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A Literature Review Framework and Open Research Challenges for Predictive Maintenance in industry 4.0

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ABSTRACT

Production issues at Volkswagen in 2016 led to dramatic losses in sales of up to 400 million Euros per week. This example shows the huge financial impact of a working production facility for companies. Especially in the data-driven domains of Industry 4.0 and Industrial IoT with intelligent, connected machines, a conventional, static maintenance schedule seems to be old-fashioned. In this paper, we present an overview of the current state of the art in predictive maintenance for Industry 4.0. Based on a structured literature survey, we present a classification of predictive maintenance in the context of Industry 4.0 based on 249 publications. Additionally, we discuss identified challenges, i.e., complexity issues, as well as missing benchmark datasets that are relevant for production and the integration of machine learning.

1. Introduction

Maintenance has always been a severe cost driver in the production industry. Studies show that depending on the industry, between 15 and 70 percent of total production costs originate from maintenance activities (You, Yi, Liu, et al., 2010). Nevertheless, most of the production industry still relies on regular maintenance (Mobley, 2002), leading to reduced production time and product quality due to inappropriate maintenance policies. On the other hand, comprehensive research regarding modern maintenance policies using modern technologies is conducted in different academic fields, such as computer science, production, and artificial intelligence. The usage of well-developed sensors and prognostic techniques allows a relatively reliable prediction of the remaining useful life of plant equipment. This so-called predictive maintenance policy is especially relevant to Industry 4.0 and severely enhances the efficiency of modern production facilities.

Predictive maintenance is based on the idea that certain machinery characteristics can be monitored and the gathered data can be used to estimate the equipment's remaining useful life. Hence, this kind of maintenance policy implicates several important improvements in the manufacturing and maintenance process, which can severely reduce production costs (Grall, Dieulle, Berenguer, & Roussignol, 2002), such as reducing unnecessary maintenance activities and avoiding belated activities resulting in equipment failures. This results in increased productivity and reduced production downtime. Therefore, depending on the accuracy of the prognostic method applied, predictive maintenance can be considered an overall efficiency improvement in contrast to conventional maintenance (Nguyen, Do, & Grall, 2015; Yam, Tse, Li, & Tu, 2001).

The existing research on predictive maintenance is comprehensive and dates back decades ago. Nevertheless, as the environment changes and new technologies (especially new forms of data analytics such as deep learning) become more affordable, there is still a wide range of potential for new research in predictive maintenance. The possibilities to integrate predictive maintenance and connect it to other systems of the production process are increasing, especially in the context of the (Industrial) Internet of Things (IoT) and Industry 4.0. The objective of the present article is to structure the complexity of topics regarding predictive maintenance and put the extensive research into a transparent and comprehensible framework to identify potential starting points for further research. Such a framework can help practitioners to decide which aspects are relevant for implementing predictive maintenance. Additionally, it helps researchers to classify relevant literature and

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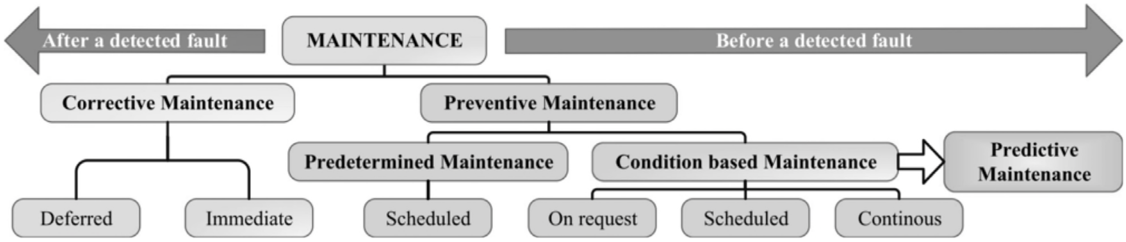

Fig. 1. Maintenance policies (Schmidt & Wang, 2018).

identify research challenges. We apply this framework in this paper to structure the identified literature. Further, we focus on the machine learning aspect and resulting challenges and discuss the rising complexity of those approaches.

We applied a structured literature review (SLR) to achieve our research goals. After filtering based on exclusion criteria, all relevant attributes of the selected 249 papers are captured for constructing the framework. Further, we cluster the identified literature using the derived framework. Based on this analysis, we discuss in detail different aspects that are relevant for research in the field of predictive maintenance with a focus on the required data, the complexity of sensor data analysis, and machine learning challenges. We decided to focus on machine learning aspects, as there is recently fast development in the field with new types of algorithms and fewer comparative works yet. However, due to the large body of research and space limitations, we will neither provide a comparative analysis between the studies nor discuss the differences of mathematical models or the applied machine learning techniques/algorithms.

The remainder of the survey is structured as follows: Section 2 explains the theoretical foundations of predictive maintenance. Next, Section 3 describes the methodical procedure of the literature review and the framework construction. Section 4 explains in detail the categories and the most important attributes of the predictive maintenance framework. Section 5 follows a discussion of different research challenges and trends we identified while analyzing the literature. Section 6 summarizes related surveys and distinguishes this work from others. Finally, Section 8 concludes the survey by summarizing the main findings and giving recommendations for future research.

2. Foundations of predictive maintenance

This section introduces terminology and concepts relevant to the remainder of this paper. First, a short overview of the common maintenance policies is given as context. Next, a definition of predictive maintenance is built upon that overview. The main advantages of predictive maintenance over conventional policies are discussed to conclude the foundations.

2.1. Maintenance policies

Generally, maintenance policies can be divided into two categories: Corrective maintenance and preventive maintenance. The main difference between these policies is the timing relative to the possible machine failure. An illustration and overview of conventional maintenance policies can be seen in Fig. 1.

The first approach, called corrective maintenance or reactive maintenance (Mobley, 2002), occurs after a failure. A production plant using this approach follows a *run-to-failure* management (Mobley, 2002). Afterward, the machine can be repaired immediately or at a later point, which will result in machine downtime and critical equipment failure. Corrective maintenance incurs the lowest upfront costs, as it does not involve any investment in monitoring systems. When downtimes are acceptable and do not lead to significant costs upstream, this approach can prove to be highly cost-effective. However, if downtimes are critical to the business, production facilities should closely monitor the condition of their equipment, as is the case with preventive or proactive maintenance strategies (Mobley, 2002). This maintenance approach is carried out before a fatal failure occurs. These additional measures incur costs that must be carefully weighed against the costs associated with downtimes or disruptions, which can have cascading effects throughout the production process.

Preventive maintenance policies can be further divided into two categories: Predetermined and condition-based. First, predetermined maintenance, where the maintenance activities are conducted at prescheduled intervals based on historic average equipment lifetime (Schmidt & Wang, 2018). On the contrary, condition-based maintenance monitors the current condition of a machine and schedules maintenance activities based on the observations made (Schmidt & Wang, 2018). Here, three distinct condition monitoring methods are feasible: Monitoring on request, scheduled monitoring, and continuous monitoring (Grall et al., 2002; Zhou, Xi, & Lee, 2007). The first two methods are mostly inspection-based, while sensors generally implement continuous monitoring.

The issue with condition-based maintenance is that even with continuous monitoring, the acquired data only represents a snapshot of a machine's current condition. The approach does not allow for efficiently scheduled maintenance activities ahead of failure because it lacks knowledge about a machine's or component's presumable future state.

2.2. Definition of predictive maintenance

The paradigm of predictive maintenance has been introduced to improve the drawbacks of condition-based maintenance further. It builds on the idea of continuous condition-based monitoring but includes using data-driven models to determine the future state of a machine or component (Mobley, 2002). This approach is based on condition monitoring, ideally conducted by sensors, allowing for continuous monitoring of relevant machine parameters such as vibration or temperature. Suitable analytics models can be implemented for various tasks, such as anomaly detection, failure classification, remaining useful lifetime estimation, or trend detection, using historical data recordings.

Predictive maintenance is a policy that improves efficiency in the overall operation and maintenance process (Mobley, 2002). This improvement in efficiency can be observed in multiple facets: more machine uptime, reduced overall cost, reduced resource consumption, and a more transparent information presentation.

First, the machine uptime is increased by mitigating breakdowns or complete machine failures. In those cases, reactive maintenance would be implemented, which is generally slow as not all information about the needed repairs is available immediately. Second, reducing downtime through preventive methods and executing maintenance before a critical failure reduces overall monetary cost. Maintenance actions after such a failure are usually more expensive than scheduled repairs. Third, resource usage is more efficient as a component's useful lifetime is effectively used for machine operation. Unlike scheduled preventive maintenance, components still in working condition are not replaced. Additionally, a less efficient machine operation is a state

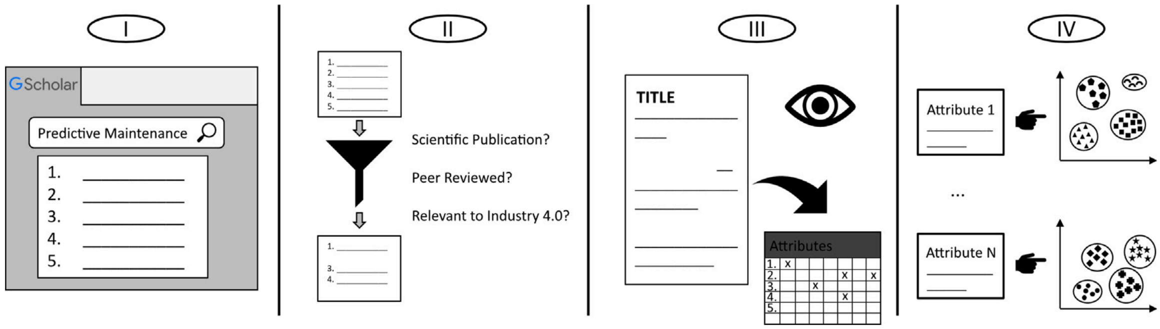

Fig. 2. Visualized workflow of literature search.

that can be detected and fixed using the available monitoring data. Finally, continuously monitoring equipment improves the efficiency of conveying information about the machine. Not only can the current status be monitored at any time, but suitable analytics algorithms can also extract more specific or aggregated information for maintenance personnel.

These advantages make predictive maintenance a highly valuable application of modern techniques and are why much effort is put into researching the possibilities for the industry.

3. Methodical procedure

The following section describes the methodology used to select the relevant papers and construct the framework. In total, 249 papers are selected to derive the framework. All the attributes are clustered into 9 categories that build the main layer of the framework (see Fig. 2).

3.1. Structured literature review

The Structured Literature Review (SLR) is a systematic approach to finding relevant literature to answer one or multiple research questions by searching for papers based on a set of keywords (Kofod-Petersen, 2014). The method allows us to identify, sort, and categorize the most relevant articles among a vast amount of literature. Even though SLR does not provide a guarantee to find all relevant articles, it has the advantage of approaching a selected topic from numerous directions, allowing authors to cover an entire field of research. Thereby, SLR helps uncover existing research gaps and identify areas where additional research might be needed (Kofod-Petersen, 2014).

The field of predictive maintenance is broad and the existing pool of papers is large. As this survey aims to construct a framework addressing the distinctive facets of predictive maintenance in Industry 4.0, we needed to identify the relevant papers from this domain. However, the only keyword we used in the present survey to detect the relevant literature with a Google Scholar search was *Predictive Maintenance*. We then selected those peer-reviewed articles from the results that dealt thematically with the area of Industry 4.0 by screening the papers' titles and abstracts. We refrained from explicitly using the term "Industry 4.0" in our search queries, as otherwise, papers that were thematically related to this area but did not explicitly use the term would fall through the cracks. Therefore, the selection was done manually by checking the list of results from a Google Scholar search from the top down. As in Google Scholar, the publications are sorted according to their relevance for the search term; this allows us to find the most relevant papers first while the usefulness of the later papers is steadily decreasing. A paper for the framework was selected by first scanning the title and abstract to identify the detail in which the paper covers the topics of predictive maintenance and Industry 4.0. If a paper explains the applied predictive maintenance approach and its context, e.g., system size and condition monitoring in detail, it was selected to build the framework. The first search was conducted in October 2018 and resulted in 140 articles from journals and conference proceedings that we considered relevant. These articles were published between the years 1993 and 2018. We conducted another search in June 2023. This search resulted in an additional 109 results that we also used to build our framework.

Another literature review method considered for the present survey is the berry-picking method. In this method, the review starts by identifying a starting paper that matches the addressed topic and objectives (Booth, 2008). The following step in the process is footnote chasing, where the list of references for the starting paper is checked for more relevant literature. Furthermore, the search for relevant literature can be extended by checking the references of the starting paper and the papers that cite the starting paper. The drawback of this method is that the papers are most likely connected based on a similar sub-theme that is addressed by these papers, thereby potentially missing important other subsections of the main topic. This issue can be approached by choosing multiple starting papers to cover the missing sub-themes. As the amount of literature addressing predictive maintenance is so broad and contains numerous sub-themes, the berry-picking method would likely still miss relevant fields even with an increased number of starting papers. Hence, the SLR is considered a better method for the present survey as it allows us to find more diversified relevant literature to cover a much broader scope of the topic, and we applied it for building the framework.

3.2. Overview of selected publications

In total, 249 publications have been selected for this survey. Fig. 3 shows a stacked bar chart to provide an overview over the publication year, grouped by publication type (conference, journal, others).

As can be seen, the number of journal entries is higher than conference papers. Additionally, some book chapters are included in the study because of their relevance; those are listed as *Other*.

Another interesting aspect is that the number of relevant publications has risen to the present. This can be due to the selection procedure using the search engine, but it may indicate that the application in Industry 4.0 has become more important for the industry and is technically feasible. A few papers were selected for 2023 as the selection was carried out before June.

3.3. Construction of the framework

To construct the framework of predictive maintenance approaches in Industry 4.0 scenarios, we started by examining the first paper selected from the potentially relevant literature of the Google Scholar search. Note that it is not important with which paper this process is started as the whole process has an iterative characteristic. While a paper is examined, a table is filled with data about the relevant attributes covered. Thus, whenever an important attribute or characteristic concerning predictive maintenance is identified, a new column is added to the table, and the attribute is ticked for this paper. Thereafter,

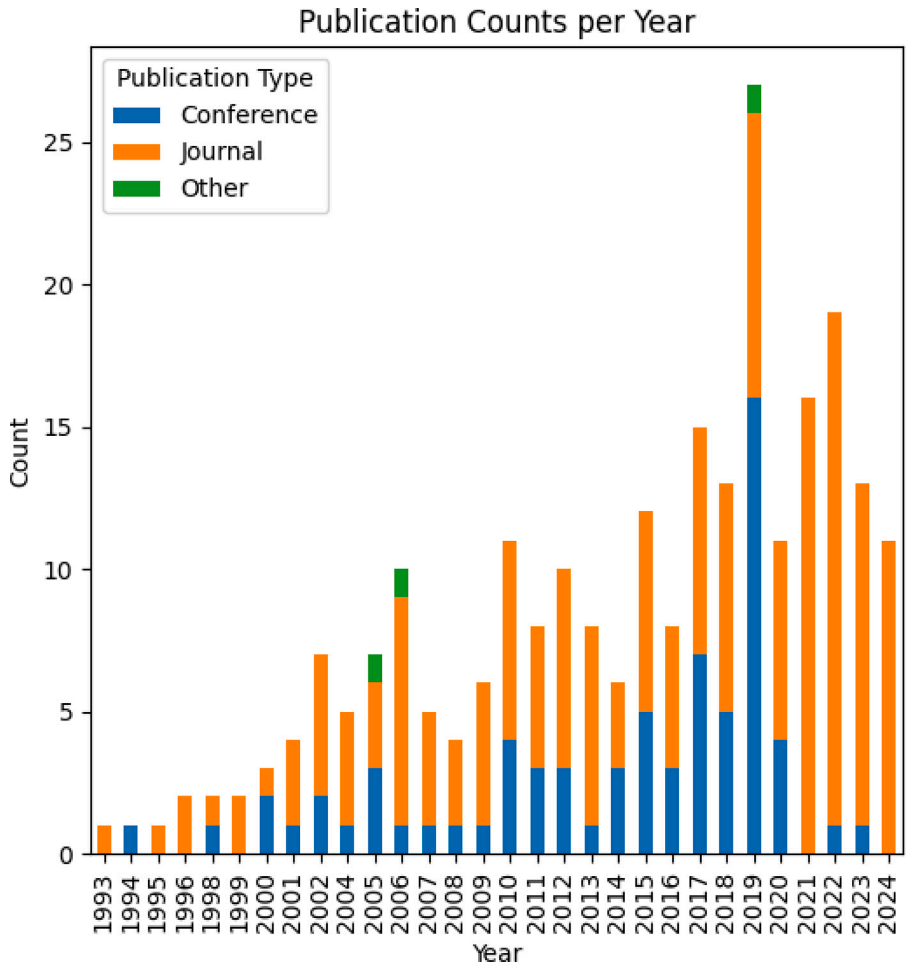

Fig. 3. Yearly overview of the selected publications, grouped by publication type (conference, journal, others).

every paper categorized in the table gets a separate row to mark the attributes covered. The following papers are checked iteratively for each attribute listed in the table and for additional relevant attributes. After all papers are checked, the data grid resembles a triangle, as the papers at the beginning of the process were not tested for the relevant attributes identified later in the process. Thus, a second round of scanning is performed, and the data grid is completed. The result of this process serves as the foundation of the predictive maintenance framework.

