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Predictive maintenance in Industry 4.0: A systematic multi-sector mapping

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ABSTRACT

Industry 4.0 is strongly intertwined with big data streaming flows from intelligent sensors and machinery installed in industrial facilities. Failures can disrupt production and lead the supply chain ecosystem to malfunction. Maintenance strategies are necessary to safeguard the continuous operation of production lines, minimize supply chain disruptions, and improve sustainability indicators. Within the context of smart manufacturing, predictive maintenance (PdM) approaches could decrease downtimes, reduce operational costs, and increase productivity, improving system performance and decision-making. The overarching aim of this research is to systematically review state-of-the-art predictive maintenance applications across diverse manufacturing sectors to provide customized insights from academic and operational perspectives, summarized into a comparative decision support map. The study classifies predictive maintenance solutions based on prevailing methodologies, input features, predicted variables, applied algorithms, evaluation metrics, and state-of-the-art software tools per industry sector. The outcomes highlight that data-driven predictive maintenance constitutes a cutting-edge solution with a growing interest in modern manufacturing. Moreover, this research provides insights into the technology readiness of each industrial sector, covering modern areas for PdM implementation, while raising the extant challenges. The proposed multi-sector framework is expected to act as a guiding light for researchers and practitioners towards the development of PdM driven applications in data driven industries.

1. Introduction

The advent of digitalization, including the most recent advances in robotics, 5G technology and artificial intelligence (AI), has supported the digital transformation of businesses, supply chains and operations management, accelerating the implementation of smart technologies in production, maintenance, and organizational processes [1,2]. The industrial revolution has radically changed production activities, starting from the steam-based mechanization (Industry 1.0) and the use of electricity in mass production systems (Industry 2.0) and shifting towards Industry 3.0 technologies for automating the production processes, including cyber-physical systems, Internet of Things (IoT), cloud computing, and big data [3]. At the same time, data retrieved from sensors of high velocity, variability, veracity, volume, and value [4] -through a thorough analysis- can generate production forecasts, facilitate maintenance management, provide equipment information and create a digital, resilient and sustainable manufacturing process [5,6]. The aforementioned digital interventions, known as Industry 4.0 [7,8], promote digitalization by enhancing digital innovations, interoperability, and data integration. However, the need of re-purposing technology-driven industries into a sustainable, resilient, human-centric, and value-driven ecosystem (Industry 5.0) emerges [9].

Industry 4.0 applications, and specifically the growing volumes of heterogenous data generated throughout the production process, have accelerated the implementation of digitalized maintenance operations in manufacturing facilities [10]. As maintenance expenditures increase over time, companies are prompted to modify their maintenance approaches to reduce costs and increase productivity and safety conditions in the production lines [10–13]. Moreover, lack of data availability, estimation accuracy, technological advances, product life cycle, and dynamic uncertainties can negatively affect overall maintenance cost estimation [14]. The disassembly operations constitute an additional economic factor to be considered for optimal maintenance planning. During disassembly, the likelihood of component failure is increased, reducing the reliability and operating performance of the overall system.

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Nomenclature

(AI)	Artificial intelligence.
(ANN)	Artificial neural network.
(ARIMA)	Autoregressive integrated moving average.
(CBM)	Condition based maintenance.
(CNN)	Convolutional neural network.
(DT)	Decision tree.
(DL)	Deep learning.
(KNN)	K-nearest neighbor.
(LSTM)	Long short-term memory.
(ML)	Machine learning.
(NLP)	Natural Language Processing.
(PdM)	Predictive maintenance.
(RF)	Random forest.
(RNN)	Recurrent neural network.
(RUL)	Remaining useful life.
(RMSE)	Root mean squared error.
(SVM)	Support vector machine.

In [15], the authors quantified the impact of disassembly operations regarding component malfunction rate, producing an efficient maintenance strategy plan on a spindle of a milling machine and optimizing the overall production process. In this light, state-of-the-art maintenance strategies, along with smart production processes and systems, in industrial environments could ensure reliability and increase profitability and competitiveness among industrial firms [16,17]. Notably, predictive maintenance (PdM) can reduce scheduled repairs and maintenance costs by up to 12% and 30%, respectively, and significantly decrease malfunctions by predicting approximately 70% of failures [18]. PdM is established as an important aspect of the prospective global industrial development. Industrial sector-wise PdM applications in manufacturing, transportation and the energy sector are expected to have a significant growth in revenue by 2030. According to [19], 81% of companies are currently investing in PdM related areas of implementation, namely sensor technology, condition monitoring and diagnosis, data and signal processing, and predictive applications. An extensive market research report [20], showcased that 50% of industrial benefits in PdM applications concern operational aspects, such as machine uptime and product manufacturing improvement, while 38% refer to product quality and financial effectiveness. Moreover, the majority of the respondents (over 90%) stated that a moderate-to-significant return of investment was experienced in the first two years, highlighting the importance of PdM in future industry. Current trends of Industry 4.0 technologies for maintenance include digital twins [21], deep learning (DL), machine learning (ML) [13,22], IoT, big data analytics, cyber security, additive manufacturing, and autonomous robots [23,24]. In this context, several literature efforts analyzed up to date PdM methods [25] and solutions that focus on specific industries, namely automotive [26,27], railway [28], and aviation [29]. However, to the best of our knowledge, there is a lack of a comparative review on PdM applications across diverse manufacturing industries.

To this end, this research aims to provide a comprehensive multi-sector overview of state-of-the-art PdM applications through the lens of Industry 4.0. In particular, we pose the following research questions (RQs) in the context of smart manufacturing ecosystems:

- RQ#1: How is PdM defined, and which are the key industrial sectors of application?
- RQ#2: Which are the most common PdM methods, predicted variables, applied algorithms, evaluation metrics, and software tools per industrial sector?
- RQ#3: Which are the potential trends and insights derived from the comparative multi-sector analysis?

To respond to the RQs, a systematic review methodology was adapted from [30] to identify, study, and classify PdM publications within Industry 4.0. In response to RQ#1, industry-related literature reviews were explored to provide a brief scientific background of the PdM domain and its relation to Industry 4.0. In response to RQ#2, the extant literature was thoroughly analyzed to collect 54 pertinent state-of-the-art applications of PdM classified per manufacturing sector. Important information, such as methods, input features, predicted variables, applied algorithms, evaluation metrics, and available software solutions of the use cases were taken into consideration to create a systematic taxonomy. Finally, in response to RQ#3, the outcomes of our research work were compared and combined into a concise decision support map to: (i) highlight current challenges and potential opportunities; and (ii) provide customized insights in the field of PdM according to the distinctive needs of each industrial sector.

Overall, the contribution of this research is twofold. From an academic perspective, this review intends offering a comparative synopsis of the most recent research efforts and the technology readiness in the field of PdM across manufacturing sectors. From a practical and applied perspective, the proposed decision support map could act as a guiding technical framework, including key elements that practitioners should consider when designing and performing sector-specific maintenance operations. The remainder of the paper is structured as follows. In Section 2, we provide the conceptual context of PdM based on previous literature reviews. Then, Section 3 describes the systematic research methodology underpinning this research. In Section 4, we provide the multi-sector analysis and critical taxonomy of the extant literature on state-of-the-art PdM applications, while, in Section 5, we present the comparative results of the review, along with industry-specific insights. Finally, Section 6 discusses the academic contributions and practical implications of this work, concluding with future research directions.

2. Literature background: an analysis of extant reviews

To identify the main research concepts and provide a theoretical context for our analysis, a brief discussion of existing maintenance-related and industry-specific review articles that primarily focus on Industry 4.0 PdM solutions was initially conducted (as a response to RQ#1).

2.1. Maintenance-related reviews

Predicting a machine's condition and remaining useful life (RUL) can significantly reduce unexploited downtime and expensive labor costs, while ensuring an efficient maintenance plan and safety in industrial operations [31]. Smart manufacturing transforms information acquired across the product's lifecycle into manufacturing intelligence, thus improving the performance of industrial machinery and the safety of maintenance personnel [32]. [33–35] divided the maintenance strategies into three main categories: (i) **corrective**; (ii) **preventive;** and (iii) **predictive** (Fig. 1). Corrective maintenance, named also as run-to-failure or immediate maintenance, is a strategy that focuses on repairing equipment or system components after a malfunction has occurred [36,37]. Preventive maintenance is performed periodically in certain scheduled time sequencies regardless of whether the system is malfunctioning or not [38]. However, [39,40] proposed a methodology for estimating production gains and improving maintenance energy efficiency by identifying opportunistic windows to perform preventive maintenance actions in high-volume production environments and machine part replacements, respectively. Focusing on PdM, [33] state that PdM utilizes the current health status of a given critical component to predict its future condition and plan maintenance actions. [38] defined PdM as historic data-based models that identify trends, behavior

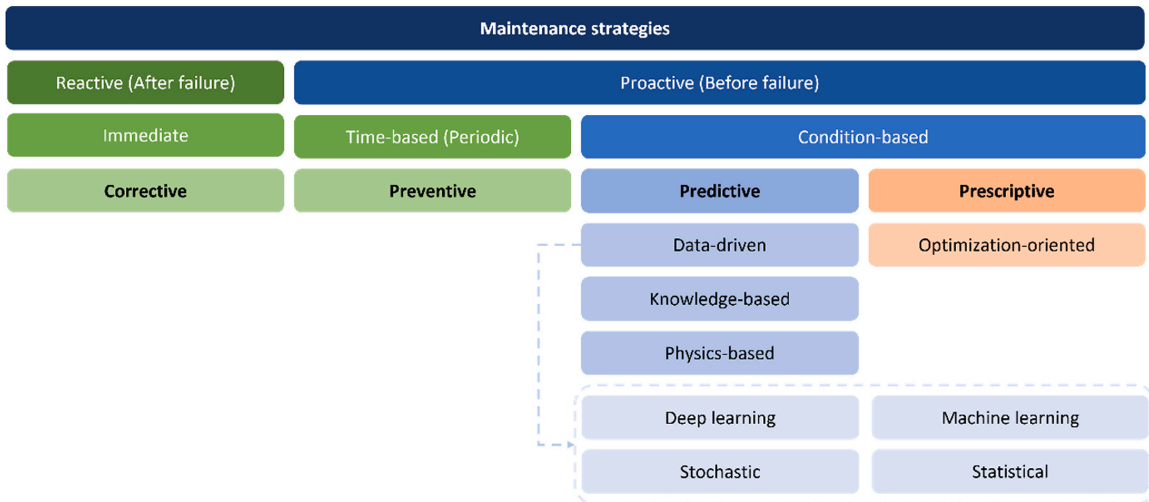

Fig. 1. Categorization of maintenance approaches
[Adapted from [35]].

patterns, and correlations in failures based on statistical or ML models. It is worth mentioning that an advanced maintenance strategy, named **prescriptive maintenance,** has been recently employed as an extension of PdM [41]. Prescriptive maintenance improves and optimizes input features retrieved from sensors and maintenance processes by controlling the occurrence of specific events [42,43].

In more detail, [24,44] divided PdM methods into three separate types: (i) **physics-based**; (ii) **knowledge-based**; and (iii) **data-driven**. Physics-based methods focus on approaches based on mathematical models of system behaviors that derive from physical laws and probability distribution functions [36]. Knowledge-based methods refer to models based on human experience, facts, rules, or previous cases, which improve the maintenance process [24]. When the maintenance action is considered as appropriate, actions are stored as rules for creating a knowledge base that will be used in the decision-making process. Data-driven intelligence models identify the multivariate non-linear relationships among data without the need of understanding the system's physical behaviors [11]. More specifically, [24,45] analyzed data-driven decision-making methods emphasizing manufacturing and maintenance operations; **ML**, **DL**, **statistical**, **stochastic**, and **hybrid** models are selected as the main models applied to industrial maintenance sectors for cost estimation and maintenance planning, joint scheduling and planning, as well as multi-state and multi-component system optimization. Symbolic AI refers to human readable knowledge-based approaches that employ high-level symbolic representations of the problem with logical rules [46]. Common algorithms in symbolic AI are the widely known tree-based models where results are extracted based on if-then rules. ML is the application of algorithms, to imitate human learning behavior for discovering valuable patterns in large volume, high dimensional data [47]. DL however is a subfield of ML that uses neural networks made up of multiple layers of neurons, which transform input streams according to an activation function and learn by calculating the error of the output and back-propagating it through all the neurons to update their weights [48]. On the other hand, statistical models combine descriptive approaches with regression analysis to determine the quantitative relationship among two or more variables [49]. Furthermore, stochastic data-driven models generate probability distributions of likely options and are often considered within the Bayesian approach by presenting the current state of a system and evaluating future trends before a given threshold [45]. In addition, [24] highlighted that the plethora and continuous growth of sensor-generated data within Industry 4.0 have increased the demand for data-driven decision-making methods developed for maintenance applications.

After defining and categorizing the available maintenance methods with emphasis on predictive ones, in order to identify the literature gaps of maintenance related reviews and strengthen the motivation of this research, a comprehensive analysis of the topics discussed in relevant literature reviews is conducted. [50] presented a systematic review on condition-based maintenance (CBM) and specifically on the vibration measurement and signal processing techniques as well as machine tools in manufacturing operations. On the other hand, [51] focused on behavioral inquires of PdM implementation from a work system perspective. The authors addressed the issues of: (i) data-driven system-generated advice acceptance in industrial working procedures, highlighting the importance of trust between decision-makers and predictive models, (ii) sufficient cognitive resources, and (iii) proper control and organizational allocation of the decision-making process for PdM adoption. At the same context, a review on uncertainty quantification for engineering systems and decision-making was conducted [52]. The proposed methodologies aimed to quantify, aggregate, and forecast quantitative and qualitative uncertainties by acknowledging their significance on cost and availability. Two research gaps were identified, namely a lack of frameworks to aggregate multivariate uncertainty, as well as of approaches forecasting individual and aggregated uncertainties. Additionally, a comprehensive analysis of maintenance and self-healing for smart manufacturing was presented [53]. The scope of this research was to develop a fault detection and diagnosis and self-healing-fault-tolerant strategy to identify potential anomalies in optimal timeline improving system safety and overall productivity. The review focused on fault detection and diagnosis classification approaches based on physical model, data, and signal processing manipulation. Moreover, [54] discussed the procedure and impact of optimal maintenance scheduling on product quality. Using ANNs, a real-word application in production process of cooking pots, they validated the concept of quality-oriented maintenance scheduling in modern industry. Furthermore, [23] performed a systematic literature review on intelligent sensors, PdM methods, and smart manufacturing. The authors proposed a smart and intelligent PdM solution and presented the recent trends in maintenance applications. [42] reviewed several Industry 4.0 maintenance applications. In their taxonomy, predictive, preventive, corrective, and prescriptive maintenance are discussed based on their impact on sustainability, safety, costs, time, and social aspects. An analytical review of challenges in predictive maintenance was presented [55]. The authors focused on challenges regarding anomaly detection, prognostic methods and applied architectures throughout industry. Emphasis was given in the existence of raw and erroneous input data, the lack of prognostic model generalization and the difficulty of collecting insightful process data in distinct industrial applications. Furthermore, [56] reviewed AI applications in Industry 4.0. Specifically, a thorough analysis of existing literature regarding supervised, unsupervised, reinforcement, and DL algorithms used for fault detection, prediction, and regression was conducted. [57] explored PdM applications through emphasizing AI methods; an extensive review of ML and DL, a taxonomy of use cases, key metrics, data sources, and equipment for each AI method was performed. The authors concluded that DL algorithms predicting fault detection and failure classification are gaining traction in the field of PdM. A similar review dealt with ML techniques exclusively for PdM [58]. In the same context, [59] performed a systematic review focusing on AI use cases regarding decision support systems in manufacturing process. The authors highlighted that hybrid models combining AI models with fuzzy logic and genetic algorithms generate promising results in prevailing research areas, such as PdM. [11] presented a systematic review of DL applications for smart manufacturing; convolutional neural networks (CNN), restricted Boltzmann, autoencoder, and recurrent neural networks (RNNs) were thoroughly analyzed with a detailed comparison among different DL models. In addition, the categorization of applications and use cases for each model, along with a list of DL tools, was discussed. [60] investigated the performance of flexible unit systems based on degradation and upgradation models, residual life distribution, workload adjustment strategy, and PdM. The authors defined flexible unit systems as a special type of configuration, proposing one or multiple-layer architectures for achieving flexibility in the reconfiguration and upgradation of a machine unit within Industry 4.0. Finally, a systematic review of data-driven approaches for smart manufacturing from the perspective of big data manipulation was conducted [10]. The authors analyzed the lifecycle and characteristics of big data, along with a framework for handling manufacturing data, and concluded that big data approaches could increase the maintenance efficiency of an industrial facility layout.

Based on this analysis, and to the best of our knowledge, there is an absence of a comparative review on PdM applications across diverse manufacturing sectors, namely manufacturing of machinery and equipment, transport-related and energy. A systematic multi-sector mapping regarding PdM in Industry 4.0 will enhance the academic literature by combining previous work and addressing the gap of a comprehensive synopsis of PdM approaches. Additionally, through this study, identification of state-of-the art methodologies, challenges of PdM implementation, future trends, and research gaps will be clarified alongside with the technology readiness of each reviewed sector. In this context, we conduct a comprehensive overview of sector specific PdM elements, methods, and algorithms. We particularly focus on providing both the academic community and practitioners with up-to-date sector specific solutions, potential opportunities, and possible gaps within the Industry 4.0 context.

2.2. Industry-specific reviews

This section analyzes review articles that refer to specific industrial sectors. Concerning the **manufacturing of machinery and equipment**, [61] conducted a review on ML and DL techniques for fault diagnosis. Through a set of previous experiments and reviews, the authors concluded that DL models are more efficient than ML for the detection of multi-dimensional data and fault bearing. [62] presented an extensive analysis on ML algorithms applied for PdM, while their findings on the features were used (i.e., data from sensors) as an input for the algorithms regarding real-world system components (i.e., machinery, motors, turbines). Vibration was considered as one of the most crucial parameters for fault detection and RUL prediction. The relation between ML methods and the type of investigated equipment was also investigated. A review on diagnostic and prognostic methods for gears regarding PdM was also performed [63]. The authors analyzed physics-based approaches with a taxonomy on failures and issues addressed, as well as data-driven approaches with a classification of fault classification models, for gear fault classification and RUL predictions. In addition, they focus on hybrid approaches, highlighting that, by implementing both methods successively (i.e., physics-based and data-driven), the proposed PdM solutions were more efficient and less time-consuming. Overall, the authors suggested that prognostic approaches should not only predict the RUL but also report the associated uncertainty of prediction probability. [64] conducted a review on PdM for rolling element bearings. A review of models for bearing faults and crucial parameters was presented. Vibration and acoustic emission were considered some of the most common features implemented on the algorithms for the faulty bearings' detection. In addition, a summary of diagnostic methods for fault identification, along with an analysis of data-driven and physics-based models used for the prognosis of wear on rolling element bearings, was provided. Finally, a review on data-driven techniques for different use cases of additive manufacturing and 3D printing was presented [65]. ANNs, Markov decision processes, genetic algorithms, and gaussian processes were examined as ML models for error compensation in additive manufacturing. A DL model with a Unet topology and a long short-term memory (LSTM) RNN was also examined. Specifically, the LSTM-based predictive model outperformed ML techniques, such as support vector regression and random forest (RF). The authors concluded that error compensation methods and data-driven models could improve: (i) the final product's quality and the production timeline in additive manufacturing; and (ii) applications such as fused deposition technology (FDM) and direct metal laser sintering (DMLS).

With respect to the **transport-related** sector, [26] conducted a review focused on ML applications for PdM in the automotive industry. The authors classified the use cases identified in the extant literature (i.e., classification, detection, regression, forecasting) and the ML algorithms used. ANNs and decision trees (DTs) were some of the commonly used ML algorithms for regression and classification tasks. Furthermore, the authors surveyed approaches for different use cases of malfunction, categorizing their results into statistical, condition-based, and RUL PdM. Finally, the authors highlighted the lack of open-access real-word data sets and labelled data, the complexity of problem setting, and the acceptance of ML-based maintenance, proposing relevant solutions. [29] developed a review on anomaly detection methods implemented in the aviation industry. The authors thoroughly analyzed different methods, including statistical and data-driven ones, for anomaly (or outlier) detection in large-scale high-dimensional timeseries data, such as flight trajectories. In addition, a taxonomy of the prevailing algorithms and their application for anomaly detection in aviation use cases was presented. It was concluded that research mainly focused on DL algorithms (i.e., RNN, CNN, autoencoder) was considered as well-suited for processing due to the algorithms' capability to process large-scale high-dimensional time series data. [28] performed a systematic review on data-driven methods for PdM for railway tracks. The authors presented a taxonomy to classify methods, models, and applications of data-driven PdM in the railway industry. The authors concluded that ML and statistical models were the most common methods, presenting an analysis of the advantages and disadvantages of each use case. Geometry irregularity, rail head defect, and missing rail components' detection were also the most considered track defects. In addition, a taxonomy of crucial parameters, sensors, and implemented algorithms was performed for various use cases of track defects.

