots [84] and remaining useful life estimation on lithium-ion batteries [76]. Physics-based models offer a possibility to study and assess degradation by means of computational simulations. However, many physics phenomena cannot yet be accurately described. The outcomes of a physics-based model will be as good as the “accuracy” or “completeness” of the model. The operational context of a technical system affects its performance. External influence such as temperature, pressure or any other environmental conditions might drastically change the expected operational parameters and the actual behaviour. Incorporating external influence data is a challenge already mentioned by other studies such as [108,153]. These may be solved by adding complementary models (potentially other physics-based model).

6. Multi-model approaches for predictive maintenance

Single-model approaches hardly address all the diagnostics and prognostics tasks of complex systems; the consulted studies with single-model approaches often proposed complementary models to overcome the weak points of some models. It is increasingly common to find research studies that combine different models in multi-model approaches to overcome complexity of predictive maintenance tasks. Increasing complexity includes the number potential faults and failure modes of the technical system, the type and number of information and/or data sources obtained from it and the number of diagnostics and prognostics tasks that are targeted, all these apart from the design complexity of the selected model. Most of the consulted studies had limited case studies with only few failure modes (sometimes only one) which poses a challenge to extrapolate single-model approaches to real complex systems applications [98,103]. Identified studies that had more complex case studies usually applied multiple models to fulfil the predictive maintenance system tasks.

However, even when the consulted studies in this section usually had simple and limited case studies, multiple models were often involved. As explained in Section 2, predictive maintenance systems include different functional blocks depending on their initial requirements and the complexity of the available knowledge, data and/or information for the implementation. A multi-model approach is often implemented to fulfil all functional blocks for the predictive tasks (except for some deep learning approaches, see Section 5.3).

A related term to multi-model approaches is “hybrid model”. Hybrid models are usually presented as the fourth classification of model types along with knowledge-based, data-driven and physics-based. However, there exist many multi-model approaches which cannot be named as hybrid. The definition of a hybrid model evolves over the different consulted publications. After a careful analysis this literature review suggests that hybrid models are part of multi-model approaches in which two or more models are combined to fulfil one single functional block (F3, F4 or F5 in Fig. 2, see Section 2) of the predictive maintenance systems and there is mutual cooperation among the combined

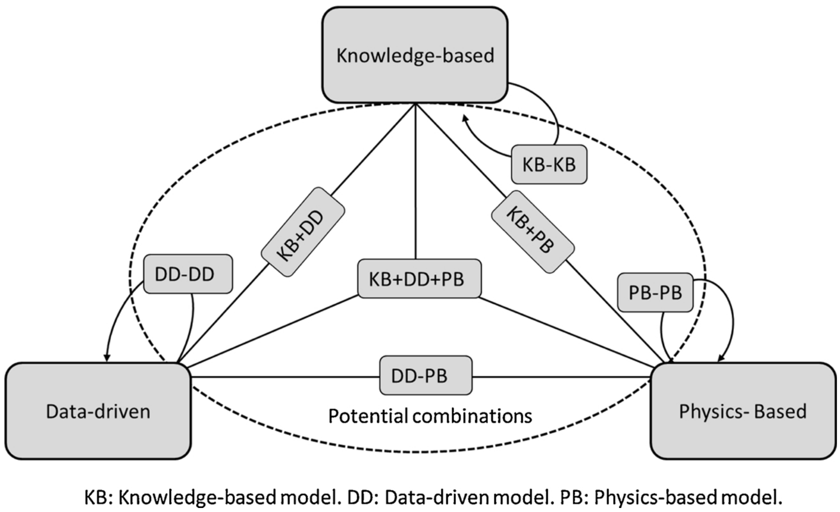

Fig. 9. Potential combinations for multi-model approaches.

models to obtain their outputs.

An introduction to the notion of different types of multi-model approaches (under the name of hybrid models) can be found in [154]. The authors classified them into 5 groups: knowledge-based models combined with data-driven models, knowledge-based models combined with physics-based models, combination of multiple data-driven models, data-driven models combined with physics-based models, and a combination of one models of each type. However, multi-model approaches can also include two more categories not mentioned in their proposed hybrid model taxonomy: combination of multiple knowledge-based models and combination of multiple physics based models. Fig. 9 presents a diagram of the potential combinations of multi-model approaches for predictive maintenance purposes.

6.1. Configurations for multi-model approaches

Before presenting the findings on the different model combinations and expand on the potential opportunities for future research in multi-model approaches, it is important to explain how they could be combined from a systems architecture point of view. There are many possible combinations, however, there are three basic configurations on top of which more complex architectures can be built: models working in series, models working in parallel, a model working as a subpart of another model (embedded model), see Fig. 10. These configurations explain the flow of information, data or knowledge through the predictive maintenance system. When architecting new predictive maintenance systems, it is important to consider the potential configurations in order to find the "best" solutions to fulfil the requirements for the system.

Two models are *in series* when the output of a first model is the input for a second one. The functional blocks presented in Section 2 present intuitively a configuration in series where a single model is used to fulfil each functional block. For example [147] presents a series configuration of SOM along with a statistics model using probability density function to address the functional blocks of degradation modelling and fault detection. Nevertheless, as complexity in the information or data increases, two complementary models could be used in series to fulfil a single functional block. Multi-model approaches using a series configuration are not usually referred to as hybrid, even when combined models are used to fulfil one single functional block; there is no mutual cooperation among the models to obtain the outputs.

Two models are *in parallel* when they process their input simultaneously and their outputs are combined in a single one. It is important to point out that the input could be the same for both models working in parallel or they could have different but related inputs. For example, given a technical system, one model could address text-based data (from operational or maintenance logs), while another could address measured data from sensors. Paper [2] gives a good example of a multi-model approach in parallel, with a data-driven model to address all the data coming from the technical system along with a physics-based model for RUL computation for bogie components. Two parallel models fulfilling one single functional block are usually referred as a hybrid model as there is mutual cooperation between the models to obtain the final result.

For the *embedded* configuration a model is incorporated as a subpart of another one. [155] presents for example a neuro-fuzzy model including a hidden Markov model as part of its internal functioning. Actually, neuro-fuzzy models could be seen as an example of a model embedding another one. They implement a fuzzy inference system within a neural-network architecture. Some identified applications of neuro-fuzzy models in the current survey are degradation prognostics on bearings [90] and fault diagnostics on railways track circuits [156]. Paper [94] combines a Kalman filter embedded an online sequential extreme learning machine (OS-ELM) for remaining useful life

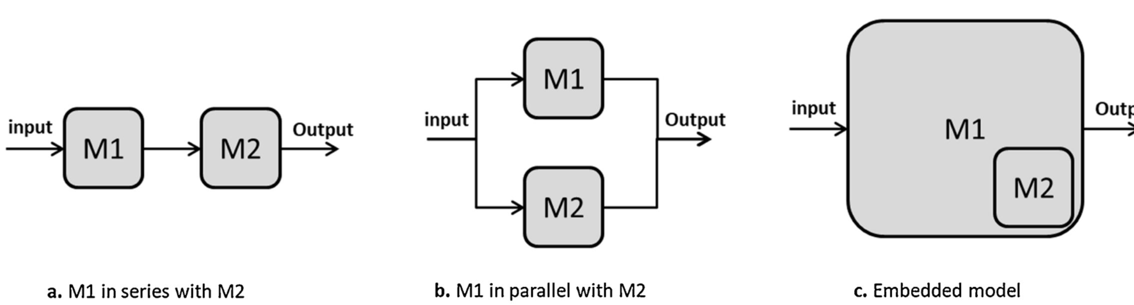

Fig. 10. Generic basic configurations for multi-model approaches.

estimation, and refer to it as KFOS-ELM. Another example for embedded models could be a case-based reasoning system embedding a rule-based system for one or more tasks of the case-based reasoning cycle as proposed by [157]. Multiple models in embedded configuration are usually referred as a hybrid model.

The configurations shown in Fig. 10 could include more than two models and could be combined among them. This means that one can propose for example a set of many parallel models (more than two) followed by another model to combine their result, which is what paper [69] proposes for fault diagnostics on aircraft turbojet engines. They present nine data-driven models in parallel and in the end, the outputs where assessed and combined with a knowledge based model. Having a clear idea of the basic configurations and their potential combinations allows expending the creativity process at architecting new predictive maintenance systems.

6.2. Combinations for multi-model approaches

This section summarizes the survey findings on the different combinations for multi-model approaches presented in Fig. 10. The explanation of the identified examples for each combination includes the architecture configuration used to combine the different models, and which functional blocks of predictive maintenance system they are covering.

6.2.1. Multiples knowledge-based models

This type of multi-model approaches has not been widely used in recent research on predictive maintenance applications. A multi-model approach using only knowledge-based models keeps the same challenges as for single-model approaches and besides, it has an additional difficulty component at designing the combination of multiple models. Nevertheless, the combination of multiple knowledge-based models allows addressing complex diagnostics tasks while explaining the reasoning. The authors of [158] present a case-based system combined with a rule-based system for problem diagnostic in IT services, the rule-based system is embedded in reuse phase of the case-based system. A comprehensive review of case-based, reasoning systems combined with other knowledge-based models can be seen in [157].