For the framework, we only included primary research papers that directly addressed issues in predictive maintenance applications. We excluded surveys and literature reviews in this step. However, we discuss these papers in Section 6 to situate our approach within existing related work.

In the final step, we mapped the data grid from the SLR to a set of categories by clustering the attributes into discrete categories. Each category is named by a term that represents the content of this cluster. These umbrella terms build the main categories of the framework. If appropriate, the clusters can have further subdivisions to allow for a finer classification within the categories. Thus, the entire framework can be best represented as a tree. The main categories of the predictive maintenance framework and the tree structure for every category are presented in Section 4.

4. Framework for predictive maintenance

For the purpose of analyzing the collected papers, a framework of attributes has been constructed. The attributes consist of information about the scope, type, and complexity of the application proposed in the respective articles and have been guided by three research questions:

How can the scope of the application be described? By including a flag for the implemented step in the PdM pipeline, which are condition monitoring, fault detection, degradation process modeling, and scheduling.

How can the complexity of the application in the article be estimated? By including the system size and maintenance scope.

How can similar approaches be grouped in the category? This includes the application methodology, which consists of prognostic techniques, data handling, and evaluation.

The analysis of the papers resulted in a grid that consists of a total of 73 different attributes, described in the following sections. The framework built from this data grid can be found at Predictive Maintenance Literature Review Framework (2023). The entire framework for predictive maintenance consists of 9 categories: Condition Monitoring, Maintenance Scope, Degradation Process, Fault Detection, System Size, Scheduling, Prognostic Techniques, Data Handling, and Evaluation. Fig. 4 shows these 9 categories, which represent the highest level of the framework. In the remainder of this section, we describe the categories in detail, with all the attributes summarized within a specific category. It is important to mention that some papers dealt with multiple attributes within a category. Therefore, the frequency does not represent the total number of papers in a category.

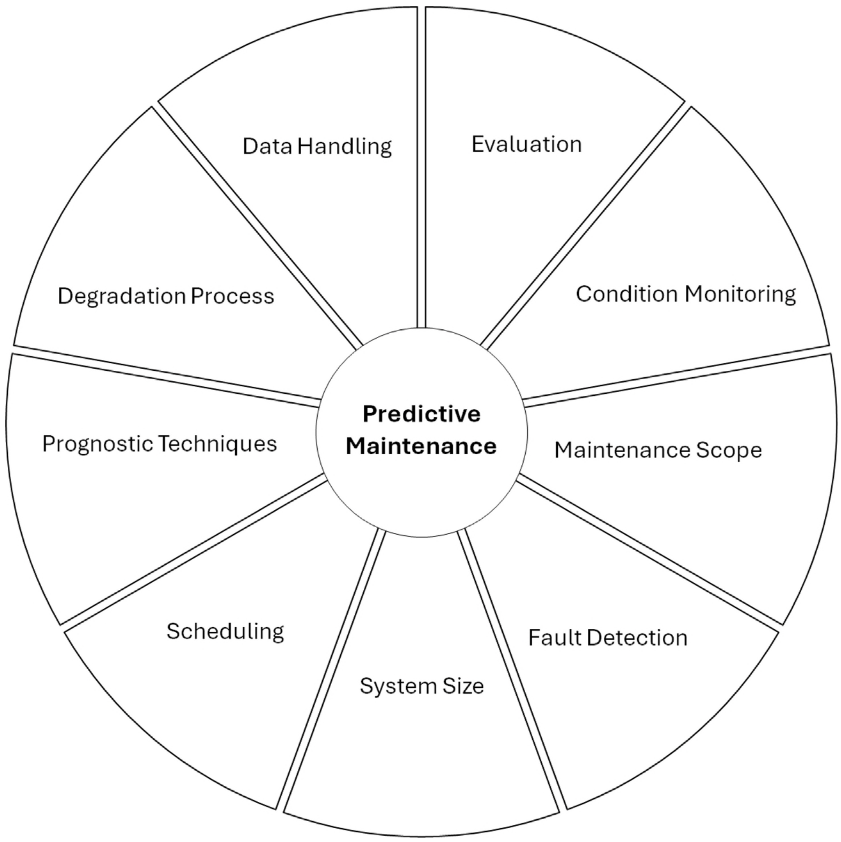

Fig. 4. Overview over the categories of the framework for predictive maintenance.

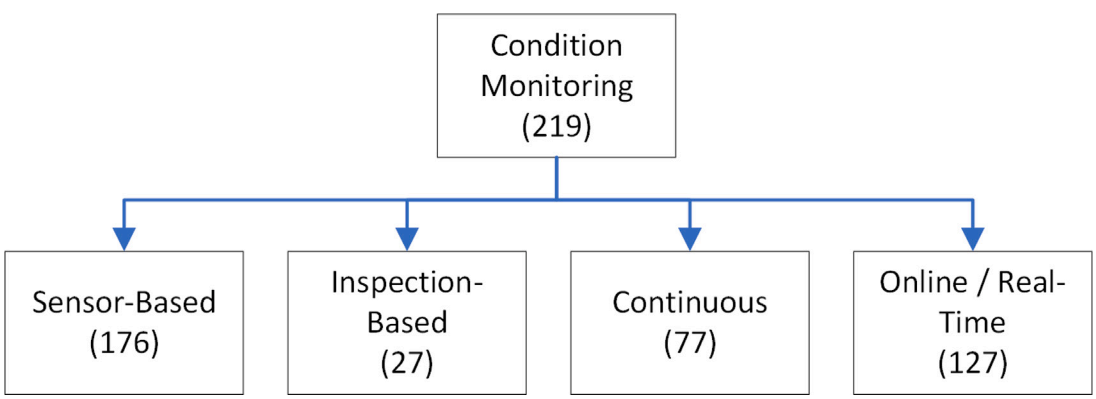

Fig. 5. Overview of the category condition monitoring.

4.1. Condition monitoring

A predictive maintenance approach is based on collecting data from a machine or component, which indicates its health status and allows the prediction of the residual useful life based on this monitoring data (Gebraeel, Lawley, Li, & Ryan, 2005). The analysis of the papers has identified 4 different attributes for the category of condition monitoring: Sensor-Based Monitoring, Online/Real Monitoring, Continuous Monitoring, and Inspection-Based Monitoring. 219 out of 249 papers dealt with at least one of the 4 attributes within their research. All attributes and their corresponding frequency of occurrence are shown in Fig. 5.

Since advancements in sensor technology made sensors for various types of parameters more affordable, most studies base their research on sensor-based monitoring (80%). With sensor-based monitoring, different sensors, such as observing vibration and temperature, are used to collect the relevant data (Orhan, Akturk, & Celik, 2006). Generally, sensor technology is more appropriate for an integrated predictive maintenance system as it is crucial for efficient continuous monitoring.

Online/real monitoring is a condition monitoring technique (58%) that allows data collection in the running state of a machine (Lindstrom, Larsson, Jonsson, & Lejon, 2017). Furthermore, it is the prerequisite for continuous monitoring as a continual collection of data is merely feasible in the machine's running state. Therefore, researchers always address online monitoring when implementing a continuous monitoring approach in their studies. However, online monitoring is also possible for inspection-based methods, but it does not resemble a requirement in this case.

As the term already indicates, continuous monitoring (35%) is the continual collection of relevant monitoring data to estimate the remaining useful life of a machine or component (Traore, Chammas, & Duviella, 2015). In contrast to inspection-based monitoring, the

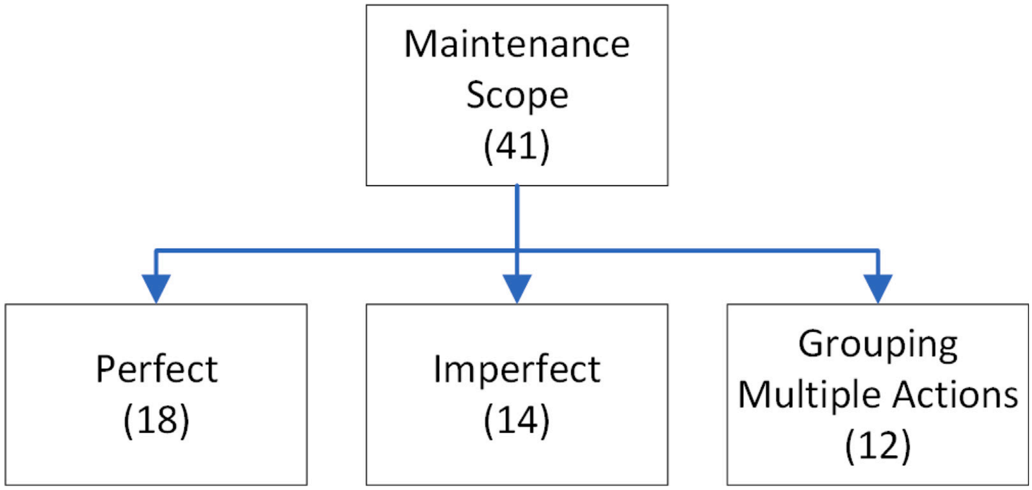

Fig. 6. Overview of the category maintenance scope.

amount of data collected is significantly higher since inspection-based monitoring is simply a periodic snapshot of a machine's conditional state. Hence, inspection-based monitoring and continuous monitoring are the only two attributes in this category that are mutually exclusive. All other attribute combinations are feasible.

Finally, inspection-based monitoring (12%), the least addressed approach, enables assessing a machine's condition and gathering crucial data. With inspection-based monitoring, the data is merely collected in inspection intervals. However, the intervals are not predefined, as in conventional maintenance policies. The intervals are adapted concerning the observed and collected data about a machine's or component's current and predicted conditional state (Jardine, Lin, & Banjevic, 2006). Note that sensor-based and inspection-based monitoring are not mutually exclusive, as sensor equipment is often necessary to perform the inspection (Kaiser & Gebraeel, 2009).

4.2. Maintenance scope

The category of maintenance scope is not often addressed explicitly. Each maintenance action requires an assumption about the maintenance scope, yet only a few studies (N = 41) explicitly address this category. Therefore, the framework solely integrates the number of times the topic of maintenance scope is mentioned. The present survey makes no assumptions about the maintenance scope in cases where no maintenance scope is mentioned directly. The analysis of the papers revealed three different attributes for the category maintenance scope: Perfect Maintenance, Imperfect Maintenance, and Grouping Maintenance Actions. Fig. 6 shows all attributes belonging to the category of maintenance scope.

First, perfect maintenance assumes that every maintenance action conducted at a machine or component restores functionality and durability to its original level (Dieulle, Berenguer, Grall, & Roussignol, 2001).

This assumption follows an *as good as new* approach for every maintenance action (Dieulle et al., 2001). In contrast to this approach, the assumption of imperfect maintenance is based on the premise that a maintenance action cannot restore the functionality and durability of a particular machine into an *as good as new* state, but only into an *as good as old* condition (Tan & Raghavan, 2010). Thus, the machine or component is still assumed to be used equipment even after maintenance. Generally, the category of maintenance scope is rare in predictive maintenance research because continuous monitoring and prediction updates usually make the assumption about the maintenance scope obsolete.

The third and final attribute of the category of maintenance scope is far more important for predictive maintenance but is not severely represented in the academic literature. The possibility to efficiently group maintenance actions leads to an overall cost reduction for maintenance activities as downtimes can be reduced (Ladj, Varnier, & Tayeb, 2016; Nguyen, Do, & Grall, 2017). A precondition for grouping maintenance actions is a holistic predictive maintenance approach that monitors the entire manufacturing equipment to identify certain maintenance actions best-conducted simultaneously (Nguyen et al., 2017). While the assumptions about perfect and imperfect maintenance are mutually exclusive, the attribute of grouping maintenance actions can be addressed in combination with the other two attributes of the category.

4.3. Fault detection

A pure predictive maintenance approach solely focuses on predicting the future conditional state of machinery and components to schedule maintenance activities appropriately and in scope. Nevertheless, 67 of the examined academic papers additionally address the topic of fault detection, meaning that the predictive maintenance approach does not only attempt to predict the remaining useful life of the machine but also tries to identify the root cause of the failure based on the collected data (Yam et al., 2001). The category of fault detection includes the following attributes: Root Cause Analysis and Machinery Diagnostics.

Fault detection covers the additional function of diagnostics. Thereby, root cause analysis and machinery diagnostics address the same issue. More researchers refer to machinery diagnostics (80%) when dealing with fault detection, while others specify their fault detection technique as root cause analysis (28%) or mention both terms. The general idea is processing acquired monitoring data to uncover the reasons for future failure. Thus, vibration or other machine monitoring data is used for diagnostic purposes (De Faria, Costa, & Olivas, 2015). The feasibility and accuracy of a fault detection approach depends on the level of monitoring activity, i.e., monitoring more machine parts and components individually improves the feasibility of identifying the root cause for a future failure (De Faria et al., 2015).

4.4. Scheduling

The scheduling category is addressed by 108 of the papers and, therefore, has an important role in predictive maintenance. It does not seem unusual as the main motivation behind a predictive maintenance approach is to identify the need and timing for maintenance activities in advance, allowing efficient scheduling. The attributes identified in

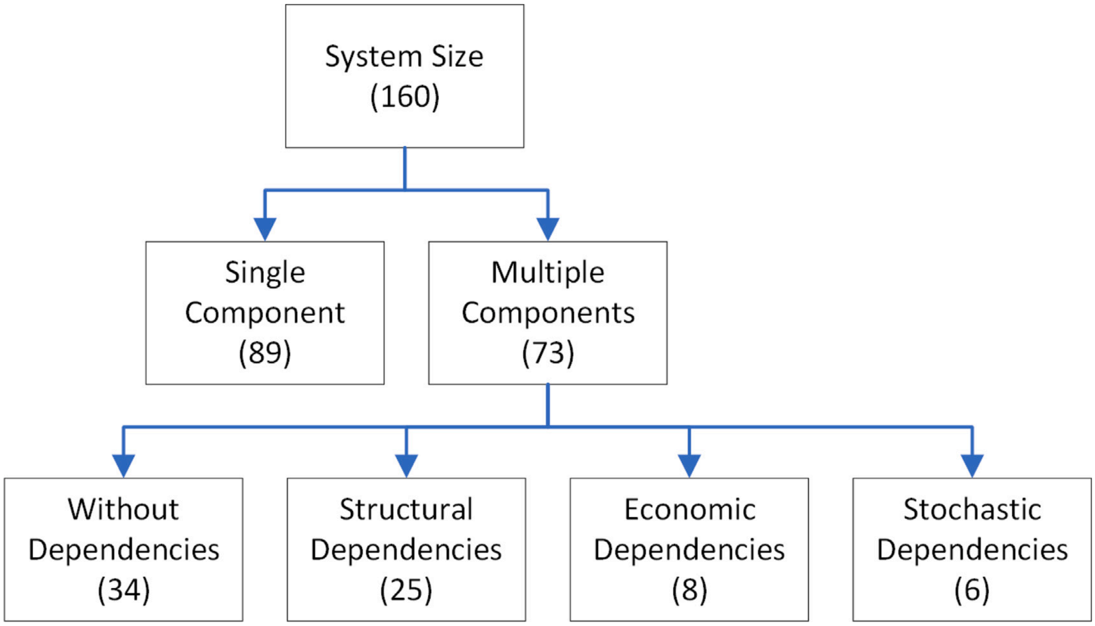

Fig. 7. Overview of the category system size.

this category are Dynamic Action Scheduling and Dynamic Spare Part Availability.