Within the **energy** sector, [66] developed a review on data-driven methods used in nuclear power plants. The authors placed a strong emphasis on state-of-the-art data-driven methods for prognostics and health management, primarily on AI and ML, identifying the overarching gaps (namely limited pilot applications of fault detection and diagnostics) of the nuclear industry. A review on PdM applications for thermal power plants and pump systems was also provided [45]. The authors analyzed existing literature for PdM based on different data-driven models (i.e., stochastic, statistical, AI) and provided a taxonomy of algorithms, type of machinery, and input features. An additional taxonomy focusing on PdM of centrifugal pumps with an analysis of the type of faults, algorithms, features, and objectives for each use case was performed. Regarding the **chemical and process** industry, [67] analyzed different maintenance solutions (i.e., corrective, preventive, predictive) and presented an overview of recently published literature for maintenance risk assessment. The limited availability of data was identified as a critical issue. In addition, the authors concluded that, for the chemical and process industry, PdM applications will dominate in future research.

3. Research methodology

[35] argue that there are four major steps that guide a systematic literature review: (i) research questions, (ii) search strategy, (iii) study selection, and (iv) data synthesis. After defining the research questions, a structured approach for exploring, collecting, and classifying existing use cases will support the identification of areas of interest, literature trends, current challenges, and future opportunities. To this end, we followed a systematic review methodology adapted from [68] to optimally explore current literature concerning maintenance and classify PdM applications in each manufacturing sector. A combination of generic keywords, namely 'Industry 4.0' AND 'maintenance', was selected for an initial literature screening. The software tool VOSviewer was utilized to identify the most correlated keywords and determine the domains of interest [23,38,44]. VOSviewer applies bibliometric data methods generated from files and executes an algorithm for filtering and relating keywords by co-occurrences (i.e., the number of times a specific term appears in the article). In our research, we analyzed articles retrieved from the Scopus and Web of Science databases, which were selected due to their broad and consistent collections of peer-reviewed journals [35,60,69]. Fig. 2 illustrates the prevailing keywords, their correlations, and their evolution over time as generated by VOSViewer. The keywords 'predictive maintenance', 'machine learning', 'artificial intelligence', 'big data' and 'decision making' are most commonly related to Industry 4.0 and maintenance (the greater circle size, the more frequent the term occurrence). 'Predictive maintenance' and 'machine learning' are highly cited in recent research indicating a potential trend (red color depicts recent term occurrence). In addition, 'condition-based maintenance', 'anomaly detection', 'remaining useful life' and 'deep learning' constitute some of the newly prevalent keywords.

After identifying the correlated keywords based on the VOSViewer outcomes, the final search terms were determined. Table 1 shows the keyword combinations and the number of the related studies retrieved; a total number of 428 studies from Scopus and 1725 from Web of Science were collected. We further applied filters focusing on the article type (i.e., only peer-reviewed articles), the time span (i.e., 2017–2022), and the language (i.e., only in English). Since technology is advancing at an accelerating pace, the 5-year period of the analysis is selected to highlight the latest research on PdM. After excluding the duplicates, a total

Table 1
Literature review search terms.

Search terms	Scopus articles	Web of Science articles
'Industry 4.0' AND 'Predictive Maintenance'	136	259
'Industry 4.0' AND 'Maintenance' AND 'Data-driven' OR 'Data Analytics' OR 'Big Data'	80	339
'Industry 4.0' AND 'Maintenance' AND 'Machine Learning' OR 'Deep Learning'	65	290
'Industry 4.0' AND 'Maintenance' AND 'Condition-based' OR 'Remaining Useful Life'	5	331
'Industry 4.0' AND 'Maintenance' AND 'Digitalization' OR 'Internet of Things' OR 'Smart Manufacturing'	110	294
'Industry 4.0' AND 'Maintenance' AND 'Digital Twin'	32	212
Sum of articles	428	1725

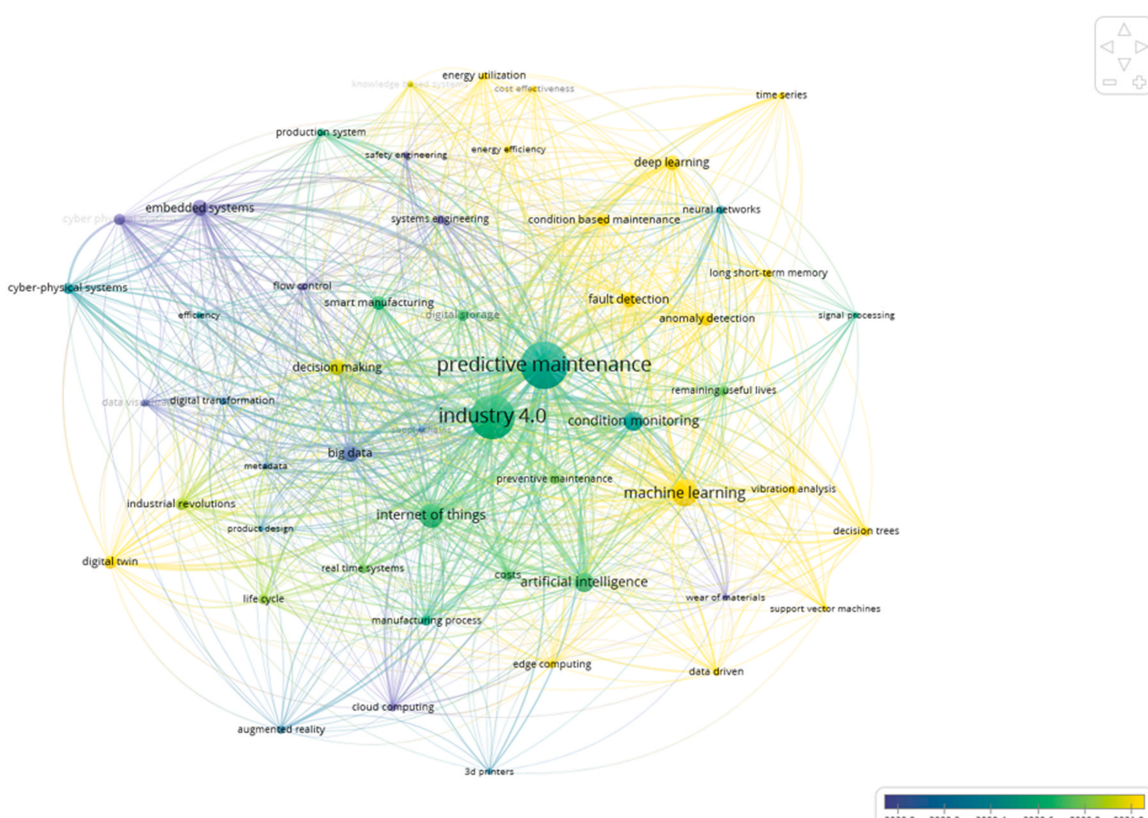

Fig. 2. Common 'maintenance' domains keywords and their correlations within the 'Industry 4.0' [Created with VOSviewer].

number of 251 articles were selected for additional processing.

The screening of the titles, abstracts, and keywords of each research paper enabled the authors to proceed only with papers related to the reviewed topics of maintenance in Industry 4.0 and PdM methods. In case the publication was considered relevant, the authors proceeded with the full-text screening, otherwise, the paper was rejected. Only the research papers that clearly defined the industrial sector, along with the methodology used, the algorithms implemented, and the input parameters were included. In the last step, after thoroughly studying the publications selected, the authors categorized the results per industrial sector to create an analytical taxonomy and identify prevailing solutions, current trends, and potential gaps for each manufacturing sector. In addition, we used cross-references to retrieve additional sources potentially relevant to the topic under study. Finally, a total number of 78 research articles were comprehensively included and analyzed in the systematic review. Overall, Fig. 3 illustrates the methodological approach of the systematic literature review as a stepwise process.

4. Overview of predictive maintenance applications

Our thorough systematic analysis of the research articles identified an extensive variety of use cases highlighting the importance of PdM research in industry. Specifically, we observed that data-driven applications are the most frequent ones, including research of both scientific and technical interest. Between 2017 and 2022, our analysis indicated growing attention in the sectors of manufacturing of machinery and equipment, transportation, and energy, as well as a notable interest in the chemical and electronic industries.

The review outcomes, with an emphasis on data-driven methods, confirmed that PdM is a state-of-the-art maintenance strategy, employed in various manufacturing sectors at an accelerating pace. Our review further endorses the results of [58,59,70] that demonstrate a rising trend in PdM research between 2009 and 2020. Except for classifying each case depending on the manufacturing sector, we further identify specific attributes, including input features, predicted variable(s), applied methodology, experimented algorithms, evaluation metrics, and software tools used (as a response to RQ#2). In particular, the input features constitute the variables inserted in the experimented algorithms for predicting specific values, such as the RUL or the upcoming failure. The methodological approach refers to the main subcategories of PdM (e.g., ML, DL, statistical, stochastic) that utilize specific prediction algorithms (e.g., ANNs, SVMs, DTs, RFs). Finally, we highlight the evaluation metrics used for comparing the performance of the implemented algorithms and software tools. A taxonomy of the collected publications, highlighting all abovementioned key features, is provided in Table 2.

4.1. Manufacturing of machinery and equipment

4.1.1. Computerized mechanical control machines

The literature review indicated that PdM is an advanced approach, commonly employed in machinery and equipment applications, with a special focus on computerized numerical control (CNC) machines. [71] proposed a ML solution for anomaly detection in CNC milling machines. The authors attempted to train a small amount of historical data, using ML models, namely naive Bayes, DT, K-nearest neighbor (KNN), RF, SVM, and XGBoost. Vibration, x-y-z movements, temperature, rotational speed, torque, power, and acoustic emissions, along with statistical measurements (e.g., mean, standard deviation), were collected to predict upcoming failures on a milling machine stepwise process. The experiments were conducted using the R programming language with accuracy, precision, recall, F1 score, and Matthew's correlation coefficient (MCC) as evaluation metrics. The results showcased that DT provided the optimal results with an F1 score of 92.9%. Similarly, [72] presented a PdM solution for health state prediction of a milling CNC machine. The authors compared AI algorithms, such as ANN, SVM, and KNN, for condition state prediction of tool wear in a CNC machine. Statistical outputs of vibration measurements (i.e., root mean square and standard deviation) were utilized as input parameters for the classification algorithm. Score, recall, and precision were used as evaluation metrics for the comparison of the selected models. The results highlighted that the ANN performed optimally in condition state classification of tool wear demonstrating recall of 96.8%, score of 94.4% and precision of 93.3%.

In addition to anomaly identification and health state prediction, research on the RUL prognosis of CNC milling machines was also performed. [73] presented their findings on tool wear status estimation and RUL prediction using data-driven algorithms namely linear regression, bayesian linear regression, decision forest, boosted decision tree and

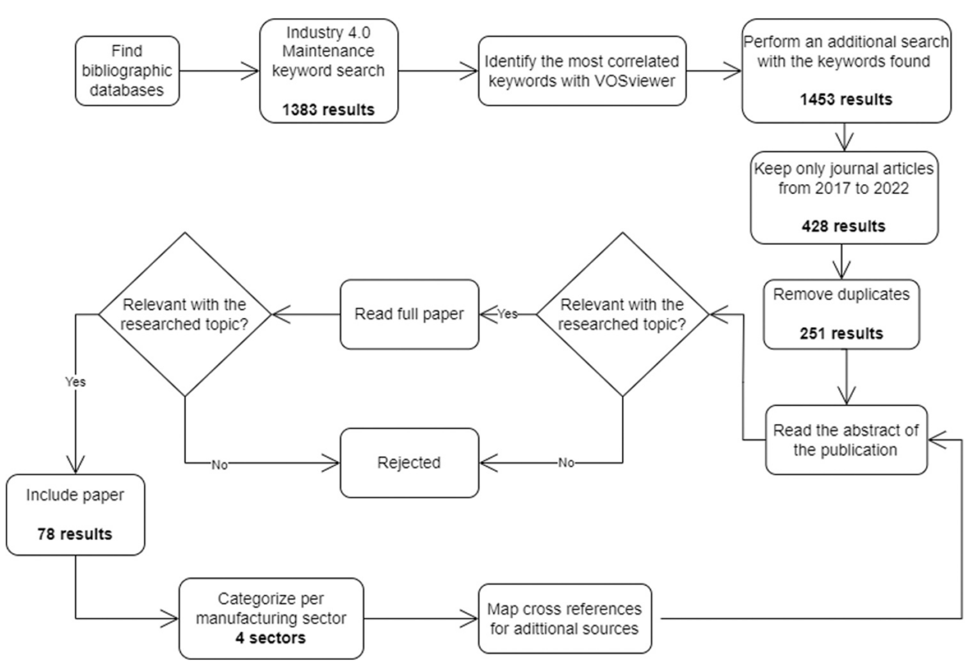

Fig. 3. Research methodology flowchart
[Adapted from [42]].

Table 2
Taxonomy of Computerized mechanical control machines applications.

Authors / Year	Specific case	Input Features	Predicted variables	Method-Best performing Algorithm	Evaluation Metrics	Software tools
Züfle et al. 2021	CNC milling machine	Vibration, x-y-z movements, temperature, rotational speed, torque, power, acoustic emissions	Anomaly detection	ML-DT	Accuracy, Precision, Recall, F1 score	N/A
Hesser & Markert2019	CNC milling machine	Statistical outputs of vibration measurements	Health state prediction	ML/DL-ANN	Precision, Recall, F1 score	Bosch XDK
Traini et al. 2021	CNC milling machine	Statistical outputs of vibration, acoustic emissions, direct and alternate currents	Health state estimation and RUL prognosis	ML-ANN	Root-mean square error, root relative squared error	R
Sundaram & Zeid. 2021	CNC milling machine	Vibration, acoustic emission, current, Case Id, run, flank wear, time taken, depth of cut and statistical methods	RUL prognosis	ML/DL-N/A	N/A	MATLAB
Sang et al. 2021	CNC milling machine	Machine Id, vibration, voltage, pressure, rotational speed, age, cycle, condition	RUL prognosis	DL-LSTM	RMSE	FIREWARE using NoSQL Hadoop database
Luo et al. 2020	CNC milling machine tool	Time domain force X RMS, and frequency domain forces X at 1042 Hz and 521.1 Hz	RUL prognosis and optimal maintenance timeline identification	ML/Physics based-RF and Johnson-Cook model	RMSE	MWorks, SimulationX, ANSYS, Abaqus, Dymola and Python
Kumar et al. 2019	CNC cutting machine	Thrust force and torque collected from an accelerometer	Health state classification and RUL prognosis	Stochastic-Hidden Markov Model	RMSE, R2	LabVIEW
Li et al. 2017	CNC cutting machine	Vibration, temperature, rotational speed, acoustic emission and for prognosis backslash error	Failure prediction and failure diagnosis	DL/Stochastic-ANN and Fuzzy logic system	Backslash error	N/A
Teoh et al. 2021	CNC cutting machine	Vibration, voltage, pressure, rotational speed, age, error Id, components replaced	Health state prediction	ML-Genetic regression algorithm	Accuracy, Precision, Recall, F1 Score	FogWorkflowSim, Microsoft Azure

ANN. Time domain, frequency domain and polynomial regression coefficients of measurements such as the vibrations and the acoustic emissions of the table and of the spindle and the alternate and the direct motor currents were considered. Their analysis was conducted using the R software environment. Their findings indicated that the ANN algorithm outputted the most optimal results using root-mean square error and root relative squared error as evaluation metrics. Following a thorough analysis of a multi-faceted industrial approach to prognostics and health management, a smart manufacturing framework for RUL prognosis was developed using MATLAB software [74]. The authors elaborated on data acquisition and preprocessing methods using vibration, acoustic emission, electrical current, case identification number, flank wear, time (duration), depth of cut, and statistical values. The authors further compared DL and ML methods for the RUL prediction. In addition to the aforementioned research, [75] developed a framework for RUL prognosis in a CNC machine using a DL LSTM model. The solution was implemented on the FIREWARE open-source framework using the NoSQL Hadoop database. Machine identification number, vibration, voltage, pressure, rotational speed, age, cycle, and machine's condition were used as input features for the RUL prediction using the LSTM algorithm. The proposed model evaluation demonstrated a root mean squared error (RMSE) of 21.79 indicating that the prediction model is effective, further saving 4–11% of the expected maintenance cost.

At the same time, [76] developed a hybrid PdM approach combining a physics model-based simulation of a digital twin with data-driven algorithms to predict the RUL of a cutting tool and the optimal maintenance timeline of a CNC milling machine. Time domain force X RMS and the frequency domain forces X at 1042 Hz and 521.1 Hz were some of the features with the highest correlation for the RUL estimation of the cutting tool. RF with RMSE as evaluation metric and physics model-based approaches, such as Kalman filter, Particle filter, and ensemble learning, were implemented for RUL prognosis. Software, such as MWorks, SimulationX, ANSYS, Abaqus, and Dymola, were used for the digital twin simulation, while the Python programming language was utilized for the data-driven algorithms. The results indicated that the hybrid approach provides the optimal solution with a significantly lower error ratio (3.17%) than the physics-based and data-driven (9.51% and 26.31%, respectively). In the same vein, a stochastic hidden Markov model and a polynomial regression algorithm were proposed for the classification of the health state and RUL prediction of a CNC cutting machine [77]. Thrust force and torque data, collected through an accelerometer, constituted the input features for the prediction algorithm and the machine state identification. The LabVIEW software was used for signal processing and the PCI-MIO-16XE-10 card for data acquisition. Average model R2 and median RMSE were used as the evaluation metrics of the algorithms. The results generated an average R2 value of 72.6% and 75.6% for the hidden Markov model and the polynomial regression algorithm, respectively. An additional hybrid approach for failure prediction and failure diagnosis was proposed [78]. For predicting failures, the authors implemented an ANN using historical data of backslash errors as input features. In contrast, for the diagnosis application, a hybrid model of ANN and a fuzzy logic system were employed using sensor measurements, such as vibration, temperature, rotating speed, and acoustic emission, as input parameters. Both methods' results were satisfactory indicating that PdM solutions could be applied in CNC machine fault diagnosis and prognosis scenarios. Finally, [79] proposed a hybrid PdM solution for health state prediction on die casting machines, laser cut machines, and plasma cutting machines, using fog computing and the genetic ML algorithm. For simulation purposes, the authors developed their use case in the FogWorkflowSim and the Microsoft Azure ML cloud server. A total set of 14,482 samples were analyzed containing input features, such as error identification number, vibration, voltage, pressure, rotational speed, age, and components replaced, regarding the health state of the machine. The results of the genetic algorithm were compared using statistical approaches, such as MinMin, MaxMin, and RoundRobin. The genetic algorithm demonstrated optimal performance in execution time, operational cost, and energy usage. In conclusion, the model was able to predict efficiently the health state of the machine (accuracy of 94.1%, precision of 94.6%, recall of 93.3%, and F1 score of 93.9%).