6.2.2. Multiple data-driven models

This approach combines several data-driven models to perform either diagnostics or prognostics. Neural networks are the most used data-driven models to build this kind of multi-model approaches because of the current trends in machine learning and deep-learning research that aim at incorporating more autonomous and intelligent systems. However, as mention in Section 5.2.3 these models still face problems as their results remain non-explicative [101]. Within the examples found in this literature review [159], presents a multi-layer perceptron and a radial basis function neural network in a parallel model to estimate the remaining useful life from input sensors on simulated jet-engines data [160]. performs fault prognostic with a mixture of Gaussian hidden Markov model (stochastic model) to evaluate the health index and fixed size least squares support vector regression (statistical model) for remaining useful life estimation on the same jet-engines simulated data. A more recent article [91] suggests a hybrid deep learning neural network for RUL estimation on the simulated jet-engines data. The authors propose a parallel analysis of the input data by a convolutional neural network and a long-short term neural network. The fusion of the results is done by three layers of neurons with different activation functions. Some of the presented examples show that the combination of data-driven models gives more accurate results compared to single-model approaches for the same tasks.

6.2.3. Multiple physics-based models

Multiple physics-based models can be used to increase the accuracy of a more general model. The precision usually brought by the laws of physics embedded in a mathematical model may indeed allow improving the accuracy of diagnostics and prognostics estimations. Most of the identified applications of multiple physics-based model approaches present a series configuration. Initially, a model is used to assess the health state of the technical system (diagnostics), then, another model for remaining useful life estimation (prognostics) [161] mixes physics based models (crack and fatigue models) for helicopter gear prognostics [162] applied a physic-based model to predict the machine condition (i.e. diagnostic), complemented by Forman crack growth remaining useful life estimation in a series configuration [163]. presents an example of multiple physics-based models in parallel configuration. The multiple Kalman filter models are used for single fault detection in jet-engines using temperature, pressure and rotation speed as parameters. The use of multiple physical based models is not widespread. Their implementation requires high skills in mathematics, physics and a large knowledge of the technical system under study, making their implementation difficult. However, they offer a large set of opportunities to obtain accurate and explicative results in the predictive maintenance domain. Several commercial solutions for finite-element analysis include multi-physics models working in parallel to improve the accuracy of the technical system model. Such solutions are widely used for structures and fluid dynamics modelling and simulations [83,85].

6.2.4. Knowledge-based models with data-driven models

This multi-model approach has allowed taking advantage of the strong points of both model types. Knowledge-based models could incorporate valuable information from human experts to complement the results of data-driven models for diagnostics or prognostics tasks. For example [87], presents a combination of a fuzzy knowledge-based model and Markov chain for degradation prognostics in aero-engines. The already mentioned neuro-fuzzy systems are other examples of fuzzy logic combined with a data-driven model [90,156,69]. presents a rule-based system to summarize and combine the diagnostics coming from multiple neural networks assessing the same aero- engines data base. Knowledge-based combined with data-driven models offer a vast field of opportunities to innovate at architecting new predictive maintenance systems, allowing analyzing more complex and heterogeneous data coming not only from sensors but also from declared data obtained from the technical system operators or extracted from large databases [118,119] by means of data-mining techniques. This declared data, normally assessed by knowledge base systems may reduce the uncertainty in data-driven models. One example of this is presented in [2] on a train suspension case study.

6.2.5. Knowledge-based models with physics-based models

These models use the experts' knowledge to improve the accuracy of physics-based models. The number of studies related to this approach is limited for predictive maintenance applications as this combination gathers the main drawbacks from both model types: difficulty to gather the experts' semantic knowledge and high mathematics complexity to develop physics-based models. However, a strong point of this model combination is the high explicative results they may offer. Within the identified studies [164], combines a fuzzy knowledge-based system with a physics based model for different prognostics tasks on mechanical parts. Potential unexplored applications could include hybrid parallel models using knowledge-based systems to address the declared knowledge by the technical system user, combined with a physics-based model to model its degradation. Another application option could be this multi-model approach to incorporate external influence data to predictive maintenance models. External factors affect directly the performance of technical systems and so their degradation. It is a challenging unexplored field that could offer many interesting solutions in the maintenance field.

6.2.6. Data-driven models with physics-based models

This multi-model approach is the most common in recent research because of the increasing popularity of data-driven models and their complementarity with physics-based models for degradation modelling. Within the possible combinations of data-driven and physics-based models, three main combinations were identified for predictive maintenance applications:

- Statistic models with physics-based models such as [165] uses a physics-based model to build a health index that is later analysed by a support vector-machine to estimate the health state of the system, fitted with an exponential regression. A similarity-based approach is finally used to compute the remaining useful life.
- Stochastic models with physics-based models, such as [145] that uses a stochastic process (Wiener process) combined with a data analysis method (Principal Component Analysis) to model the deterioration of the components that is fitted by an exponential physical degradation, and to estimate the remaining useful life on a case study [92]. presents a more recent example of this type of combination. It uses a physics-based model along with hidden Markov chains and particle filter model for RUL computation of railway tracks.
- Neural network models with physics-based models, such as [166] that use a multi-layer network to generate the system health state, then a physical degradation model of exponential type is used to evaluate the remaining useful life. [167] presents a regression vector machine (which is already a combination of two data-driven models) along with a physics based model to predict the remaining useful life of aluminium plates under fatigue stresses. This is not precisely predictive maintenance but the predictability approach can be extended to other mechanical components.

6.2.7. Knowledge- based models with data-driven models and physics-based models

This approach combines at least one of each model type. It benefits from the strengths of every model type, the explicability from knowledge-based models, and physics-based models and the ability to analyse past data to gather additional important information. As an illustration [168], combines a physics based models with a support-vector machine to obtain an analytical health index of rolling bearings, the results combination is performed by a fuzzy rule-based system [169]. proposes the combination of the three model types to address the diagnostics and prognostics of rolling bearing, it presented the models to address different but complementary input data. The number of studies in predictive maintenance combining the three model types remains limited, based on the literature findings. As [2,154] state, this combination could be extremely difficult. The implementation of a multi-model approach combining knowledge-based, data-driven and physics-based models not only represents the individual complexity of each model type but also includes the complexity at architecting the whole system and fusing the outputs of each model.

6.3. Some general observations on multi-model approaches

The development of multi-model approaches of any type of the mentioned combinations face particular challenges. Besides the difficulty to develop the individual models composing the multi-model approach, their combination poses additional challenges. The lack of systematic approach for designing predictive maintenance systems is an important challenge [108,170]. However, multi-model approaches present a vast field of opportunities in research for the coming years. The number of unexplored alternative combinations remains huge. These multi-model approaches may help incorporating external influence data, semantic knowledge from experts, and the laws of physics governing the degradation of components or systems to manage uncertainty and improve the accuracy in diagnostics and prognostics. Also, combining different models may give the opportunity to extrapolate diagnostics and prognostics approaches (today focused on single failure mode applications) to complex systems that include many components with many failure modes.

7. Summary of the identified challenges and research opportunities

This systematic literature review allowed the study of the different models, the different approaches to implement them, their benefits, drawbacks and challenges for diagnostics and prognostics in predictive maintenance. This section summarizes the most relevant challenges for diagnostics and prognostics identified in the literature review.

- *The extrapolation of existing solutions to complex system applications, including multiple components, and their associated faults* [98,103]. Most of the identified applications were focused on a single component with a limited number of faults. However, real-life applications are frequently complex systems composed of many components and many faults associated to each component and to the system itself. Multi-model approaches offer a potential solution to overcome complexity in predictive maintenance systems. As [171] states, complexity can be reduced by functional decomposition and later each function can be addressed individually. As explained in Section 2, a predictive maintenance system could have several functional blocks for each component and/or failure mode in a complex system. It is necessary at least one model to fulfil each functional block for each component and failure mode. However, the implementation of these models is not trivial and adds another complexity factor for the model combination.
- *The lack of a systematic approach to design and develop predictive maintenance systems* [108,170]. There exist standards, norms and generic architectures to develop new predictive maintenance systems, such as OSA-CBM [15]. However, they only focus on the basic functional components of the system and do not cover important aspects regarding performance indicators or context constraints of the technical system. Besides, they do not offer yet a consistent explanation on which models to use depending on the initial needs of the predictive maintenance system. The lack of a systematic approach limits the implementation of predictive maintenance systems on real scale industrial applications. When developing a new predictive maintenance system the number of potential models to solve the problem is too high. For engineers the simple fact of choosing the right model or a reduced set of models remains a challenging task. It turns out to be very difficult to perform an objective selection of models as there are not enough comparative studies of the use of different models on the same tasks for predictive maintenance systems. None of the consulted publications in this survey gives extensive explanations for the selection of the proposed method and the architecture methodologies to create a concept of the system varies from one study to another. Besides, many studies do not present detailed design parameters for their proposed models, or the case study data is not available. All these aspects make it difficult to reproduce results and even more difficult to retrieve models from previous studies for use in new predictive maintenance systems. There are no clear guidelines for selecting the right model or models for a specific task given the operational modes and available data to perform diagnostics and prognostics.
- *The fusion of large and different sources of condition monitoring data* [3,153]. This challenge is related to the extrapolation of current models in predictive maintenance to complex technical systems. Technical systems may have different types of data sources, for example sensor measurements, maintenance logs, operational logs, design documents, etc. Important knowledge could be gathered from all these sources to implement new predictive maintenance systems. However, the heterogeneity of these data sources makes