First, dynamic action scheduling describes the possibility of dynamically adapting the maintenance schedule based on new and processed condition monitoring data (Yang, Djurdjanovic, & Ni, 2008). This dynamic scheduling is only possible in a predictive maintenance environment due to the forecast of a machine's future conditional state. Optimization algorithms can be applied to define the most cost-effective maintenance schedule and continuously update this schedule when new machinery prognostics information becomes available (Yang et al., 2008). Hence, the maintenance schedule is not static as it would be for conventional maintenance policies but rather dynamic.

Additionally, a few papers cover the attribute of dynamic spare part availability, where the maintenance activities and the necessary spare part ordering are linked to the predictive maintenance system (Nguyen et al., 2017). Compared to an isolated policy, this broader and more integrated approach better fits the modern idea of Industry 4.0 and smart factories.

4.5. System size

Another relevant parameter identified during the literature review is the category of system size. This category addresses how the predictive maintenance approach is applied or assumed to be applied when implemented in real life. The analysis revealed two attributes: Single-Component Systems and Multi-Component Systems. Furthermore, the attribute of multi-component systems is further divided into the subcategory of component dependencies, which are divided into the following attributes: Structural Component Dependence, Economic Component Dependence, Stochastic Component Dependence, and Without Dependencies. Fig. 7 shows all category attributes. 160 papers analyzed in the present survey mention or reveal the addressed system size.

First, single-component systems are defined by the present survey as single components, e.g., experimental studies that conduct laboratory tests with mere bearings of single machine components or single machines considered solely in an isolated context (Hashemian, 2011), i.e., the machine might consist of multiple components. However, the whole machine is considered as a single unit. The definition chosen for this category results in less mentioned true multi-component systems (46%) compared to single-component systems (56%).

As described in the previous paragraph, the true multi-component system consists of separate components that form or are part of a larger system, e.g., an entire manufacturing line (Van Horenbeek & Pintelon, 2013), or multiple machines. Implementing a successful predictive maintenance system is much more complicated for these multi-component systems since more data needs to be processed and dependencies between the system's components become relevant (Van Horenbeek & Pintelon, 2013). However, while a significant number of papers address multi-component systems, 39 of the 73 papers (54%) additionally address the topic of dependencies.

Dependency in multi-component systems can be divided into three different types. First, structural dependencies result from components that form a unified part in that the maintenance of one component directly implies the maintenance of all structural dependent components (Nguyen et al., 2015). Second, economic dependencies are such dependencies that enable cost reduction when parts of the system are maintained simultaneously, e.g., because, for the maintenance of one component, other components have to be offline as well, thereby reducing downtime when maintenance actions for these components are conducted jointly (Nguyen et al., 2015). Finally, stochastic dependencies are dependent on stochastic relations between components of their deterioration process. Hence, the degradation of one component affects the state of one or multiple other components of the system (Nguyen et al., 2015). Furthermore, the existence of these dependencies is why single-component predictive maintenance approaches are not simply scalable to a multi-component level but must be adapted about the effects of these dependencies (Nguyen et al., 2015).

4.6. Prognostic techniques

The category of prognostic techniques is one of the most important ones for predictive maintenance. While all the monitoring and data acquisition is indispensable, the prognostic technique is what transforms the raw data into valuable information. Note that since a prognostic technique attempts to predict a prospective failure of a machine or component, the generated information is just probabilities. For the predictive maintenance framework of the present survey, 29 different prognostic techniques were identified and shown with their occurrence count in Table 1.

The analysis of the papers showed that the number and diversity of different techniques are enormous. Many techniques are often

Table 1
List of prognostic techniques identified through the SLR.

Prognostic techniques	Count
Artificial Neural Network	74
Random Forest	28
Bayesian Model/Networks	23
Statistical Pattern Recognition	21
(Semi-Hidden/Hidden) Markov Model	17
Fuzzy Logic	15
(Multiple) Linear Regression	11
Kalman Filter/Prediction	11
Decision Tree	11
Auto-Regressive Moving Average (ARMA)	10
Gamma Process	10
Support Vector Machines (SVM)	10
Genetic Algorithm	8
Regression Trees	4
XG Boost	4
k-Nearest Neighbors (kNN)	4
Particle Filtering	3
Logistic Regression	3
Hazard Rate Model	3
Wiener Process	3
Multiple Classifier	2
Kriging Statistical Technique	1
Linear Discrimination Analysis	1
Multiple Logistic Function	1
Non-homogeneous Poisson Process	1
Rules (SWRL)	1
Rough Set Theory Algorithm	1
Bansal–Jones Estimation Algorithm	1
Margin Analysis	1

found only once or twice within all the publications. Thus, the present survey will not present and discuss all the different techniques in detail. 222 out of the 249 examined papers explicitly mention the prognostic technique, whilst the remaining articles do not directly mention their applied approach. This section delves into the most prominent prognostic techniques, elucidating their application in predictive maintenance.

In recent years, a noticeable shift has been observed towards integrating artificial intelligence (AI) and machine learning (ML) in prognostics. With 74 counts, Artificial Neural Networks (ANN) (e.g., Garcia, Sanz-Bobi, & del Pico, 2006; Garga et al., 2001; Wu, Gebraeel, Lawley, & Yih, 2007; Yam et al., 2001) lead the pack in prognostic techniques. In the case of an ANN, nodes, also called neurons, are structured in multiple layers where every neuron passes on a value to all nodes in the next layer (Agatonovic-Kustrin & Beresford, 2000). Every value is weighted by some real number representing the weight of the connection between two neurons. The idea of the network is that a specific input results in a specific outcome with a certain probability (Agatonovic-Kustrin & Beresford, 2000). The network mostly depends on the weights of every connection. However, finding these weights is not easy and requires tremendous training data to build a reliable artificial neural network (Agatonovic-Kustrin & Beresford, 2000).

Also, classification methods, such as Random Forest (RF), are often used in predictive maintenance. This technique was used by 28 authors in their papers (e.g., Mattes, Schöpka, Schellenberger, Scheibelhofer, & Leditzky, 2012; Scheibelhofer & Gleispach, 2012, Traini, Bruno, D'Antonio, & Lombardi, 2019, Ayvaz & Alpay, 2021). RF is an ensemble learning technique aggregating predictions from multiple decision trees to enhance accuracy and robustness Mattes et al. (2012), Scheibelhofer and Gleispach (2012). Bootstrap sampling creates diverse subsets of training data, with each subset responsible for training an individual tree. The collective votes of these trees determine the final classification.

In predictive maintenance, uncertainties are inevitable, often arising from sensor errors, unpredictable wear and tear, or machinery-related factors. Bayesian networks suit this environment, offering a structured approach to represent and process these uncertainties. This approach was mentioned by 23 publications (e.g., Engel, Gilmartin, Bongort, & Hess, 2000; Gebraeel, 2006; Gebraeel et al., 2005; Kaiser & Gebraeel, 2009). To cope with aging equipment or operating under varying conditions, the network can be updated with new data, refining the probabilities and predictions. One of the pivotal advantages of Bayesian networks in predictive maintenance is their ability to quantify the probability of potential failures. This is invaluable for maintenance planning, as it allows for prioritization based on the likelihood and potential impact of failures.

Another more often appearing technique for predictive maintenance is statistical pattern recognition (N = 21; e.g., Chen & Blue, 2009; Hashemian, 2011; Liao, Wang, & Pan, 2012; Pedregal, Garcia, & Schmid, 2004). This technique detects and interprets patterns or trends within datasets Liao et al. (2012). Machines and equipment often exhibit specific behavioral trends or data signatures as they approach the end of their remaining useful life or when defects begin to manifest. Recognizing these patterns early on allows for proactive intervention, significantly reducing, e.g., the risk of failures or unplanned downtime.

(Semi-Hidden/Hidden) Markov Models (HMM) (mentioned by, e.g., Carnera, 2005; Carnero, 2006; Cartella, Lemeire, Dimiccoli, & Sahli, 2015; De Saporta, Dufour, Zhang, & Elegbede, 2012) are statistical frameworks designed to estimate the remaining useful lifetime, primarily drawing insights from present conditions and historical data. These models operate on the principle of states, where each state represents a specific condition or configuration of a system. In the realm of predictive maintenance, the applicability of HMMs becomes evident. Over their life, machines transition through various health states, some of which may not be directly observable through sensors or measurements. HMMs assist in inferring these hidden states, providing a clearer picture of the machine's health trajectory Jardine et al. (2006).

In addition, mathematical approaches like Fuzzy Logic are also used in predictive maintenance. The primary purpose of this approach is to provide a structured framework that deals with uncertainty Jardine et al. (2006). In predictive maintenance, sensor readings often come with a degree of uncertainty. Fuzzy Logic becomes helpful in these scenarios, allowing for better interpretations of the data. This supports better decision-making when determining machinery or systems' health and potential risks. This approach has been discussed and highlighted in various studies (N = 15; e.g., Garcia et al., 2006; Swanson, 2000; Traore et al., 2015; Yan, Lu, & Andrew, 2005).

In predictive maintenance, regression models are a frequently used prognostic technique. For example, (Multiple) Linear Regression seeks to establish a relationship between variables. The complexity of Multiple Linear Regression allows us to predict potential future failures by correlating different indicators from a maintenance dataset (Lucifredi, Mazzieri, & Rossi, 2000). Such predictions are crucial for the reduction of downtime. The significance and application of these regression models in maintenance contexts have been elaborated upon in 11 studies (e.g., Lucifredi et al., 2000; Onanena, Oukhellou, Candusso, Same, Hissel, & Aknin, 2010; Susto, Beghi, & De Luca, 2011; Zhou et al., 2005). However, for a reliable regression model, there must be a tremendous amount of training data to define the model before it can be applied to new test data. The same holds for Bayesian-based models (Si, Wang, Hu, & Zhou, 2011).

The significance of the Kalman filter is emphasized in 11 studies (e.g., Abdennadher, Venet, Rojat, Retif, & Rosset, 2010; Susto et al., 2011; Wang et al., 2017; Yang, 2002). It is a renowned algorithm in the world of data processing and estimation. In predictive maintenance, the Kalman filter assumes an indispensable role. Many assets and systems rely on sensor data, which can be subject to various forms of noise or interference. The Kalman filter helps isolate the genuine signals from this noise, providing a clearer picture of asset health (Jardine et al., 2006). Doing so assists in making informed decisions regarding maintenance, ensuring longevity and efficiency.

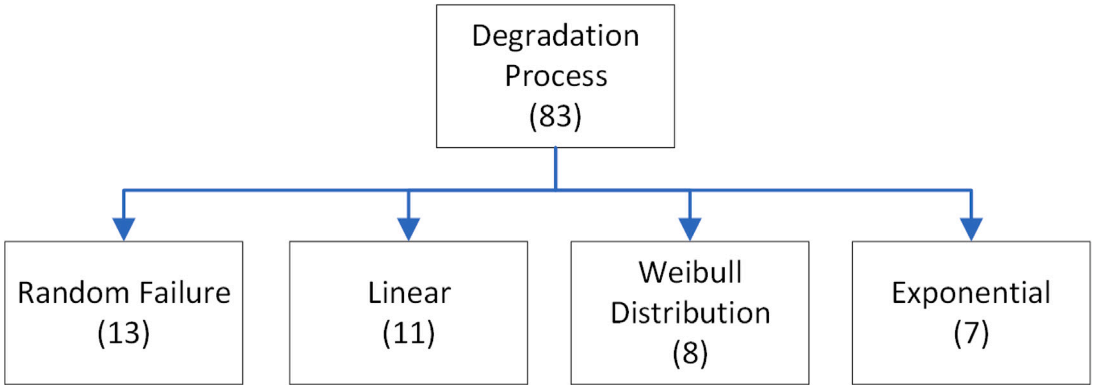

Fig. 8. Overview of the category degradation process.

Furthermore, other trend analysis techniques are time series models, for example, the Auto-Regressive Moving Average (ARMA) approach (N = 10; e.g., Baptista et al., 2018; Lee, Qiu, Ni, & Djurdjanovic, 2004; Liao et al., 2012; You, Yi, Li, et al., 2010). In predictive maintenance, machinery and assets often generate time-series data, capturing their operational behavior over periods. ARMA models help to analyze patterns, anomalies, or trends. By forecasting, ARMA aids in anticipating potential issues or machinery faults Assis-lopes, Steiger-gaqiio, and Campus (1996).

Another stochastic approach that provides a mathematical framework to understand machinery's wear and tear dynamics is the Gamma Process (mentioned by ,e.g., Grall et al., 2002; Langeron, Grall, & Barros, 2015; Nguyen et al., 2015; Van Horenbeek & Pintelon, 2013). A more detailed and probabilistic model of how machinery degrades over time can be derived. Moreover, it offers deep insights into the degradation process of various assets.

This category's main purpose is not to find a generally valid classification of every prognostic technique. Instead, we highlighted the range of techniques we found in 249 research papers, which shows how diverse this field is. There are many different approaches to improve and create new feasible methods for predictive maintenance.

4.7. Degradation process

The category degradation process is addressed by 83 of the 249 analyzed papers. It covers the direct modeling of the degradation process of a machine or using a predefined model of its deterioration course. The different assumptions on which the predefined models rely are Random Failure Assumption, Weibull Distribution Assumption, Linear Degradation Assumption, and Exponential Degradation Assumption. Please note that papers often indicated that the degradation process was modeled but did not provide further modeling details. Hence, the number of papers in this category is much higher than the accumulated sum of the four assumption models. Fig. 8 shows the category degradation process and all its attributes.

Initially, the process of degradation modeling is the derivation of the deterioration course of a machine or component based on relevant machine health indication data such as vibration or temperature (Gebraeel, 2006). This procedure gathers information about a particular machine's typical conditional state over its lifetime (Gebraeel, 2006). Modeling the deterioration process is beneficial because knowledge about a machine's degradation pattern can support a predictive maintenance system to predict future breakdowns more accurately. Nevertheless, the predictive maintenance approach is not meant to merely rely on the average degradation of a machine to decide on the maintenance intervals. The primary indicator is still the predictive maintenance system and its prognostic approach, which the information of the degradation modeling could support. Fig. 9 shows an

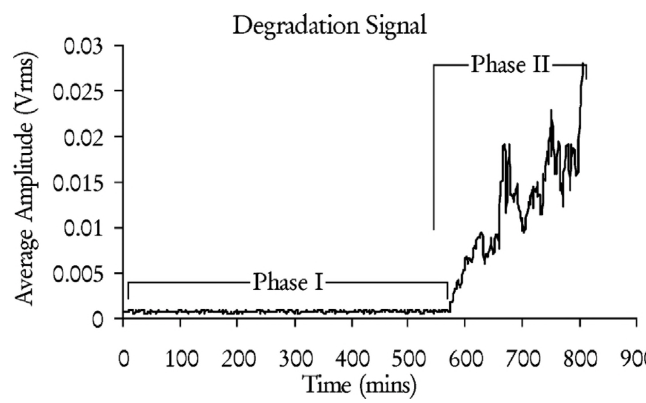

Fig. 9. Vibration-based degradation modeling (Gebraeel, 2006).

example of a vibration-based degradation course where phase I represents the non-defective state and phase II is the conditional state close to failure (Gebraeel, 2006). Thus, the objective is to model these phases to support the machinery prognostics of the predictive maintenance decision regarding the timing and need for maintenance activities.