4.1.2. General machinery

Further literature analysis revealed a variety of PdM solutions concerning other general machinery except for CNC machines, namely pressing machines, centrifugal fans, electric motors, hydraulic sand molding machinery, and woodworking industrial machines. Anomaly detection, health state classification, RUL prognosis, failure prediction, as well as classification and oil contamination prognosis, constituted the most common predicted variables of the use cases under study. [80] developed a PdM application for anomaly detection in a pressing machine. The authors compared machine and DL algorithms, such as SVM, null space, and 2D convolutional networks, with autoencoders to identify the optimal model. Rotational speed, power consumption, force, and position were selected for the feature data collection. Four types of failures were classified for artificial model predictions. The simulation was performed using Python programming language and the TensorFlow, Scikit-learn, MiniSom and SHAP libraries, while evaluation metrics, such as F1 score, precision, and recall, were utilized for the models' comparison. The results were promising with null-space and 2D-CNN-AE leading to average F1 scores of 92% and 99%, respectively. Similarly, a ML XGBoost algorithm for behavior prediction of an industrial paper pressing machine was proposed [81]. Using Python and sklearn, pressure, temperature, current, torque, oil level, velocity, and statistical values (mean, median, variance etc) were applied as input features in order to predict system behavior in terms of 15, 30, and 90 days. XGBoost outperformed other DL algorithms, such as ANN or LSTM, with MSE and MAPE as evaluation metrics. Finally, the authors highlighted that pressure is the most difficult variable to predict, on the other hand their results indicated that torque is the easiest. Furthermore, [82] conducted research on anomaly detection for centrifugal fans. The authors tackled the issues of imbalance growth, bearing deterioration, wrong balancing procedure, and intact state monitoring. Crucial parameters, such as vibration, rotational speed, and acceleration, were inserted as input features in the nearest-neighbor ML algorithm. The results were compared with knowledge-based solutions, concluding that the algorithm generates only a few false positive indications. In the same context, [83] designed an expert system for centrifugal fans on a Sugar factory that classifies failure namely misalignment, looseness, bearing and pulley. The Multilayered Bayesian Network on MATLAB software was experimented using vibration amplitudes at various component frequencies and rotating speed as inputs. Following the addition of ML algorithm, the probability of predicting centrifugal damage increased up to 93.2%. Similarly, a failure classification approach regarding centrifugal pumps was conducted [84]. The authors, using vibration, temperature, and pressure as input features classified failure data into multiple classes based on the estimated fault magnitude. A context-based Multilayered Bayesian algorithm outperformed KNN, XGboost, and Auto Encoders outputting an F1-Score of 98%. Additionally, [85] presented a PdM solution for anomaly detection in an electrical motor-driven system connected with a gearbox. An ANN model was proposed, using vibration, rotation axis, and current signals as input features for the detection algorithm. In addition, a genetic algorithm was employed for the selection of the optimal hyperparameters (i.e., parameters whose values control the learning process). The diagnostic solution was developed in the MATLAB programming environment. Overall, the average accuracy of the proposed methodology reached 92.03%, outperforming various AI methods, such as LSTM. Furthermore, [86] proposed a deep transfer learning approach for failure prediction, namely friction on the main spindle and load imbalance, on a Bently Nevada rotor kit. Vibration x-y-z, rotational speeds, noises of wavelet coefficients and energy percentages were used as input features on a fully connected deep neural network model with accuracy as evaluation metric. The authors highlighted the importance of transfer learning on reducing the values of input data and thus the computational demands without reducing prediction performance.

Regarding health state classification, [87] developed a deep CNN model for machine state identification (i.e., dangerous or not) of conveyor motors. Vibration speed, air pressure, temperature, acceleration, rotational speed, and torque were used as the input features, while accuracy, precision, and recall as evaluation metrics. The authors highlighted that, based on the ISO 2372, vibration velocity above 4.5 mm/s indicated an unsatisfactory vibration severity. The results of the CNN were optimal, indicating a 100% correct failure classification, which was much higher than that of ML algorithms, such as SVM. In the same context, [88] presented an ANN algorithm for health state classification of conveyor belts. Three stages of belt tension namely, low, optimal, and over-tensed were examined with 75% to 85% tension proposed as the optimal value. Power consumption measurements and load information as input features provided the best outcomes with an accuracy of 96.8%. In addition, [89] proposed a ML approach for health state classification and vibration failure diagnosis on electric inductive motors. The MatrikonOPC simulation server was used as an interface among data sources, while the NI LabVIEW software was utilized for data acquisition and the solution systems' development. Accelerometers were installed on the motor shaft to measure the vibration on different axes, which was used as input on the classification algorithm. KNN as a ML model was employed for determining the condition of the motor shaft (i.e., good, satisfactory, unsatisfactory, unacceptable) based on the vibration. The proposed algorithm detected the vibration failure of the motor shaft successfully.

[90] presented a ML solution for RUL prediction of woodworking industrial machines. The authors aimed to predict the failure of a broken ball bearing component in RUL batches of 30, 20, and 10 days. Gradient boosting, RF, extreme gradient boosting, SVM, and DT algorithms were compared, implementing accuracy, recall, precision, receiver operating characteristic (ROC), and confusion matrix as evaluation metrics. The average frequency of procedures, overheating error, tool change, and global errors were used as input features. The author used Azure Blog Storage for data acquisition, Python and Apache Spark for data processing, and Scikit-learn and H2O software for the ML deployment. The results indicated that the ML algorithm could effectively predict the woodworking machine RUL with the gradient boosting model performing better with 98.9% accuracy. A machine learning solution for maintenance requirement prediction based on machine status parameters, namely machine id, shift status, production time, number of setups, and total production quantity, was proposed [91]. SVM, RF, Naïve Bayes, Logic Boost and DT were experimented with SVM outputting the best prediction results based on accuracy and F1 score as evaluation metrics. The contribution of this research was a semi-double-loop machine learning approach utilizing the outputs of the best performing algorithm for training and reinforcing an additional model to increase the overall prediction accuracy of the maintenance prediction. Moreover, [92] proposed an adaptive ML model, based on the autoregressive integrated moving average (ARIMA) time series method, which was implemented on a high-pressure hydraulic sand molding machinery setup for oil contamination estimation. The proposed approach focused on achieving zero downtime maintenance by using the ARIMA model to forecast oil contamination values, based on threshold values and preventive maintenance techniques. The methodology was tested through the metrics of mean time between failures and mean time to rectify. The authors calculated the RUL using a 95% confidence level. (Table 3).

4.1.3. Machine parts' manufacturing

Our research further identified PdM use cases regarding specific machinery parts.[93] proposed a ML approach for failure prediction of different gearboxes. The prediction of the probability of machine failure within 24 h related to each gearbox constituted their main objective. Machine identification number, vibration, voltage, pressure, rotational speed, age, and their mean values were considered as input features of the algorithms. The authors used an online open-access database of Microsoft PdM, software packages, such as Matplotlib, Numpy, Pandas and Scikit-Learn, as well as the Python programming language. The algorithms RF and ANN were tested, both exhibiting approximately 99% of precision, recall, and F1 score, which were used as evaluation metrics. Similarly, a framework predicting oil degradation in an industrial

Table 3
Taxonomy of general machines applications.

Authors / Year	Specific case	Input Features	Predicted variables	Method-Best performing Algorithm	Evaluation Metrics	Software tools
Serradilla et al. 2021	Pressing machine	Rotational speed, power consumption, force, position	Anomaly detection	ML/DL-2d CNN with autoencoders	Precision, Recall, F1 score	Python, Tensorflow, Scikit-learn, MiniSom and SHAP
Rodrigues et al. 2022	Pressing machine	Temperature, current, pressure torque, oil level, velocity and statistical values	Failure prediction	ML-XGBoost	MSE, MAPE	Python and Scikit-learn
Lis et al. 2021	Centrifugal fans	Vibration, rotational speed, acceleration	Anomaly detection	ML-KNN	Confusion Matrix	N/A
Romahadi et al. 2022	Centrifugal fans	Vibration, frequencies, rotational speed	Failure classification	ML-Multilayered Bayesian	Conditional Probability Table	MATLAB
Selvaraj et al. 2022	Centrifugal pumps	Vibration, temperature pressure	Failure classification	ML-Multilayered Bayesian	Accuracy, Precision, Recall, F1 Score, Area Under Curve	N/A
Arellano-Espitia et al. 2020	Electrical motor-driven system connected with gearbox	Perpendicular vibration with the axis of rotational speed and current signals	Anomaly detection	DL-ANN	Accuracy	MATLAB
Li et al. 2022	Rotor Kit	Vibration x-y-z, rotational speed, noises of wavelet coefficients, energy percentages	Anomaly detection and failure classification	DL-Transfer learning and DNN	Accuracy	N/A
Kiangala & Wang 2020	Conveyor motors	Vibration speed, air pressure, temperature, acceleration, rotational speed	Health state classification	DL-CNN	Accuracy, Precision, Recall	N/A
Elahi et al. 2022	Conveyor belts	Power consumption, current	Health state classification	DL-ANN	Accuracy, confusion matrix	N/A
Rubio et al. 2018	Electric inductive motors	x-y-z vibration	Health state classification and vibration failure diagnosis	ML-KNN	N/A	MatrikonOPC Simulation Server and NI LabVIEW
Calabrese et al. 2020	Woodworking industrial machines and ball bearings	The average frequency of procedures, overheating error, tool change, and global errors	RUL prognosis	ML-Gradient Boosting	Accuracy, Precision, Recall	Azure Blog Storage, Python, Apache Spark, Scikit-learn and H2O
Putnik et al. 2021	Manufacturing plant	Machine id, shift status, production time and quantity, number of setups	Maintenance prediction	ML-SVM	Accuracy, F1 Score	N/A
Roosefert et al. 2021	Hydraulic sand molding machinery	oil contamination threshold values and preventive maintenance techniques	RUL prognosis and oil contamination prognosis	ML-ARIMA	Mean Time between Failures, Mean Time to Repair	SCADA, a cloud server and a mobile application

gearbox was presented[94]. A hybrid approach with ANN for prediction and deep convolutional autoencoder for data analysis and feature engineering respectively was considered. Mechanical quantities of a specific cogwheel pair exhibited the highest corelations amongst other variables and thus proposed as the most suitable input features. Finally, the authors concluded that cogwheel pair is the most sensitive to the lubricant quality in the machinery and that's the reason oil degradation prediction is important. Furthermore, [95] developed a ML application for fault bearing detection in a motor shaft. The authors focused on predicting the threshold values required to distinguish between healthy and damaged bearings. In addition, they implemented a condition monitoring application that generated alerts and notifications for the maintenance team members. The Arduino IDE software was employed for programming a microcontroller platform, Virtuino for human machine interface, R and R-studio for ML algorithms, and finally PLX-ADQ for data acquisition. The input features for the classification algorithm included x-y-z vibration, voltage, ambient and bearing temperature, rotational speed, current, age of the equipment, and sound intensity. Linear discriminant analysis, DTs, KNN, SVM, and RF constituted the experimented algorithms. Accuracy, precision, recall, specificity, F1 score, false positive rate, false negative rate, expected accuracy, and kappa were utilized as evaluation metrics. The authors concluded that DTs was considered the optimal approach demonstrating an accuracy of 99.84%. In the same context, [96] presented an anomaly detection and failure classification approach for electric motor bearing. A convolutional Auto-Encode for anomaly detection and CNN for failure classification of detected anomalies with vibration, rotational speed, and current as input features were examined. The results were promising with up to 99.61% detection accuracy and 94.83% classification accuracy for 9 different failure classes. An additional study for RUL prediction of slow speed bearing was presented [97]. The authors, examined specific dynamic loading peak amplitudes and frequencies in order to simulate real working conditions enough to induce bearing malfunction. A model-based solution namely the Affine Mean Gaussian Process Regression using acoustic emission as input feature outputted the most accurate results with Mean Absolute Percentage Error and RMSE as evaluation metrics.

On contrary, a DL approach was proposed for RUL prognosis on thrust bearings [98]. CNN-LSTM and Autoencoder-LSTM algorithms were compared, using thermal images as input features and median absolute precision error as an evaluation metric, while the experiments were executed with a Tensorflow-GPU. The results were satisfactory indicating that both solutions could be applied in real-world industrial scenarios. However, the authors concluded that in case the number of samples and observations were sparse, the proposed approaches performed worse than ML algorithms; in contrast, DL algorithms tackled higher dimensional inputs, such as images, more successfully. From a different methodological view, [99] adopted a physics-model based methodology to propose a health assessment program (HAP) for diagnosing the health status of industrial robot joints with torque signature analysis. The authors compared the torque applied by both a faulty robot and a healthy one in a set of experiments. They proved that a faulty joint could be detected by measuring the increment of the torque applied in the robot joints, suggesting that an additional in-depth mechanical inspection should be conducted for identifying the root causes. The results showcased that the RUL of the industrial robot wrist was correlated with the carried load and the orientation of the fifth joint in the waiting state. Thus, in a horizontal orientation, the effort increased requiring higher torque, which, in turn, raised the temperature of the motor and the current in the motor coil, leading to deforming and wearing of the brake magnets. (Table 4).

4.1.4. Steel and metal industry

In this subsection, we present PdM approaches for machinery specifically utilized in the steel and metal industry. A ML Bayesian filter algorithm was selected for the prediction of the condition state and the degradation of machine components in a steel hot rolling mill process [100]. Following an analysis of the data manipulation process, the authors employed various ML algorithms, such as Bayesian filter, nearest neighbors, SVMs, DTs, ANNs, and a preventive maintenance knowledge-based approach to identify the optimal algorithm for the degradation state prediction. Important parameters, such as steel type, weight, length, and thickness at the entrance, temperature, and information regarding the maintenance dates, were collected for the degradation state identification. Regarding the experimental configuration, Python programming language and the Scikit-learn library were employed. The authors concluded that the Bayesian filter ML algorithm provided the optimal results with a RMSE of 2.98. In the same context, a hybrid-based model combining data-driven and knowledge-based methods for RUL prediction of pumps in the hot strip mill process was presented [101]. The authors highlighted the importance of data augmentation in low-failure industrial datasets to improve overall prognostic results. Moreover, they concluded that time-based data augmentations produce more accurate outputs in contrast with amplitude-based approaches which modify the system's physical properties. Pressure, temperature, flow rate, and vibrations were considered features for the data-driven model in combination with SVM and RMSE as evaluation metrics. In addition, a qualitative knowledge-based analysis containing relationships between components, signals, and signal evolutions was introduced to improve the overall RUL prediction accuracy. Furthermore, a wearing detection solution on a rotating metal bush of a TATA steel manufacturing line was proposed [102]. The bush operated in a melted zinc pot, while the problem of data availability appeared in every maintenance cycle (i.e., every four weeks). For the components' wearing prediction, the authors compared the results provided through partial least squares regression, ANN, and RF using RMSE and R2 as the evaluation metrics. For experimental purposes, the R programming language, IBA, EMASS, the Setup sheet, and the data warehouse were used. The authors concluded that the most important variables for the wearing prediction referred to statistical measurements of tension, total length, scrap length, total surface, remaining bush width, days roll, and diameter. The results indicated that the partial least squares regression generated the optimal outputs with an RMSE of 3.91 and an R2 of 55% on average. In the same context, a ML approach for anomaly detection and event prediction in a cold forming manufacturing line was presented [103]. The authors tackled the problems of discontinuous data, noise, log errors, and production bottleneck by employing data mining. Principal component analysis and matrix profile were used as PdM algorithms, using data collected over a year period. Acoustic emissions, maintenance logs, and statistical measures, such as mean and standard deviation of the aforementioned inputs, were inserted in the classification algorithm, while F1 score, recall, and precision were used as evaluation metrics. The results indicated a classification of the healthy state of cold forming manufacturing line using acoustic emissions exhibiting an F1 score of 63%.(Table 5).

4.2. Transport-related industry

4.2.1. Aerospace industry

A turbofan engine degradation simulation dataset, provided by the Prognostic Centre of Excellence of the National Aeronautics and Space Administration (NASA), initiated a set of PdM research in the aerospace industry. A solution regarding RUL prognosis with DL algorithms acted as a common ground for the reviewed use cases. [104] implemented a custom-made CNN DL algorithm, namely Senvis-Net, to predict the RUL of a turbofan engine and tackle the problem of highly imbalanced input data. Serial data collected from sensors were formed into a grayscale 2D image to be used as an input feature for the DL model. Scoring function and mean square error were implement as evaluation metrics of the model. [105] proposed a hybrid method combining stochastic variational gaussian processes, deep gaussian processes, deep sigma point processes, feed-forward neural network, and the Monte Carlo dropout technique. PyTorch and the open-source library GpyTorch were used for the model implementation. Engine identification number, time cycle, and health state of the system were used as input features to predict the system's RUL. RMSE, negative log-likelihood, and probabilistic α-λ were implemented as evaluation metrics for comparing the proposed models. The results indicated that the deep sigma point processes performed better for RUL prediction with an RMSE of 7.38 and a negative log-likelihood of 3.10. A similar approach was conducted by [106]. The authors proposed a solution using CNN on a tensor processing unit (TPU) for RUL prediction. For experimental purposes, Python, TensorFlow, and a web Interface, named as Tekon IoT Gateway, were used. Input features, such as Engine Id, column records, time cycle, operational

Table 4
Taxonomy of machine parts manufacturing applications.

Authors / Year	Specific case	Input Features	Predicted variables	Method-Best performing Algorithm	Evaluation Metrics	Software tools
Cardoso and Ferreira 2021	Gearboxes	Machine Id, vibration, voltage, pressure, rotational speed, age	Failure prediction	ML-RF	Precision, Recall, F1 Score	Python, Matplotlib, Numpy, Pandas and Scikit-Learn
Hajgató et al. 2022	Gearboxes	Mechanical quantities of a specific cogwheel pair	Failure prediction	DL-ANN and Autoencoder	N/A	N/A
Cakir et al. 2021	Bearings on a motor shaft	x-y-z vibration, voltage, ambient and bearing temperature, rotational speed, current, age and sound intensity	Failure detection and failure classification	ML-DT	Accuracy, Precision, Recall, F1 Score	Arduino IDE, Virtuino, R and R-studio
Vitolo et al. 2022	Bearings on a motor shaft	Vibration, rotational speed, current	Anomaly detection and failure classification	DL-CNN and Autoencoder	Accuracy and Area Under Curve	TensorFlow and Larq framework
Aye & Heyns 2018	Slow speed bearings	Acoustic emission	RUL prognosis	Model based- Mean Gaussian Process Regression	Mean Absolute Percentage Error and RMSE	N/A
Aydemir & Paynabar 2020	Thrust bearing	Thermal images	RUL prognosis	DL-CNN LSTM	Median Absolute Precision Error	Tensorflow-GPU
Izagirre et al. 2020	Industrial robot joints	Torque signature analysis	Health state classification	Knowledge-based-N/A	N/A	N/A

Table 5
Taxonomy of steel and metal industry applications.

Authors / Year	Specific case	Input Features	Predicted variables	Method-Best performing Algorithm	Evaluation Metrics	Software tools
Ruiz-sarmiento et al. 2020	Steel hot rolling mill process	Steel type, weight, length and thickness at the entrance, temperature, maintenance logs	Health state prediction	ML-Bayesian filter	RMSE	Python, Scikit-learn
Gay et al. 2022	Steel hot rolling mill process	Vibrations, pressure, temperature, flow rate	RUL prediction	ML/ Knowledge based-SVM	RMSE	N/A
Chen et al. 2021	Rotating metal bush operating in a melted zinc pot	Tension, total length, scrap length, total surface, remaining bush width	A wearing behavior solution	ML/DL-Partial least squares regression	RMSE, R2	R, IBA, EMASS
Nieves Avendano et al. 2021	Cold forming manufacturing line	Acoustic emissions, maintenance logs	Anomaly detection	ML-Principal component analysis and Matrix profile	Precision, Recall, F1 score	N/A

settings, and sensor measurements, were implemented on the DL algorithm. RMSE, mean absolute percentage error, and the inference time were used as evaluation metrics. In addition, the results of the CNN-TPU model were compared with a CNN model implemented in a core processor unit. CNN-TPU performed better than the CNN-CPU model with an RMSE of 12.05 regarding the RUL prediction. Both [104] and [106] concluded that a CNN model could optimally prognose the RUL of a turbofan engine. Adding on the aforementioned research, [107] proposed a hybrid algorithm combining CNN for Rul prognosis and a genetic algorithm for parameter optimization. Using operation and fault conditions as input features, the authors prognosed the optimal timeline of maintenance schedule based on the RUL output and a safety margin. The algorithm was developed in Python programming language with RMSE, Cumulative Relative Accuracy and the Convergence of the RMSE as evaluation metrics. On the other hand, [108] proposed an LSTM DL algorithm for predicting the RUL of a turbofan engine. With the implementation of Pearson correlation, the authors selected temperature, pressure, ratio flow, fan speed, and coolant bleed as input features with RMSE as evaluation metric. It was highlighted that the degradation speed will accelerate until the failure occurs and thus maintenance strategy should be based on the degradation rate. Similar input features, namely temperature, engine id, pressure, fuel, and coolant bleed, were also used for health state classification on turbofan engines [109]. The predicted output was divided into healthy, critical condition, repair engine, and engine failure and a hybrid DNN-LSTM and Genetic Algorithm was experimented in Apache Spark, Python and Keras software. The results were promising showing up to 83% accuracy. Finally, [110] compared DL techniques, such as semi-supervised feature learning with random interval, semi-supervised feature learning with fixed interval, unsupervised feature learning with random interval, and unsupervised feature learning with fixed interval. Engine Identification number and sensor measurements constituted the input features. The proposed methodology resulted in a satisfactory RUL prediction, with semi-supervised feature learning-random interval scoring the lowest RMSE of 15.27.