knowledge modelling and fusion a difficult task for predictive maintenance purposes. Today, the main part of studies uses time series to perform diagnostics and prognostics and important information coming from text-based data is frequently ignored [17]. Text-based data is difficult to analyse when it is not in a structured form. Current trends in maintenance aim at analysing natural text log to extract information that can be used to improve maintenance tasks. Different models are needed to address text-based data while others address measured data from sensors. Multi-model approaches can be used to fuse heterogeneous data sources.
- *The incorporation of external influence data* [108,153]. Systems operation may differ depending on their operational context. Changes in the operational context may affect directly the performance of the technical system and consequently the readings on the health monitoring. It may trigger false alarms suggesting fault existence, or it may prevent existing fault identification. This could be addressed by complementary models able to incorporate the external influence for predictive maintenance purposes.
- *Uncertainty management* [3,104,108,127]. Uncertainty affects directly the accuracy of the diagnostics and prognostics. It can be due to the collected data or to imperfections of the model used for the analysis. It may affect the trustworthiness of the results. Uncertainty management is vital for critical systems subject to authorities' regulations. This is the case for critical systems like nuclear power plants and aircrafts on which the regulations are restrictive to keep safety standards and avoid catastrophic events. Probability theory, Dempster–Shafer theory and fuzzy logic have been the most common techniques used to manage uncertainty observed in the systematic literature review. Multi-model approaches may be a solution to address uncertainty in complex systems.

8. Conclusion

This systematic literature review performed on predictive maintenance shows that its importance in research has been increasing dramatically over the last 25 years. The search was performed initially using three related terms: "Predictive Maintenance", "Condition Based Maintenance" and "Prognostics and Health Management". Different contributions were found under the different terms but referring to the same activities. Considering all the terms helped to have a wider overview on the current trends used for diagnostics and prognostics in the maintenance field. The survey allowed to answer research question 1 by identifying two main approaches for model implementation: single model approach and multi-model approach. The current trends lead towards the use of multi-model approaches as one single model is not able to cover all necessary functional blocks in a predictive maintenance system.

Deepening in both approaches, the survey allowed to answer research question 2. The identified models for single-model approaches can be clustered in knowledge-based models, data-driven models and physics-based models. A brief explanation of the most single models used in recent research was presented in Section 5. It is a complementary point of view to other recent reviews that already covered single model approaches. Most of the consulted papers already used complementary models but they are not presented as multi-model approaches. For multi-model approaches, seven different combinations considering the model type were identified: knowledge-based models combined with data-driven models, knowledge-based models combined with physics-based models, data-driven models combined with physics-based models, combination of multiple data-driven models, combination of multiple knowledge-based models, combination of multiple physics-based models, and the combination of one model from each model type. Some of these combinations have not been widely explored in predictive maintenance applications. Besides, three basic configurations are presented to perform the combination of models: in series, in parallel and embedded. Out of these basic configurations more complex architectures can be conceived. Depending on the configuration and the task to fulfil, multi-model approaches can be named hybrid models; however, not all multi-model approaches are hybrid models. There must be mutual cooperation among the models to be a true hybrid model.

To answer the research question 3, the identified challenges are the extrapolation of current solutions on diagnostics and prognostics to complex systems, the lack of a systematic approach for predictive maintenance system design, fusion of different types of data sources, incorporation of external influence data and uncertainty management. These challenges open a branch of opportunities for future research in the topic.

Declaration of Competing Interest

Juan José Montero Jiménez, Sébastien Schwartz, Rob Vingerhoeds, Bernard Grabot and Michel Salaün declare that they do not have conflict of interests.

Appendix A. Systematic literature review process

The methodology used in this paper concerns a systematic literature review methodology that aims at summarizing the existing work of a specific topic [5]. Systematic literature reviews help to carry out the literature review process in a structured manner to ensure impartial results and thus a better overview of the subject under study [5]. stresses the importance of a well-structured protocol to carry out the systematic literature review. This protocol spans from the planning of the review until its reporting. For the work presented here, the protocol consists of four steps: research questions definition, search strategy, study selection, and data synthesis. The protocol is summarized in Fig. A1.

Research questions

The systematic literature review starts by defining the Research Questions (RQ) that drive the review process to define the state of the art of a specific topic and identify the opportunities for future research, setting the boundaries for the search. As the goal of the survey is an update of models or techniques used for diagnostics and prognostics for predictive maintenance, the research questions were chosen as follow:

- RQ1: What are the current trends in diagnostics and prognostics for predictive maintenance?
- RQ2: What kinds of models, techniques or methods are used to address diagnosis and prognosis in predictive maintenance?
- RQ3: What are the current challenges facing predictive maintenance in diagnostics and prognostics?

Search strategy

In the search strategy phase, the search terms and resources are selected, as well as the time lapse to be covered by the search. For predictive maintenance, the strategy divides the search into two steps, and both of them considered the last 25 years as time lapse. Older papers were consulted

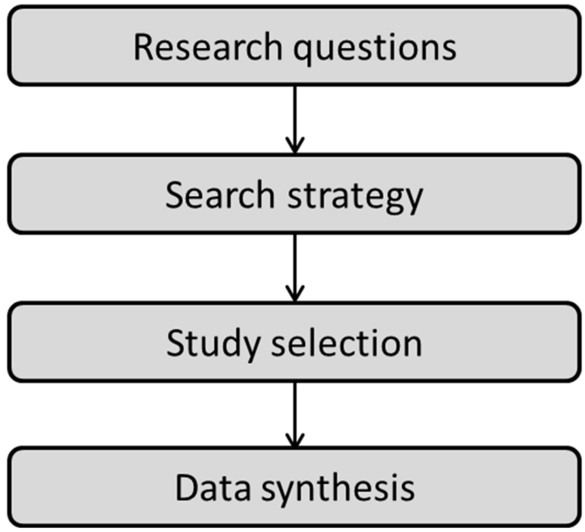

Fig. A1. Systematic literature review protocol [5].

to identify when exactly some of the terms started to be used. Four search sources were selected: IEEE Xplore, ScienceDirect, Springer and Web of Science.

The first search step focuses on existing literature reviews on predictive maintenance to check if any of them answer to the proposed research questions. To do so, the following search terms pattern have been used: ("Predictive" OR "Prognosis" OR "Diagnosis" OR "Prognostics" OR "Diagnostics") AND ("Maintenance" OR "Condition-based" OR "Health Management") AND ("Survey" OR "Review" OR "Benchmark"). This leads to search "Predictive Maintenance Survey" or "Diagnostics Maintenance Benchmark" for example. Since many terms used for predictive maintenance are also present in medical research, a refinement on the search is done by discarding all papers and journals on human medicine and diseases. The search on previous literature reviews topics helped to study the evolution of the topic over the last 14 year since the first review was published in 2006 [104]. It was possible to identify some research opportunities that were used to perform the second research step.

The second search step is based on trial searches using terms derived from the identified models in the first search step. The search terms have been refined for this search step. The following terms pattern have been used: ("Predictive" OR "Prognostics" OR "Diagnostics" OR) AND ("Maintenance" OR "Condition-based" OR "Health monitoring") AND ("Data-driven" OR "Physics-based" OR "Knowledge-based" OR "Hybrid" OR "Multi-model). The terms "diagnosis" and "prognosis" were not used in this second search step as there were no differences when using "diagnostics" and "prognostics" in the first search step.

Study selection

The search considers publications from four different search sources. The types of publications could be from journals articles, conference proceedings, workshops, symposiums, bulletins or book chapters. For the scrutiny of relevant publications, a first analysis through the titles is performed. The search was limited to publications in the English language. If a publication appeared in more than one search list, it was considered only once. All publications out of the scope of the research questions were discarded such as publications regarding maintenance scheduling optimization, maintenance management, corrective maintenance, scheduled maintenance, signal processing, and requirements elicitation for maintenance systems. Some publications turned out to be extensions of previous published works. In such cases, only the most recent and complete were considered. The references of these identified publications were consulted to identify relevant studies missed in the search process. In the end, 187 relevant publications were found, from which 23 are previous reviews and 164 correspond to the second search step.

After the scrutiny, a quality assessment of the publications took place to consider only the most relevant publications. For the first research step, all identified reviews were kept. For the second research step, four characteristics were assessed for the quality assessment: the clearness of research objectives, the explanation of proposed model to fulfil a specific task, the case study explanation, and the comparison to other models or approaches.

