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Predictive Maintenance Approaches: A Systematic Literature Review

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Abstract:

Purpose: Predictive Maintenance (PdM) aims to optimize maintenance operations by detecting operational anomalies and potential equipment failures before they lead to costly unplanned downtime. The goal is to minimize reactive maintenance and reduce the frequency of preventive maintenance interventions. This paper evaluates PdM strategies using knowledge-based, physics-based, and data-driven models to propose an integrated approach that enhances prediction accuracy, aligning with Industry 4.0 goals.

Design/methodology/approach: A Systematic Literature Review (SLR) is conducted to examine the strengths and weaknesses of knowledge-based, physics-based, and data-driven models in predictive maintenance. The study assesses existing research, compares methodologies, and identifies opportunities for integrating these models to improve PdM outcomes.

Findings: The review indicates that no single approach —whether knowledge-based, physics-based, or data-driven— is sufficient to meet the comprehensive demands of predictive maintenance. Instead, an integrated approach that combines these three models provides more accurate and cost-effective maintenance solutions, supporting the automation and efficiency goals of Industry 4.0.

Research limitations/implications: The study's findings are limited by the availability of real-world data and case studies. Future research should focus on testing the proposed integrated model in diverse industrial contexts to validate its effectiveness across different sectors.

Practical implications: The proposed approach offers industries a more reliable framework for optimizing maintenance strategies, improving operational efficiency, and reducing costs associated with equipment failures and excessive preventive measures.

Social implications: By enhancing predictive maintenance, the integrated model supports sustainability efforts by reducing waste, improving resource utilization, and contributing to the longevity of machinery and equipment.

Originality/value: This research offers a novel contribution by integrating knowledge-based, physics-based, and data-driven models into a unified PdM approach. It provides valuable insights for both academia and industry, especially in the context of Industry 4.0.

Keywords: predictive maintenance, data-driven models, physics-based models, knowledge-based models, industry 4.0

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1. Introduction

In addition to causing a loss of production, a malfunction in industrial equipment can also result in delayed customer services, safety issues, and environmental concerns. This highlights how important maintenance is to an organization's manufacturing processes. Maintaining production facilities' levels of availability and dependability, product quality, etc., depends heavily on maintenance (Van-Tung & Yang, 2009).

With its major effects on prices and dependability, maintenance is an essential industrial activity that significantly affects the capacity of an enterprise to compete in terms of performance, quality, and low cost. Any unscheduled downtime of machinery, equipment, or devices would impair or interrupt a business's primary operations, possibly leading to severe fines and irreversible damage to the company's reputation. For example, in 2013, Amazon lost $4 million in sales due to just 49 minutes of downtime. Data center outages cost businesses $138,000 an hour on average, according to a Ponemon Institute market analysis. Additionally, it is stated that the expenses associated with Operation and Maintenance (O&M) for offshore wind turbines range from 20% to 35% of the entire revenue generated by the power generated, while the expenses associated with maintenance in the oil and gas business range from 15% to 70% of the overall cost of production. Thus, in order to minimize unplanned outages, increase overall reliability, and save operating expenses, businesses must create a well-executed and effective maintenance plan (Ran, Zhou, Lin, Wen, & Deng, 2019).

Digitalized maintenance activities in manufacturing facilities have been expedited by Industry 4.0 applications, particularly by the increasing volumes of heterogeneous data generated throughout the production process (Mallioris, Aivazidou & Bechtsis, 2024). Technological developments in data analytics and data-driven models are driving the transition of industries from traditional preventive maintenance (PM) to predictive maintenance (PdM). Large volumes of sensor data are produced by modern production systems, allowing for continuous equipment monitoring. PdM employs real-time data to anticipate problems and optimize maintenance, cutting costs and downtime, in contrast to PM, which depends on scheduled chores. Data-driven algorithms anticipate the equipment's remaining useful life (RUL) and identify anomalies by analyzing intricate data patterns. Asset management is revolutionized by this data-driven strategy, which improves operational performance, efficiency, and dependability (Achouch, Dimitrova, Ziane, Sattarpanah-Karganroudi, Dhouib, Ibrahim et al., 2022).