Focusing specifically on aircraft PdM, [111] studied the problem of structural damage diagnosis using a DL CNN algorithm. 1D time domain signals from each crack condition were transformed into a 2D time-frequency representation (distinct images) to be used as input for the convolution network. Stochastic gradient descent and Adam optimizers were compared in two simulation scenarios. COMSOL software, Python programming language, as well as TensorFlow and Keras libraries, were used for simulation purposes. The results indicated that the CNN model with Adam optimizer performed better exhibiting higher validation accuracy of 98.4%. CNN, TensorFlow, and Keras were also tested in a remote aircraft maintenance application using mixed reality [112]. Differentiating from [111], audio parameters, such as Mel frequency cepstral coefficients, and spectrograms with 2D convolutions were used as input parameters. The authors developed a remote maintenance education application for a Boeing 737 aircraft by combining speech recognition and HoloLens smart glasses. The DL model was able to classify commands and speech, using accuracy, precision, recall, F1 score, and confusion matrix as evaluation metrics. The results were promising and highly accurate regarding command and language recognition with outputs of 99% and 99.8% accuracy, respectively. Additionally, [113] proposed a hybrid model combining autoencoders to detect rare aircraft failures and bidirectional gated recurrent unit networks to predict the next occurrence of a failure. Collecting error messages, flight deck effects and maintenance records as input features with accuracy, precision, recall, and confusion matrix as evaluation metrics. The authors achieved an 18% increase in precision, and 5% increase in recall predictions addressing simultaneously the issue of imbalance dataset during model training. Finally, a gaussian process learning algorithm and a novel adaptive sampling method for designing optimal maintenance timeline to address the gradual degradation of components was proposed [114]. The authors selected as input features historical measurements of arrivals, departures, wear, erosion, fatigue, corrosion, crack growth with RMSE, Pareto diagram, maximization of mean-cycles-to-replacement, minimization of the expected number of maintenance tasks as evaluation metrics. The results indicated that PdM outperformed other conventional maintenance approaches namely corrective or preventive in aspects of safety, reliability, and costs.

Regarding additional PdM applications in aerospace industry, [115] developed a RF algorithm for tool wear evolution classification in aerospace industry. Specifically, six wear levels were considered based on size, extension, and location. The authors selected cumulative cutting time, maximum spindle power consumption, energy consumption at bit tip entry and 1 mm after bit tip entry respectively as the most suitable input features. The algorithms were conducted in Python programming language and Tkinter interface with RMSE, Mean Absolute Error and Absolute Error as performance metrics. Random Forest outperformed similar ML algorithms namely linear regression and KNN, and Random Forest ML algorithms with RMSE of 0.218. Furthermore, a health state prediction algorithm for electromechanical actuators was proposed [116]. The authors developed a model-based approach to extract relevant health indicators using physical quantities and back-electromotive force signals and a simple feed-forward neural network for health status estimation with promising results. MATLAB and Simulink Accelerator software were used with voltages, currents, motor angular position, and speed as input features and Mean Absolut Percentage Error (MAPE), as evaluation metric. Similarly, [117]presented an integration of a physics-based Short-Time Fourier Transform (STFT) and Hilbert Spectrum model with a data-driven multi-layer perceptron model for RUL prognosis of aircraft cooling units. Time-frequency health indicators were selected as input features with accuracy, F1-score, RMSE, and Area Under Curve as evaluation metrics. The authors concluded that the cooling units experienced a normal degradation stage prior to an abnormal degradation within the last flight hours of remaining useful life. Finally, [118] proposed a statistical condition-based PdM solution for addressing the failure of high-speed baggage carts. The collected data tracked the vibration of tires over time and determined the wheel's health status. Using statistical methods, namely peak-to-peak vibration velocity and standard deviation measures, it is concluded that the carts close to end-of-life generated a vibration over 60 mm/s. Thus, the authors confirmed that a statistical condition-based PdM approach on the airway industry could be used for predicting failures. (Table 6).

4.2.2. Automotive industry

Car production lines generally utilize various machinery equipment in numerous production layouts. The majority of the recent use cases in the automotive industry described an increasing trend for PdM applications in production lines. More specifically, [119] used sensor-based data retrieved from different welding spots to group synchronous multi-dimensional maintenance time series. The authors proposed a ML algorithm, namely K-Multi-Dimensional Time series Clustering, and compared the K-MDSTSC and K-shape outputs using the sum of squares error and the adjusted rand index as key evaluation metrics. The results revealed that although both K-Shape and K-MDSTSC perform well, the latter algorithm outperforms. Similarly, [120] developed a statistical data-driven ARIMA method to predict bottlenecks of forthcoming production in the automotive industry. Time series data were examined, containing important input parameters, such as producing, downtime, and blocked machine states for specific timelines. The solution was tested using R programming language. Mean absolute percentage error, accuracy, recall, precision, and intersection over union were utilized as evaluation metrics. The classification results indicated that the ARIMA model could outperform a naive method model and partially predict upcoming bottlenecks with 86.13% accuracy, 36.34% precision, 62.53% recall, and 29.89% intersection over union. Additional research for improving the production process was presented by [121]. The authors proposed an open-source ecosystem, named as BiDrac, which combined industrial cyber–physical systems, internet of things, and AI technologies, to optimally manage production processes within Industry 4.0. Five years of historical data, namely measurements of voltage, chilled water, technological heat (steam), gas, water, demineralized water, and compressed air, were collected to predict maintenance-related variables, such as RUL, based on a predetermined failure threshold, and forecast energy demands across operating plants. K-means, Xgboost, GradientBoostingClassifier, BaggingClassifier, and DT were employed as ML models. The authors concluded that XGBClassifier provided the optimal results with F1 score on the testing data of 0.5047. Furthermore, [122] proposed a DL DNN approach for anomaly detection and failure classification vehicle parts, such as tire pressure fail or tire wear. Using a voiceprint recognition, the authors focused on the development of voice recognition applications regarding vehicle PdM. The DNN algorithm was developed on Python, PyTorch, and MATLAB software with accuracy and confusion matrix as evaluation metrics. The results were promising indicating that the solution can improve failure identification

Table 6
Taxonomy of aerospace industry applications.

Authors / Year	Specific case	Input Features	Predicted variables	Method-Best Performing Algorithm	Evaluation Metrics	Software tools
Guo et al. 2018	Turbofan engine	Serial data collected from sensors, formed into a grayscale 2d image	RUL prognosis	DL-Custom made CNN named Senvis-Net	Scoring Function and mean square error	N/A
Biggio et al. 2021	Turbofan engine	Engine id, time cycle and health state of the system	RUL prognosis	DL-Deep sigma point processes	RMSE, negative log-likelihood, α-λ the probabilistic α-λ	PyTorch and GPyTorch
Resende et al.2021	Turbofan engine	Engine id, time cycle, sensor measurements	RUL prognosis	DL-CNN on a Tensor processing unit (TPU)	RMSE and the inference time	Python, TensorFlow, Tekon IoT Gateway
Pater et al. 2022	Turbofan engine	Operating and fault conditions	RUL prognosis	ML/DL-CNN and Genetic Algorithm	RMSE, Accuracy and Convergence	Python
Wang & Zhao. 2022	Turbofan engine	Temperature, pressure, ratio flow, fan speed, coolant bleed	RUL prognosis	DL-LSTM	RMSE	N/A
Tasabat & Aydin. 2022	Turbofan engine	Engine id, temperature, pressure, fuel, and coolant bleed	Health state classification	ML/DL-DNN LSTM and Genetic Algorithm	Accuracy, confusion matrix	Apache Spark, Python, Keras
Verstraete et al. 2020	Turbofan and a rolling element	Engine id, column records, sensor measurements	RUL prognosis	DL-semi-supervised feature learning with random interval	RMSE	N/A
Ewald et al. 2021	Aircraft maintenance	Crack conditions transformed into distinct images	A PdM solution	DL-CNN	Accuracy	COMSOL, Python, Tensorflow and Keras
Siyaev & Jo. 2021	Aircraft maintenance	Audio features and spectrograms with 2D convolutions.	Remote aircraft maintenance education	DL-CNN	Accuracy, Precision, Recall, F1 score and confusion matrix	TensorFlow and Keras
Dangut et al. 2022	Aircraft maintenance	Error messages, flight deck effects, maintenance records	Failure prediction	DL-Auto encoder and convolutional recurrent unit	Accuracy, Precision, Recall and confusion matrix	N/A
Lee & Mitici. 2022	Aircraft maintenance	Arrivals, departures, wear, erosion, fatigue, corrosion, crack growth	Failure prediction	Statistical-Gaussian process	Pareto diagram, RMSE	N/A
Domínguez-Monferrer et al. 2022	CFRP automatic drilling	Cutting time, maximum spindle power, energy consumption	Health state prediction	ML-Random Forest	RMSE, MAE, Absolute Error	Python and Tkinter
Quattrocchi et al. 2022	Electromechanical actuator	Voltages, currents, motor angular position and speed	Health state prediction	DL/Other-Feed forward neural network and physics-based approach	MAPE	MATLAB, Simulink Accelerator
Rosero et al. 2022	Aircraft cooling units	Time-frequency Health Indicators	RUL prognosis	DL/Other-Multi-layer perceptron, Hilbert Spectrum	Accuracy, F1-score, RMSE, Area Under Curve	N/A
Koenig et al. 2019	High-speed baggage carts	Vibration measurements	Failure prediction	Statistical-Peak-to-peak Vibration velocity and Standard deviation measures	N/A	N/A

up to 16.57% and reduce the model training time by up to 21.5% compared with other algorithms.

Focusing on specific machinery, [123] proposed a DL solution that examines historical data of the production process to predict the condition (i.e., good, fair, fault) of a cylinder part of a trolley. A deep neural network with Relu activation function and softmax classifier was implemented for the state prediction. For experimental purposes, Python programming language, Tensorflow and Keras libraries, Apache Kafka data stream, and InfluxDB were used, while accuracy was selected as an evaluation metric. In addition, the authors compared the results of a principal component analysis method with those of a hidden Markov algorithm concluding that the deep neural network could provide more accurate solutions for predicting the equipment status with 85% accuracy. [124] employed a smart system to predict the failure of a wheel bearing on the carrier during the deterioration phase and before its complete seizure. An online condition monitoring system was also developed to provide the maintenance personnel with early failure warnings. The Yandex ClickHouse database stored the collected data, while a data evaluation procedure utilized the Multilayer Perceptron network that identified the bearing failure as a prediction parameter. The results provided an effective PdM solution with 94.03% accuracy, 81.39% precision, 80.45% recall, and 80.92% F1 score. Finally, [37] studied a case of PdM on a gearbox and mechanism crankcase. A business process management and notation (BPMN) model was introduced, focusing on improving preventive maintenance techniques and providing better communication and transparency in the decision-making process. The authors concluded that the combination of condition-based and PdM approaches within industry 4.0 could assist in preventing productivity losses, while maximizing the machinery usage.

Although the majority of PdM research in the automotive industry concerns production process and machinery, existing literature further offers PdM solutions in specialized cases, such as construction vehicles or delivery services. More specifically, [125] developed a ML approach for fault prediction in construction vehicles. The authors attempted to predict the upcoming failure of construction vehicles using data mining and ML algorithms in a condition monitoring application. Retrieved from integrated microchips on the machine, sensor signal strength, type of fault, service date, as well as machine identification number and model, were implemented as input features for the prediction algorithms. C5.0, gradient boosting, and logistic regression were experimented as the ML algorithms. F1 score, recall, and precision were considered as evaluation metrics. The results indicated that the gradient boosting algorithm generated the optimal results overall, with an F1 score of 37.1% in the train set. Additionally, a PdM framework, named as REDTag, was developed for fault identification in a delivery service application [126]. Using ML algorithms and REDTag, the authors worked on classifying and predicting the package condition (i.e., broken or not). Apache Kafka, Spark ML library, and Cassandra databases were used for experimental purposes. Attributes, such as tag identification number, timestamp, event type, sum of the absolute values, and absolute energy collected from the REDTag, were used as input features for the classification algorithms. Gradient boosting, SVMs, and logistic regression algorithms were compared, using accuracy, precision, recall, and F1 score as key evaluation metrics. The results indicated that the ML algorithm could predict the condition of the delivered package, with gradient boosting demonstrating the best results exhibiting 74.2% accuracy.(Table 7).

4.2.3. Railway industry

The identified solutions focus on failure prediction, failure classification, and health state classification of train wheels and doors, railway switches, and tools on railway surfaces. Following a thorough analysis of big data technologies and software applied in PdM, [127] proposed a ML algorithm emphasizing the prediction of failure of train wheels and door malfunctions. Furthermore, in terms of failure identification, important input parameters, such as temperature, light, vibration, geolocation, audio, video, surveillance data, and maintenance datetimes, were collected through sensors. Regression models, such as SVM algorithms, and data mining techniques were considered as essential for feature selection and accurate failure prognosis. To propose software solutions, the authors discussed Kafka, RabbitMQ, Kinesis, and Azure Event Hub as queue management technologies, Storm, Spark and Flink as analysis

Table 7
Taxonomy of automotive industry applications.

Authors / Year	Specific case	Input Features	Predicted variables	Method-Best Performing Algorithm	Evaluation Metrics	Software tools
Giordano & Mellia. 2021	Welding spots	Sensor-based data taken from different welding spots	Optimal maintenance timeline identification	ML-K Multi Dimensional Time series Clustering	Sum of Squares Error and the Adjusted Rand Index	N/A
Subramaniyan et al. 2018	Welding spots	Time series of producing, downtime and blocked states of machines	Prediction of bottlenecks on future production	DL-ARIMA	Accuracy, Precision, Recall and Intersection over Union	N/A
Sanz et al. 2021	Operating plants	Voltage, chilled water, technologicalheat (steam)	Energy demand forecasts and RUL prognosis	ML-XgBoost	GridSearchCV and F1 score	BiDrac
Gong et al. 2022	Driving fault identification system	Acoustic emissions	Anomaly detection and failure classification	DL-DNN	Accuracy and confusion matrix	Python, PyTorch, MATLAB
Chen et al. 2020	Cylinder part of a trolley	time series historical data of production process	RUL prognosis	DL-Deep neural network	Accuracy	Python, TensorFlow, Keras, Apache Kafka, InfluxDB
Tanuska et al. 2021	Wheel bearing on the carrier	Temperature and sound	Failure prediction	ML/Stochastic-Multilayer Perceptron network	Accuracy, Precision, Recall, F1 score, Kurtosis, THIKAT	Yandex ClickHouse
Fernandes et al. 2021	Gearbox and mechanism crankcase	Pressure and temperature	RUL prognosis	ML-N/A	N/A	business process management and notation (BPMN) model
Taşabat et al. 2020	Construction vehicles	Sensor signal strength, type of fault, service date, machine id and model	Failure prediction	ML-Gradient boosting	Precision, Recall, F1 score	N/A
Proto et al. 2020	Delivery service application	Tag ID, timestamp, event type, absolute energy	Failure diagnosis	ML-Gradient Boosting	Accuracy, Precision, Recall, F1 score	Apache Kafka, Spark ML Lib and Cassandra database

platforms, as well as HBase as database and Spark SQL, Table API, and StreamCQL as SQL engines. Similarly, [128] presented a ML solution attempting to predict and classify upcoming failure of railway switches. The authors tackled the problem of the imbalanced dataset and examined various ML algorithms, such as DT, RF, and gradient boosting, while they utilized accuracy, precision, recall, F-score, Kappa score, and confusion matrix as evaluation metrics. For experimental purposes, Python programming language and Scikit-learn library were employed. Error Identification number, switch component, switch functional location, track type, technical details, and age constituted the main input features of the classification algorithms. The results highlighted that RF generated the optimal results on held-out tests with 70% accuracy. On the other hand, a physics based approach using Continuous Wavelet Transform and the Morlet function for damage evolution prediction on subway track and substructures was proposed [129]. Vibration x-y-z measurements and deformations measured at different locations on the track were considered as appropriate input features for the health state classification of the subway track. Similarly, a stochastic approach was presented for condition classification of rail surface and the corresponding pantograph in different seasons based on thermal images and fuzzy logic [130]. The method was tested in a MATLAB environment and the thermal images were retrieved using a NEC F30W thermal camera. The results of the proposed complex fuzzy logic algorithm were compared with those of a classical fuzzy logic approach for condition classification. The evaluation metrics utilized (i.e., accuracy, precision, recall, F1 score specificity) indicated that the complex fuzzy logic algorithm with thermal images provided the optimal results with 87% accuracy.(Table 8).

4.3. Energy industry

4.3.1. Wind turbines

Regarding wind turbines applications, [131] proposed a DL solution for failure prediction of wind turbines. Following a data mining approach, the authors predicted and classified upcoming failures at specific time intervals (i.e., 24, 48, and 72 h) on various wind turbines. A deep neural network and ML models (i.e., KNN, SVM, RF) were compared, using precision as an evaluation metric. 31 different features (e.g., speed, voltage, power, temperature measurements) were collected through sensors attached on wind turbine components to act as inputs to the prediction algorithm. The results indicated that the deep neural network performed better, exhibiting the highest precision results of approximately 90%. Similarly, by using a hybrid solution for failure prediction and false alarm identification on wind turbines, [132] improved the results of [131] by demonstrating a precision rate of 99.7%. The authors combined a statistical maximum mean discrepancy algorithm with a CNN model and classified the health status of a wind turbine by comparing the distributions of real-time observations with data collected after major maintenance. Temperature measurements, rated speed, wind speed, output power, grid voltage, and pitch control were collected and used as input features in the prediction algorithm. KL divergence, Bhattacharyya distance, PC2-DEV algorithm, confusion matrix, recall, and precision were chosen for evaluating the hybrid MMD-CNN approach. In the same context, [133] proposed a ML SVM algorithm for failure diagnosis on bearing failure for 18 different wind turbines. Using confusion matrix and false alarms indications as evaluation metrics and ambient temperature, wind speed and main saft temperature as input features the authors correctly predicted upcoming failures. In addition, they highlighted the high correlation between mean main shaft temperature measurement and bearing failure. Similarly, [134] proposed a hybrid solution and a PdM framework for failure classification. The authors detected and collected, using a Microsoft Hololens2 camera, important features, namely the rotational speed and vibrations. Additionally, they implemented a statistical fast Fourier transform combined with a deep neural network model (i.e., NET2_HF) to classify the machine failure of wind turbines into six different states. Precision, recall, efficiency, RMSE, and confusion matrix were used as evaluation metrics. The results indicated that the hybrid solution was able to accurately classify wind turbine malfunction with efficiency up to 98.6%.

At the same time, [135] presented a statistical data-driven approach focusing on RUL prediction. The authors dealt with the problem of variable operational conditions and continuously changing rotational speeds, which impacted the degradation rates and observation amplitudes. Three different thresholds, namely warning, alarm, and failure, were considered. Linear, power, exponential, and logarithmic models were implemented using Bayesian information criterion (BIC) as an evaluation metric to test the accuracy of each model. The automatic approach selected the best fitting model for RUL prognosis, based on the root mean square of monitored vibration signals and rotating speeds. The experimented results showcased that the proposed methodology scored 100% and 85.37% in two different use cases, outperforming all other models (i.e., linear, power, exponential, logarithmic) applied individually. Finally, [127] conducted a study on the optimal maintenance timeline identification. Collected data from turbine operational behavior, such as records of stress and acceleration, temperature, wind direction, power generated, generator speed, and status code logs, were analyzed and imported to the prediction algorithms. Support vector regression and RNN were implemented to predict any upcoming failures and the future condition state of the wind turbines. The authors highlighted that the life cycle of wind systems could increase by implementing PdM strategies. In addition, the authors proposed RabbitMQ as a queue management technology, as well as Storm, Spark or Flink as analysis platforms. Moreover, they suggested that the Cassandra database could be used, while Spark SQL, Table API or StreamCQL could be employed as SQL engines. Finally, they proposed the utilization of Python programming language and the TensorFlow library for the algorithm implementation. Differentiating from prementioned research, [136] focused on predicted different states of fan-blade damage. Using x-y-z vibration measurements taken on the platform of the wind

Table 8
Taxonomy of railway industry applications.