A few papers make an assumption about the degradation process instead of following a modeling approach. However, since the predictive maintenance approach is based on monitoring the conditional state and prognostics, the assumption about the deterioration course of a machine is not relevant for a predictive maintenance approach. Hence, only a fraction of the academic literature mentions such an assumption before implementing a predictive maintenance approach. The assumptions about linear degradation, exponential degradation, and random failure are straightforward (Elwany & Gebraeel, 2008; Gebraeel et al., 2005; Hashemian & Bean, 2011). A predictive maintenance approach would be most efficient in the presence of random failure since conventional maintenance policies usually fail. Additionally, the academic literature mentions a distribution called Weibull Distribution (Gebraeel et al., 2005). It is a continuous probability distribution based on adjustable parameters used to model the lifespan of machines or components (Gebraeel et al., 2005). By characterizing the probability of failure over time, the Weibull Distribution aids in anticipating equipment breakdowns and optimizing intervention schedules.

4.8. Data handling

The category data handling deals with the amount of data acquired by condition monitoring. Especially in continuous monitoring with multiple sensors, the amount of data collected by these sensors results in an enormous amount of data to be handled (Munirathinam & Ramadoss, 2014; Yan, Meng, Lu, & Li, 2017). The analysis of the papers covered

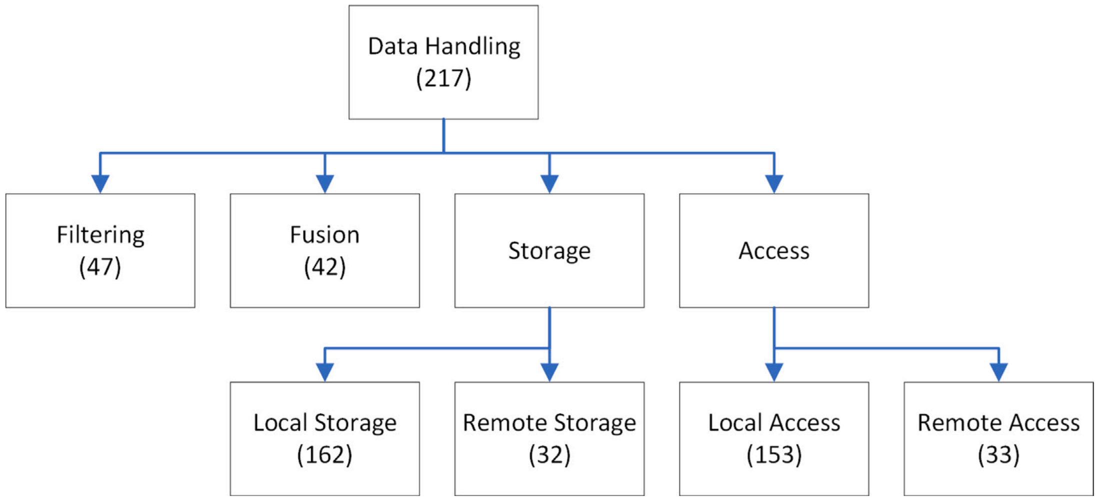

Fig. 10. Overview of the category data handling.

in the present survey reveals the following relevant attributes: Data Filtering, Storage, Access, and Data Fusion. Additionally, the attributes of storage and access are divided into the sub-attributes of Local Storage and Remote/Cloud Storage, as well as Local Access and Remote Access. Of those attributes, at least one is mentioned in 217 out of 249 papers. Fig. 10 shows all category attributes and their corresponding frequency of occurrence.

First, data fusion and data filtering are two methods that deal with big data generated by continuous monitoring. The data fusion approach utilizes the idea of integrating multiple data sources to generate more reliable data compared to any individual data source. In the case of sensor-generated data, data fusion combines the data of multiple sensors. The resulting more reliable and accurate data is then processed and analyzed (Kandukuri, Klausen, Karimi, & Robbersmyr, 2016; Lee, Ni, Djurdjanovic, Qiu, & Liao, 2006). On the other hand, data filtering also deals with the issue of large amounts of data by filtering uninformative data (Yamato, Fukumoto, & Kumazaki, 2017). For the most part, continuous monitoring will generate data that shows that a particular machine is in a normal state (Wang, 2016). Therefore, data filtering models identify the useless data and only analyze the informative parts of the total amount of data, thus making the data processing more accurate and efficient (Schirru, Pampuri, & De Nicolao, 2010).

Second, unlike data fusion and filtering, data storage and access are attributes often addressed by papers. Every paper includes some monitoring, which inevitably generates data that needs to be stored and made accessible for further processing. The analysis shows that for storage location and data access, the remote alternative is addressed less and mostly in combination with IoT, Industry 4.0, and cloud computing (Chiu, Cheng, & Huang, 2017; Lee et al., 2006; Yan et al., 2017). This fact is interesting as the remote approach seems more suitable for an efficient predictive maintenance system in an Industry 4.0 environment, especially with a manufacturing structure consisting of multiple production sites. Hence, the methods of remote storage and access are not covered as much as expected in the recent academic literature. We will discuss this issue in Section 5.

4.9. Evaluation

Finally, the evaluation category concludes the framework of the present survey for predictive maintenance. This category covers the application-oriented part of the studies. Most studies (N = 227) implement some way of testing their predictive maintenance approach and prove its feasibility. The following attributes were identified for this category: Evaluation based on Real Data, (Numerical) Simulation, Experiment Evaluation, and Comparison with Conventional Maintenance Policies. Fig. 11 shows all category attributes and their corresponding frequency of occurrence.

Note that none of the attributes are mutually exclusive. First, for the evaluation based on real data (63%), the researchers acquire actual data from companies who monitor their machines (Elwany & Gebraeel, 2008; Schmidt, Wang, & Galar, 2017). The data includes the monitoring data as well as information about the corresponding state of the machine, e.g., whether a failure occurred. This data can then be used to validate the accuracy and performance of the introduced predictive maintenance approach. The advantage of real data is that it allows the testing of the predictive maintenance approach with long-term data and data gathered from multiple large and complex machines. For example, the NASA Dataset, which can be seen as a benchmark dataset in this area, was used to test approaches for predictive maintenance techniques in some publications (e.g., Kumar Sharma, Brahmachari, Singhal, & Gupta, 2022, Xiong, Wang, Fu, & Xu, 2021). The provided dataset includes sensor data from turbofan engines or a milling dataset till their failure (Traini et al., 2019). The use of such benchmark datasets to increase the validity of the different methods will be discussed in Section 5.2

Second, studies mentioned that experiments (35%) were used to validate the different approaches. Mostly, the experiments are kept very small because merely one component, e.g., bearings or a detached engine, are used as experimental subjects (Gebraeel et al., 2005; Yang, 2002). Thus, experiments are usually limited to small-scale test setups, making them unsuitable to validate approaches that include multi-component systems and dependencies and connections with other related processes.

Further, the numeric simulation (30%) is an evaluation based merely on simulated data, e.g., a Monte Carlo Simulation that generates data about hypothetical failures, which must then be identified by the researcher's predictive maintenance approach (De Saporta et al., 2012; Lei, Sandborn, Goudarzi, & Bruck, 2015). Finally, some authors benchmarked their predictive maintenance approach with conventional maintenance policies (16%). These comparisons are generally based on comparing total costs for different maintenance policies, including predictive maintenance (Nguyen et al., 2015; Van Horenbeek & Pintelon, 2013), thus attempting to prove predictive maintenance's superior efficiency and cost reduction opportunities.

5. Discussion

In the literature review we identified various aspects that motivate the use of predictive maintenance. The goal that was mentioned the most is cost minimization (N = 150). Three further highly mentioned

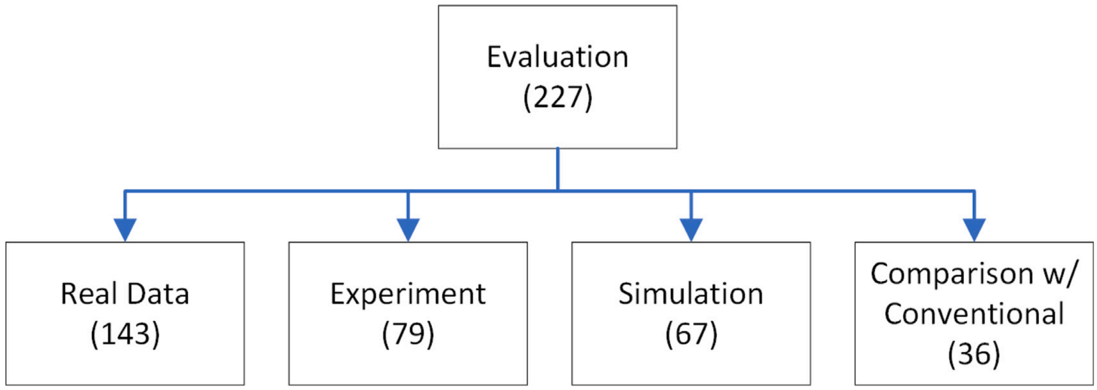

Fig. 11. Overview of the category evaluation.

goals are: availability (N = 103), downtime minimization (N = 98), and productivity (N = 60)—all represent a need for improving efficiency in the current industrial setting. Further, the aspects of reliability (N = 98) and safety (N = 58) can be seen as a third field of motivation, driven by more critical industrial applications.

The number of papers analyzed in this survey is merely a fraction of the available academic literature addressing predictive maintenance. However, the analysis provides insights about which aspects the literature mostly focuses on. Based on the observations from the collected sources, the following section will discuss the topics of (i) implementation complexity, (ii) data handling, and (iii) the trend from machine learning to deep learning. Furthermore, we summarize important aspects for practitioners that can be derived from our framework and help implement predictive maintenance processes. Additionally, we discuss possible threats to the validity of our results. Please note: We reference existing works as examples of approaches that apply a specific technique. The main objective of the section is a technique-based discussion of the literature; hence, also, due to space limitations, we will not explain the details of those approaches.

5.1. Complexity of current implementations

The first point of discussion is based on the categories System Size (cf. Section 4.5), Fault Detection (cf. Section 4.3), and Scheduling (cf. Section 4.4). Those three factors describe aspects of complexity issues that arise from predictive maintenance.

When looking at the system size, it is clear that only a small part of the publications mention systems with multiple components, with still fewer dependencies among those components. This means that most applications focus on machines or systems that have only one piece of hardware for the analysis, where no interdependence or influence from other parts of the systems would complicate the problem.

The task of fault detection is another important point that most publications fail to include. This could be due to the predominance of single-component applications, where an anomaly can be immediately related to a failure without further root cause analysis. However, the actual diagnostics of a detected anomaly are key to effectively using a predictive maintenance system in a real-world scenario.

Going even further in the maintenance process, less than half of the publications, especially recent ones, address scheduling appropriate actions. This point is also important in deploying predictive maintenance in real-world scenarios.

Considering these three observations, the current complexity and scope of applications for the industry is still quite low. Not only could more complex machines be the focus of research, but the implementation of the predictive maintenance process could also be more advanced by:

1. including fault detection or diagnosis on top of anomaly detection and
2. including the problem of maintenance scheduling to use the extracted information in actual operations.

Research Gaps in Application Complexity: The first research gap identified here is that research should focus on machines and systems built from multiple components. Further, the dependencies between the components and the resulting influences upon each other need to be accounted for. Handling increased complexity is an issue that, once solved, can enable many more realistic applications of predictive maintenance in the industry.

A second gap emerges in the completeness of implementations. Predictive maintenance can be seen as a holistic process ranging from data collection to pre-processing, anomaly detection, failure diagnosis, scheduling, and mitigation. However, current research fails to go far beyond anomaly detection. To implement the paradigm in real applications, research needs to focus on implementing all of these process activities, from gathering data to including relevant results in plant operations.

5.2. Common datasets and data handling

This second point of discussion is based on the observations for the framework categories Data Handling (cf. Section 4.8), Evaluation (cf. Section 4.9), and Condition Monitoring (cf. Section 4.1). When looking at how data is gathered, handled, and used in current applications, some possible directions for future research can be defined.

Gathering data for an application is the first important step of predictive maintenance. In our observation, most applications use a sensor-based monitoring approach, mostly in real-time. Only a portion of these sensor-based approaches are mentioned to be continuous, which means that most implementations are restricted to selected processes or test runs.

Most publications describe their process of data handling for their specific implementation. Looking at these descriptions, the most widely used approach is to store and access data locally. Only about 13% of publications mention a cloud or remote infrastructure for gathering, storing, or accessing data. Such infrastructures would enable aggregating data from different machines or production lines, e.g., to facilitate learning of ML models. Those ML models would be more robust through data aggregation and can be re-used across different production lines or plants, e.g., through transfer learning.

Real data is the predominant method when evaluating implemented solutions, with simulated data being less prominent. There were 61 experimental evaluations mentioned, which means there are many independently evaluated applications that are difficult to compare. Only 7% (19) of publications specifically mention using a NASA benchmark dataset for comparability. Using a standard dataset like the NASA dataset as a benchmark might be beneficial for reproducibility and comparison with state-of-the-art algorithms; however, the data must fit the specific patterns of the targeted application domain and machines. Additionally, only 14% of publications compare the predictive maintenance performance to regular maintenance paradigms.

Combining these observations creates a clear image of current implementation setups. Data is often recorded from specifically selected tests and stored locally for specific research applications. This straightforward approach leads to fast results when testing a single application; however, it does not incorporate the possibilities and flexibility of a remote or cloud solution. Also, errors are highly important in analyzing the resulting data patterns. Naturally, errors do not happen frequently, hence, those might be triggered artificially. Continuous real-time monitoring would support the data collection in a productive environment. Further, those data is not bound to any locale. Data from multiple devices could also be combined using remote technologies to extract even more information across machines.

Another conclusion based on the observed statistics is that evaluations are specific to every study and are often isolated from comparable applications. This conclusion is supported by the fact that only a small amount of publications evaluate their models using the well-known NASA datasets.

Research Gaps for Data Handling: An obvious gap in research is the lack of using remote infrastructure for data gathering. Implementing cloud technologies could gather more data from different machines and locations and incorporate it into more sophisticated models.

Further, although each application is unique in some points, evaluations should compare themselves to other methods, either conventional maintenance or similar applications, to enable a basis for discussion and to find common problems. This could be made possible by creating more application-specific benchmark datasets, such as the sets provided by NASA, and using them for evaluation purposes.

5.3. Machine learning for predictive maintenance

Our analysis identified a shift from mathematical methods towards machine learning (and, more recently, deep learning) for predictive maintenance in the last decade. While traditional mathematical methods for anomaly detection or identification of degradation patterns handle linear correlations and simple patterns, machine learning models handle complex, non-linear relationships and interactions in data, resulting in more accurate failure predictions, improved efficiency, and reduced downtime. In this section, we describe the differences between the identified types of machine learning and the respective challenges.