Accurate predictive maintenance outcomes require the integration of data-driven models with knowledge- and physics-based models. Using enormous volumes of historical data and machine learning techniques, data-driven models are excellent at finding trends and forecasting failures. On the other hand, scenarios with insufficient data or those with new failure modes may provide challenges for them. By providing insights into the underlying mechanisms of wear and failure, physics-based models —which are based on the fundamental principles of how machines and components physically behave— offer predictive potential even in situations where data is scant. Knowledge-based models can fill in gaps by combining real-world experience and contextual awareness, as they are derived from expert domain knowledge and established criteria. Predictive maintenance systems can benefit from the strengths of each of these approaches by combining them: knowledge-based models' contextual relevance, data-driven models' adaptability and scalability, and physics-based models' fundamental accuracy. This will ultimately result in more robust and reliable predictions.

Despite the growing body of literature on predictive maintenance, existing reviews often focus narrowly on specific approaches, such as purely data-driven techniques or prognostics, without offering an integrated perspective that systematically compares and synthesizes the full range of methodologies. Moreover, few studies highlight the critical need to integrate heterogeneous approaches —data-driven, physics-based, and knowledge-based— into unified frameworks capable of addressing real-world industrial challenges. This lack of a comprehensive, comparative synthesis represents a gap in the literature that this paper aims to address.

Our work makes several contributions to the field. First, we provide a systematic comparison of knowledge-based, physics-based, and data-driven models, highlighting their respective strengths, limitations, and complementarities in predictive maintenance applications. Second, our analysis identifies current implementation challenges and future research directions that can guide both academic research and industrial practice in developing more effective predictive maintenance solutions. Third, we propose a novel hybrid architecture that integrates these three approaches to enhance prediction accuracy, interpretability, and robustness.

This paper aims to perform a thorough evaluation of the predictive maintenance literature, the current state of the art for models used in prognostics and diagnostics, current research roadblocks, and future research opportunities. Thanks to quickly developing technologies like Industry 4.0, predictive maintenance is being employed more frequently, and interest in the topic is only rising. The majority of current reviews focus on specific subjects, like prognostics and data-driven models. This motivates an annual update of the reviews due to the hundreds of publications published on the topic (Achouch et al., 2022).

The structure of our work is as follows: In the Methodology section, we explain the approach used to obtain our study results. The Predictive Maintenance section provides the scientific community with an in-depth exploration of predictive maintenance, including its various approaches and strategies. Following that, we begin our Scientific Literature Review by addressing the questions we have identified for this research. We then propose a new approach. Finally, we conclude with a discussion and conclusion section.

2. Methodology

The approach used to do the literature review is based on (Lame, 2019) and is a systematic approach with the goal of providing an overview of the body of work that has already been done on a particular subject. For the sake of getting a deeper understanding of the issue under research, systematic literature review aids in carrying out the literature review process in an organized manner. The definition of the research questions, the search technique, the study selection, and the data synthesis are the four essential components of the protocol for a systematic literature review. The following are the research questions:

- RQ1: What are predictive maintenance fields of application and the type of used approaches?
- RQ2: What are the different models applied in predictive maintenance and their perspective?
- RQ3. What are the data used to apply PdM?
- RQ4: Which type of approaches are the most optimal to respond to predictive maintenance goals?
- RQ5: What are the current challenges facing predictive maintenance?

These 5 questions are the fruit of conducting a preliminary scoping review of PdM literature published between 2018 and 2024 and analyzing conceptual frameworks, we identified recurring themes and methodological gaps. This analysis guided the formulation of five structured research questions to explore:

- RQ1: application domains and used approaches, reflecting gaps identified.
- RQ2: variety of predictive maintenance models (statistical, machine learning, hybrid, digital twin).
- RQ3: types of input data deployed in PdM.
- RQ4: comparative evaluation of approach effectiveness (e.g., ML vs. hybrid vs. physics-based).
- RQ5: current challenges PdM is facing.

Important databases like IEEE Xplore, ScienceDirect, Springer, and Google Scholar were searched, the choice of aforementioned databases was based on our university access and the selection of studies was based on predetermined research topics. Then, we used these specific keyword strings: ("Predictive Maintenance" OR "PdM") AND ("Data-driven Based Models"), ("predictive maintenance" OR "PdM") AND ("Knowledge-Based Models"), ("predictive maintenance" OR "PdM") AND ("Physics-Based Models"), ("predictive maintenance" OR "PdM") AND ("Artificial Intelligence"), the main objective was to obtain relevant results in relation to the scope of our manuscript.