Authors / Year	Specific case	Input Features	Predicted variables	Method-Best Performing Algorithm	Evaluation Metrics	Software tools
Sahal et al. 2020	Train wheels and door malfunctions	Vibration, temperature, geolocation, audio, surveillance data and maintenance datetimes	Failure prediction	ML-SVM	N/A	Kafka, Spark, Spark SQL
Allah Bukhsh et al. 2019	Railway switches	Detected problem, switch component, track type and age	Failure prediction and failure classification	ML-RF	Accuracy, Precision, Recall, F1 score	Python and Scikit-learn
Jauregui-Correa et al. 2022	Subway track	x-y-z vibration and track deformations	Health state classification	Other-Wavelet Transform, Morlet function	N/A	N/A
Karakose & Yaman. 2020	Railway surface and pantograph	Thermal images	Health state classification	Stochastic-Fuzzy logic model	Accuracy, Precision, Recall, F1 score, specificity	MATLAB

turbine's base and their statistical outputs (i.e., mean, peak/valey and variances), the authors observed and predicted the fan-blades degradation patterns effectively. (Table 9).

4.3.2. Oil and gas industry

Regarding the oil and gas industry, [137] developed a novel PdM assessment matrix to detect, diagnose, and prognose malfunctions and the RUL of a centrifugal compressor. The authors used regression ML algorithms and empirical knowledge. The proposed study focused on transforming qualitative descriptions into quantitative values to enable the identification of the most suitable solution, recognize the levels of the existing monitoring solution, and determine how an existing monitoring solution could achieve improved performance. The authors elaborated on the PdM assessment matrix and concluded that the rotor and the bearing with failure modes of looseness and vibration, respectively, constituted the most critical components of the centrifugal compressor. Similarly, [138] proposed a semi-supervised approach for health state classification and failure prediction on gas turbines. A hybrid model combining a Gaussian Mixture Model for state classification and Autoencoders for failure prediction was developed. Temperature, pressure, air humidity, rotational speed, and active load were selected as input features, with accuracy Impostor Pass Rate, False Alarm Rate, confusion matrix as evaluation metrics. The results were promising with 98% accuracy on the test dataset. An additional approach regarding PdM in oil and gas industry specified in revamping topping plant was presented [139]. The authors collected sensor measurements namely timestamp, error id, fault type (blockage, corrosion, damage), equipment (compressors, pumps, and furnaces) and developed a hybrid model combining natural language processing for failure classification and ARIMA for failure prediction with average error as evaluation metric. The authors highlighted the importance of special hardware systems equipped with ad hoc software guiding maintenance workers to appropriately fill maintenance reports for historical purposes. Furthermore, [140] presented a LSTM prediction model for defect diagnostics in industrial transformers. Important features namely simulation id, fault type, type of cooling, frequency, and weight were considered, with performance accuracy ratio and confusion matrix as evaluation metrics. The LSTM model was developed in MATLAB, R2021a and MathWorks software environments, outperforming similar approaches such as CNN and SVM with performance accuracy ratio up to 99.83%. Finally, [3] presented an intelligent PdM management architecture that controlled the critical compression system and determined whether end users received gas or not. Vibration, bearing temperature, gas temperature, and pressure constituted the crucial input indicators of the equipment's health state. Following an extending description of an intelligent maintenance management architecture, the authors concluded that the enhanced maintenance management architecture should acquire, store, analyze, and visualize the data, information, and knowledge related to all maintenance management programs. (Table 10).

4.4. Other industries

4.4.1. Chemical, pharmaceutical, and plastic industries

Within the chemical sector, [141] proposed an anomaly prediction method for a high-pressure pump in a complex chemical plant. The authors dealt with the problems of failure prediction, feature extraction, feature selection, and imbalanced learning. Logistic regression with elastic net regulation was used for the RUL estimation. In addition, a feature-based approach, using time series of important parameters (i.e., ammonia inflow, pressures, current, temperatures, loop-back rate, rotating speed) was selected. Cohen's kappa statistic, area under the receiving operating characteristic and the precision recall curve, precision recall, and F1 score were utilized as evaluation metrics. The methodology was implemented using the R programming language. The results highlighted that the proposed algorithm could predict an abrupt charge failure with 25% accuracy and a gradual degradation failure with 100% accuracy. In the pharmaceutical industry, [142] developed an anomaly detection solution for industrial machinery in water purification systems. A SVM learning algorithm and a model-based approach were compared in terms of fault detection diagnosis. Pressure and conductivity were considered as the most important parameters both for the classification algorithm and the model-based solution. According to the authors, the two major concerns referred to the decrease in the output volume of the machine and the increase in the water conductivity at the system outlet. The results showed that the ML approach was effective, but unlike the research of [141], the proposed model-based approach performed more effectively in detecting unknown and unseen anomalies. Additionally, [143] proposed a RF algorithm developed with Python and C+ +, for predicting the damage components of a tube filling machine in a toothpaste factory. Vibrations x-y-z and temperatures were used as input features, while accuracy, mean square error, RMS,E and overall equipment effectiveness were utilized as evaluation metrics. The results highlighted an increase of overall equipment effectiveness value by 13.10% and decrease of unplanned machine failure by 62.38%.

Concerning the plastic industry, [144] provided a stochastic approach for pattern recognition and anomaly detection. The study was conducted on an auxiliary polymer manufacturing process using two stochastic approaches. The first algorithm included sequential use of common segmentation and clustering algorithms, while the second one a Toeplitz inverse-covariance clustering, which is a collaborative

Table 9
Taxonomy of wind turbines applications.

Authors / Year	Specific case	Input Features	Predicted variables	Method-Best Performing Algorithm	Evaluation Metrics	Software tools
Chen et al. 2021	Wind turbines maintenance	Temperature, speed, voltage and power	Failure prediction	ML/DL-Deep neural network	Precision	N/A
Peng et al. 2022	Wind turbines maintenance	Temperature, rotational speed, wind speed, output power, grid voltage and pitch control	Failure prediction and false alarm identification	DL/Statistical-MMD-CNN	Precision, recall, confusion matrix, Bhattacharyya distance	N/A
Tutivén et al. 2022	Wind turbines maintenance	Ambient temperature, wind speed, main saft temperature	Failure diagnosis	ML-SVM	Confusion Matrix	N/A
Lalik & Atorek 2021	Wind turbines maintenance	Vibration, rotational speed, images	Failure classification	DL/Statistical-Fast Fourier transform and a deep neural network	Precision, recall, efficiency, RMSE and a confusion matrix	N/A
Li et al. 2022	Wind turbines maintenance	Root mean square of vibration signals and rotating speeds	RUL prognosis	Statistical-Linear, power, exponential and logarithmic models	Bayesian information criterion	N/A
Sahal et al. 2020	Wind turbines maintenance	Stress and acceleration, temperature, wind direction, power generated	Optimal maintenance timeline identification	ML/DL-Support Vector regression and RNN	N/A	RabbitMQ, Storm, Spark, TensorFlow

Table 10
Taxonomy of oil and gas industry applications.

Authors / Year	Specific case	Input Features	Predicted variables	Method-Best Performing Algorithm	Evaluation Metrics	Software tools
Nordal & El-Thalji. 2021	Oil and gas maintenance management	Vibration, pressure, bearing temperature and gas temperature	PdM management architecture	N/A-N/A	N/A	Smart Connect
Barrera et al. 2022	Gas turbines	Temperature, Pressure, Air humidity, rotational speed, active load	Anomaly detection and health state classification	DL/Statistical-Gaussian Mixture Model and Autoencoder	Accuracy, confusion matrix, Impostor Pass Rate, False Alarm Rate	N/A
Arena et al. 2022	Revamping topping plant	Timestamp, error id, fault type, equipment	Failure prediction and failure classification	DL/Statistical-ARIMA and Natural language processing	Average Error	N/A
Sarma et al. 2022	Transformers	Simulation id, fault type, type of cooling, frequency, weight	Failure diagnosis	DL-LSTM	Performance accuracy ratio, confusion matrix	MATLAB, R2021a, MathWorks
Nordal & El-Thalji. 2021	Centrifugal compressor	Vibration and temperature	Failure classification, failure prediction and RUL prognosis	ML/Knowledge based-PdM assessment matrix	Quantitive values of Pdm	N/A

method with a built-in time dependency structure. Historical datasets containing measurements of temperature sensors were implemented as inputs to the pattern recognition algorithm. Hausdorff measure, Rand index, and F1 score were used as evaluation metrics. The authors compared four different cost functions, namely least absolute deviation, least squared deviation, linear regression, and Gaussian time series, with least squared deviation scoring the optimal overall results.

4.4.2. Electronic industry

Finally, focusing on the electronic industry, our review unveiled two ML applications. [145] developed a supervisory control and data acquisition (SCADA) system for a condition-based maintenance approach to analyze different data sources and improve the detection of failures with undermined origin. In addition, an anomaly detection algorithm was applied to numerous chip removal machine processes to predict the occurrence of unregistered failures, identify error patterns, and further estimate the remaining lifetime of the machinery. The installation of an analogue sensor in the cooling system of a milling machine acted as a real-world application. Implementing the Gaussian probability distribution function and the key metric epsilon, the authors accomplished to detect malfunctioning machinery and reduce machine breakdown times. Similarly, [146] presented a hybrid approach using ANN and Markov method to predict failure on transmission lines. Using a Simulink software, the authors implemented the hybrid algorithm with current, voltage, frequency, and power as input features and MSE as evaluation metric. The results showed an accuracy of 99% on predicting target values at various type of faults. In the same context, [147] attempted to identify semiconductor failures using ML algorithms, such as multilayer perceptron, DT, naive Bayesian, C4.5, and SVM. Using Python programming language and feature reduction techniques (e.g., principal component analysis), the authors selected 17 (out of 591) different sensor attributes of the manufacturing process. To evaluate the detection algorithms, precision, F1 score, accuracy, true positive rate, and false positive rate were used. The results were promising, indicating that the multilayer perceptron performed better compared to other ML algorithms with an accuracy of 91.95%. (Table 11).

5. Discussion and insights

5.1. Analysis of the results

In this section, we discuss and compare the findings of the multi-sector review on PdM to showcase potential trends and provide meaningful insights (as a response to RQ#3). According to the extant literature review, three major sectors, namely manufacturing of machinery and equipment (40% of publications), transport-related (36%), and energy (15%), along with a few other applications in the chemical (including pharmaceutical and plastic) and electronic industries (9%),

Table 11
Taxonomy of chemical, pharmaceutical, plastic, and electronic industry applications.

Authors / Year	Specific case	Input Features	Predicted variables	Method-Best Performing Algorithm	Evaluation Metrics	Software tools
Langone et al. 2020	High-pressure pump in chemical plant	Pressure, temperature, rotational speed current, ammonia inflow	Anomaly detection	ML-Logistic regression	Cohen's Kappa statistic, Precision, Recall and F1 score	R
Garmaroodi et al.2021	Water purification systems in pharmaceuticals	Pressure and conductivity	Anomaly detection	Model based-N/A	N/A	N/A
Natanael & Suntano. 2022	Tube filling machine	x-y-z vibration, temperature	Failure prediction	ML-Random Forest	MSE, RMSE, Performance rate, Availability rate	Python, C+ +
Kapp et al. 2020	Auxiliary polymer manufacturing process	Temperature	Anomaly detection and pattern recognition	Stochastic-Common segmentation, Toeplitz Inverse-Covariance Clustering	Harsdorf measure, Rand index and F1 score	N/A
Maseda et al. 2021	Chip Removal Process	Production process data affected by intermittent faults and malfunctions	Failure prediction, RUL prognosis and error patterns identification	ML-Gaussian probability distribution function	key metric epsilon	N/A
Mawle et al. 2022	Transmission lines	Current, voltage, frequency, power	Failure diagnosis	DL/Statistical-ANN and Markov method	MSE and correlation	Simulink
Mourabit et al. 2020	Semiconductor manufacturing process	17 different sensor attributes of manufacturing process	Failure diagnosis	ML-Multilayer perceptron network	Accuracy, Precision, F1 score, true positive rate, false positive rate	Python

were identified. In more detail, our analysis classified the use cases of machinery and equipment related into CNC machines, general machinery, machine parts' manufacturing, and steel and metal applications, those of the transport-related sector into aerospace, automotive, and railway industries, and finally those included in the energy sector into wind turbines and oil and gas applications. The results of the systematic multi-sector mapping indicated that the most prominent areas of research are general machinery and aerospace industry followed by automotive industry, CNC machines and wind turbines applications (Fig. 4).

With respect to the methodological approaches, a trend in PdM applications implementing data-driven methods, with higher interest in machine (33%) or deep (20%) learning approaches is evident (Fig. 5). At the same time, we have identified a significant amount of hybrid (33%) (i.e., combining data-driven, physics- and/or knowledge-based methodologies) statistical (7%) and stochastic (4%) methods that provided high-accuracy solutions.

The results of our analysis based on the literature review matched empirical results and technical research reports [19,20] discussing PdM areas of implementation in modern industry. Comparatively both our review and market reports depict a significant growth for PdM applications in manufacturing of machinery and equipment, transportation, and energy sectors. Moreover, the implementation of condition monitoring and sensor technology collecting critical features, such as vibration and electrical measurements, and data processing combined with predictive algorithms, is apparent. Finally, similar results were noticed regarding the expected outputs, namely health state classification, anomaly detection, and RUL prognosis, confirming the prioritization and benefits of PdM in machinery safety and resilience, product manufacturing improvement, along with product quality and financial effectiveness.

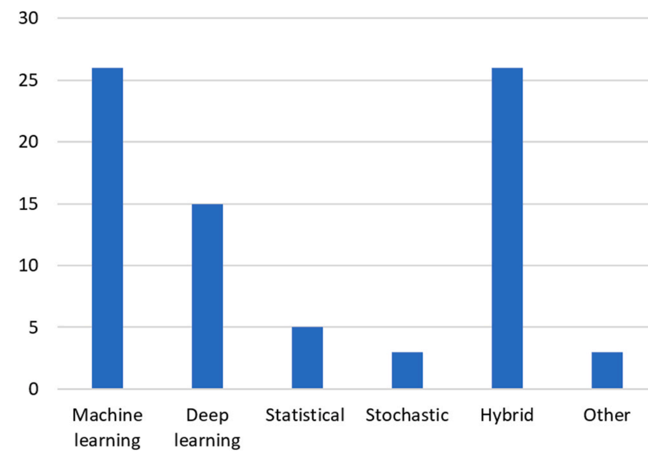

Fig. 5. Distribution of PdM applications by method.

5.2. Technology readiness by sector

An interesting topic of discussion is the technology readiness of each sector to implement PdM methodologies, clarifying the state-of-the-art of this multi-sector mapping. It is worth stating that the domain of the PdM implementation is sector and industry depended. As extracted from our comprehensive analysis, we consider that the "manufacturing of machinery and equipment", "transportation", and "energy" depict the most "technological-ready'' sectors for implementing PdM solutions. Several examples were reviewed from previous use cases where PdM was applied in real-world industrial environments with successful results. The predictive outcomes include health state classification and anomaly detection (CBM), as well as RUL prognostics (Prognostics and Health Management). Moreover, specific industries, focus on state-of-the-art PdM solutions, while others are limited to widely used basic condition-monitoring techniques. More specifically, **steel and metal and railway** industries refer to CBM approaches, highlighting a literature gap and opportunity for future research. Furthermore, the majority of the use cases in **general machinery, generic parts, and oil and gas industries**, represent a significant number of CBM, as well as RUL prognostics, depicting a trend for technology advancement and PdM development. Last but not least, the **CNC**, **aerospace, automotive and wind turbines** industries seem to have the highest technology readiness maturity, as they focus on state-of-the-art PdM methodologies such as the RUL prognosis. The advanced technological readiness of the aforementioned industries, indicate a competitive environment where the majority of research is focused, providing state-of-the art solutions for PdM implementation.

5.3. Decision support framework

Our analytic taxonomy showcased the problem specific perspective of every methodology in every industrial sector. We have noticed a variety of predicted values, such as RUL prognosis, anomaly detection, health state prediction, and failure classification. Additionally, depending on the methodology, accuracy, precision, recall, F1 score, confusion matrix, RMSE, and R2 are primarily used as evaluation metrics. Regarding the input variables, in the manufacturing of machinery and equipment sector, an extensive use of vibration, rotational speed, and temperature for the detection algorithms is common [50]. However, in the steel and metal industry, steel type, length, surface, and temperature were selected as critical parameters. Focusing on the transportation sector, a variety of applied features were utilized in each respective industry. In the case of aviation industry, RUL prognosis is

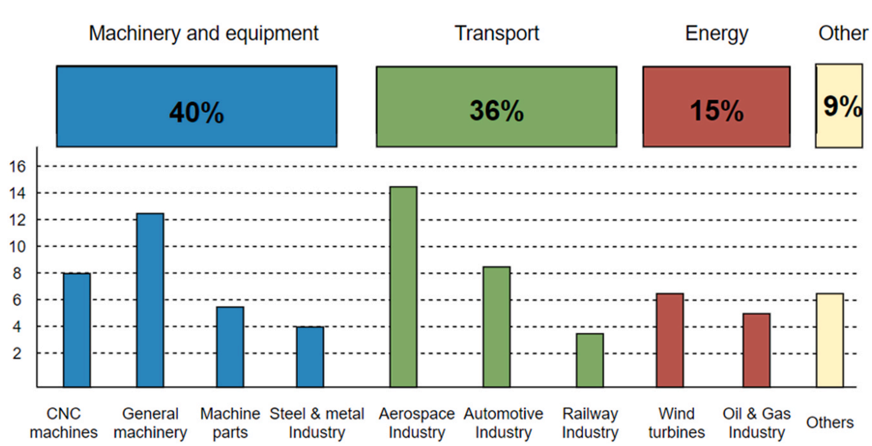

Fig. 4. Distribution of PdM applications by industry.

mainly considered using engine id, time cycle, crack conditions, and sensor measurements as input features. Additionally, for the automotive industry both CBM and RUL approaches were noticed implementing historical data of production process, malfunction type and maintenance logs. Similarly, malfunction types, maintenance logs, vibration, and temperature were used in the railway industry. Furthermore, in the case of the energy industry, our research identified PdM solutions commonly applied on wind turbines and oil and gas applications. As also highlighted in the review of [45], temperature, vibration, and rotational speed measurements are mainly utilized as input variables for failure prediction classification and RUL prognosis. At the same time, several use cases of PdM in other industries, namely chemical, pharmaceutical, plastic, and electronic, were identified. As also mentioned by [67], PdM solutions showcase an upcoming trend in the chemical and process industry. The predicted outcomes focus on anomaly detection, failure prediction, and RUL prognosis, using temperature, pressure, and vibration as input features.

Based on the outputs of the systematic review, we have built a decision support map proposing the optimal PdM maintenance solutions for each industrial sector. As mentioned, the majority of the use cases examine a variety of predicted variables, such as RUL prognosis, anomaly detection, health state prediction, failure classification with accuracy, precision, recall, F1 score, confusion matrix OR RMSE, R2 as evaluation metrics, but on the other hand, the summarization of input features methodology and applied algorithms could be specified. Additionally, although a significant amount of use cases avoids mentioning the respective applied software our efforts focused on organizing and suggesting adequate software tools.

Our goal is to suggest state-of-the art software tools for each respective sector that utilize leading programming languages and AI competitive ML approaches. As stated in [61,74], and further highlighted in our analysis, ML and DL models are frequently implemented in the manufacturing of machinery and equipment sector, while we have also identified a set of hybrid approaches thar confirm the research of [63]. Regarding PdM in the aviation industry, most approaches employ DL algorithms. Thus, due to the complexity of the aviation industry processes and based on previous research, our analysis indicated that DL models for PdM could provide more efficient and accurate results [29]. On the contrary, within the automotive and railway industry, we identified a variety of input features and predicted variables, namely failure prediction, RUL prognosis, and optimal maintenance timeline identification, where the utilization of ML algorithms constitutes a common ground in the majority of the related cases [127,128]. Finally, in the energy sector, we identified a significant number of hybrid approaches combining DL and statistical models.