Machine Learning for Predictive Maintenance: Machine learning for predictive maintenance utilizes historical and real-time data to anticipate equipment failures, enabling proactive actions to prevent downtime. It involves anomaly detection, failure prediction, and lifecycle estimation, using techniques like regression, classification, and deep learning to provide timely alerts and optimize maintenance schedules. Traditional machine learning employs algorithms for pattern recognition and computational learning, typically using handcrafted features and statistical models. Deep learning, a subset of machine learning, uses artificial neural networks with many layers (“deep” architectures). As shown by Fig. 12, the amount of deep learning algorithms increased in the last years, especially the last five years. The main reason is that deep learning avoids time-consuming feature engineering and data manual pre-processing, as both are integrated into the learning process. Further, the technology involved has evolved and become more easily used as the required approaches are integrated into common machine learning frameworks.

Deep Learning for Predictive Maintenance: As deep learning focuses on the application of artificial neural networks, we discuss them in detail. Fig. 12 shows which types of artificial neural networks we identified in the literature research. As can be seen, a wide range of techniques were applied. This includes approaches using autoencoders, Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Transformers, especially for deep learning. In general, it can be observed that recent models got more sophisticated, including one instance of Reinforcement Learning (RL) and some Hybrid approaches. Autoencoders find applications by learning intrinsic patterns from sensor data collected from machinery. By compressing raw sensor readings into a lower-dimensional representation, autoencoders enable anomaly detection and fault identification, aiding in predicting potential breakdowns before they occur (e.g., Kim, Lee, & Kim, 2021; Sun et al., 2019). RNNs prove indispensable for predictive maintenance because they can model sequential data, such as time-stamped sensor readings. By analyzing the temporal dependencies in sensor data, RNNs can forecast equipment failures, allowing for proactive maintenance interventions (e.g., Abidi, Mohammed, & Alkhalefah, 2022; Yam et al., 2001). Often, Long Short-Term Memory (LSTM) networks as a specialized type of RNNs are used to address the vanishing gradient problem, and it can be applied in predictive maintenance by effectively modeling sequential sensor data to forecast equipment failures based on temporal dependencies (e.g., Abbasi, Lim, & Yam, 2019; Chen, Shi, Lu, Zhu, & Jiang, 2022; Nguyen & Medjaher, 2019). CNNs are well-suited for analyzing images and visual data from equipment components. In predictive maintenance, CNNs can detect visual defects, identify wear and tear on parts, and assist in the early detection of impending failures, ultimately optimizing maintenance schedule (e.g., De Santo, Ferraro, Galli, Moscato, & Sperlì, 2022; Jiang, Dai, Fang, Zhong, & Cao, 2022; Mitici, de Pater, Barros, & Zeng, 2023; Silva & Capretz, 2019). GANs are increasingly used to generate synthetic sensor data for training predictive models, making them more robust and adaptable to different conditions. The synthetic data can also detect sensor anomalies (e.g., Lu, Du, Qian, He, & Wang, 2022). Transformers play a role in predictive maintenance by handling multivariate time series data from diverse sensors. Their ability to capture complex temporal relationships and dependencies is crucial in accurately predicting equipment failures (e.g., Luca et al., 2023).

Despite their versatility and strong predictive capabilities, deep learning models come with certain limitations that need to be considered. A primary challenge is the interpretability of these models, often called the “black-box” problem, which complicates understanding the rationale behind predictions and decisions. This lack of transparency can hinder their adoption in critical maintenance scenarios where explainability is essential for trust and accountability. Furthermore, deploying deep learning models requires substantial computational resources, including high-performance hardware and energy consumption, which may not be feasible in resource-constrained environments. These limitations highlight the importance of balancing predictive performance with practical considerations, especially in industries where explainability and cost-efficiency are pivotal.

Hybrid Deep Learning for Predictive Maintenance: Further, some approaches also combine techniques that differ from the mentioned categories of deep learning. The authors of Liu et al. (2022) propose an intelligent predictive maintenance framework for machine tools using CNN-LSTM, where CNN extracts features from vast IoT-acquired data, and LSTM models their nonlinear relationships. Another approach introduces a new predictive maintenance method using improved deep adversarial learning combining LSTM and GAN (Liu, Tang, Zhu, & Nie, 2021). The LSTM network addresses the issues of vanishing gradients and mode collapse in GAN, enabling self-detection of abnormal data. In Bampoula, Siaterlis, Nikolakis, and Alexopoulos (2021), the authors present a novel approach for prediction and fault detection relying on autoencoders with LSTM networks to evaluate the operational status of production equipment. The approach utilizes multiple neural networks, each trained for a specific label, and capitalizes on the reconstruction error when the LSTM-autoencoder encounters unfamiliar data. This work in Dangut, Jennions, King, and Skaf (2023) introduces a new deep learning method that combines autoencoders and bidirectional gated recurrent unit networks for addressing infrequent failure predictions. The autoencoder is tailored and trained to identify these rare failures, and its output is then input into the convolutional bidirectional gated

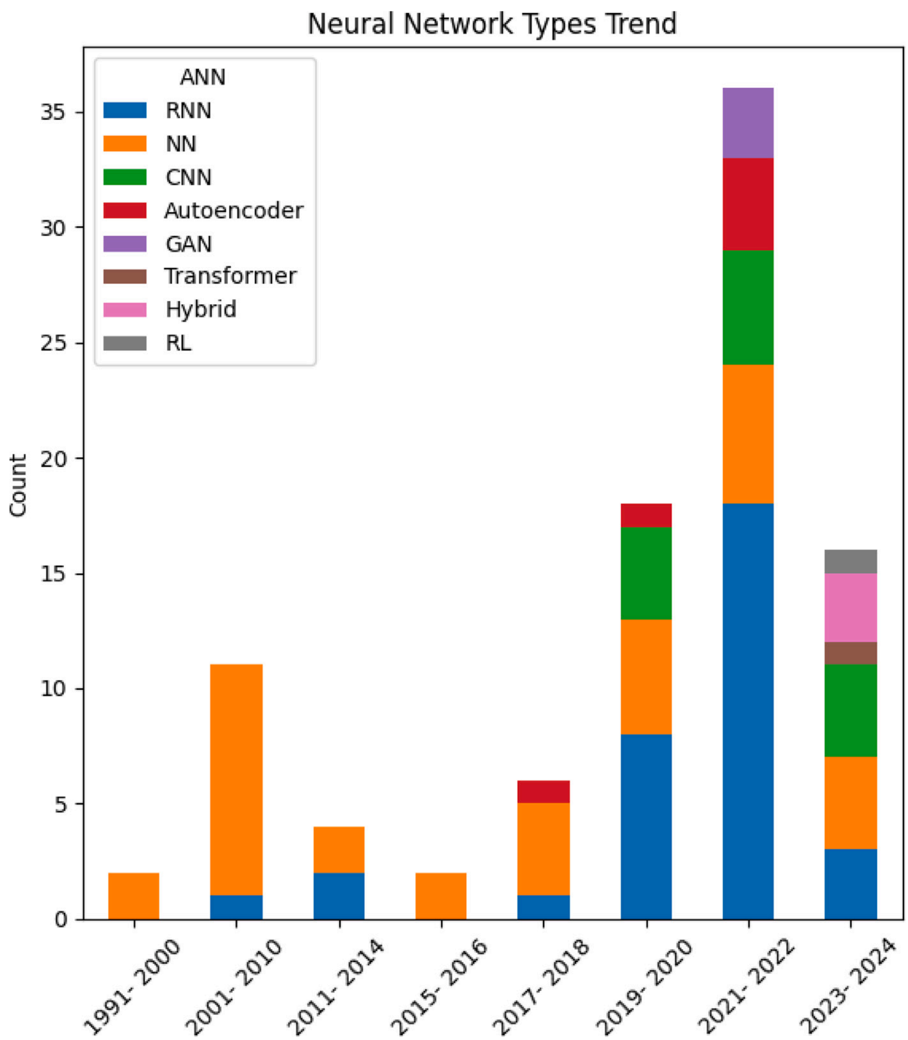

Fig. 12. Overview of the trend in deep learning.

recurrent unit network (type of RNN) to anticipate the next failure event. The suggested network design, together with the rescaled focal loss, tackles the issue of data imbalance during training.

Comparisons of Machine Learning for Predictive Maintenance: The “No Free Lunch” theorem (Wolpert & Macready, 1997) posits that no single algorithm consistently outperforms all other algorithms across all possible problem domains. In essence, there is no universally superior machine learning algorithm, and the best choice always depends on the specific problem and pattern of the data. Accordingly, several papers compare different machine learning or deep learning techniques. In the following, we summarize those papers; however, we do not report the specific performances of the approaches but rather want to show pointers for the comparison studies. Several studies evaluate different techniques for RNN. Koprinkova-Hristova, Hadjiski, Doukovska, and Beloreshki (2011) compared the Elman architecture with Echo State Networks. The study of Mateus, Mendes, Farinha, Assis, and Cardoso (2021) focuses on the differences between Gated Recurrent Units and LSTMs. The authors of Chen, Chen, Liu, Cheng, and Li (2021) extensively analyze different RNN variations, namely Vanilla RNN, LSTM, Bidirectional LSTM, and Gated Recurrent Units. Further studies compare CNNs and RNNs. The study of Zonta, da Costa, Zeiser, de Oliveira Ramos, Kunst, and da Rosa Righi (2022) compares traditional CNNs with a range of RNN structures, namely Gated Recurrent Units, the straightforward Simple Recurrent Network, and the LSTMs. The work of Kumar Sharma et al. (2022) analyzes the performance of Temporal Convolutional Networks (a type of CNNs), hybrid CNN-LSTM networks, and meta-heuristically optimized LSTMs. Similarly, the authors of Silvestrin, Hoogendoorn, and Koole (2019) provide an examination of LSTMs and Temporal Convolutional Networks. The authors of Ding, Yang, and Yang (2019) contribute to the discourse by focusing on the differences between autoencoders and RNNs, specifically emphasizing the Deep Bidirectional Gated Recurrent Units. The studies mentioned so far, compared solely deep learning approaches. The work of Del Buono, Calabrese, Baraldi, Paganelli, and Regattieri (2022) casts a wider view, juxtaposing Multilayer Perceptron (i.e., traditional neural networks) with LSTMs and CNNs as examples for deep learning approaches. Serradilla, Zugasti, Ramirez de Okariz, Rodriguez, and Zurutuza (2021) compare Extreme Learning Machines, a feedforward neural network variant, with autoencoders. This inclusion is a gentle reminder that while RNNs and CNNs might dominate the discourse, the broader machine-learning field remains vast and varied.

Summary: Machine learning models, particularly simpler ones, have an edge over deep learning regarding interpretability. They offer a clear understanding of the key features driving predictions. Moreover, they often require less data to make reasonable predictions and are less computationally intensive, making them more efficient and suitable for devices with limited resources. However, machine learning models have their drawbacks when compared to deep learning. They rely heavily on time-consuming feature engineering and domain knowledge. In contrast, deep learning models automatically extract features from raw data. While traditional methods may outperform simpler tasks with structured data, deep learning excels with large, complex, unstructured data like images and text, capturing intricate structures for high-level abstraction. Furthermore, deep learning models tend to improve as data availability increases, outpacing machine learning models, which often plateau after a certain data size. However, in contrast to traditional machine learning, the required amount of data for deep learning approaches is way larger, ending up in millions of required data points. Independent from the decision for traditional machine learning or deep learning, according to the "No Free Lunch" theorem (Wolpert & Macready, 1997), it is important to compare different techniques to find the one that best suits the specific application and data pattern.

5.4. Implications for practitioners

In this section, we describe several aspects of the framework from a practitioner's point of view. This shows how such a framework can help practitioners to decide which aspects are relevant for implementing predictive maintenance.

With the progression in sensor technology making various parameter sensors more cost-effective, a significant portion of research (69%) relies on sensor-driven monitoring. Such monitoring employs diverse sensors, like those measuring vibration and temperature, to gather pertinent data (Orhan et al., 2006). Nowadays, manufacturing machines usually have over 100 sensors that record different metrics in crucial machine components. In general, sensor technology appears well-suited for a comprehensive predictive maintenance system due to its capability for effective ongoing monitoring. In many instances, the makers of these production machines already offer analytical tools designed to identify the wear and tear patterns of essential machine components.

In academic writings, the aspect of maintenance scope should be explicitly tackled. This dimension determines whether maintenance can entirely restore a machine's condition or only do so partially. Such a narrow perspective might suffice for studies primarily concentrating on degradation patterns. However, every maintenance activity in real-world applications necessitates understanding its scope since it could affect subsequent predictive maintenance observations. The notion that maintenance brings a machine back to a pristine state is not of much concern: after parts replacement, the machine is assumed to be in brand-new condition. However, incomplete maintenance could have ramifications for the predictive maintenance workflow. It could alter future degradation patterns if we presume that the machine does not revert to a "brand-new" state post-maintenance. This is especially relevant for machine learning techniques, as the degradation process's recognition might need recalibration, learning, or changing the prediction algorithm. Future studies must consider these long-term predictive maintenance and degradation trajectories. For now, professionals should recognize the potential effects of maintenance on subsequent degradation detection.

Fault identification encompasses the extended role of diagnostics. The central premise involves analyzing collected monitoring data to discern potential causes for upcoming malfunctions. Data from vibration or other machine monitoring activities is utilized for diagnostic evaluations. The viability and precision of a fault identification strategy are contingent upon the extent of monitoring, meaning that observing more machine elements individually enhances the likelihood of pinpointing the primary reason for a future malfunction (De Faria et al., 2015). While academic pursuits largely center on degradation patterns, pinpointing the primary cause can be crucial for businesses, particularly when faced with unusual or recurrent wear of certain components. Making the identified malfunction comprehensible poses a challenge, demanding the algorithm interpret specific data and provide an intelligible summary. Achieving this is no simple task; it demands understanding degradation patterns and insights into the process, as factors like process parameters and attributes of manufactured items can affect machine component wear.

Research's emphasis on degradation patterns has led to a somewhat narrowed approach towards scheduling. We pinpointed two crucial actions in this domain: dynamic action scheduling and dynamic spare part readiness. While the former occasionally garners attention, the latter is touched upon by only a handful of research studies. Incorporating both actions is challenging, especially since they necessitate understanding the primary cause of degradation. This becomes even more intricate in multiple-part scenarios, where one component's wear and tear might affect others. Some of these critical components might not be monitored under the predictive maintenance strategy. Furthermore, timing is of the essence. Spare parts must be ordered well in advance to ensure their availability before maintenance, especially if they need to be readily stocked. Maintenance tasks are sometimes outsourced, making ample lead time imperative for proper planning. For instance, an industry associate once said they needed a two-week notice to coordinate maintenance with the relevant firm. All these facets are integral in practical applications, with the prediction time frame for degradation being a pivotal research topic.

During the literature review, system size emerged as a significant parameter. This category delves into how the predictive maintenance methodology is envisioned or expected to function in real-world applications. The review discerned two main traits: Single-Component Systems and Multi-Component Systems. While academia tends to focus on individual system parts, a broader perspective encompassing multiple components or levels is crucial in practical settings. In processes like batch production of food products, subsequent machines might have interdependencies. This adds another layer of intricacy to the process. Such intricacies necessitate a comprehensive approach to data management. Although much of the research is centered around localized data storage, in practice, accumulating data from (edge) servers might offer a more cohesive data overview.

As discussed in the previous subsection, the set of identified approaches for machine learning in degradation prediction is large. One reason is the "No Free Lunch" theorem (Wolpert & Macready, 1997), i.e., the machine learning algorithm must be chosen depending on the specific data pattern. It is essential to know about the assumed degradation process to support this. This covers either the direct modeling of a machine's degradation process (e.g., based on historical data) or a predefined assumption about its deterioration course (e.g., assumptions of the machine producer). We identified the frequent use of the following patterns: Random Failure Assumption, Weibull Distribution Assumption, Linear Degradation Assumption, and Exponential Degradation Assumption. Having an assumption about the degradation process helps limit the possible prognostic techniques. Further, adaptive software systems (Krupitzer, Roth, VanSyckel, Schiele, & Becker, 2015) might support the choice of the prognostic technique. For example, in Zuefle et al. (2019), we describe an approach for a recommendation system for choosing at runtime the best algorithm for time series forecasting depending on the characteristics of the data that should be analyzed. Such a recommendation system can be integrated directly, or the corresponding workflow for setting up the recommendation system can be used with the relevant set of algorithms. Similarly, in Züfle, Moog, Lesch, Krupitzer, and Kounev (2022), we describe a workflow that first identifies the machine's activities (hence, the production process) and chooses, depending on this profile, a suitable algorithm for degradation prediction.