The consulted studies were ranked with points. For each study, each characteristic is ranked with one out three possible values: 0, 0.5 and 1. The max score for a publication is 4 points. For this review, publications with a score higher than 3 points were kept. This process narrowed down the number of publications from 187 to 158; from which 23 are previous reviews and 135 correspond to the second search step. An important reason to discard certain papers was the absence of sufficient explanation of the case study and/ comparisons with other existing models to fulfil the same tasks.

The current paper includes 175 references, 158 are from the structured literature review and 17 of them are for theoretical background of some models. These background references were not identified in the systematic literature review.

Appendix B. Summary of previous reviews

Year	Author	REF.	Single model approach			Multi-model approach
			Physics-based	Data-driven	Knowledge based	
2006	Jardine et al.	[104]	Physics of failure	Statistical models, AI models (FFNN, CCNN)	Experts systems, Fuzzy Logic	No

2006	Kothamasu et al.	[6]	N/A	Statistics and Stochastic models. Bayesian models and Markov models	Rule-based systems and Fuzzy logic	No
2007	Vachtsevanos et al.	[102]	FEM, Physics of failure	ANN, stochastic and statistics	Expert systems	Yes
2009	Dragomir et al.	[109]	Physics of failure	AI techniques, ANN, NFL, Bayesian, Markov models	N/A	
2009	Liu et al.	[113]	N/A	HMM, ANN,	Experts systems, Fuzzy Logic	No
2010	Peng et al.	[172]	First principle modeling.	ANN, state space model, hazard rate, proportional hazard rate, gray model	Experts systems, Fuzzy Logic	Yes
2011	Sikorska et al.	[110]	Physics of failure	Statistical models, stochastic models, ANN	Experts systems, Fuzzy Logic	Yes
2012	Prajapati et al.	[10]	N/A	Statistics, stochastic, artificial intelligence	Expert systems	Yes
2014	Okoh et all	[111]	Physics of failure	Statistics and Stochastic.	Experts systems	Yes
2014	Liao and Köttig	[154]	In hybrid models	In hybrid models	In hybrid models	Yes
2015	An et al.	[106]	Physics of failure	Neural Networks, Gaussian process regression	Out of scope	Yes
2015	Bailey et al.	[173]	Physics of failure	Statistical, Machine learning.	Out of scope	Yes
2015	Schmidt and Wang	[108]	Physics of failure	Stochastic, Statistic, ANN (Bayesian)	Experts systems	Yes
2016	Elattar et al.	[174]	Physics of failure	Probabilistic models, machine learning	Reliability-models	Yes
2016	Vanraj et al.	[175]	FEM	ANN with BPN, SOM	N/A	No
2017	Alaswad and Xiang	[98]	N/A	Markov, Gamma process, Gaussian, among others.	N/A	No
2017	Javed et al.	[96]	Physics of failure	Machine learning, ANN, Bayesian, MC, NFL, CBR.	Included in the data-driven models.	Yes
2017	Wang et al.	[105]	Physics of failure	Statistical models, machine learning	N/A	No
2017	Atamuradov et al.	[2]	Paris' Law, Forman Law, Others	ARIMA, Gaussian models, ANN, Bayesian Network	Experts systems, Fuzzy Logic	Yes
2018	Lei et al.	[3]	Physics of failure	Statistics, Stochastic, ANN, SVM/RVM	N/A	Yes
2018	Sakib and Wuest	[97]	N/A	MC Bayesian, MC, Machine learning, Monte Carlo.	N/A	No
2019	Zhang and Yang	[4]	N/A	ANN, DNN, Logistic regression, SVM, Random Forest, auto-encoder.	N/A	No

References

[1] Sullivan GP, Pugh R, Melendez AP, Hunt WD. Operations & maintenance best practices: a guide to achieving operational efficiency. U S Dep Energy, Fed Energy Manag Progr. 2010. https://doi.org/10.2172/1034595.

[2] Atamuradov V, Medjaher K, Dersin P, Lamoureux B, Zerhouni N. Prognostics and health management for maintenance practitioners - review, implementation and tools evaluation. Int J Progn Heal Manag 2017.

[3] Lei Y, Li N, Guo L, Li N, Yan T, et al. Machinery health prognostics: a systematic review from data acquisition to RUL prediction. Mech Syst Signal Process 2018;104:799–834. https://doi.org/10.1016/j.ymssp.2017.11.016.

[4] Zhang W, Yang D, Wang H. Data-driven methods for predictive maintenance of industrial equipment: a survey. IEEE Syst J 2019;13:2213–27. https://doi.org/10.1109/JSYST.2019.2905565.

[5] Kitchenham B, Charters S. Guidelines for performing systematic literature reviews in software engineering. Eng Rep EBSE-2007-01, Keele Univ Univ Durham 2007. https://doi.org/10.1145/1134285.1134500.

[6] Kothamasu R, Huang SH, Verduin WH, Kothamasu R, Huang SH, Verduin WH. System health monitoring and prognostics -a review of current paradigms and practices. Int J Adv Manuf Technol 2006;28:1012–24. https://doi.org/10.1007/978-1-84882-472-0_14.

[7] Montero Jimenez JJ, Vingerhoeds R. Enhancing operational fault diagnosis by assessing multiple operational modes. Proc. - Int. Conf. Model. Optim. Simul. MOSIM 2018. 2018. p. 237–44.

[8] Adams S, Malinowski M, Heddy G, Choo B, Beling PA. The WEAR methodology for prognostics and health management implementation in manufacturing. J Manuf Syst 2017;45:82–96. https://doi.org/10.1016/j.jmsy.2017.07.002.

[9] Vingerhoeds RA, Janssens P, Netten BD, Aznar Fernández-Montesinos M. Enhancing off-line and on-line condition monitoring and fault diagnosis. Control Eng Pract 1995;3:1515–28. https://doi.org/10.1016/0967-0661(95)00162-N.

[10] Prajapati A, Bechtel J, Ganesan S. Condition based maintenance: a survey. J Qual Maint Eng 2012;18:384–400. https://doi.org/10.1108/13552511211281552.

[11] Scott D, Westcott VC. Predictive maintenance by ferrography. Wear 1977;44:173–82. https://doi.org/10.1016/0043-1648(77)90094-1.

[12] Tinga T, Loendersloot R. Aligning PHM, SHM and CBM by understanding the physical system failure behaviour. Proc. Eur. Conf. Progn. Heal. Manag. Soc. 2014.

[13] Kothamasu R, Huang SH, Verduin WH. System health monitoring and prognostics - A review of current paradigms and practices. Handb Maint Manag Eng 2006;28:1012–24. https://doi.org/10.1007/978-1-84882-472-0_14.

[14] Albrice D, Branch M. A deterioration model for establishing an optimal mix of time-based maintenance (TbM) and condition-based maintenance (CbM) for the enclosure system. Fourth Build. Enclos. Sci. Technol. Conf. 2015.

[15] MIMOSA. Open system architecture for condition-based maintenance (OSA-CBM) Available on 2001Http://WwwMimosaOrg/Mimosa-Osa-Cbm/.

[16] Lebold M, Reichard K, Byington CS, Orsagh R. OSA-CBM architecture development with emphasis on XML implementations. Maint Reliab Conf 2002.

[17] Montero Jiménez JJ, Vingerhoeds R. A system engineering approach to predictive maintenance systems: from needs and desires to logical architecture. 5th IEEE Int. Symp. Syst. Eng. 2019, Edinburgh 2019. https://doi.org/10.1109/ISSE46696.2019.8984559.

[18] Hussain A, Lee SJ, Choi MS, Brikci F. An expert system for acoustic diagnosis of power circuit breakers and on-load tap changers. Expert Syst Appl 2015;42:9426–33. https://doi.org/10.1016/j.eswa.2015.07.079.

[19] Zhou A, Yu D, Zhang W. A research on intelligent fault diagnosis of wind turbines based on ontology and FMECA. Adv Eng Informatics 2015;29:115–25. https://doi.org/10.1016/j.aei.2014.10.001.

[20] Gang M, Linru J, Guchao X, Jianyong Z. A model of intelligent fault diagnosis of power equipment based on CBR. Math Problems Eng 2015.

[21] Chemweno P, Pintelon L, Jongers L, Muchiri P. I-RCAM: intelligent expert system for root cause analysis in maintenance decision making. 2016 IEEE Int. Conf. Progn. Heal. Manag. ICPHM 2016 2016. https://doi.org/10.1109/ICPHM.2016.7542830.

[22] Zhong Z, Xu T, Wang F, Tang T. Text case-based reasoning framework for fault diagnosis and predication by cloud computing. Math Probl Eng 2018:10. https://doi.org/10.1155/2018/9464971.

[23] Baban M, Baban CF, Moisi B. A fuzzy logic-based approach for predictive maintenance of grinding wheels of automated grinding lines. 2018 23rd Int. Conf. Methods Model. Autom. Robot. MMAR 2018 2018. https://doi.org/10.1109/MMAR.2018.8486144.