In a nutshell, following the trends of competitive ML approaches, Python programming language (commonly applied with Jupyter Notebooks) is commonly used among researchers and practitioners along with the NumPy, Pandas, SciPy, Scikit-learn libraries for data analysis and AI implementations, Optuna library for hyperparameter optimization and Matplotlib or Seaborn libraries for data visualization. Moreover, ensemble models, such as Gradient Boosting Decision Trees (e.g., LightGBM, CatBoost, XGBoost) are widely used in ML approaches for predictive applications [81,90,121,125,126]. Gradient Boosting algorithms are implemented upon decision trees. Boosting methodologies differentiate from bagging methodologies, such as RF, which extract the decision outputs based on the majority of the decision outcomes amongst the decision trees. In contrast, boosting methodologies sequentially build weaker models that minimize the errors from previous models by assigning higher weights to the misclassified examples [148]. An advantage of Gradient Boosting methodologies is their robustness, reducing the need for extensive fine-tuning regarding the model parameters and decreasing the possibility of overfitting. As a result, Gradient Boosting is a widely used ML algorithm for failure prediction in predictive maintenance applications. Furthermore, focusing on DL, PyTorch is undoubtedly considered the main modelling package over TensorFlow, with over 95% popularity in 2022. Additionally, as highlighted in several use cases of the proposed systematic multi-sector mapping [80,87,96,98,106,107,111,112,132,149], CNN yielded promising results when applied for predictive solutions. In the reviewed use cases, CNN was applied to images or sequential data collected from multiple sensors and transformed into 2D vectors. CNN combines convolutional layers, activation functions, pooling layers, and a fully connected layer in order to perform multiclass predictions, such as health state classification of the machinery, based on given input features. By applying this technique, CNN yielded promising results when handling numerous input features for predictive solutions [87].

Finally, an increasing trend in RNN approaches for sequential data inputs is evident. In the systematic literature reviews of [29,48,65], the authors highlight the effectiveness and accurate performance of RNN models in the machinery and equipment sector and aerospace industry, respectively. Additionally, in the use case of [127], a support vector regression approach combined with an RNN model yielded promising results predicting upcoming failures and future condition states of wind turbines. An advantage of RNN models due to their architecture is the capability of handling time-series data as input features by applying the predictive RNN model in each time step. In general, RNNs operate over sequences of vectors with the possibility of processing inputs of any length, each computation considers historical information through hidden states, and weights are shared across time [150]. Furthermore, Deep Transformer Models denote a suitable solution in complex industrial systems using multivariate time-series data for event forecasting [151]. A predictive maintenance approach combining Transformers with three linear networks was presented to predict the health condition of machinery, upcoming malfunction, and upcoming malfunction severity [152]. According to the authors, this approach outperformed commonly used statistical, ML, and DL models. RNNs and Transformers can be considered an interesting topic for future research in PdM applications especially in case of handling sensor measurements for time-series forecasting.

Our concise decision support map (Fig. 6) aims to guide researchers and technicians in the construction of PdM applications for each respective industry, by suggesting common input features, methods/ algorithms, and software tools in the commonly cited sectors of machinery and equipment, transport, and energy. It should be mentioned that chemical, plastic, pharmaceutical, and electronic industries were not included in the map due to a lack of a substantial number of use cases that could offer reliable generalized insights.

5.4. Predictive maintenance handling unstructured data

Although the multi-sector analysis is based-on data-driven applications for PdM using structured data from multiple sensors, unstructured data were also used for maintenance solutions. Unstructured records consist of maintenance text reports and audio, or images documented on management systems [153]. Thus, a significant amount of historical data in manufacturing environments is stored in written text or inherited by natural conversation through technicians. Both text and conversations can effectively express system requirements, maintenance decisions, troubleshooting, root cause analysis, and downtime prediction, while they are capable of describing and transferring knowledge [154]. Natural Language Processing (NLP) is a promising research field, characterizing the methodology of transforming natural language into vital information in order to process existing knowledge and output valuable results, assisting human-machine interaction [155]. However, [156] raises the issue of developing domain knowledge from domain engineers to data scientists for condition-based maintenance solutions. Knowledge of the system design, operational requirements, and maintenance logs denote crucial unstructured information provided by domain technicians to predict upcoming equipment failure. To assist domain knowledge acquisition, the authors designed an analytics process collecting technicians' feedback at each production step and supporting

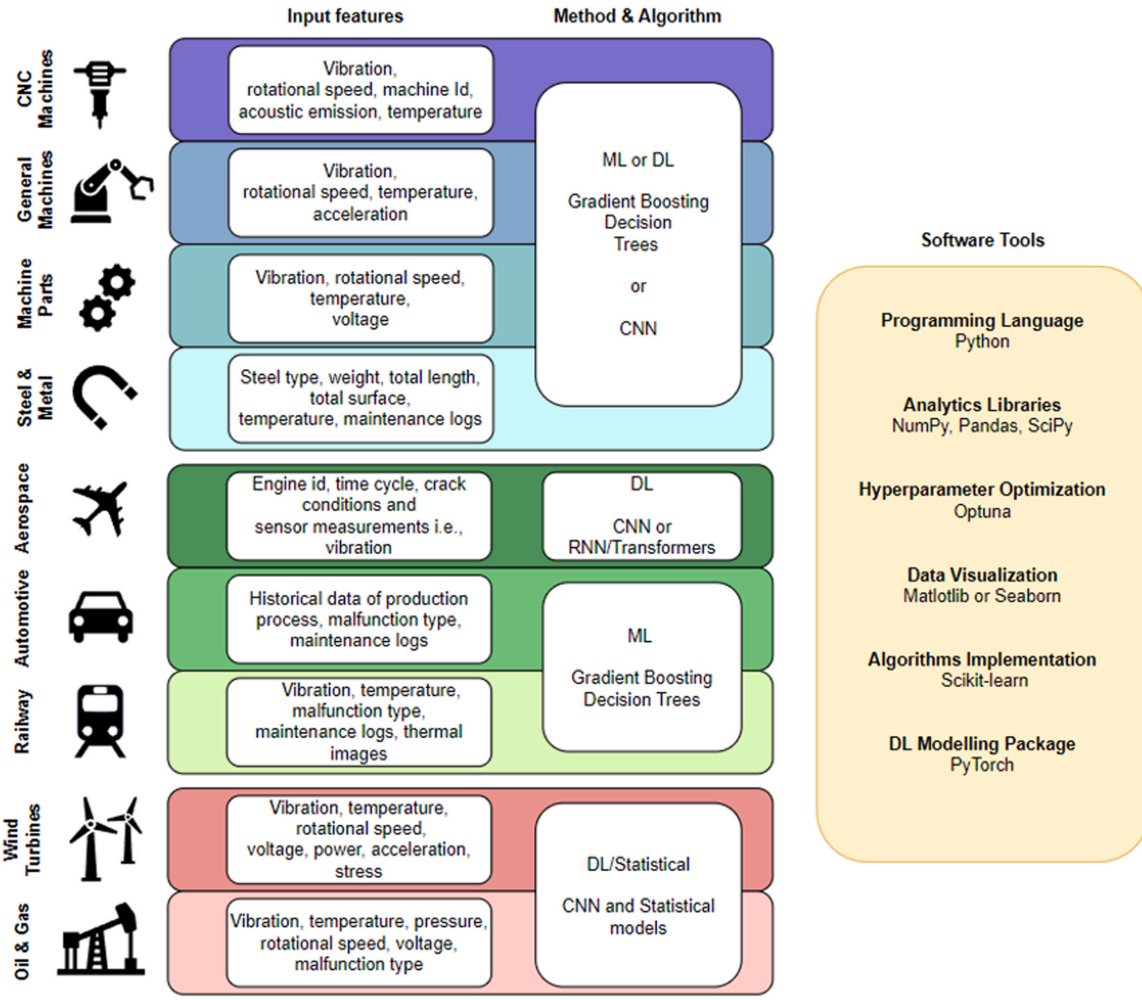

Fig. 6. Decision support map of PdM applications per industry.

condition-based maintenance of the target systems. Moreover, an engineering tool was developed to support data-scientists with the design and evaluation phases of the analytics process. In the same context, [157] provided a transferable and scalable AI maintenance solution utilizing structured and unstructured data, specifically digital shift book entries and text mining of CNC machines on the automotive and semiconductor industries. The proposed methodology generated: (i) appropriate word recommendations to technicians for issue description, (ii) accurate downtime predictions using a deep neural network combined with a TFIDF vectorization model, and (iii) selection of most suitable on duty maintenance technician based on word similarity calculations. This research resulted in significant improvement of machine uptime, mean failure detection time, and overall equipment efficiency in industrial environments, while it investigated the significance of AI in improving KPIs in industrial maintenance. Similarly, in their research, [158] highlighted the importance of investigating influential equipment actions and environmental factors from maintenance documents and reports in order to identify key performance indicators, critical tasks, and assets that improve maintenance performance and classify system behavior. However, the application of NLP in modern manufacturing is merely focused on specific tasks rather than end-to-end predictions based on textual knowledge. To address this challenge, [159] developed an NLP pipeline solution for end-to-end prediction and classification based on unstructured historical data. This approach provided a transferable and applicable methodology for downtime prediction and health state classification in manufacturing sectors. Nevertheless, they highlighted the necessity of large data volumes and standardized comment formats for enabling large-scale NLP in manufacturing. Similar limitations were also mentioned in [160] by emphasizing maintenance reports' accuracy in terms of orthography and keyword standardization. In the presented use case, data-driven maintenance methods were applied using information from repair and maintenance reports in order to detect and classify abnormal behavior of directly driven compressors. By using NLP and ontological methodologies, authors effectively classified machine behavior (i.e., valve leaking, lower point draining) increasing maintenance efficiency and overall system performance. Similarly, a fault analysis approach for compressors using maintenance reports and NLP clustering was presented [161]. The aim of the proposed research was the collection and clustering of unstructured data (maintenance reports) collected from service employees to improve the prediction accuracy of data-driven models. Based on maintenance reports and NLP methodology, authors efficiently identified and clustered several failure information, namely valve leaking, bearings inspection, and earth-failure shutdown, while correlating extracted outputs with the respective time domain. Additionally, [162] proposed a sematic-based common taxonomy for the identification of nozzle guide vans degradation, which are critical components of aerospace engines. Authors collected publicly available textual data to identify and correlate existing literature with terms, such as degradation, damage, deterioration, and defect of nozzle guide vans. For data processing, Named Entity Recognition (NER) was used to identify and index collected data regarding corrosion, fatigue, thermal, wear, fracture, and magnitude. Furthermore, bidirectional encoder representation from transformers (BERT) was applied for terminology recognition and relationship extraction, along with causal relationship recognition (CCRR) and F1 score for output verification and model evaluation, respectively. Despite the promising results, the authors highlighted the need for a standard textual set for optimal model accuracy. Accordingly, [163] focused on electrical fault classification and diagnosis, using verbal expressions, technical terms of electronics, and imbalanced fault-type data inputs. The proposed deep learning methodology, combining supervised sentence embedding with an imbalanced classification approach, outputs more accurate results with an 80% average F1 score compared to similar algorithms, such as TextCNN and XGBoost. Furthermore, a hybrid architecture for data transfer and manipulation amongst industrial devices and software applications was presented [164]. In more depth, the authors emphasized structured, semi-structured, and unstructured data management and storage in two industrial scenarios, namely hard metal manufacturing complex and semiconductor glue deposition process. The proposed framework utilized the Apache Cassandra NoSQL database for the storage of semi-structured and unstructured collected data. Additionally, ML software applications generated fault detection predictions for the near future. The authors achieved an improvement in data retrieval and deployed a user-friendly platform in the context of overall manufacturing efficiency. Finally, a ML approach using maintenance text records to classify failure in an industrial process was presented [165]. Selected algorithms namely Naïve Bayes and SVM accurately classified the health state of the experimented system assisting maintenance personnel in identifying upcoming breakdowns. Overall, text analysis and NLP techniques are promising research fields in future PdM solutions. Real-world industrial environments generate a high volume of unstructured data and could further assist data-driven maintenance approaches and increase system safety and reliability. However certain limitations were identified for upcoming research including keyword standardization and collected text volume.

5.5. Prescriptive maintenance in cyber physical production systems

Prescriptive maintenance, an advanced maintenance approach and emerging topic of interest, is applied in combination with PdM in modern Cyber Physical Production Systems (CPPS). Prescriptive maintenance introduces the concept of root cause analysis and recommends measurements for the optimization of CPPS [166]. Differentiating from PdM that questions ‘when an event will occur’ and ‘what will happen’, prescriptive maintenance inquiries refer to ‘what shall be done with a particular event and how’ [153]. Both maintenance approaches establish a direct link to optimal maintenance planning in CPPS. The impact of data-driven approaches, including predictive and prescriptive maintenance, focusing on economic and profitability factors was discussed in [167]. However, [168] raises the issue of data-driven maintenance that tends to focus merely on fault detection by implementing AI algorithms. In the proposed work, a competence-based maintenance planning approach aimed to reduce the overall mean time of repair of a semi-conductor factory through efficient workforce scheduling and task maintenance. Combined with linear programming and genetic algorithms, a knowledge graph produced optimal maintenance planning using semantically linked inputs for shift scheduling and task allocation. This research efficiently utilized heterogenous data inputs, namely production plans, associated costs, technicians and spare parts availability, machine criticality, and technicians’ competence to reduce the mean time of repair by 18%.

Several cases were identified in the context of prescriptive maintenance. A conceptual design of an autonomous production control model combined with a prescriptive maintenance approach was proposed for decision improvement and maintenance scheduling optimization [153]. Authors achieved the deployment of an integrated maintenance scheduling system linked to prescriptive decision-making by using a structured conceptual model. Maintenance systems, autonomous production control, and production planning are the main topics of interest in the integrated autonomous production control model. More specifically, regarding the maintenance system, the prescriptive model provided the directory facilitator with the RUL of production components. Moreover, the authors’ approach concerning production control and production planning established a link with prescriptive maintenance and maintenance planning, respectively, and contributed to achieving higher process stability and overall efficiency in industrial environments. A prescriptive maintenance approach in triaxial machining centres of the automotive industry was proposed [169]. The proposed system architecture combined data acquisition, pre-processing, analysis and simulation, a failure reaction prediction, and a prescriptive maintenance decision support model, to optimally predict upcoming malfunctions and prescribe suggesting maintenance measurements to technicians. This research contributed to the effective development of a conceptual framework for machine overview, condition prediction, maintenance suggestions, and KPIs visualization to reduce the overall maintenance costs by 30% and increase maintenance planning savings and system availability by 20% and 12%, respectively. In [170], authors presented a conceptual model combining a classification prediction model of time to failure occurrence with a fault diagnosis prescriptive maintenance model for etching equipment in semiconductor manufacturing. The proposed architecture consisted of data cleaning and pre-processing, predictive and prescriptive model development, and finally decision support. The results indicated that SVM outperformed similar experimented ML models in terms of failure occurrence prediction. Furthermore, a three-layer Bayesian Network approach was considered the preferable prescriptive approach for failure root cause extraction of certain production components. Furthermore, [171] highlighted the importance of prescriptive maintenance in combination with predictive approaches suggesting the solution of emerging production malfunctions. In their approach, a digital twin of turbomachinery components’ production plant was developed for system optimization through prescriptive analysis. Except for the anylogic digital twin, the integrated framework combines a predictive analytics module developed with MATLAB and a platform, named Heuristics Lab, for efficient maintenance scheduling using heuristic-based decisions. The proposed solution efficiently identified the root of production delays in several processes connecting production planning control and prescriptive maintenance.

5.6. Challenges of predictive maintenance

This research addressed the application of PdM approaches across several industries and presented a decision support map for guiding researchers and practitioners in the development of optimal PdM applications based on the unique characteristics of each respective manufacturing sector. Based on the reviewed literature, the authors identified the need to discuss the major challenges encountered while applying PdM solutions in the industry:

- **A significant amount of historical data should be collected and stored in order to construct an efficient solution.** Collecting and storing data of high value can be a long-term procedure that requires a suitable database architecture managed by experienced data-scientists.
- **Handling unstructured data is crucial.** A high volume of historical data in real-world industrial applications is stored on maintenance reports. Additionally, the collection, digitalization and standardization of technicians’ verbal argot is limited. Text and speech analysis, such as NLP methodologies, could further assist data-driven methods.
- **A sufficient number of failure data is also important.** In a real-life application, the imported dataset shall be distinguished regarding input features into two categories, measurements that are generated in a healthy system and measurements generated during a malfunction. The majority of the input measurements address a healthy state of the experimented system, creating a challenging issue of collecting and training input features in a malfunctioning system.

- **The construction of a database with optimal PdM solutions regarding input features, predicted variables, applied algorithms, evaluation metrics, and applied software tools per industry sector is meaningful.** In fact, this research comprehensively addresses this issue providing an analytical list of previous works and a decision support map for each industrial sector.
- **The values collected from sensors should be constantly analyzed to provide an efficient PdM solution.** Experienced researchers and data-scientists should map and update the imported dataset to improve their respective applications with state-of-the-art data-driven algorithms and updated input features.

6. Conclusions

This paper provides a systematic review of the literature regarding PdM through a multi-sector lens. Our analysis first identified and classified the theoretical background of PdM approaches through previous state-of-the-art reviews and then examined the prevailing methodologies by exploring state-of-the-art use cases within Industry 4.0. After thoroughly reviewing and studying 78 use cases, we have concluded that PdM in general, specifically data-driven methodologies, demonstrate a growing interest in modern manufacturing and, thus, constitute a promising research topic. Overall, the manufacturing sectors of machinery and equipment, transportation, and energy, along with a few applications in the chemical-related and electronic industries, were identified and analyzed. Through our analytical taxonomy, we have extensively categorized the PdM applications in the various manufacturing industries, emphasizing the different aspects and characteristics of each proposed solution. To the best of our knowledge, our review is the first effort towards conducting a multi-sector taxonomy regarding methods, predicted variables, input features, applied algorithms, evaluation metrics, and available software tools per use case.

Our research contribution is twofold. From an academic/scientific perspective, we argue that PdM, and data-driven approaches in particular, are considered cutting-edge solutions for all industrial sectors [24,35,38,172]. The manufacturing sectors of machinery and equipment, transportation, and energy were identified with the highest technology readiness for PdM implementation. Moreover, our analysis indicated that RUL prognosis, failure prediction, health state classification, anomaly detection, and optimal maintenance timeline selection are some of the most common predicted variables. Additionally, we have highlighted that accuracy, precision, recall, F1 score, and confusion matrix were selected for classification predictions, while RMSE, R2 for the regression ones [56]. Python programming language and related data analytics and AI libraries, namely NumPy, Pandas, SciPy, Scikit-learn, Optuna and PyTorch were proposed as appropriate software tools. However, the selection of the data mining approach and the appropriate prediction methodology is a challenging issue for researchers.

Additionally, from a technical/operational perspective, we identified that sensor measurements from heterogeneous data sources, such as vibration, temperature, voltage, rotational speed, and machine identification number, are critically important and frequently selected as input features for the decision algorithms [62,64]. Thus, a major issue for the technicians is the optimal acquisition and storage of high-volume heterogeneous data in real-time industrial environments. Although several use cases [76,89,90,123,127] explained in depth the applied software, a considerable amount of the published papers lack emphasis on the technical perspective of the PdM solution. Overall, our review attempted to identify the prevailing PdM input features, methodologies, and software solutions for each industrial sector, based on state-of-the-art literature findings, for designing a concise decision support map that could act as a guideline for both prospective research efforts and technical applications.

Regarding future research directions, we propose further implementation of PdM methods and models in industries where little research has been conducted thus far, such as energy, chemical, plastic, pharmaceutical, and electronic industries. Additionally, since prescriptive maintenance is a rapidly evolving maintenance area alongside PdM, further research activities are highly recommended. Finally, prospective efforts may explore the outcomes of the presented review through novel research lenses, exploiting in depth the PdM solutions for more innovative, human-centric, and energy-efficient approaches in modern industries, expressing the core pillars of Industry 5.0.