5.5. Threats to validity

In the following, we discuss several threats to validity that might impact the quality of this study and further evaluate their potential impact.

We conducted a structured literature review to provide a structured analysis. One of the authors read and classified each identified paper; unclear classifications were discussed by all authors. We followed a well-defined approach. This significantly helps to reduce human bias in the process. Still, subjective bias cannot be entirely excluded as humans are involved.

The choice of keywords might be restricted as we fully focus on "predictive maintenance" as a keyword. Although this survey revealed many relevant publications, we did not explicitly search with keywords concerning variations of the term or other similar concepts. This may lead to a lower outcome of search results. However, it is common practice to narrow the scope to handle a topic's complexity.

Further, the free web search using a search engine (rather than a scientific database) provided many results, including scientific publications, press releases, offered product ranges, project announcements, explanation videos, and more. Despite our great efforts for this survey, we could not analyze all search results in detail and to the fullest extent. Therefore, non-peer-reviewed applications (e.g., company whitepaper) are not analyzed even though they might deliver valuable insights. However, our analysis also showed that non-scientific publications from the industry often missed the required depth of detail to analyze and classify those publications thoroughly. Hence, the additional contribution would be limited.

Although the number of papers in the research field of predictive maintenance ranges into the thousands, the number of papers in this survey represents an informative cross-section of the topic, focused on works in the field of Industry 4.0. Hence, the framework provides a comprehensive overview of predictive maintenance. The concept of deducing attributes, grouping them into categories, and building a framework related to a specific topic is very beneficial for gaining a structured and deeper understanding of a subject and revealing potential gaps in the existing literature. The framework structures and classifies papers published between 1993 and 2023. We make no claims of the framework's or attributes' completeness.

6. Related work

Predictive maintenance has gained more importance with the increased availability of sensors for data collection and higher computational capacity for real-time data analytics. Hence, various surveys and overviews presented the state of the art in various topics related to predictive maintenance. The following section discusses the aspects covered and distinguishes our work.

Several surveys focus on remaining life estimation, e.g., Si et al. (2011) or Zhang, Si, Hu, and Kong (2015). Those works focus on predicting when one or several components might fail, which is an integral part of predictive maintenance. Mostly, the works focus on either data-driven or statistical approaches.

Estimating the remaining life describes only the prediction of when an error in a component might appear. Further, a diagnostic of the resulting errors and how this influences the production is important. Several overviews in this regard are available. Bousdekis et al. highlight the state of the art for decision-making for predictive maintenance (Bousdekis, Lepenioti, Apostolou, & Mentzas, 2019). Other works (e.g., Baur, Albertelli, & Monno, 2020) target machines' prognostics and health management.

Industry 4.0 relies on sensors for real-time data collection and analysis, enabling automation, predictive maintenance, and process optimization in smart factories. Several works provide an overview of the Industry 4.0 concept, e.g., Zonta, da Costa, da Rosa Righi, de Lima, da Trindade, and Li (2020) or Dalzochio et al. (2020). Often, industry 4.0 approaches integrate technology known from IoT for predictive maintenance. Some survey papers highlight this combination, e.g., Compare, Baraldi, and Zio (2020) or Hafeez, Xu, and Mcardle (2021).

Recently, the application of machine learning gained more importance in the field. Several overviews highlight specific topics concerning machine learning. Some works present a general overview for applying machine learning, e.g., Carvalho, Soares, Vita, da P. Francisco, Basto, and Alcalá (2019) or Cınar, Abdussalam Nuhu, Zeeshan, Korhan, Asmael, and Safaei (2020). Other focus on more specific topics, such as transfer learning (Azari, Flammini, Santini, & Caporuscio, 2023), continual learning (Hurtado, Salvati, Semola, Bosio, & Lomonaco, 2023), explainable artificial intelligence (Vollert, Atzmueller, & Theissler, 2021), specific unsupervised learning techniques (Amruthnath & Gupta, 2018), or deep learning (Zhang et al., 2019; Zhao, Yan, Chen, Mao, Wang, & Gao, 2019).

Further works target a more specific topic or machine/industry domain. For example, Wang, Tsui, and Miao present an overview of vibration-based bearing and gear health indicators (Wang, Tsui, & Miao, 2018). Lee et al. target the field of rotary machines (Lee, Wu, Zhao, Ghaffari, Liao, & Siegel, 2014). In contrast, we focus on different production machines, not limiting them to a specific type of machine. As a different approach, You, Chen, Hu, Liu, and Ji (2022) present an overview of the application of digital twins for predictive maintenance. In Xia, Zheng, Li, Gao, and Wang (2022), the authors discuss graph-based approaches to predictive maintenance.

Unlike existing overviews, we strive to encompass a wider range of methodologies. Our review includes remaining life estimation, root cause analysis, and scheduling facets rather than an isolated view of one of those topics. We concentrate on developing machine learning applications but also incorporate the analysis of applied statistical approaches. Further, we incorporate practical aspects like managing complexity and reference datasets as benchmarks, providing a holistic perspective.

7. Future work

In the discussion of this survey we identified multiple research gaps that should be the focus of future research. This section provides outlines for the next steps of addressing the identified research gaps.

Enhancing complexity of PdM applications: The first actionable point of this research gap is to aid the discussion on complexity by setting a discussion baseline. There is an article that aims at establishing a taxonomy that can be used for categorizing the complexity of any PdM application (Meitz, Heider, Schöler, & Hähner, 2024). The authors give an overview of existing definitions of complexity in the field and refer to other review papers highlighting the lack of complexity in recent research. A further step from this article is to elaborate on the taxonomy, for example by including measurable metrics instead of continuous scales. Further, a more comprehensive overview of applications that have been categorized inside of this taxonomy could aid further discussion. As mentioned in the conclusion of that article, the taxonomy will aid the discussion and provide a tool to identify the lack or presence of complexity in a data-driven application. This in turn will further highlight open gaps in applications, that can be selected as subject for further research.

By incorporating complex machinery in future research projects, the necessity for more sophisticated diagnosis and prediction will become dominant. Simple anomaly detection models are not sufficient for failure diagnosis in a machine consisting of multiple sensors and actuators, which could lead to research for more sophisticated models to use in real-world scenarios.

Creation of new public benchmark datasets: The creation of benchmark datasets is one step that could enable research on the behavior of existing models in new and more complex applications. Among those could be machines consisting of multiple interdependent actuators and sensors, such as product automation systems or production lines. There is one article that describes the creation of a dataset based on sensor recordings of a fischertechnik factory model (Klein & Bergmann, 2019). Analogous to this approach, the just mentioned taxonomy article (Meitz et al., 2024) proposes the use of easily accessible product automation systems, such as hobby-grade cnc mills, 3d printers or coffee makers for dataset generation. These machines can execute complex processes and consist of multiple different components, creating new challenges in the generated datasets for benchmarking

PdM models. By collecting these data from easily accessible machines, contrary to most industrial research projects, the resulting datasets do not contain proprietary information and can be published.

Improvement of remote infrastructure in PdM applications: Most research projects consist of efforts for data collection and analysis at the same time. By dividing this into two separate steps, first establishing a stable and long-lasting monitoring solution and afterwards focusing on the analysis of the collected data, this issue could be addressed. We highly recommend implementing cloud-based monitoring solutions as a basis for collecting operational data of machinery that is subject to future PdM research. By including more than one instance of a machine, e.g. monitoring a fleet of the same machine type, the resulting datasets contain more variation and enable more sophisticated model training.

Comparative analysis of model performances and applications: In this survey paper, we did not include an in-depth comparison of model performances for PdM. This is due to the fact that a comparison of different models in PdM remains a major challenge. Most of the reviewed applications are set in a unique environment, with proprietary datasets, different machines and models that have been fine-tuned to the specific application domain. In the majority of the articles, there is no exact explanation of the implementation details. The reproducibility of the results is hard to achieve without access to all of the original authors resources. We again refer to the effort of creating a taxonomy for categorization of PdM applications. By using such a taxonomy to exactly describe the complexity of a given system, similar applications can be identified and compared. Afterwards, a group of similar applications can be used for model performance evaluation.

This enables another way of implementing PdM, which would consist of first identifying the type and complexity of the available data, and based on this knowledge compare the application to similar other ones. If there already are models that work well with the type of data, these can be seen as a starting point for development.

Focus not only on neural networks and machine learning for future applications: Machine Learning is a tool that has proved its versatility and capability of dealing with data. This knowledge was gained by researching the application of machine learning, especially deep learning using neural networks, in many different scenarios and articles. As shown in the previous discussion of this review, most of the recent applications are about implementing deep learning models for PdM. However, there are scenarios in which this may not be the most useful tool. Especially in simple applications, applications with a computational power constraint or in the case of low data availability, simple models are often more appropriate. There is still an open gap in researching classical models for the different tasks in predictive maintenance. This is why we propose to further focus on implementing simpler models in scenarios that do not necessitate big deep learning models.

8. Conclusion

The present survey represents a comprehensive analysis of the topic of predictive maintenance. Predictive maintenance distinguishes itself from conventional maintenance policies by attempting to detect an anomaly of a machine or component and predict when the failure might occur in order to schedule maintenance actions in advance efficiently. Minimized downtime, prolonged machine life, increased productivity, and reduced costs are merely a few promising prospects of predictive maintenance. The objective of the present survey is to detect and categorize a variety of aspects with regard to the comprehensive topic of predictive maintenance. Given the extensive body of research and space constraints, we could not include a comparative analysis of the studies or delve into the distinctions between the mathematical models and applied machine learning techniques or algorithms — this would be an interesting possibility for future work.

For the survey, 249 papers were analyzed and categorized. The result is a data grid with 73 attributes, which are clustered into the following 9 categories: Condition Monitoring, Maintenance Scope, Degradation Process, Fault Detection, System Size, Scheduling, Prognostic Techniques, Data Handling, and Evaluation. These categories and their corresponding attributes built a framework for predictive maintenance. The framework structures and classifies papers published between 1993 and 2023. The framework does not claim completeness; neither are the attributes within each category. Nevertheless, the framework of the present survey covers relevant aspects and facets of predictive maintenance and provides a comprehensive introduction to the research field. We decided to focus on approaches that apply machine learning, as recently, new algorithms were used, and fewer overview works exist. However, the analysis can be extended to other categories, like statistical models or hybrid approaches.

The framework of the present survey shows that further research might be appropriate in certain directions of the topic. This survey specifically discussed three points: application complexity, data handling, and the trend towards deep learning models.

Regarding application complexity, this study finds that future applications should incorporate more complex machines regarding components and applications. Additionally, the implementations often lack completeness, with only a part of the predictive maintenance paradigm realized. Data handling still suffers from the lack of comparability over different applications. More benchmark datasets, such as NASA Turbofan, should be available to compare different predictive maintenance systems. However, those benchmark datasets need to represent different applications and, hence, various data patterns. By using cloud and remote infrastructure for data collection, future projects could profit from a more flexible approach to data processing and the collection of information from multiple devices. When looking at the trend towards deep learning, one must not forget that simpler machine learning algorithms exist and sometimes have the edge over the big neural networks, especially when the results' interpretability and explainability are highly relevant. Depending on the amount and structure of data, an individual decision has to be made to select the best model for each use case.

By conducting more focused research on realistic implementations, the paradigm of predictive maintenance could be implemented more effectively and for a broader spectrum of applications in the future.

CRediT authorship contribution statement

Lukas Meitz: Writing – review & editing, Writing – original draft, Visualization, Resources, Project administration, Formal analysis, Data curation. **Julia Senge:** Writing – original draft, Investigation, Data curation, Conceptualization. **Tim Wagenhals:** Writing – original draft, Methodology, Conceptualization. **Thorsten Schöler:** Resources, Project administration, Investigation. **Jörg Hähner:** Supervision, Resources, Investigation. **Janick Edinger:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Data curation. **Christian Krupitzer:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None reported.

Data availability

The Dataset containing information on all of the used publications is available on Zenodo Predictive Maintenance Literature Review Framework (2023).

References

Abbasi, T., Lim, K. H., & Yam, K. S. (2019). Predictive maintenance of oil and gas equipment using recurrent neural network. *IOP Conference Series: Materials Science and Engineering*, *495*(1), Article 012067. http://dx.doi.org/10.1088/1757-899X/495/1/012067.

Abdennadher, K., Venet, P., Rojat, G., Retif, J. M., & Rosset, C. (2010). A real-time predictive-maintenance system of aluminum electrolytic capacitors used in uninterrupted power supplies. *IEEE Transactions on Industry Applications*, *46*(4), 1644–1652. http://dx.doi.org/10.1109/TIA.2010.2049972.

Abidi, M. H., Mohammed, M. K., & Alkhalefah, H. (2022). Predictive maintenance planning for industry 4.0 using machine learning for sustainable manufacturing. *Sustainability*, *14*(6), http://dx.doi.org/10.3390/su14063387, URL https://www.mdpi.com/2071-1050/14/6/3387.

Agatonovic-Kustrin, S., & Beresford, R. (2000). Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. *Journal of Pharmaceutical and Biomedical Analysis*, *22*(5), 717–727.

Amruthnath, N., & Gupta, T. (2018). A research study on unsupervised machine learning algorithms for early fault detection in predictive maintenance. In *2018 5th international conference on industrial engineering and applications* (pp. 355–361). http://dx.doi.org/10.1109/IEA.2018.8387124.

Assis-lopes, J. A., Steiger-gaqiio, A., & Campus, T. (1996). Application of Stochastic Modelling to Support Predictive Maintenance for Industrial Environments. *Manufacturing Systems*, 117–122. http://dx.doi.org/10.1109/ICSMC.1996.569751.

Ayvaz, S., & Alpay, K. (2021). Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. *Expert Systems with Applications*, *173*, Article 114598. http://dx.doi.org/10.1016/j.eswa.2021.114598, URL https://www.sciencedirect.com/science/article/pii/S0957417421000397.

Azari, M. S., Flammini, F., Santini, S., & Caporuscio, M. (2023). A systematic literature review on transfer learning for predictive maintenance in industry 4.0. *IEEE Access*, *11*, 12887–12910. http://dx.doi.org/10.1109/ACCESS.2023.3239784.

Bampoula, X., Siaterlis, G., Nikolakis, N., & Alexopoulos, K. (2021). A deep learning model for predictive maintenance in cyber-physical production systems using LSTM autoencoders. *Sensors*, *21*(3), http://dx.doi.org/10.3390/s21030972, URL https://www.mdpi.com/1424-8220/21/3/972.

Baptista, M., Sankararaman, S., de Medeiros, I. P., Nascimento, C., Prendinger, H., & Henriques, E. M. (2018). Forecasting fault events for predictive maintenance using data-driven techniques and ARMA modeling. *Computers & Industrial Engineering*, *115*(October 2017), 41–53. http://dx.doi.org/10.1016/j.cie.2017.10.033.

Baur, M., Albertelli, P., & Monno, M. (2020). A review of prognostics and health management of machine tools. *International Journal of Advanced Manufacturing Technology*, *107*, 2843–2863.

Booth, A. (2008). Using evidence in practice. Unpacking your literature search toolbox: on search styles and tactics. *Health Information and Libraries Journal*, *25*, 313–317.