[24] Berredjem T, Benidir M. Bearing faults diagnosis using fuzzy expert system relying on an Improved Range Overlaps and Similarity method. Expert Syst Appl 2018;108:134–42. https://doi.org/10.1016/j.eswa.2018.04.025.

[25] Li-Qiang H, Chao-Feng H, Zhao-Quan C, Long W, Teng R. Track circuit fault predicition method based on grey theory and expert systems. J Vis Commun Image Represent 2019;58:37–45.

[26] Tang X, Xiao M, Liang Y, Zhu H, Li J. Online updating belief-rule-base using Bayesian estimation. Knowl-Based Syst 2019;171:93–105. https://doi.org/10.1016/j.knosys.2019.02.007.

[27] Boral S, Chaturvedi SK, Naikan VNA. A case-based reasoning system for fault detection and isolation: a case study on complex gearboxes. J Qual Maint Eng 2019;25:213–35. https://doi.org/10.1108/JQME-05-2018-0039.

[28] Vafaei N, Ribeiro RA, Camarinha-Matos LM. Fuzzy early warning systems for condition based maintenance. Comput Ind Eng 2019;128:736–46. https://doi.org/10.1016/j.cie.2018.12.056.

[29] Bagheri B, Siegel D, Zhao W, Lee J. A stochastic asset life prediction method for large fleet datasets in big data environment. ASME 2015 Int. Mech. Eng. Congr. Expo. Vol. 14 Emerg. Technol. Saf. Eng. Risk Anal. Mater. Genet. to Struct. 2015. https://doi.org/10.1115/IMECE2015-52458.

[30] Menon S, Jin X, Chow TWS, Pecht M. Evaluating covariance in prognostic and system health management applications. Mech Syst Signal Process 2015;58–59:206–17. https://doi.org/10.1016/j.ymssp.2014.10.012.

[31] Verbert K, De Schutter B, Babuška R. Reasoning under uncertainty for knowledge-based fault diagnosis: a comparative study. IFAC-Papers OnLine 2015;48:422–7. https://doi.org/10.1016/j.ifacol.2015.09.563.

[32] Jin W, Shi Z, Siegel D, Dersin P, Douziech C, Pugnaloni M, et al. Development and evaluation of health monitoring techniques for railway point machines. 2015 IEEE Conf. Progn. Heal. Manag. Enhancing Safety, Effic. Availability, Eff. Syst. Through PHAf Technol. Appl. PHM 2015 2015. https://doi.org/10.1109/ICPHM.2015.7245016.

[33] Dababneh A, Ozbolat IT. Predictive reliability and lifetime methodologies for circuit boards. Int J Ind Manuf Syst Eng 2015;37:141–8. https://doi.org/10.1016/