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CRediT authorship contribution statement

Panagiotis Mallioris: Conceptualization, Investigation, Writing – original draft, Visualization. **Eirini Aivazidou**: Conceptualization, Methodology, Validation, Writing – review & editing, Visualization. **Dimitrios Bechtsis:** Conceptualization, Methodology, Validation, Writing – review & editing, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] JRC. The impact of Technological Innovation on the Future of Work 2019. ⟨https://ec.europa.eu/jrc/sites/jrcsh/files/jrc117212.pdf⟩.
[2] Dolgui A, Ivanov D. 5G in digital supply chain and operations management: fostering flexibility, end-to-end connectivity and real-time visibility through internet-of-everything. Int J Prod Res 2022;60:442–51. https://doi.org/10.1080/00207543.2021.2002969.
[3] Nordal H, El-Thalji I. Modeling a predictive maintenance management architecture to meet industry 4.0 requirements: a case study. Syst Eng 2021;24:34–50. https://doi.org/10.1002/sys.21565.
[4] Fosso Wamba S, Akter S, Edwards A, Chopin G, Gnanzou D. How "big data" can make big impact: findings from a systematic review and a longitudinal case study. Int J Prod Econ 2015;165:234–46. https://doi.org/10.1016/j.ijpe.2014.12.031.
[5] Ruiz-Carcel C, Starr A. Data-based detection and diagnosis of faults in linear actuators. IEEE Trans Instrum Meas 2018;67:2035–47. https://doi.org/10.1109/TIM.2018.2814067.
[6] Choi TM, Dolgui A, Ivanov D, Pesch E. OR and analytics for digital, resilient, and sustainable manufacturing 4.0. Annals of Operations 2022;310. https://doi.org/10.1007/s10479-022-04536-3.
[7] Jiang Z, Yuan S, Ma J, Wang Q. The evolution of production scheduling from Industry 3.0 through Industry 4.0. Int J Prod Res 2021;0:1–21. https://doi.org/10.1080/00207543.2021.1925772.
[8] Ivanov D, Tang CS, Dolgui A, Battini D, Das A. Researchers' perspectives on Industry 4.0: multi-disciplinary analysis and opportunities for operations management. Int J Prod Res 2021;59:2055–78. https://doi.org/10.1080/00207543.2020.1798035.
[9] Xu X, Lu Y, Vogel-Heuser B, Wang L. Industry 4.0 and Industry 5.0—Inception, conception and perception. J Manuf Syst 2021;61:530–5. https://doi.org/10.1016/j.jmsy.2021.10.006.
[10] Tao F, Qi Q, Liu A, Kusiak A. Data-driven smart manufacturing. J Manuf Syst 2018;48:157–69. https://doi.org/10.1016/j.jmsy.2018.01.006.
[11] Wang J, Ma Y, Zhang L, Gao RX, Wu D. Deep learning for smart manufacturing: Methods and applications. J Manuf Syst 2018;48:144–56. https://doi.org/10.1016/j.jmsy.2018.01.003.
[12] Dolgui A, Bakhtadze N, Pyatetsky V, Sabitov R, Smirnova G, Elpashev D, et al. Data Mining-Based Prediction of Manufacturing Situations, vol. 51. Elsevier B.V.; 2018. p. 316–21. https://doi.org/10.1016/j.ifacol.2018.08.302.
[13] Xu Z, Saleh JH. Machine learning for reliability engineering and safety applications: Review of current status and future opportunities. Reliab Eng Syst Saf 2021;211. https://doi.org/10.1016/j.ress.2021.107530.
[14] Erkoyuncu JA, Namoano B, Kozjek D, Vrabič R. Cognitive data imputation: Case study in maintenance cost estimation. CIRP Annals 2023;72:385–8. https://doi.org/10.1016/j.cirp.2023.03.036.
[15] Dinh DH, Do P, Iung B. Maintenance optimisation for multi-component system with structural dependence: Application to machine tool sub-system. CIRP Annals 2020;69:417–20. https://doi.org/10.1016/j.cirp.2020.04.004.
[16] Dalzochio J, Kunst R, Pignaton E, Binotto A, Sanyal S, Favilla J, et al. Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status

and challenges. Comput Ind 2020;123:103298. https://doi.org/10.1016/j.compind.2020.103298.
[17] Peng Y, Dong M, Zuo MJ. Current status of machine prognostics in condition-based maintenance: A review. International Journal of Advanced Manufacturing Technology 2010;50:297–313. https://doi.org/10.1007/s00170-009-2482-0.
[18] Maher Y, Danouj B. Survey on deep learning applied to predictive maintenance. International Journal of Electrical and Computer Engineering 2020;10:5592–8. https://doi.org/10.11591/ijece.v10i6.pp5592-5598.
[19] Feldmann S., Buechele R., Preveden V. Predictive maintenance-From data collection to value creation Management summary A TURNING POINT IN INDUSTRIAL SERVICES. 2018.
[20] Predictive Maintenance Strategies Gain Ground Leaders move to capture productivity gains and data-savvy talent. 2022.
[21] Aivaliotis P, Georgoulias K, Chryssolouris G. The use of Digital Twin for predictive maintenance in manufacturing. Int J Comput Integr Manuf 2019;32:1067–80. https://doi.org/10.1080/0951192X.2019.1686173.
[22] Rai R, Tiwari MK, Ivanov D, Dolgui A. Machine learning in manufacturing and industry 4.0 applications. Int J Prod Res 2021;59:4773–8. https://doi.org/10.1080/00207543.2021.1956675.
[23] Pech M, Vrchota J, Bednář J. Predictive maintenance and intelligent sensors in smart factory: Review. Sensors 2021;21:1–39. https://doi.org/10.3390/s21041470.
[24] Bousdekis A, Lepenioti K, Apostolou D, Mentzas G. A review of data-driven decision-making methods for industry 4.0 maintenance applications. Electronics 2021;10. https://doi.org/10.3390/electronics10070828.
[25] Serradilla O, Zugasti E, Ramirez de Okariz J, Rodriguez J, Zurutuza U. Methodology for data-driven predictive maintenance models design, development and implementation on manufacturing guided by domain knowledge. Int J Comput Integr Manuf 2022. https://doi.org/10.1080/0951192X.2022.2043562.
[26] Theissler A, Pérez-Velázquez J, Kettelgerdes M, Elger G. Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry. Reliab Eng Syst Saf 2021;215:107864. https://doi.org/10.1016/j.ress.2021.107864.
[27] Ciancio V, Homri L, Dantan JY, Siadat A. Development of a flexible data management system, to implement predictive maintenance in the Industry 4.0 context. Int J Prod Res 2023. https://doi.org/10.1080/00207543.2023.2217293.
[28] Xie J, Huang J, Zeng C, Jiang SH, Podlich N. Systematic literature review on data-driven models for predictive maintenance of railway track: Implications in geotechnical engineering. Geosciences (Switzerland) 2020;10:1–24. https://doi.org/10.3390/geosciences10110425.
[29] Basora L, Olive X, Dubot T. Recent advances in anomaly detection methods applied to aviation. Aerospace 2019;6. https://doi.org/10.3390/aerospace6110117.
[30] Kaiwartya O, Abdullah AH, Cao Y, Altameem A, Prasad M, Lin CT, et al. Internet of vehicles: motivation, layered architecture, network model, challenges, and future aspects. IEEE Access 2016;4:5356–73. https://doi.org/10.1109/ACCESS.2016.2603219.
[31] Zhang W, Yang D, Wang H. Data-driven methods for predictive maintenance of industrial equipment: a survey. IEEE Syst J 2019;13:2213–27. https://doi.org/10.1109/JSYST.2019.2905565.
[32] O'Donovan P, Leahy K, Bruton K, O'Sullivan DTJ. An industrial big data pipeline for data-driven analytics maintenance applications in large-scale smart manufacturing facilities. J Big Data 2015;2(1):26. https://doi.org/10.1186/s40537-015-0034-z.
[33] Jardine AKS, Lin D, Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mech Syst Signal Process 2006;20:1483–510. https://doi.org/10.1016/j.ymssp.2005.09.012.
[34] Susto GA, Schirru A, Pampuri S, McLoone S, Beghi A. Machine learning for predictive maintenance: A multiple classifier approach. IEEE Trans Industr Inform 2015;11:812–20. https://doi.org/10.1109/TII.2014.2349359.
[35] Montero Jimenez JJ, Schwartz S, Vingerhoeds R, Grabot B, Salaün M. Towards multi-model approaches to predictive maintenance: A systematic literature survey on diagnostics and prognostics. J Manuf Syst 2020;56:539–57. https://doi.org/10.1016/j.jmsy.2020.07.008.
[36] D. Wu, C. Jennings, J. Terpenny, S. Kumara, Cloud-based machine learning for predictive analytics: Tool wear prediction in milling Proceedings - 2016 IEEE International Conference on Big Data, Big Data 2016 2016 2062 2069 doi: 10.1109/BigData.2016.7840831.
[37] Fernandes J, Reis J, Melão N, Teixeira L, Amorim M. The role of industry 4.0 and bpmn in the arise of condition-based and predictive maintenance: a case study in the automotive industry. Appl. Sci. 2021;11. https://doi.org/10.3390/app11083438.
[38] Zonta T, André C, Righi R, José M, Lima D, Silveira E, et al. Predictive maintenance in the Industry 4. 0: a systematic literature review. Comput Ind Eng 2020;150:106889. https://doi.org/10.1016/j.cie.2020.106889.
[39] Colledani M, Magnanini MC, Tolio T. Impact of opportunistic maintenance on manufacturing system performance. CIRP Annals 2018;67:499–502. https://doi.org/10.1016/j.cirp.2018.04.078.
[40] Bi L, Tao F, Zhang P, Nee AYC. Opportunistic maintenance for multi-unit series systems based on gated recurrent units prediction model. CIRP Annals 2020;69:25–8. https://doi.org/10.1016/j.cirp.2020.04.019.
[41] Ansari F, Glawar R, Nemeth T. PriMa: a prescriptive maintenance model for cyber-physical production systems. Int J Comput Integr Manuf 2019;32:482–503. https://doi.org/10.1080/0951192X.2019.1571236.
[42] Silvestri L, Forcina A, Introna V, Santolamazza A, Cesarotti V. Maintenance transformation through Industry 4.0 technologies: a systematic literature review. Comput Ind 2020;123:103335. https://doi.org/10.1016/j.compind.2020.103335.
[43] Matyas K, Nemeth T, Kovacs K, Glawar R. A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. CIRP Ann Manuf Technol 2017;66:461–4. https://doi.org/10.1016/j.cirp.2017.04.007.
[44] Sayyad S, Kumar S, Bongale A, Bongale AM, Patil S. Estimating remaining useful life in machines using artificial intelligence: a scoping review. Library Philosophy and Practice 2021;2021:1–26.
[45] Olesen JF, Shaker HR. Predictive maintenance for pump systems and thermal power plants: State-of-the-art review, trends and challenges. Sensors 2020;20. https://doi.org/10.3390/s20082425.
[46] Hitzler P, Eberhart A, Ebrahimi M, Sarker MK, Zhou L. Neuro-symbolic approaches in artificial intelligence. Natl Sci Rev 2022;9. https://doi.org/10.1093/nsr/nwac035.
[47] Shin CK, Park SC. A machine learning approach to yield management in semiconductor manufacturing. Int J Prod Res 2000;38:4261–71. https://doi.org/10.1080/00207540050205073.
[48] Wang J, Ma Y, Zhang L, Gao RX, Wu D. Deep learning for smart manufacturing: methods and applications. J Manuf Syst 2018;48:144–56. https://doi.org/10.1016/j.jmsy.2018.01.003.
[49] Ning F, Shi Y, Cai M, Xu W, Zhang X. Manufacturing cost estimation based on a deep-learning method. J Manuf Syst 2020;54:186–95. https://doi.org/10.1016/j.jmsy.2019.12.005.
[50] Goyal D, Pabla BS. Condition based maintenance of machine tools-A review. CIRP J Manuf Sci Technol 2015;10:24–35. https://doi.org/10.1016/j.cirpj.2015.05.004.
[51] van Oudenhoven B, Van de Calseyde P, Basten R, Demerouti E. Predictive maintenance for industry 5.0: behavioural inquiries from a work system perspective. Int J Prod Res 2022. https://doi.org/10.1080/00207543.2022.2154403.
[52] Grenyer A, Erkoyuncu JA, Zhao Y, Roy R. A systematic review of multivariate uncertainty quantification for engineering systems. CIRP J Manuf Sci Technol 2021;33:188–208. https://doi.org/10.1016/j.cirpj.2021.03.004.
[53] Aldrini J, Chihi I, Sidhom L. Fault diagnosis and self-healing for smart manufacturing: a review. J Intell Manuf 2023. https://doi.org/10.1007/s10845-023-02165-6.
[54] Siener M, Aurich JC. Quality oriented maintenance scheduling. CIRP J Manuf Sci Technol 2011;4:15–23. https://doi.org/10.1016/j.cirpj.2011.06.014.
[55] Nunes P, Santos J, Rocha E. Challenges in predictive maintenance – a review. CIRP J Manuf Sci Technol 2023;40:53–67. https://doi.org/10.1016/j.cirpj.2022.11.004.
[56] Angelopoulos A, Michailidis ET, Nomikos N, Trakadas P, Hatziefremidis A, Voliotis S, et al. Tackling faults in the industry 4.0 era—a survey of machine-learning solutions and key aspects. Sensors 2020;20:1–34. https://doi.org/10.3390/s20010109.
[57] Lima AL da CD, Aranha VM, Carvalho CJ de L, Nascimento EGS. Smart predictive maintenance for high-performance computing systems: a literature review. J Supercomput 2021. https://doi.org/10.1007/s11227-021-03811-7.
[58] Carvalho TP, Soares FAAMN, Vita R, Francisco R, da P, Basto JP, et al. A systematic literature review of machine learning methods applied to predictive maintenance. Comput Ind Eng 2019;137:106024. https://doi.org/10.1016/j.cie.2019.106024.
[59] Mumali F. Artificial neural network-based decision support systems in manufacturing processes: A systematic literature review. Comput Ind Eng 2022;165. https://doi.org/10.1016/j.cie.2022.107964.
[60] Samala T, Manupati VK, Varela MLR, Putnik G. Investigation of degradation and upgradation models for flexible unit systems: A systematic literature review. Future Internet 2021;13:1–18. https://doi.org/10.3390/fi13030057.
[61] Mushtaq S, Islam MMM, Sohaib M. Deep learning aided data-driven fault diagnosis of rotatory machine: a comprehensive review. Energies 2021;14:5150. https://doi.org/10.3390/en14165150.
[62] Nacchia M, Fruggiero F, Lambiase A, Bruton K. A systematic mapping of the advancing use of machine learning techniques for predictive maintenance in the manufacturing sector. Appl Sci 2021;11:1–34. https://doi.org/10.3390/app11062546.
[63] Kundu P, Darpe AK, Kulkarni MS. A review on diagnostic and prognostic approaches for gears. Struct Health Monit 2020. https://doi.org/10.1177/1475921720972926.
[64] El-Thalji I, Jantunen E. A summary of fault modelling and predictive health monitoring of rolling element bearings. Mech Syst Signal Process 2015;60:252–72. https://doi.org/10.1016/j.ymssp.2015.02.008.
[65] Omairi A, Ismail ZH. Towards machine learning for error compensation in additive manufacturing. Appl Sci 2021;11:1–27. https://doi.org/10.3390/app11052375.
[66] Zhao X, Kim J, Warns K, Wang X, Ramuhalli P, Cetiner S, et al. Prognostics and health management in nuclear power plants: an updated method-centric review with special focus on data-driven methods. Front Energy 2021;9:1–29. https://doi.org/10.3389/fenrg.2021.696785.
[67] Chin HH, Varbanov PS, Klemeš JJ, Benjamin MFD, Tan RR. Asset maintenance optimisation approaches in the chemical and process industries – A review. Chem Eng Res De 2020;164:162–94. https://doi.org/10.1016/j.cherd.2020.09.034.
[68] Nguyen T, ZHOU L, Spiegler V, Ieromonachou P, Lin Y. Big data analytics in supply chain management: A state-of-the-art literature review. Comput Oper Res 2018;98:254–64. https://doi.org/10.1016/j.cor.2017.07.004.

[69] Talwar S, Kaur P, Fosso Wamba S, Dhir A. Big Data in operations and supply chain management: a systematic literature review and future research agenda. Int J Prod Res 2021;0:1–26. https://doi.org/10.1080/00207543.2020.1868599.

[70] Turner CJ, Emmanouilidis C, Tomiyama T, Tiwari A, Roy R. Intelligent decision support for maintenance: an overview and future trends. Int J Comput Integr Manuf 2019;32:936–59. https://doi.org/10.1080/0951192X.2019.1667033.

[71] Züfle M, Moog F, Lesch V, Krupitzer C, Kounev S. A machine learning-based workflow for automatic detection of anomalies in machine tools. ISA Trans 2021. https://doi.org/10.1016/j.isatra.2021.07.010.

[72] Hesser DF, Markert B. Tool wear monitoring of a retrofitted CNC milling machine using artificial neural networks. Manuf Lett 2019;19:1–4. https://doi.org/10.1016/j.mfglet.2018.11.001.

[73] Traini E, Bruno G, Lombardi F. Tool condition monitoring framework for predictive maintenance: a case study on milling process. Int J Prod Res 2021;59:7179–93. https://doi.org/10.1080/00207543.2020.1836419.

[74] Sundaram S, Zeid A. Smart prognostics and health management (SPHM) in smart manufacturing: An interoperable framework. Sensors 2021;21. https://doi.org/10.3390/s21185994.

[75] Sang GM, Xu L, de Vrieze P. A predictive maintenance model for flexible manufacturing in the context of Industry 4.0. Front Big Data 2021;4:1–23. https://doi.org/10.3389/fdata.2021.663466.

[76] Luo W, Hu T, Ye Y, Zhang C, Wei Y. A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin. Robot Comput Integr Manuf 2020;65:101974. https://doi.org/10.1016/j.rcim.2020.101974.

[77] Kumar A, Chinnam RB, Tseng F. An HMM and polynomial regression based approach for remaining useful life and health state estimation of cutting tools. Comput Ind Eng 2019;128:1008–14. https://doi.org/10.1016/j.cie.2018.05.017.

[78] Li Z, Wang Y, Wang KS. Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: Industry 4.0 scenario. Adv Manuf 2017;5:377–87. https://doi.org/10.1007/s40436-017-0203-8.

[79] Teoh YK, Gill SS, Parlikad AK. IoT and fog computing based predictive maintenance model for effective asset management in Industry 4.0 using machine learning. IEEE Internet Things J 2021;0:0-7. https://doi.org/10.1109/JIOT.2021.3050441.

[80] Serradilla O., Zugasti E., Okariz J.R.De, Rodriguez J., Zurutuza U. applied sciences 2021.

[81] Rodrigues JA, Farinha JT, Mendes M, Mateus RJG, Cardoso AJM. Comparison of different features and neural networks for predicting industrial paper press condition. Energies 2022;15. https://doi.org/10.3390/en15176308.

[82] Lis A, Dworakowski Z, Czubak P. An anomaly detection method for rotating machinery monitoring based on the most representative data. J Vibroeng 2021;23:861–76. https://doi.org/10.21595/jve.2021.21622.

[83] Romahadi D, Luthfie AA, Suprihatiningsih W, Xiong H. Designing expert system for centrifugal using vibration signal and bayesian networks. Int J Adv Sci Eng Inf Technol 2022;12:23–31. https://doi.org/10.18517/ijaseit.12.1.12448.

[84] Selvaraj S, Prabhu Kavin B, Kavitha C, Lai WC. A multiclass fault diagnosis framework using context-based multilayered bayesian method for centrifugal pumps. Electronics 2022;11. https://doi.org/10.3390/electronics11234014.

[85] Arellano-Espitia F, Delgado-Prieto M, Martinez-Viol V, Saucedo-Dorantes JJ, Osornio-Rios RA. Deep-learning-based methodology for fault diagnosis in electromechanical systems. Sensors 2020;20:1–23. https://doi.org/10.3390/s20143949.

[86] Li Z, Kristoffersen E, Li J. Deep transfer learning for failure prediction across failure types. Comput Ind Eng 2022;172. https://doi.org/10.1016/j.cie.2022.108521.

[87] Kiangala KS, Wang Z. An effective predictive maintenance framework for conveyor motors using dual time-series imaging and convolutional neural network in an Industry 4.0 environment. IEEE Access 2020;8:121033–49. https://doi.org/10.1109/ACCESS.2020.3006788.

[88] Elahi M, Afolaranmi SO, Mohammed WM, Lastra JLM. Energy-based prognostics for gradual loss of conveyor belt tension in discrete manufacturing systems. Energies 2022;15. https://doi.org/10.3390/en15134705.

[89] Rubio EM, Dionísio RP, Torres PMB. Predictive maintenance of induction motors in the context of industry 4.0. Int J Mechatron Appl Mech 2018;2018:238–42. https://doi.org/10.17683/ijomam/issue4.33.

[90] Calabrese M, Cimmino M, Fiume F, Manfrin M, Romeo L, Ceccacci S, et al. SOPHIA: an event-based IoT and machine learning architecture for predictive maintenance in industry 4.0. Information 2020;11:1–17. https://doi.org/10.3390/INFO11040202.