Bousdekis, A., Lepenioti, K., Apostolou, D., & Mentzas, G. (2019). Decision making in predictive maintenance: Literature review and research agenda for industry 4.0. *IFAC-PapersOnLine*, *52*(13), 607–612. http://dx.doi.org/10.1016/j.ifacol.2019.11.226, 9th IFAC Conference on Manufacturing Modelling, Management and Control MIM 2019. URL https://www.sciencedirect.com/science/article/pii/S2405896319311772.

Carnera, M. C. (2005). Selection of diagnostic techniques and instrumentation in a predictive maintenance program. A case study. *vol. 38*, In *Decision support systems* (4), (pp. 539–555). http://dx.doi.org/10.1016/j.dss.2003.09.003.

Carnero, M. C. (2006). An evaluation system of the setting up of predictive maintenance programmes. *Reliability Engineering & System Safety*, *91*(8), 945–963. http://dx.doi.org/10.1016/j.ress.2005.09.003.

Cartella, F., Lemeire, J., Dimiccoli, L., & Sahli, H. (2015). Hidden semi-markov models for predictive maintenance. *Mathematical Problems in Engineering*, *2015*, http://dx.doi.org/10.1155/2015/278120.

Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., da P. Francisco, R., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering*, *137*, Article 106024. http://dx.doi.org/10.1016/j.cie.2019.106024, URL https://www.sciencedirect.com/science/article/pii/S0360835219304838.

Chen, A., & Blue, J. (2009). Recipe-independent indicator for tool health diagnosis and predictive maintenance. *IEEE Transactions on Semiconductor Manufacturing*, *22*(4), 522–535. http://dx.doi.org/10.1109/TSM.2009.2028215.

Chen, J. C., Chen, T.-L., Liu, W.-J., Cheng, C., & Li, M.-G. (2021). Combining empirical mode decomposition and deep recurrent neural networks for predictive maintenance of lithium-ion battery. *Advanced Engineering Informatics*, *50*, Article 101405. http://dx.doi.org/10.1016/j.aei.2021.101405, URL https://www.sciencedirect.com/science/article/pii/S1474034621001579.

Chen, C., Shi, J., Lu, N., Zhu, Z. H., & Jiang, B. (2022). Data-driven predictive maintenance strategy considering the uncertainty in remaining useful life prediction. *Neurocomputing*, *494*, 79–88. http://dx.doi.org/10.1016/j.neucom.2022.04.055, URL https://www.sciencedirect.com/science/article/pii/S0925231222004428.

Chiu, Y. C., Cheng, F. T., & Huang, H. C. (2017). Developing a factory-wide intelligent predictive maintenance system based on Industry 4.0. *Journal of the Chinese Institute of Engineers*, *40*(7), 562–571. http://dx.doi.org/10.1080/02533839.2017.1362357.

Cınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. *Sustainability*, *12*(19), http://dx.doi.org/10.3390/su12198211, URL https://www.mdpi.com/2071-1050/12/19/8211.

Compare, M., Baraldi, P., & Zio, E. (2020). Challenges to IoT-enabled predictive maintenance for industry 4.0. *IEEE Internet of Things Journal*, *7*(5), 4585–4597. http://dx.doi.org/10.1109/JIOT.2019.2957029.

Dalzochio, J., Kunst, R., Pignaton, E., Binotto, A., Sanyal, S., Favilla, J., et al. (2020). Machine learning and reasoning for predictive maintenance in industry 4.0: Current status and challenges. *Computers in Industry*, *123*, Article 103298. http://dx.doi.org/10.1016/j.compind.2020.103298, URL https://www.sciencedirect.com/science/article/pii/S0166361520305327.

Dangut, M. D., Jennions, I. K., King, S., & Skaf, Z. (2023). A rare failure detection model for aircraft predictive maintenance using a deep hybrid learning approach. *Neural Computing and Applications*, *35*(4), 2991–3009.

De Faria, H., Costa, J. G. S., & Olivas, J. L. M. (2015). A review of monitoring methods for predictive maintenance of electric power transformers based on dissolved gas analysis. *Renewable and Sustainable Energy Reviews*, *46*, 201–209. http://dx.doi.org/10.1016/j.rser.2015.02.052.

De Santo, A., Ferraro, A., Galli, A., Moscato, V., & Sperlì, G. (2022). Evaluating time series encoding techniques for predictive maintenance. *Expert Systems with Applications*, *210*, Article 118435. http://dx.doi.org/10.1016/j.eswa.2022.118435, URL https://www.sciencedirect.com/science/article/pii/S0957417422015342.

De Saporta, B., Dufour, F., Zhang, H., & Elegbede, C. (2012). Optimal stopping for the predictive maintenance of a structure subject to corrosion. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, *226*(2), 169–181. http://dx.doi.org/10.1177/1748006X11413681, arXiv:arXiv:1101.1740v2.

Del Buono, F., Calabrese, F., Baraldi, A., Paganelli, M., & Regattieri, A. (2022). Data-driven predictive maintenance in evolving environments: A comparison between machine learning and deep learning for novelty detection. In S. G. Scholz, R. J. Howlett, & R. Setchi (Eds.), *Sustainable design and manufacturing* (pp. 109–119). Singapore: Springer Singapore.

Dieulle, L., Berenguer, C., Grall, A., & Roussignol, M. (2001). Continuous time predictive maintenance scheduling for a deteriorating system. *Reliability and Maintainability Symposium Proceedings*, 150–155. http://dx.doi.org/10.1109/RAMS.2001.902458.

Ding, H., Yang, L., & Yang, Z. (2019). A predictive maintenance method for shearer key parts based on qualitative and quantitative analysis of monitoring data. *IEEE Access*, *7*, 108684–108702. http://dx.doi.org/10.1109/ACCESS.2019.2933676.

Elwany, A. H., & Gebraeel, N. Z. (2008). Sensor-driven prognostic models for equipment replacement and spare parts inventory. *IIE Transactions (Institute of Industrial Engineers)*, *40*(7), 629–639. http://dx.doi.org/10.1080/07408170701730818.

Engel, S. J., Gilmartin, B. J., Bongort, K., & Hess, A. (2000). Prognostics, the real issues involved with predicting life remaining. *vol. 6*, In *IEEE aerospace conference proceedings* (pp. 457–470). http://dx.doi.org/10.1109/AERO.2000.877920.

Garcia, M. C., Sanz-Bobi, M. A., & del Pico, J. (2006). SIMAP: Intelligent System for Predictive Maintenance. Application to the health condition monitoring of a windturbine gearbox. *Computers in Industry*, *57*(6), 552–568. http://dx.doi.org/10.1016/j.compind.2006.02.011, arXiv:arXiv:1011.1669v3.

Garga, A. K., McClintic, K. T., Campbell, R. L., Yang, C. C., Lebold, M. S., Hay, T. A., et al. (2001). Hybrid reasoning for prognostic learning in CBM systems. *6*, In *IEEE aerospace conference proceedings* (pp. 62957–62969). http://dx.doi.org/10.1109/AERO.2001.931316.

Gebraeel, N. (2006). Sensory-updated residual life distributions for components with exponential degradation patterns. *IEEE Transactions on Automation Science and Engineering*, *3*(4), 382–393. http://dx.doi.org/10.1109/TASE.2006.876609.

Gebraeel, N. Z., Lawley, M. A., Li, R., & Ryan, J. K. (2005). Residual-life distributions from component degradation signals: A Bayesian approach. *IIE Transactions (Institute of Industrial Engineers)*, *37*(6), 543–557. http://dx.doi.org/10.1080/07408170590929018, arXiv:arXiv:1011.1669v3.

Grall, A., Dieulle, L., Berenguer, C., & Roussignol, M. (2002). Continuous-time predictive-maintenance scheduling for a deteriorating system. *IEEE Transactions on Reliability*, *51*(2), 141–150. http://dx.doi.org/10.1109/TR.2002.1011518, arXiv:arXiv:1011.1669v3.

Hafeez, T., Xu, L., & Mcardle, G. (2021). Edge intelligence for data handling and predictive maintenance in IIOT. *IEEE Access*, *9*, 49355–49371. http://dx.doi.org/10.1109/ACCESS.2021.3069137.

Hashemian, H. M. (2011). Wireless sensors for predictive maintenance of rotating equipment in research reactors. *Annals of Nuclear Energy*, *38*(2–3), 665–680. http://dx.doi.org/10.1016/j.anucene.2010.09.012.

Hashemian, H. M., & Bean, W. C. (2011). State-of-the-art predictive maintenance techniques. *IEEE Transactions on Instrumentation and Measurement*, *60*(10), 3480–3492. http://dx.doi.org/10.1109/TIM.2009.2036347.

Hurtado, J., Salvati, D., Semola, R., Bosio, M., & Lomonaco, V. (2023). Continual learning for predictive maintenance: Overview and challenges. *Intelligent Systems with Applications*, *19*, Article 200251. http://dx.doi.org/10.1016/j.iswa.2023.200251, URL https://www.sciencedirect.com/science/article/pii/S2667305323000765.

Jardine, A. K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, *20*(7), 1483–1510. http://dx.doi.org/10.1016/j.ymssp.2005.09.012, arXiv:0208024.

Jiang, Y., Dai, P., Fang, P., Zhong, R. Y., & Cao, X. (2022). Electrical-STGCN: An electrical spatio-temporal graph convolutional network for intelligent predictive maintenance. *IEEE Transactions on Industrial Informatics*, *18*(12), 8509–8518. http://dx.doi.org/10.1109/TII.2022.3143148.

Kaiser, K. A., & Gebraeel, N. Z. (2009). Predictive maintenance management using sensor-based degradation models. *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*, *39*(4), 840–849. http://dx.doi.org/10.1109/TSMCA.2009.2016429.

Kandukuri, S. T., Klausen, A., Karimi, H. R., & Robbersmyr, K. G. (2016). A review of diagnostics and prognostics of low-speed machinery towards wind turbine farm-level health management. *Renewable and Sustainable Energy Reviews*, *53*, 697–708. http://dx.doi.org/10.1016/j.rser.2015.08.061.

Kim, D., Lee, S., & Kim, D. (2021). An applicable predictive maintenance framework for the absence of run-to-failure data. *Applied Sciences*, *11*(11), http://dx.doi.org/10.3390/app11115180, URL https://www.mdpi.com/2076-3417/11/11/5180.

Klein, P., & Bergmann, R. (2019). Generation of complex data for AI-based predictive maintenance research with a physical factory model.. In *ICINCO (1)* (pp. 40–50). Scite Press, http://dx.doi.org/10.5220/0007830700400050.

Kofod-Petersen, A. (2014). How to do a structured literature review in computer science. *Researchgate*, 1–7.

Koprinkova-Hristova, P., Hadjiski, M., Doukovska, L., & Beloreshki, S. (2011). Recurrent neural networks for predictive maintenance of mill fan systems. *International Journal of Electronics and Telecommunications*, *57*(3), 401–406. http://dx.doi.org/10.2478/v10177-011-0055-2.

Krupitzer, C., Roth, F. M., VanSyckel, S., Schiele, G., & Becker, C. (2015). A survey on engineering approaches for self-adaptive systems. *Pervasive Mob. Comput.*, *17*(PB), 184–206. http://dx.doi.org/10.1016/j.pmcj.2014.09.009, URL http://dx.doi.org/10.1016/j.pmcj.2014.09.009.

Kumar Sharma, D., Brahmachari, S., Singhal, K., & Gupta, D. (2022). Data driven predictive maintenance applications for industrial systems with temporal convolutional networks. *Computers & Industrial Engineering*, *169*, Article 108213. http://dx.doi.org/10.1016/j.cie.2022.108213, URL https://www.sciencedirect.com/science/article/pii/S0360835222002832.

Ladj, A., Varnier, C., & Tayeb, F. B.-S. (2016). IPro-GA: an integrated prognostic based GA for scheduling jobs and predictive maintenance in a single multifunctional machine. *IFAC-PapersOnLine*, *49*(12), 1821–1826. http://dx.doi.org/10.1016/j.ifacol.2016.07.847, 8th IFAC Conference on Manufacturing Modelling, Management and Control MIM 2016 URL https://www.sciencedirect.com/science/article/pii/S2405896316311326.

Langeron, Y., Grall, A., & Barros, A. (2015). A modeling framework for deteriorating control system and predictive maintenance of actuators. *Reliability Engineering & System Safety*, *140*, 22–36. http://dx.doi.org/10.1016/j.ress.2015.03.028.

Lee, J., Ni, J., Djurdjanovic, D., Qiu, H., & Liao, H. (2006). Intelligent prognostics tools and e-maintenance. *Computers in Industry*, *57*(6), 476–489. http://dx.doi.org/10.1016/j.compind.2006.02.014, arXiv:arXiv:1011.1669v3.

Lee, J., Qiu, H., Ni, J., & Djurdjanovic, D. (2004). Infotronics Technologies and Predictive Tools for Next-Generation Maintenance Systems. *IFAC Information Control Problems in Manufacturing*, *37*(4), 291–302. http://dx.doi.org/10.1016/S1474-6670(17)36133-5.

Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., & Siegel, D. (2014). Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. *Mechanical Systems and Signal Processing*, *42*(1), 314–334. http://dx.doi.org/10.1016/j.ymssp.2013.06.004, URL https://www.sciencedirect.com/science/article/pii/S0888327013002860.

Lei, X., Sandborn, P. A., Goudarzi, N., & Bruck, M. A. (2015). PHM Based Predictive Maintenance Option Model for Offshore Wind Farm O&M Optimization. In *Proceedings of the annual conference of the prognostics and health management society 2015* (pp. 1–10).

Liao, W., Wang, Y., & Pan, E. (2012). Single-machine-based predictive maintenance model considering intelligent machinery prognostics. *International Journal of Advanced Manufacturing Technology*, *63*(1–4), 51–63. http://dx.doi.org/10.1007/s00170-011-3884-3.

Lindstrom, J., Larsson, H., Jonsson, M., & Lejon, E. (2017). Towards Intelligent and Sustainable Production: Combining and Integrating Online Predictive Maintenance and Continuous Quality Control. *vol. 63*, In *The 50th CIRP conference on manufacturing systems* (pp. 443–448). The Author(s), http://dx.doi.org/10.1016/j.procir.2017.03.099.

Liu, C., Tang, D., Zhu, H., & Nie, Q. (2021). A novel predictive maintenance method based on deep adversarial learning in the intelligent manufacturing system. *IEEE Access*, *9*, 49557–49575. http://dx.doi.org/10.1109/ACCESS.2021.3069256.

Liu, C., Zhu, H., Tang, D., Nie, Q., Zhou, T., Wang, L., et al. (2022). Probing an intelligent predictive maintenance approach with deep learning and augmented reality for machine tools in IoT-enabled manufacturing. *Robotics and Computer-Integrated Manufacturing*, *77*, Article 102357. http://dx.doi.org/10.1016/j.rcim.2022.102357, URL https://www.sciencedirect.com/science/article/pii/S073658452200045X.

Lu, H., Du, M., Qian, K., He, X., & Wang, K. (2022). GAN-based data augmentation strategy for sensor anomaly detection in industrial robots. *IEEE Sensors Journal*, *22*(18), 17464–17474. http://dx.doi.org/10.1109/JSEN.2021.3069452.

Luca, R., Ferraro, A., Galli, A., Gallo, M., Moscato, V., & Sperlì, G. (2023). A deep attention based approach for predictive maintenance applications in IoT scenarios. *Journal of Manufacturing Technology Management*, *34*, http://dx.doi.org/10.1108/JMTM-02-2022-0093.

Lucifredi, A., Mazzieri, C., & Rossi, M. (2000). Application of multiregressive linear models, dynamic kriging models and neural network models to predictive maintenance of hydroelectric power systems. *Mechanical Systems and Signal Processing*, *14*(3), 471–494. http://dx.doi.org/10.1006/mssp.1999.1257.