j.jmsy.2015.08.001.
[34] Berecibar M, Devriendt F, Dubarry M, Villarreal I, Omar N, Verbeke W, et al. Online state of health estimation on NMC cells based on predictive analytics. J Power Sources 2016. https://doi.org/10.1016/j.jpowsour.2016.04.109.
[35] Mosallam A, Medjaher K, Zerhouni N. Data-driven prognostic method based on Bayesian approaches for direct remaining useful life prediction. J Intell Manuf 2016;27:1037–48. https://doi.org/10.1007/s10845-014-0933-4.
[36] Zhang D, Bailey AD, Djurdjanovic D. Bayesian identification of hidden Markov models and their use for condition-based monitoring. IEEE Trans Reliab 2016. https://doi.org/10.1109/TR.2016.2570561.
[37] Xiao Y, Wang H, Xu W, Zhou J. Robust one-class SVM for fault detection. Chemometr Intell Lab Syst 2016;151:15–25. https://doi.org/10.1016/j.chemolab.2015.11.010.
[38] Lee W-J. Anomaly detection and severity prediction of air leakage in train braking pipes. Int J Progn Heal Manag 2017;8:12. https://doi.org/10.1007/978-3-319-60045-1_22.
[39] Barraza-Barraza D, Tercero-Gómez VG, Beruvides MG, Limón-Robles J. An adaptive ARX model to estimate the RUL of aluminum plates based on its crack growth. Mech Syst Signal Process 2017;82:519–36. https://doi.org/10.1016/j.ymssp.2016.05.041.
[40] Verbert K, Babuška R, De Schutter B. Bayesian and Dempster–Shafer reasoning for knowledge-based fault diagnosis–A comparative study. Eng Appl Artif Intell 2017;60:136–50. https://doi.org/10.1016/j.engappai.2017.01.011.
[41] Li G, Wang X, Yang A, Rong M, Yang K. Failure prognosis of high voltage circuit breakers with temporal latent Dirichlet allocation. Energies 2017;10:1913. https://doi.org/10.3390/en10111913.
[42] Chen Z, Li Y, Xia T, Pan E. Hidden Markov model with auto-correlated observations for remaining useful life prediction and optimal maintenance policy. Reliab Eng Syst Saf 2017;184:123–36. https://doi.org/10.1016/j.ress.2017.09.002.
[43] Yung KC, Sun B, Jiang X. Prognostics-based qualification of high-power white LEDs using Lévy process approach. Mech Syst Signal Process 2017;82:206–16. https://doi.org/10.1016/j.ymssp.2016.05.019.
[44] Singh K, Malik H, Sharma R. Condition monitoring of wind turbine gearbox using electrical signatures. 2017 Int. Conf. Microelectron. Devices, Circuits Syst. ICMDCS 2017 2017. https://doi.org/10.1109/ICMDCS.2017.8211718.
[45] Gajewski J, Vališ D. The determination of combustion engine condition and reliability using oil analysis by MLP and RBF neural networks. Tribol Int 2017;115:557–72. https://doi.org/10.1016/j.triboint.2017.06.032.
[46] Zhao R, Wang D, Yan R, Mao K, Shen F, Wang J. Machine health monitoring using local feature-based gated recurrent unit networks. IEEE Trans Ind Electron 2017;65:1539–48. https://doi.org/10.1109/TIE.2017.2733438.
[47] Dong D, Li XY, Sun FQ. Life prediction of jet engines based on LSTM-recurrent neural networks. 2017 Progn. Syst. Heal. Manag. Conf. PHM-Harbin 2017 - Proc. 2017. https://doi.org/10.1109/PHM.2017.8079264.
[48] Mathew J, Luo M, Khiang Pang C. Regression kernel for prognostics with support vector machines. 22nd IEEE Int. Conf. Emerg. Technol. Fact. Autom. 2017.
[49] Shuangshuang J, Zhenhuan W, Yudong F, Guoan Y. The remaining life prediction of the fan bearing based on genetic algorithm and multi-parameter support vector machine. 5th Int. Conf. Mech. Automot. Mater. Eng. 2017.
[50] Haque MS, Bin Shaheed MN, Choi S. RUL estimation of power semiconductor switch using evolutionary time series prediction. 2018 IEEE Transp. Electrif. Conf. Expo, ITEC 2018 2018. https://doi.org/10.1109/ITEC.2018.8450131.
[51] Wan A, Gu F, Chen J, Zheng L, Hall P, Ji Y, et al. Prognostics of gas turbine: a condition-based maintenance approach based on multi-environmental time similarity. Mech Syst Signal Process 2018;109:150–65. https://doi.org/10.1016/j.ymssp.2018.02.027.
[52] Hu Y-W, Zhang H-C, Liu S-J, Lu H-T. Sequential Monte Carlo method toward online RUL assessment with applications. Chin J Mech Eng 2018:31. https://doi.org/10.1186/s10033-018-0205-x.
[53] Tang D, Sheng W, Yu J. Dynamic condition-based maintenance policy for degrading systems described by a random-coefficient autoregressive model: A comparative study. Eksploat I Niezawodn - Maint Reliab 2018;20:590–601. https://doi.org/10.17531/ein.2018.4.10.
[54] Wang ZQ, Hu CH, Fan HD. Real-time remaining useful life prediction for a nonlinear degrading system in service: application to bearing data. IEEE/ASME Trans Mechatron 2018;23:211–22. https://doi.org/10.1109/TMECH.2017.2666199.
[55] Zhao S, Makis V, Chen S, Li Y. Evaluation of reliability function and mean residual life for degrading systems subject to condition monitoring and random failure. IEEE Trans Reliab 2018;67:13–25. https://doi.org/10.1109/TR.2017.2779322.
[56] Kinghorst J, Geramifard O, Luo M, Chan HL, Yong K, Folmer J, et al. Hidden Markov model-based predictive maintenance in semiconductor manufacturing: a genetic algorithm approach. IEEE Int. Conf. Autom. Sci. Eng. 2018. https://doi.org/10.1109/COASE.2017.8256274.
[57] Wu Z, Luo H, Yang Y, Lv P, Zhu X, Ji Y, et al. K-PdM: KPI-oriented machinery deterioration estimation framework for predictive maintenance using cluster-based hidden Markov model. IEEE Access 2018;6:41676–87. https://doi.org/10.1109/ACCESS.2018.2859922.
[58] Man J, Zhou Q. Prediction of hard failures with stochastic degradation signals using Wiener process and proportional hazards model. Comput Ind Eng 2018;125:480–9. https://doi.org/10.1016/j.cie.2018.09.015.
[59] Zhang Z, Si X, Hu C, Lei Y. Degradation data analysis and remaining useful life estimation: a review on Wiener-process-based methods. Eur J Oper Res 2018;271:775–96. https://doi.org/10.1016/j.ejor.2018.02.033.
[60] Vališ D, Mazurkiewicz D. Application of selected Levy processes for degradation modelling of long range mine belt using real-time data. Arch Civ Mech Eng 2018;18:1430–40. https://doi.org/10.1016/j.acme.2018.05.006.
[61] Aye SA, Heyns PS. Prognostics of slow speed bearings using a composite integrated Gaussian process regression model. Int J Prod Res 2018;56:4860–73. https://doi.org/10.1080/00207543.2018.1470340.
[62] Kong D, Chen Y, Li N. Gaussian process regression for tool wear prediction. Mech Syst Signal Process 2018;104:556–74. https://doi.org/10.1016/j.ymssp.2017.11.021.
[63] Ayo-Imoru RM, Cilliers AC. Continuous machine learning for abnormality identification to aid condition-based maintenance in nuclear power plant. Ann Nucl Energy 2018;118:61–70. https://doi.org/10.1016/j.anucene.2018.04.002.
[64] Luwei KC, Yunusa-Kaltungo A, Sha'aban YA. Integrated fault detection framework for classifying rotating machine faults using frequency domain data fusion and artificial neural networks. Machines 2018:6.
[65] Luo H, Huang M, Zhou Z. Integration of Multi-Gaussian fitting and LSTM neural networks for health monitoring of an automotive suspension component. J Sound Vib 2018;428:87–103. https://doi.org/10.1016/j.jsv.2018.05.007.
[66] Hinchi AZ, Tkiouat M. Rolling element bearing remaining useful life estimation based on a convolutional long-short-Term memory network. Procedia Comput Sci 2018;127:123–32. https://doi.org/10.1016/j.procs.2018.01.106.
[67] Li X, Ding Q, Sun JQ. Remaining useful life estimation in prognostics using deep convolution neural networks. Reliab Eng Syst Saf 2018;172:1–11. https://doi.org/10.1016/j.ress.2017.11.021.
[68] Von Birgelen A, Buratti D, Mager J, Niggemann O. Self-organizing maps for anomaly localization and predictive maintenance in cyber-physical production systems. Procedia CIRP 2018;72:480–5. https://doi.org/10.1016/j.procir.2018.03.150.
[69] Nyulászi L, Andoga R, Butka P, Főző L, Kovacs R, Moravec T. Fault detection and isolation of an aircraft turbojet engine using a multi-sensor network and multiple model approach. Acta Polytech Hungarica 2018;15:189–209.
[70] Li S, Fang H, Shi B. Multi-step-ahead prediction with long short term memory networks and support vector regression. Chinese Control Conf. 2018. https://doi.org/10.23919/ChiCC.2018.8484066.
[71] Laib dit Leksir Y, Mansour M, Moussaoui A. Localization of thermal anomalies in electrical equipment using Infrared Thermography and support vector machine. Infrared Phys Technol 2018;89:120–8. https://doi.org/10.1016/j.infrared.2017.12.015.
[72] Onel M, Kieslich CA, Guzman YA, Pistikopoulos EN. Simultaneous fault detection and identification in continuous processes via nonlinear support vector machine based feature selection. Comput Aided Chem Eng 2018;44:2077–82. https://doi.org/10.1016/B978-0-444-64241-7.50341-4.
[73] Ren L, Sun Y, Cui J, Zhang L. Bearing remaining useful life prediction based on deep autoencoder and deep neural networks. J Manuf Syst 2018;48:71–7. https://doi.org/10.1016/j.jmsy.2018.04.008.
[74] Zhang J, Wang P, Yan R, Gao RX. Long short-term memory for machine remaining life prediction. J Manuf Syst 2018;48. https://doi.org/10.1016/j.jmsy.2018.05.011. 78–76.
[75] Xu M, Jin X, Kamarthi S, Noor-E-Alam M. A failure-dependency modeling and state discretization approach for condition-based maintenance optimization of multi-component systems. J Manuf Syst 2018;47:141–52. https://doi.org/10.1016/j.jmsy.2018.04.018.
[76] Downey A, Lui Y-H, Hu C, Laflamme S, Hu S. Physics-based prognostics of lithium-ion battery using non-linear least squares with dynamic bounds. Reliab Eng Syst Saf 2019;182:1–12.
[77] Li Y, Liu S, Shu L. Wind turbine fault diagnosis based on Gaussian process classifiers applied to operational data. Renew Energy 2019;134:357–66. https://doi.org/10.1016/j.renene.2018.10.088.
[78] M.Mehdi Hassani.N S, Xiaoning J, Jun N. Physics-based Gaussian process for the health monitoring for a rolling bearing. Acta Astronatica 2019;154:133–9.
[79] Huang W, Cheng J, Yang Y, Guo G. An improved deep convolutional neural network with multi-scale information for bearing fault diagnosis. Neurocomputing 2019;359:77–92. https://doi.org/10.1016/j.neucom.2019.05.052.
[80] Chen Z, Gryllias K, Li W. Mechanical fault diagnosis using convolutional neural networks and extreme learning machine. Mech Syst Signal Process 2019:133. https://doi.org/10.1016/j.ymssp.2019.106272.
[81] Chaoqun D, Chao D, Ning L. Reliability assessment for CNC equipment based on degradation data. Int J Adv Manuf Technol 2019;100:421–34.
[82] Eker OF, Camci F, Jennions IK. Physics-based prognostic modelling of filter clogging phenomena. Mech Syst Signal Process 2016;75:395–412. https://doi.org/10.1016/j.ymssp.2015.12.011.
[83] Climente-Alarcon V, Nair D, Sundaria R, Antonino-Daviu JA, Arkkio A. Combined model for simulating the effect of transients on a damaged rotor cage. IEEE Trans Ind Appl 2017. https://doi.org/10.1109/TIA.2017.2691001.
[84] Qiao G, Weiss BA. Quick health assessment for industrial robot health degradation and the supporting advanced sensing development. J Manuf Syst 2018;48:51–9. https://doi.org/10.1016/j.jmsy.2018.04.004.
[85] Li J, Xiao M, Liang Y, Tang X, Li C. Three-dimensional simulation and prediction of solenoid valve failure mechanism based on finite element model. IOP Conf. Ser. Earth Environ. Sci. 2018. https://doi.org/10.1088/1755-1315/108/2/022035.
[86] Cholette ME, Yu H, Borghesani P, Ma L, Geoff K. Degradation modeling and condition-based maintenance of boiler heat exchangers using gamma processes. Reliab Eng Syst Saf 2019;183:184–96.
[87] Liao WZ, Li D. An improved prediction model for equipment performance degradation based on Fuzzy-Markov Chain. IEEE Int. Conf. Ind. Eng. Eng. Manag. 2016. https://doi.org/10.1109/IEEM.2015.7385597.
[88] Chang Y, Fang H, Zhang Y. A new hybrid method for the prediction of the remaining useful life of a lithium-ion battery. Appl Energy 2017;206:1564–78. https://doi.org/10.1016/j.apenergy.2017.09.106.