[91] Putnik GD, Manupati VK, Pabba SK, Varela L, Ferreira F. Semi-Double-loop machine learning based CPS approach for predictive maintenance in manufacturing system based on machine status indications. CIRP Ann 2021;70:365–8. https://doi.org/10.1016/j.cirp.2021.04.046.

[92] Roosefert Mohan T, Preetha Roselyn J, Annie Uthra R, Devaraj D, Umachandran K. Intelligent machine learning based total productive maintenance approach for achieving zero downtime in industrial machinery. Comput Ind Eng 2021;157:107267. https://doi.org/10.1016/j.cie.2021.107267.

[93] Cardoso D, Ferreira L. Application of predictive maintenance concepts using artificial intelligence tools. Appl Sci 2021;11:1–18. https://doi.org/10.3390/app11010018.

[94] Hajgató G, Wéber R, Szilágyi B, Tóthpál B, Gyires-Tóth B, Hős C. PredMaX: predictive maintenance with explainable deep convolutional autoencoders. Adv Eng Inform 2022;54. https://doi.org/10.1016/j.aei.2022.101778.

[95] Cakir M, Guvenc MA, Mistikoglu S. The experimental application of popular machine learning algorithms on predictive maintenance and the design of IIoT based condition monitoring system. Comput Ind Eng 2021;151:106948. https://doi.org/10.1016/j.cie.2020.106948.

[96] Vitolo P, De Vita A, Benedetto LDi, Pau D, Licciardo GD. Low-power detection and classification for in-sensor predictive maintenance based on vibration monitoring. IEEE Sens J 2022;22:6942–51. https://doi.org/10.1109/JSEN.2022.3154479.

[97] Aye SA, Heyns PS. Prognostics of slow speed bearings using a composite integrated Gaussian process regression model. Int J Prod Res 2018;56:4860–73. https://doi.org/10.1080/00207543.2018.1470340.

[98] Aydemir G, Paynabar K. Image-based prognostics using deep learning approach. IEEE Trans Industr Inform 2020;16:5956–64. https://doi.org/10.1109/TII.2019.2956220.

[99] Izagirre U, Andonegui I, Egea A, Zurutuza U. A methodology and experimental implementation for industrial robot health assessment via torque signature analysis. Appl Sci 2020;10:1–14. https://doi.org/10.3390/app10217883.

[100] Ruiz-sarmiento J, Monroy J, Moreno F, Galindo C. A predictive model for the maintenance of industrial machinery in the. Eng Appl Artifi Intell 2020;87:103289. https://doi.org/10.1016/j.engappai.2019.103289.

[101] Gay A, Voisin A, Iung B, Do P, Bonidal R, Khelassi A. Data augmentation-based prognostics for predictive maintenance of industrial system. CIRP Annals 2022;71:409–12. https://doi.org/10.1016/j.cirp.2022.04.005.

[102] Chen X, Van Hillegersberg J, Topan E, Smith S, Roberts M. Application of data-driven models to predictive maintenance: bearing wear prediction at TATA steel. Expert Syst Appl 2021;186:115699. https://doi.org/10.1016/j.eswa.2021.115699.

[103] Neves M, Vieira M, Neto P. A study on a Q-Learning algorithm application to a manufacturing assembly problem. J Manuf Syst 2021;59:426–40. https://doi.org/10.1016/j.jmsy.2021.02.014.

[104] Guo Q, Miyamae Y, Wang Z, Taniuchi K, Yang H, Liu Y. Senvis-Net: learning from imbalanced machinery data by transferring visual element detectors. Int J Mach Learn Comput 2018;8:416–22. https://doi.org/10.18178/ijmlc.2018.8.5.722.

[105] Biggio L, Wieland A, Chao MA, Kastanis I, Fink O. Uncertainty-aware prognosis via deep gaussian process. IEEE Access 2021;9:123517–27. https://doi.org/10.1109/ACCESS.2021.3110049.

[106] C. Resende D. Folgado J. Oliveira B. Franco W. Moreira A. Oliveira-jr et al. Tip4 0: Industrial Internet of things Platform for predictive Maintenance 2021 1 23.

[107] de Pater I, Reijns A, Mitici M. Alarm-based predictive maintenance scheduling for aircraft engines with imperfect Remaining Useful Life prognostics. Reliab Eng Syst Saf 2022;221. https://doi.org/10.1016/j.ress.2022.108341.

[108] Wang Y, Zhao Y. Multi-scale remaining useful life prediction using long short-term memory. Sustainability 2022;14. https://doi.org/10.3390/su142315667.

[109] Erpolat Tasabat S, Aydin O. Using long-short term memory networks with genetic algorithm to predict engine condition. Gazi Univ J Sci 2022;35:1200–10. https://doi.org/10.35378/gujs.937169.

[110] D. Verstraete E. Droguett M. Modarres A deep adversarial approach based on multisensor fusion for remaining useful life prognostics Proc 29th Eur Saf Reliab Conf, ESREL 2020 2019 1072 1077 doi: 10.3850/978-981-11-2724-3_0302-cd.

[111] Ewald V, Sridaran Venkat R, Asokkumar A, Benedictus R, Boller C, Groves RM. Perception modelling by invariant representation of deep learning for automated structural diagnostic in aircraft maintenance: a study case using DeepSHM. Mech Syst Signal Process 2022;165:108153. https://doi.org/10.1016/j.ymssp.2021.108153.

[112] Siyaev A, Jo GS. Towards aircraft maintenance metaverse using speech interactions with virtual objects in mixed reality. Sensors 2021;21:1–21. https://doi.org/10.3390/s21062066.

[113] Dangut MD, Jennions IK, King S, Skaf Z. A rare failure detection model for aircraft predictive maintenance using a deep hybrid learning approach. Neural Comput Appl 2022. https://doi.org/10.1007/s00521-022-07167-8.

[114] Lee J, Mitici M. Multi-objective design of aircraft maintenance using Gaussian process learning and adaptive sampling. Reliab Eng Syst Saf 2022;218. https://doi.org/10.1016/j.ress.2021.108123.

[115] Domínguez-Monferrer C, Fernández-Pérez J, de Santos R, Miguélez MH, Cantero JL. Machine learning approach in non-intrusive monitoring of tool wear evolution in massive CFRP automatic drilling processes in the aircraft industry. J Manuf Syst 2022;65:622–39. https://doi.org/10.1016/j.jmsy.2022.10.018.

[116] Quattrocchi G, Berri PC, Vedova MDLD, Maggiore P. An Improved Fault Identification Method for Electromechanical Actuators. Aerospace 2022;9. https://doi.org/10.3390/aerospace9070341.

[117] Rosero RL, Silva C, Ribeiro B. Remaining useful life estimation of cooling units via time-frequency health indicators with machine learning. Aerospace 2022;9. https://doi.org/10.3390/aerospace9060309.

[118] Koenig F, Found PA, Kumar M. Condition monitoring for airport baggage handling in the era of industry 4.0. J Qual Maint Eng 2019;25:435–51. https://doi.org/10.1108/JQME-03-2018-0014.

[119] Giordano D, Mellia M. K-MDTSC: K-multi-dimensional time-series clustering algorithm. MDPI 2021:1–21.

[120] Subramaniyan M, Skoogh A, Salomonsson H, Bangalore P, Bokrantz J. A data-driven algorithm to predict throughput bottlenecks in a production system based on active periods of the machines. Comput Ind Eng 2018;125:533–44. https://doi.org/10.1016/j.cie.2018.04.024.

[121] Sanz E, Blesa J, Puig V. BiDrac Industry 4.0 framework: application to an automotive paint shop process. Control Eng Pract 2021;109:104757. https://doi.org/10.1016/j.conengprac.2021.104757.

[122] Gong CSA, Su CHS, Liu YE, Guu DY, Chen YH. Deep learning with LPC and wavelet algorithms for driving fault diagnosis. Sensors 2022;22. https://doi.org/10.3390/s22187072.

[123] Chen B, Liu Y, Zhang C, Wang Z. Time series data for equipment reliability analysis with deep learning. IEEE Access 2020;8:105484–93. https://doi.org/10.1109/ACCESS.2020.3000006.
[124] Detection S.A. Maintenance in Compliance with Industry 4. 0. Sensors 2021.
[125] Taşabat SE, Özçay T, Sertbaş S, Akca E. Industry 4.0 application on diagnosis prediction of construction machinery: A new model approach. Civ Eng Architecture 2020;8:404–16. https://doi.org/10.13189/cea.2020.080402.
[126] Proto S, Di Corso E, apiletti D, Cagliero L, Cerquitelli T, Malnati G, et al. REDTag: a predictive maintenance framework for parcel delivery services. IEEE Access 2020;8:14953–64. https://doi.org/10.1109/aCCESS.2020.2966568.
[127] Sahal R, Breslin JG, Ali MI. Big data and stream processing platforms for Industry 4.0 requirements mapping for a predictive maintenance use case. J Manuf Syst 2020;54:138–51. https://doi.org/10.1016/j.jmsy.2019.11.004.
[128] Allah Bukhsh Z, Saeed A, Stipanovic I, Doree AG. Predictive maintenance using tree-based classification techniques: A case of railway switches. Transp Res Part C Emerg Technol 2019;101:35–54. https://doi.org/10.1016/j.trc.2019.02.001.
[129] Jauregui-Correa JC, Morales-Velazquez L, Otremba F, Hurtado-Hurtado G. Method for predicting dynamic loads for a health monitoring system for subway tracks. Front Mech Eng 2022;8. https://doi.org/10.3389/fmech.2022.858424.
[130] Karakose M, Yaman O. Complex fuzzy system based predictive maintenance approach in railways. IEEE Trans Industr Inform 2020;16:6023–32. https://doi.org/10.1109/TII.2020.2973231.
[131] Chen H, Hsu J-Y, Hsieh J-Y, Hsu H-Y, Chang C-H, Lin Y-J. Predictive maintenance of abnormal wind turbine events by using machine learning based on condition monitoring for anomaly detection. J Mech Sci Technol 2021;35:5323–33. https://doi.org/10.1007/s12206-021-1105-z.
[132] Peng J, Kimmig A, Niu Z, Wang J, Liu X, Wang D, et al. Wind turbine failure prediction and health assessment based on adaptive maximum mean discrepancy. Int J Electr Power Energy Syst 2022;134. https://doi.org/10.1016/j.ijepes.2021.107391.
[133] Tutivén C, Vidal Y, Insuasty A, Campoverde-Vilela L, Achicanoy W. Early fault diagnosis strategy for WT main bearings based on SCADA data and one-class SVM. Energies 2022;15. https://doi.org/10.3390/en15124381.
[134] Lalik C.:, Atorek K.; W.. Predictive Maintenance Neural Control Algorithm for Defect Detection of the Power Plants Rotating Machines Using Augmented Reality Goggles 2021. https://doi.org/10.3390/en.
[135] Li N, Xu P, Lei Y, Cai X, Kong D. A self-data-driven method for remaining useful life prediction of wind turbines considering continuously varying speeds. Mech Syst Signal Process 2022;165:108315. https://doi.org/10.1016/j.ymssp.2021.108315.
[136] Hsu MH, Zhuang ZY. An intelligent detection logic for fan-blade damage to wind turbines based on mounted-accelerometer data. Buildings 2022;12. https://doi.org/10.3390/buildings12101588.
[137] Nordal H, El-Thalji I. Assessing the technical specifications of predictive maintenance:a case study of centrifugal compressor. Appl Sci 2021;11:1–17. https://doi.org/10.3390/app11041527.
[138] Barrera JM, Reina A, Mate A, Trujillo JC. Fault detection and diagnosis for industrial processes based on clustering and autoencoders: a case of gas turbines. Int J Mach Learn Cybern 2022;13:3113–29. https://doi.org/10.1007/s13042-022-01583-x.
[139] Arena S, Manca G, Murru S, Orrù PF, Perna R, Reforgiato Recupero D. Data science application for failure data management and failure prediction in the oil and gas industry: a case study. Appl Sci 2022;12. https://doi.org/10.3390/app122010617.
[140] Sarma GS, Reddy BR, Nirgude P, Naidu PV. A long short-term memory based prediction model for transformer fault diagnosis using dissolved gas analysis with digital twin technology. Int J Power Electro Drive Syst 2022;13:1266–76. https://doi.org/10.11591/ijpeds.v13.i2.pp1266-1276.
[141] Langone R, Cuzzocrea A, Skantzos N. Interpretable anomaly prediction: predicting anomalous behavior in industry 4.0 settings via regularized logistic regression tools. Data Knowl Eng 2020;130:101850. https://doi.org/10.1016/j.datak.2020.101850.
[142] Garmaroodi MSS, Farivar F, Haghighi MS, Shoorehdeli MA, Jolfaei A. Detection of anomalies in industrial iot systems by data mining: study of CHRIST osmotron water purification system. IEEE Internet Things J 2021;8:10280–7. https://doi.org/10.1109/JIOT.2020.3034311.
[143] Natanael D, Sutanto H. Machine learning application using cost-effective components for predictive maintenance in industry: a tube filling machine case study. J Manuf Mater Process 2022;6. https://doi.org/10.3390/jmmp6050108.
[144] V. Kapp, M.C. May, G. Lanza, Pattern Recognition in Multivariate Time Series Towards an Automated Event Detection Method for Smart Manufacturing Systems 2020.
[145] Javier Maseda F, López I, Martija I, Alkorta P, Garrido AJ, Garrido I. Sensors data analysis in supervisory control and data acquisition (Scada) systems to foresee failures with an undetermined origin. Sensors 2021;21. https://doi.org/10.3390/s21082762.
[146] Mawle PP, Dhomane GA, Burade PG. Application of artificial intelligence in early fault detection of transmission line-a case study in India. Int J Electr Comput Eng 2022;12:5707–16. https://doi.org/10.11591/ijece.v12i6.pp5707-5716.
[147] Mourabit Y el, Habouz Y el, Zougagh H, Wadiai Y. Predictive system of semiconductor failures based on machine learning approach. Int J Adv Comput Sci Appl 2020;11:199–203. https://doi.org/10.14569/IJACSA.2020.0111225.
[148] Dorogush A.V., Ershov V., Gulin A. CatBoost: gradient boosting with categorical features support. ArXiv 2018;abs/1810.11363.
[149] Guo J, Liu C, Cao J, Jiang D. Damage identification of wind turbine blades with deep convolutional neural networks. Renew Energy 2021;174:122–33. https://doi.org/10.1016/j.renene.2021.04.040.
[150] Sherstinsky A. Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. Physica D 2020;404. https://doi.org/10.1016/j.physd.2019.132306.
[151] Zerveas G, Jayaraman S, Patel D, Bhamidipaty A, Eickhoff C. A Transformer-Based Framework for Multivariate Time Series Representation Learning. Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining. New York, NY, USA: Association for Computing Machinery,; 2021. p. 2114–24. https://doi.org/10.1145/3447548.3467401.
[152] Kavasidis I, Lallas E, Gerogiannis VC, Charitou T, Karageorgos A. Predictive maintenance in pharmaceutical manufacturing lines using deep transformers. Procedia Comput Sci, vol. 220. Elsevier B.V,; 2023. p. 576–83. https://doi.org/10.1016/j.procs.2023.03.073.
[153] Glawar R, Ansari F, Kardos C, Matyas K, Sihn W. Conceptual design of an integrated autonomous production control model in association with a prescriptive maintenance model (prima). Procedia CIRP, vol. 80. Elsevier B.V,; 2019. p. 482–7. https://doi.org/10.1016/j.procir.2019.01.047.
[154] Alfeo AL, Cimino MGCA, Vaglini G. Technological troubleshooting based on sentence embedding with deep transformers. J Intell Manuf 2021;32:1699–710. https://doi.org/10.1007/s10845-021-01797-w.
[155] Kulkarni A, Shivananda A. Natural Language Processing Recipes. Apress; 2019. https://doi.org/10.1007/978-1-4842-4267-4.
[156] Hiruta T, Uchida T, Yuda S, Umeda Y. A design method of data analytics process for condition based maintenance. CIRP Annals 2019;68:145–8. https://doi.org/10.1016/j.cirp.2019.04.049.
[157] Ansari F, Kohl L, Giner J, Meier H. Text mining for AI enhanced failure detection and availability optimization in production systems. CIRP Annals 2021;70:373–6. https://doi.org/10.1016/j.cirp.2021.04.045.
[158] Navinchandran M, Sharp ME, Brundage MP, Sexton TB. Discovering critical KPI factors from natural language in maintenance work orders. J Intell Manuf 2022;33:1859–77. https://doi.org/10.1007/s10845-021-01772-5.
[159] May MC, Neidhöfer J, Körner T, Schäfer L, Lanza G. Applying Natural Language Processing in Manufacturing. Procedia CIRP, vol. 115. Elsevier B.V.,; 2022. p. 184–9. https://doi.org/10.1016/j.procir.2022.10.071.
[160] Öztürk E, Solak A, Bäcker D, Weiss L, Wegener K. Analysis and relevance of service reports to extend predictive maintenance of large-scale plants. Procedia CIRP, vol. 107. Elsevier B.V.,; 2022. p. 1551–8. https://doi.org/10.1016/j.procir.2022.05.190.
[161] Öztürk E, Solak A, Bäcker D, Weiss L, Wegener K. Analysis and relevance of service reports to extend predictive maintenance of large-scale plants. Procedia CIRP, vol. 107. Elsevier B.V,; 2022. p. 1551–8. https://doi.org/10.1016/j.procir.2022.05.190.
[162] Addepalli S, Namoano B, Oyedeji OA, Farsi M, Erkoyuncu JA. Designing a semantic based common taxonomy of mechanical component degradation to enable maintenance digitalisation. Procedia CIRP, vol. 119. Elsevier B.V.,; 2023. p. 508–13. https://doi.org/10.1016/j.procir.2023.04.008.
[163] Jing X, Wu Z, Zhang L, Li Z, Mu D. Electrical fault diagnosis from text data: a supervised sentence embedding combined with imbalanced classification. IEEE Trans Ind Electron 2023. https://doi.org/10.1109/TIE.2023.3269463.
[164] Grevenitis K, Psarommatis F, Reina A, Xu W, Tourkogiorgis I, Milenkovic J, et al. A hybrid framework for industrial data storage and exploitation. Procedia CIRP, vol. 81. Elsevier B.V.; 2019. p. 892–7. https://doi.org/10.1016/j.procir.2019.03.221.
[165] Rahman U, Mahbub MU. Application of classification models on maintenance records through text mining approach in industrial environment. J Qual Maint Eng 2023;29:203–19. https://doi.org/10.1108/JQME-08-2021-0064.
[166] F. Ansari R. Glawar W. Sihn Prescriptive Maintenance of CPPS by Integrating Multimodal Data with Dynamic Bayesian Networks 2020 doi: 10.1007/978-3-662-59084-3_1.
[167] Schenkelberg K, Seidenberg U, Ansari F. Analyzing the impact of maintenance on profitability using dynamic Bayesian networks. Procedia CIRP, vol. 88. Elsevier B.V.; 2020. p. 42–7. https://doi.org/10.1016/j.procir.2020.05.008.
[168] Ansari F, Kohl L, Sihn W. A competence-based planning methodology for optimizing human resource allocation in industrial maintenance. CIRP Annals 2023;72:389–92. https://doi.org/10.1016/j.cirp.2023.04.050.
[169] Matyas K, Nemeth T, Kovacs K, Glawar R. A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. CIRP Ann Manuf Technol 2017;66:461–4. https://doi.org/10.1016/j.cirp.2017.04.007.
[170] Biebl F, Glawar R, Jalali A, Ansari F, Haslhofer B, De Boer P, et al. A conceptual model to enable prescriptive maintenance for etching equipment in semiconductor manufacturing. Procedia CIRP, vol. 88. Elsevier B.V.,; 2020. p. 64–9. https://doi.org/10.1016/j.procir.2020.05.012.
[171] Padovano A, Longo F, Nicoletti L, Gazzaneo L, Chiurco A, Talarico S. A prescriptive maintenance system for intelligent production planning and control in a smart cyber-physical production line. Procedia CIRP, vol. 104. Elsevier B.V.,; 2021. p. 1819–24. https://doi.org/10.1016/j.procir.2021.11.307.
[172] Lee C, Lim C. From technological development to social advance: A review of Industry 4.0 through machine learning. Technol Forecast Soc Change 2021;167:120653. https://doi.org/10.1016/j.techfore.2021.120653.