Mateus, B. C., Mendes, M., Farinha, J. T., Assis, R., & Cardoso, A. M. (2021). Comparing LSTM and GRU models to predict the condition of a pulp paper press. *Energies*, *14*(21), http://dx.doi.org/10.3390/en14216958, URL https://www.mdpi.com/1996-1073/14/21/6958.

Mattes, A., Schöpka, U., Schellenberger, M., Scheibelhofer, P., & Leditzky, G. (2012). Virtual equipment for benchmarking predictive maintenance algorithms. In *Proceedings of the 2012 winter simulation conference* (pp. 1–12). http://dx.doi.org/10.1109/WSC.2012.6465084.

Meitz, L., Heider, M., Schöler, T., & Hähner, J. (2024). A taxonomy for complexity estimation of machine data in machine health applications. In *Proceedings of the 21st international conference on informatics in control, automation and robotics - volume 1: ICINCO* (pp. 341–350). SciTePress, http://dx.doi.org/10.5220/0012994900003822.

Mitici, M., de Pater, I., Barros, A., & Zeng, Z. (2023). Dynamic predictive maintenance for multiple components using data-driven probabilistic RUL prognostics: The case of turbofan engines. *Reliability Engineering & System Safety*, *234*, Article 109199. http://dx.doi.org/10.1016/j.ress.2023.109199, URL https://www.sciencedirect.com/science/article/pii/S095183202300114X.

Mobley, R. (2002). An introduction to predictive maintenance. *Plant engineering*, Elsevier Science, URL https://books.google.de/books?id=SjqXzxpAzSQC.

Munirathinam, S., & Ramadoss, B. (2014). Big data predictive analtyics for proactive semiconductor equipment maintenance. In *2014 IEEE international conference on big data* (pp. 893–902). http://dx.doi.org/10.1109/BigData.2014.7004320.

Nguyen, K. A., Do, P., & Grall, A. (2015). Multi-level predictive maintenance for multi-component systems. *Reliability Engineering & System Safety*, *144*, 83–94. http://dx.doi.org/10.1016/j.ress.2015.07.017.

Nguyen, K. A., Do, P., & Grall, A. (2017). Joint predictive maintenance and inventory strategy for multi-component systems using Birnbaum's structural importance. *Reliability Engineering & System Safety*, *168*(May), 249–261. http://dx.doi.org/10.1016/j.ress.2017.05.034.

Nguyen, K. T., & Medjaher, K. (2019). A new dynamic predictive maintenance framework using deep learning for failure prognostics. *Reliability Engineering & System Safety*, *188*, 251–262. http://dx.doi.org/10.1016/j.ress.2019.03.018, URL https://www.sciencedirect.com/science/article/pii/S0951832018311050.

Onanena, R., Oukhellou, L., Candusso, D., Same, A., Hissel, D., & Aknin, P. (2010). Estimation of fuel cell operating time for predictive maintenance strategies. *International Journal of Hydrogen Energy*, *35*(15), 8022–8029. http://dx.doi.org/10.1016/j.ijhydene.2010.05.039.

Orhan, S., Akturk, N., & Celik, V. (2006). Vibration monitoring for defect diagnosis of rolling element bearings as a predictive maintenance tool: Comprehensive case studies. *NDT&E International*, *39*(4), 293–298. http://dx.doi.org/10.1016/j.ndteint.2005.08.008.

Pedregal, D. J., Garcia, F. P., & Schmid, F. (2004). RCM2predictive maintenance of railway systems based on unobserved components models. *Reliability Engineering & System Safety*, *83*(1), 103–110. http://dx.doi.org/10.1016/j.ress.2003.09.020.

Predictive maintenance literature review framework. (2023). http://dx.doi.org/10.5281/zenodo.10006302.

Scheibelhofer, P., & Gleispach, D. (2012). A Methodology for Predictive Maintenance in Semiconductor Manufacturing. *Austrian Journal of Statitics*, *41*(3), 161–173. http://dx.doi.org/10.17713/ajs.v41i3.171.

Schirru, A., Pampuri, S., & De Nicolao, G. (2010). Particle filtering of hidden gamma processes for robust Predictive Maintenance in semiconductor manufacturing. In *2010 IEEE international conference on automation science and engineering, CASE 2010* (pp. 51–56). http://dx.doi.org/10.1109/COASE.2010.5584518.

Schmidt, B., & Wang, L. (2018). Cloud-enhanced predictive maintenance. *International Journal of Advanced Manufacturing Technology*, *99*(1–4), 5–13. http://dx.doi.org/10.1007/s00170-016-8983-8.

Schmidt, B., Wang, L., & Galar, D. (2017). Semantic framework for predictive maintenance in a cloud environment. *Procedia CIRP*, *62*, 583–588. http://dx.doi.org/10.1016/j.procir.2016.06.047, 10th CIRP Conference on Intelligent Computation in Manufacturing Engineering - CIRP ICME '16. [Edited by: Roberto Teti, Manager Editor: Doriana M. D'Addona]. URL https://www.sciencedirect.com/science/article/pii/S2212827116306655.

Serradilla, O., Zugasti, E., Ramirez de Okariz, J., Rodriguez, J., & Zurutuza, U. (2021). Adaptable and explainable predictive maintenance: Semi-supervised deep learning for anomaly detection and diagnosis in press machine data. *Applied Sciences*, *11*(16), http://dx.doi.org/10.3390/app11167376, URL https://www.mdpi.com/2076-3417/11/16/7376.

Si, X.-S., Wang, W., Hu, C.-H., & Zhou, D.-H. (2011). Remaining useful life estimation - a review on the statistical data driven approaches. *European Journal of Operational Research*, *213*(1), 1–14.

Silva, W., & Capretz, M. (2019). Assets predictive maintenance using convolutional neural networks. In *2019 20th IEEE/aCIS international conference on software engineering, artificial intelligence, networking and parallel/distributed computing* (pp. 59–66). http://dx.doi.org/10.1109/SNPD.2019.8935752.

Silvestrin, L. P., Hoogendoorn, M., & Koole, G. (2019). A comparative study of state-of-the-art machine learning algorithms for predictive maintenance. In *2019 IEEE symposium series on computational intelligence* (pp. 760–767). http://dx.doi.org/10.1109/SSCI44817.2019.9003044.

Sun, C., Ma, M., Zhao, Z., Tian, S., Yan, R., & Chen, X. (2019). Deep transfer learning based on sparse autoencoder for remaining useful life prediction of tool in manufacturing. *IEEE Transactions on Industrial Informatics*, *15*(4), 2416–2425. http://dx.doi.org/10.1109/TII.2018.2881543.

Susto, G. A., Beghi, A., & De Luca, C. (2011). A predictive maintenance system for silicon epitaxial deposition. In *IEEE international conference on automation science and engineering* (pp. 262–267). http://dx.doi.org/10.1109/CASE.2011.6042421.

Swanson, D. (2000). A general prognostic tracking algorithm for predictive maintenance. *vol. 6*, In *IEEE aerospace conference proceedings* (pp. 2971–2977). http://dx.doi.org/10.1109/AERO.2001.931317.

Tan, C. M., & Raghavan, N. (2010). Imperfect predictive maintenance model for multi-state systems with multiple failure modes and element failure dependency. In *2010 prognostics and system health management conference* (pp. 1–12). http://dx.doi.org/10.1109/PHM.2010.5414594.

Traini, E., Bruno, G., D'Antonio, G., & Lombardi, F. (2019). Machine learning framework for predictive maintenance in milling. In *9th IFAC conference on manufacturing modelling, management and control MIM 2019*: *IFAC-PapersOnLine*, In *9th IFAC conference on manufacturing modelling, management and control MIM 2019*: *52*(13), 177–182. http://dx.doi.org/10.1016/j.ifacol.2019.11.172.URL https://www.sciencedirect.com/science/article/pii/S240589631931122X,

Traore, M., Chammas, A., & Duviella, E. (2015). Supervision and prognosis architecture based on dynamical classification method for the predictive maintenance of dynamical evolving systems. *Reliability Engineering & System Safety*, *136*, 120–131. http://dx.doi.org/10.1016/j.ress.2014.12.005.

Van Horenbeek, A., & Pintelon, L. (2013). A dynamic predictive maintenance policy for complex multi-component systems. *Reliability Engineering & System Safety*, *120*, 39–50. http://dx.doi.org/10.1016/j.ress.2013.02.029.

Vollert, S., Atzmueller, M., & Theissler, A. (2021). Interpretable machine learning: A brief survey from the predictive maintenance perspective. In *2021 26th IEEE international conference on emerging technologies and factory automation* (pp. 01–08). http://dx.doi.org/10.1109/ETFA45728.2021.9613467.

Wang, K. (2016). Intelligent Predictive Maintenance (IPdM) system, Industry 4.0 scenario. *WIT Transactions on Engineering Sciences*, *113*, 259–268. http://dx.doi.org/10.2495/IWAMA150301.

Wang, Y., Gogu, C., Binaud, N., Bes, C., Haftka, R. T., & Kim, N. H. (2017). A cost driven predictive maintenance policy for structural airframe maintenance. *Chinese Journal of Aeronautics*, *30*(3), 1242–1257. http://dx.doi.org/10.1016/j.cja.2017.02.005.

Wang, D., Tsui, K.-L., & Miao, Q. (2018). Prognostics and health management: A review of vibration based bearing and gear health indicators. *IEEE Access*, *6*, 665–676. http://dx.doi.org/10.1109/ACCESS.2017.2774261.

Wolpert, D., & Macready, W. (1997). No free lunch theorems for optimization. *IEEE Transactions on Evolutionary Computation*, *1*(1), 67–82. http://dx.doi.org/10.1109/4235.585893.

Wu, S.-j., Gebraeel, N., Lawley, M. A., & Yih, Y. (2007). A Neural Network Integrated Decision Support System for Condition-Based Optimal Predictive Maintenance Policy. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *37*(2), 226–236. http://dx.doi.org/10.1109/TSMCA.2006.886368.

Xia, L., Zheng, P., Li, X., Gao, R., & Wang, L. (2022). Toward cognitive predictive maintenance: A survey of graph-based approaches. *Journal of Manufacturing Systems*, *64*, 107–120. http://dx.doi.org/10.1016/j.jmsy.2022.06.002, URL https://www.sciencedirect.com/science/article/pii/S0278612522000978.

Xiong, M., Wang, H., Fu, Q., & Xu, Y. (2021). Digital twin–driven aero-engine intelligent predictive maintenance. *International Journal of Advanced Manufacturing Technology*, *114*(11), 3751–3761. http://dx.doi.org/10.1007/s00170-021-06976-w.

Yam, R. C., Tse, P. W., Li, L., & Tu, P. (2001). Intelligent predictive decision support system for condition-based maintenance. *International Journal of Advanced Manufacturing Technology*, *17*(5), 383–391. http://dx.doi.org/10.1007/s001700170173.

Yamato, Y., Fukumoto, Y., & Kumazaki, H. (2017). Predictive Maintenance Platform with Sound Stream Analysis in Edges. *Journal of Information Processing*, *25*, 317–320. http://dx.doi.org/10.2197/ipsjjip.25.317.

Yan, L., Lu, C., & Andrew, N. Y. C. (2005). An agent-based platform for web-enabled equipment predictive maintenance. *vol. 2005*, In *Proceedings - 2005 IEEE/WIC/aCM international conference on intelligent agent technology, iAT'05* (pp. 132–135). http://dx.doi.org/10.1109/IAT.2005.38.

Yan, J., Meng, Y., Lu, L., & Li, L. (2017). Industrial Big Data in an Industry 4.0 Environment: Challenges, Schemes, and Applications for Predictive Maintenance. *IEEE Access*, *5*, 23484–23491. http://dx.doi.org/10.1109/ACCESS.2017.2765544.

Yang, S. (2002). An experiment of state estimation for predictive maintenance using Kalman filter on a DC motor. *Reliability Engineering & System Safety*, *75*(1), 103–111. http://dx.doi.org/10.1016/S0951-8320(01)00107-7.

Yang, Z., Djurdjanovic, D., & Ni, J. (2008). Maintenance scheduling in manufacturing systems based on predicted machine degradation. *Journal of Intelligent Manufacturing*, *19*(1), 87–98. http://dx.doi.org/10.1007/s10845-007-0047-3.

You, Y., Chen, C., Hu, F., Liu, Y., & Ji, Z. (2022). Advances of digital twins for predictive maintenance. *Procedia Computer Science*, *200*, 1471–1480. http://dx.doi.org/10.1016/j.procs.2022.01.348, 3rd International Conference on Industry 4.0 and Smart Manufacturing. URL https://www.sciencedirect.com/science/article/pii/S187705092200357X.

You, M. Y., Li, L., Meng, G., & Ni, J. (2010). Cost-effective updated sequential predictive maintenance policy for continuously monitored degrading systems. *IEEE Transactions on Automation Science and Engineering*, *7*(2), 257–265. http://dx.doi.org/10.1109/TASE.2009.2019964.

You, M. Y., Liu, F., Wang, W., & Meng, G. (2010). Statistically planned and individually improved predictive maintenance management for continuously monitored degrading systems. *IEEE Transactions on Reliability*, *59*(4), 744–753. http://dx.doi.org/10.1109/TR.2010.2085572.

Zhang, L., Lin, J., Liu, B., Zhang, Z., Yan, X., & Wei, M. (2019). A review on deep learning applications in prognostics and health management. *IEEE Access*, *7*, 162415–162438. http://dx.doi.org/10.1109/ACCESS.2019.2950985.

Zhang, Z., Si, X., Hu, C., & Kong, X. (2015). Degradation modeling–based remaining useful life estimation: A review on approaches for systems with heterogeneity. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, *229*(4), 343–355. http://dx.doi.org/10.1177/1748006X15579322.

Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing*, *115*, 213–237. http://dx.doi.org/10.1016/j.ymssp.2018.05.050, URL https://www.sciencedirect.com/science/article/pii/S0888327018303108.

Zhou, J., Li, X., Andernroomer, A. J. R., Zeng, H., Goh, K. M., Wong, Y. S., et al. (2005). Intelligent prediction monitoring system for predictive maintenance in manufacturing. In *IECON proceedings (industrial electronics conference)* (pp. 2314–2319). http://dx.doi.org/10.1109/IECON.2005.1569264.

Zhou, X., Xi, L., & Lee, J. (2007). Reliability-centered predictive maintenance scheduling for a continuously monitored system subject to degradation. *Reliability Engineering & System Safety*, *92*(4), 530–534. http://dx.doi.org/10.1016/j.ress.2006.01.006.

Zonta, T., da Costa, C. A., da Rosa Righi, R., de Lima, M. J., da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in the industry 4.0: A systematic literature review. *Computers & Industrial Engineering*, *150*, Article 106889. http://dx.doi.org/10.1016/j.cie.2020.106889, URL https://www.sciencedirect.com/science/article/pii/S0360835220305787.

Zonta, T., da Costa, C. A., Zeiser, F. A., de Oliveira Ramos, G., Kunst, R., & da Rosa Righi, R. (2022). A predictive maintenance model for optimizing production schedule using deep neural networks. *Journal of Manufacturing Systems*, *62*, 450–462. http://dx.doi.org/10.1016/j.jmsy.2021.12.013, URL https://www.sciencedirect.com/science/article/pii/S0278612521002624.

Zuefle, M., Bauer, A., Lesch, V., Krupitzer, C., Herbst, N., Kounev, S., et al. (2019). Autonomic forecasting method selection: Examination and ways ahead. In *2019 IEEE international conference on autonomic computing* (pp. 167–176). http://dx.doi.org/10.1109/ICAC.2019.00028.

Züfle, M., Moog, F., Lesch, V., Krupitzer, C., & Kounev, S. (2022). A machine learning-based workflow for automatic detection of anomalies in machine tools. *ISA Transactions*, *125*, 445–458.