[89] Hanachi H, Liu J, Kim IY, Mechefske CK. Hybrid sequential fault estimation for multi-mode diagnosis of gas turbine engines. Mech Syst Signal Process 2019;115:225–68. https://doi.org/10.1016/j.ymssp.2018.05.054.
[90] Jiang Y, Zhu H, Ding C, Pfeiffer O. A novel ensemble fuzzy model for degradation prognostics of rolling element bearings. J Intell Fuzzy Syst 2019;37:4449–55. https://doi.org/10.3233/JIFS-179277.
[91] Al-Dulaimi A, Zabihi S, Asif A, Mohammadi A. A multimodal and hybrid deep neural network model for remaining useful life estimation. Comput Ind 2019;108:186–96. https://doi.org/10.1016/j.compind.2019.02.004.
[92] Chiachío J, Chiachío M, Prescott D, Andrews J. A knowledge-based prognostics framework for railway track geometry degradation. Reliab Eng Syst Saf 2019;181:127–41. https://doi.org/10.1016/j.ress.2018.07.004.
[93] Che C, Wang H, Fu Q, Ni X. Combining multiple deep learning algorithms for prognostic and health management of aircraft. Aerosp Sci Technol 2019:94. https://doi.org/10.1016/j.ast.2019.105423.
[94] Lu F, Wu J, Huang J, Qiu X. Aircraft engine degradation prognostics based on logistic regression and novel OS-ELM algorithm. Aerosp Sci Technol 2019;84:661–71. https://doi.org/10.1016/j.ast.2018.09.044.
[95] Ferreiro S, Konde E, Fernández S, Prado A. Industry 4.0 : predictive intelligent maintenance for production equipment. Eur. Conf. Progn. Heal. Manag. Soc. 2016.
[96] Javed K, Gouriveau R, Zerhouni N. State of the art and taxonomy of prognostics approaches, trends of prognostics applications and open issues towards maturity at different technology readiness levels. Mech Syst Signal Process 2017;94:214–36. https://doi.org/10.1016/j.ymssp.2017.01.050.
[97] Sakib N, Wuest T. Challenges and opportunities of condition-based predictive maintenance: a review. 6th CIRP Glob. Web Conf. "Envisaging Futur. Manuf. Des. Technol. Syst. Innov. era," Elseiver B.V. 2018:267–72.
[98] Alaswad S, Xiang Y. A review on condition-based maintenance optimization models for stochastically deteriorating system. Reliab Eng Syst Saf 2017;157:54–63. https://doi.org/10.1016/j.ress.2016.08.009.
[99] International Organization for Standardization (ISO). ISO 13379-1:2012 - Condition monitoring and diagnostics of machines — Data interpretation and diagnostics techniques — Part 1: general guidelines. 2012.
[100] Gouriveau R, Medjaher K, Zerhouni N. From prognostics and health systems management to predictive maintenance 1: monitoring and prognostics. 2016. https://doi.org/10.1002/9781119371052.
[101] Vogl GW, Weiss Ba, Donmez MA. Standards for prognostics and health management (PHM) techniques within manufacturing operations. Annu Conf Progn Heal Manag Soc 2014.
[102] Vachtsevanos G, Lewis F, Roemer M, Hess A, Wu B. Intelligent fault diagnosis and prognosis for engineering systems. 2007. https://doi.org/10.1002/9780470117842.
[103] Zerhouni N, Atamuradov V, Medjaher K, Dersin P, Lamoureux B. Prognostics and health management for maintenance practitioners-review, implementation and tools evaluation. Artic Int J Progn Heal Manag 2017;8:31. https://doi.org/10.1016/j.euprot.2015.07.015.
[104] Jardine AKS, Lin D, Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mech Syst Signal Process 2006;20:1483–510. https://doi.org/10.1016/j.ymssp.2005.09.012.
[105] Wang D, Tsui KL, Miao Q. Prognostics and health management: a review of vibration based bearing and gear health indicators. IEEE Access 2017;6:665–76. https://doi.org/10.1109/ACCESS.2017.2774261.
[106] An D, Kim NH, Choi JH. Practical options for selecting data-driven or physics-based prognostics algorithms with reviews. Reliab Eng Syst Saf 2015;133:223–36. https://doi.org/10.1016/j.ress.2014.09.014.
[107] Noman MA, Nasr ESA, Al-Shayea A, Kaid H. Overview of predictive condition based maintenance research using bibliometric indicators. J King Saud Univ - Eng Sci 2018. https://doi.org/10.1016/j.jksues.2018.02.003.
[108] Schmidt B, Wang L. Predictive maintenance: literature review and future trends. Conf Proc 25th Int Conf Flex Autom Intell Manuf 2015;1:232–9.
[109] Dragomir OE, Gouriveau R, Dragomir F, Minca E, Zerhouni N. Review of prognostic problem in condition-based maintenance. Eur. Control Conf. (ECC'09) 2009. https://doi.org/10.1128/JB.00591-09.
[110] Sikorska JZ, Hodkiewicz M, Ma L. Prognostic modelling options for remaining useful life estimation by industry. Mech Syst Signal Process 2011;25:1803–36. https://doi.org/10.1016/j.ymssp.2010.11.018.
[111] Okoh C, Roy R, Mehnen J, Redding L. Overview of remaining useful life prediction techniques in through-life engineering services. Procedia CIRP 2014;16:158–63. https://doi.org/10.1016/j.procir.2014.02.006.
[112] Boullart L. A gentle introduction to artificial intelligence. In: Boullart L, Krijgsman A, Vingerhoeds RA, editors. Appl. Artif. Intell. Process Control. Pergamon Press; 1992. p. 5–40.
[113] Liu H, Yu J, Zhang P, Li X. A review on fault prognostics in integrated health management. ICEMI 2009 - Proc. 9th Int. Conf. Electron. Meas. Instruments 2009. https://doi.org/10.1109/ICEMI.2009.5274082.
[114] Majstorovic VD, Milacic VR. Expert systems for maintenance in the CIM concept. Comput Ind 1990;15:83–93.
[115] Freyermuth B. Knowledge based incipient fault diagnosis of industrial robots. IFAC Proc Vol 1991;24:369–75.
[116] Agnar A, Plaza E. Case-Based reasoning: Foundational issues, methodological variations, and system approaches. AI Commun 1994;7:39–59. https://doi.org/10.3233/AIC-1994-7104.
[117] Vepa R. Introduction to fuzzy logic and fussy sets. In: Boullart L, Krijgsm A, Vingerhoeds RA, editors. Appl. Artif. Intell. Process Control. 1991. p. 146–63.
[118] Ruiz PP, Foguem BK, Grabot B. Generating knowledge in maintenance from Experience Feedback. Knowl-Based Syst 2014;68:4–20. https://doi.org/10.1016/j.knosys.2014.02.002.
[119] Grabot B. Rule mining in maintenance: analysing large knowledge bases. Comput Ind Eng 2018;139:105501https://doi.org/10.1016/j.cie.2018.11.011.
[120] Ramasso E. Investigating computational geometry for failure prognostics. Int J Progn Heal Manag 2014;5:18.
[121] Kumar P, Srivastava RK. An expert system for predictive maintenance of mining excavators and its various forms in open cast mining. 2012 1st Int. Conf. Recent Adv. Inf. Technol. RAIT-2012 2012. https://doi.org/10.1109/RAIT.2012.6194607.
[122] Zhou ZJ, Hu CH, Xu DL, Chen MY, Zhou DH. A model for real-time failure prognosis based on hidden Markov model and belief rule base. Eur J Oper Res 2010;207:269–83. https://doi.org/10.1016/j.ejor.2010.03.032.
[123] Yang BS, Jeong SK, Oh YM, Tan ACC. Case-based reasoning system with Petri nets for induction motor fault diagnosis. Expert Syst Appl 2004;27:301–11. https://doi.org/10.1016/j.eswa.2004.02.004.
[124] Li S, Lv C, Guo Z, Wang M. Health condition-based maintenance decision intelligent reasoning method. Proc. 2012 Int. Conf. Qual. Reliab. Risk, Maintenance, Saf. Eng. ICQR2MSE 2012 2012. https://doi.org/10.1109/ICQR2MSE.2012.6246263.
[125] Phillips P, Diston D. A knowledge driven approach to aerospace condition monitoring. Knowl-Based Syst 2011;24:915–27. https://doi.org/10.1016/j.knosys.2011.04.008.
[126] Kothamasu R, Huang SH. Adaptive Mamdani fuzzy model for condition-based maintenance. Fuzzy Sets Syst 2007;158:2715–33. https://doi.org/10.1016/j.fss.2007.07.004.
[127] Sankararaman S, Daigle MJ, Goebel K. Uncertainty quantification in remaining useful life prediction using first-order reliability methods. IEEE Trans Reliab 2014;63:603–19. https://doi.org/10.1109/TR.2014.2313801.
[128] Moutinho MN. Fuzzy diagnostic systems of rotating machineries, some Eletronorte's applications. 2009 15th Int. Conf. Intell. Syst. Appl. to Power Syst. ISAP' 09 2009. https://doi.org/10.1109/ISAP.2009.5352882.
[129] Coble JB, Hines JW. Applying the general path model to estimation of remaining useful life. Int J Progn Heal Manag 2011;2:13.
[130] Du X, Zhou Y, Dong S. Residual life prediction from statistical features and a GARCH modeling approach for aircraft generators. Proc Inst Mech Eng Part G J Aerosp Eng 2014;228:137–46. https://doi.org/10.1177/0954410012472838.
[131] Zhan Y, Mechefske CK. Robust detection of gearbox deterioration using compromised autoregressive modeling and Kolmogorov-Smirnov test statistic. Part II: experiment and application. Mech Syst Signal Process 2007;21:1983–2011. https://doi.org/10.1016/j.ymssp.2006.11.006.
[132] Zhan Y, Mechefske CK. Robust detection of gearbox deterioration using compromised autoregressive modeling and Kolmogorov-Smirnov test statistic-Part I: compromised autoregressive modeling with the aid of hypothesis tests and simulation analysis. Mech Syst Signal Process 2007;21:1953–82. https://doi.org/10.1016/j.ymssp.2006.11.005.
[133] Cheng C, Yu L, Chen L. Structural nonlinear damage detection based on ARMA-GARCH model. Appl Mech Mater 2012;204–208:2891–6. https://doi.org/10.4028/www.scientific.net/AMM.204-208.2891.
[134] Ghahramani S. Fundamentals of probability: with stochastic processes. Third edition 2015. https://doi.org/10.1201/b19602.
[135] Pourbabaee B, Meskin N, Khorasani K. Multiple-model based sensor fault diagnosis using hybrid Kalman filter approach for nonlinear gas turbine engines. 2013 Am Control Conf 2013. https://doi.org/10.1109/TCST.2015.2480003.
[136] Hu C, Youn BD, Wang P, Taek Yoon J. Ensemble of data-driven prognostic algorithms for robust prediction of remaining useful life. Reliab Eng Syst Saf 2012;103:120–35. https://doi.org/10.1016/j.ress.2012.03.008.
[137] Rasmussen CE, Williams CKI. Gaussian process for machine learning. the MIT Press; 2006.
[138] Rasmussen CE. Gaussian processes in machine learning. In: Bousquet O, von Luxburg U, Rätsch G, editors. Adv. Lect. Mach. Learn. Springer; 2003. p. 63–71.
[139] Kan MS, Tan ACC, Mathew J. A review on prognostic techniques for non-stationary and non-linear rotating systems. Mech Syst Signal Process 2015;62–63:1–20. https://doi.org/10.1016/j.ymssp.2015.02.016.
[140] Markov A. Extension of the limit theorems of probability theory to a sum of variables connected in a chain. Append. B R. Howard. Dyn. Probabilistic Syst. Vol. 1 Markov Chain. John Wiley and Sons; 1971. https://doi.org/citeulike-article-id:911035.
[141] Protter PE. Stochastic integration and differential equations. Second edition Springer; 2005.
[142] Rudnicki R, Tyran-Kamińska M. Piecewise deterministic processes in biological models. Springer; 2017.
[143] Aye SA, Heyns PS. An integrated Gaussian process regression for prediction of remaining useful life of slow speed bearings based on acoustic emission. Mech Syst Signal Process 2017;84:485–98. https://doi.org/10.1016/j.ymssp.2016.07.039.
[144] Kobayashi K, Kaito K, Lethanh N. A statistical deterioration forecasting method using hidden Markov model for infrastructure management. Transp Res Part B Methodol 2012;46:544–61. https://doi.org/10.1016/j.trb.2011.11.008.
[145] Le Son K, Fouladirad M, Barros A, Levrat E, Iung B. Remaining useful life estimation based on stochastic deterioration models: a comparative study. Reliab Eng Syst Saf 2013;112:165–75. https://doi.org/10.1016/j.ress.2012.11.022.
[146] Russel S, Norvig P. Artificial intelligence—A modern approach. 3rd edition 2012. https://doi.org/10.1017/S0269888900007724.
[147] Schwartz S, Montero Jiménez JJ, Salaün M, Vingerhoeds R. A fault mode identification methodology based on self-organizing map. Neural Comput Appl 2020:1–19.
[148] Koprinkova-Hristova P. Reinforcement learning for predictive maintenance of

industrial plants. Inf Technol Control 2014;11:21–8. https://doi.org/10.2478/itc-2013-0004.
[149] Wells G. An introduction to neural networks. In: Boullart L, Krijgsm A, Vingerhoeds RA, editors. Appl. Artif. Intell. Process Control. 1992. p. 164–200.
[150] Hailesilassie. Rule extraction algorithm for deep neural networks: a review. Int J Comput Sci Inf Secur 2016;14:371–81.
[151] Zhao Y, Wang S, Xiao F. Pattern recognition-based chillers fault detection method using Support Vector Data Description (SVDD). Appl Energy 2013;112:1041–8. https://doi.org/10.1016/j.apenergy.2012.12.043.
[152] Nasution FP, Sævik S, Gjøsteen JKØ. Fatigue analysis of copper conductor for offshore wind turbines by experimental and FE method. Energy Procedia 2012;24:271–80. https://doi.org/10.1016/j.egypro.2012.06.109.
[153] Si XS, Wang W, Hu CH, Zhou DH. Remaining useful life estimation - A review on the statistical data driven approaches. Eur J Oper Res 2011;213:1–14. https://doi.org/10.1016/j.ejor.2010.11.018.
[154] Liao L, Köttig F. Review of hybrid prognostics approaches for remaining useful life prediction of engineered systems, and an application to battery life prediction. IEEE Trans Reliab 2014;63:191–207. https://doi.org/10.1109/TR.2014.2299152.
[155] Soualhi A, Razik H, Clerc G, Doan DD. Prognosis of bearing failures using hidden markov models and the adaptive neuro-fuzzy inference system. IEEE Trans Ind Electron 2014;61:2864–74. https://doi.org/10.1109/TIE.2013.2274415.
[156] Chen J, Roberts C, Weston P. Fault detection and diagnosis for railway track circuits using neuro-fuzzy systems. Control Eng Pract 2008;16:585–96. https://doi.org/10.1016/j.conengprac.2007.06.007.
[157] Prentzas J, Hatzilygeroudis I. Combinations of case-based reasoning with other intelligent methods. CEUR Workshop Proc. 2008. https://doi.org/10.3233/his-2009-0096.
[158] Tung YH, Tseng SS, Weng JF, Lee TP, Liao AYH, Tsai WN. A rule-based CBR approach for expert finding and problem diagnosis. Expert Syst Appl 2010. https://doi.org/10.1016/j.eswa.2009.07.037.
[159] Peel L. Data driven prognostics using a Kalman filter ensemble of neural network models. 2008 Int. Conf. Progn. Heal. Manag. PHM 2008 2008. https://doi.org/10.1109/PHM.2008.4711423.
[160] Li X, Qian J, Wang GG. Fault prognostic based on hybrid method of state judgment and regression. Adv Mech Eng 2013. https://doi.org/10.1155/2013/149562.
[161] Kacprzynski GJ, Sarlashkar A, Roemer MJ, Hess A, Hardman W. Predicting remaining life by fusing the physics of failure modeling with diagnostics. JOM 2004;56:29–35. https://doi.org/10.1007/s11837-004-0029-2.
[162] Oppenheimer CH, Loparo KA. Physically based diagnosis and prognosis of cracked rotor shafts. Compon. Syst. Diagn., Progn. Heal. Manag. 2002;II. https://doi.org/10.1117/12.475502.
[163] Meskin N, Naderi E, Khorasani K. A multiple model-based approach for fault diagnosis of jet engines. IEEE Trans Control Syst Technol 2013;21:254–62. https://doi.org/10.1109/TCST.2011.2177981.
[164] Swanson DC. A general prognostic tracking algorithm for predictive maintenance. IEEE Aerosp. Conf. Proc. 2001. https://doi.org/10.1109/aero.2001.931317.
[165] Wang P, Youn BD, Hu C. A generic probabilistic framework for structural health prognostics and uncertainty management. Mech Syst Signal Process 2012;28:622–37. https://doi.org/10.1016/j.ymssp.2011.10.019.
[166] Riad AM, Elminir HK, Elattar HM. Evaluation of neural networks in the subject of prognostics as compared to linear regression model. Int J Eng Technol 2010;10:52–8.
[167] Neerukatti RK, Liu KC, Kovvali N, Chattopadhyay A. Fatigue life prediction using hybrid prognosis for structural health monitoring. J Aerosp Inf Syst 2014;11:211–32. https://doi.org/10.2514/1.I010094.
[168] Hong J, Miao X, Han L, Ma Y. Prognostics model for predicting aero-engine bearing grade-life. Proc. ASME Turbo Expo 2009. https://doi.org/10.1115/GT2009-59641.
[169] Orsagh RF, Sheldon J, Klenke CJ. Prognostics/diagnostics for gas turbine engine bearings. IEEE Aerosp. Conf. Proc. 2003. https://doi.org/10.1109/AERO.2003.1234152.
[170] Lee J, Wu F, Zhao W, Ghaffari M, Liao L, Siegel D. Prognostics and health management design for rotary machinery systems - reviews, methodology and applications. Mech Syst Signal Process 2014;42:314–34. https://doi.org/10.1016/j.ymssp.2013.06.004.
[171] Crawley E, Cameron B, Selva D. System architecture: strategy and product development for complex systems. Pearson Higher Education, Inc.; 2015.
[172] Peng Y, Dong M, Zuo MJ. Current status of machine prognostics in condition-based maintenance: a review. Int J Adv Manuf Technol 2010;50:297–313. https://doi.org/10.1007/s00170-009-2482-0.
[173] Bailey C, Sutharssan T, Yin C, Stoyanov S. Prognostic and health management for engineering systems: a review of the data-driven approach and algorithms. J Eng 2015;2015:215–22. https://doi.org/10.1049/joe.2014.0303.
[174] Elattar HM, Elminir HK, Riad AM. Prognostics: a literature review. Complex Intell Syst 2016;2:125–54. https://doi.org/10.1007/s40747-016-0019-3.
[175] Vanraj Goyal D, Saini A, Dhami SS, Pabla BS. Intelligent predictive maintenance of dynamic processing techniques-A review. Proc. - 2016 Int. Conf. Adv. Comput. Commun. Autom. ICACCA Systems Using Condition Monitoring and Signal 2016 2016. https://doi.org/10.1109/ICACCA.2016.7578870.