Key words used: Predictive Maintenance, Data-driven Based Models, Knowledge-Based Models, Physics-Based Models, Artificial Intelligence.

In our Systematic Literature Review (SLR), we carefully curated research articles published between 2018 and 2024, applying rigorous selection criteria to ensure relevance and focus. We systematically excluded works that fell outside our research scope, specifically eliminating studies unrelated to Predictive Maintenance (PdM), publications predating 2018, and papers that did not address the three specific models central to our investigation or provide a comprehensive review of PdM.

Regarding inclusion criteria, we have selected all scholarly articles published between 2018 and 2024 that specifically explore the three primary Predictive Maintenance (PdM) methodological approaches: Data-driven models, Knowledge-based models, and Physics-based models, along with comprehensive review articles that provide an in-depth examination of the Predictive Maintenance domain and its prevalent analytical strategies.

We had to go through multiple procedures in order to collect paper references for our review analysis because the process of acquiring findings was not simple. First, 405 items were found. Subsequently, we proceeded to the screening stage, eliminating papers that lacked relevance to our subject matter or failed to present noteworthy or significant scientific findings. Additionally, we divided the remaining articles into review and application categories. As a result, the final count for our analysis was 68 included publications. All these steps are shown just later in Figure 1.

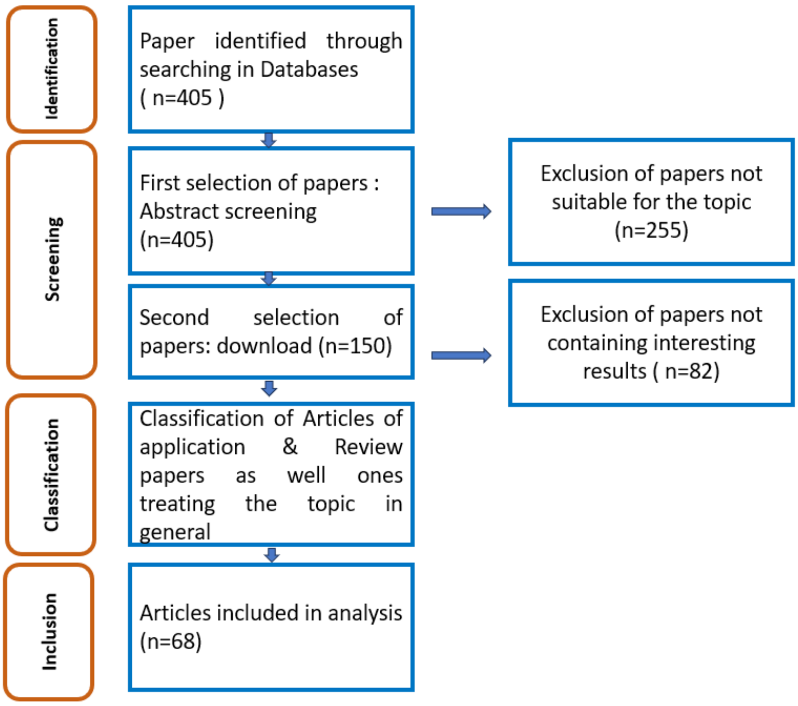

Figure 1. Process of getting articles

3. Predictive Maintenance

Three terminologies are typically used in maintenance methods to trigger maintenance actions: corrective maintenance, preventive maintenance, and predictive maintenance, with the addition of prescriptive maintenance recently. Corrective maintenance initiates maintenance actions following the breakdown of a component or system. Preventive maintenance employs time periods such as cycles, kilometers, flights, and so on to determine the best time to initiate maintenance procedures. According to (Kothamasu, Huangn & VerDuin, 2006) the presence of defects in preventive maintenance is frequently undetected. This could result in the expensive replacement of components that still have life left in them. One way to think of PdM is as a maintenance approach that tries to pinpoint the precise moment to start performing actual maintenance. By altering components with a significant

Remaining Useful Life (RUL), too early treatments could be a waste of money, while too late interventions could result in disastrous failures. Predictive maintenance is an approach that works in tandem with corrective and preventative maintenance. The foundation of PdM is the application of specialized methods and instruments to detect malfunctions in technical systems and estimate the remaining usable life of those systems. To achieve an effective maintenance management system, a mix of the three methodologies is required (Ran et al., 2019). The different types of PdM are well categorized in Figure 2.

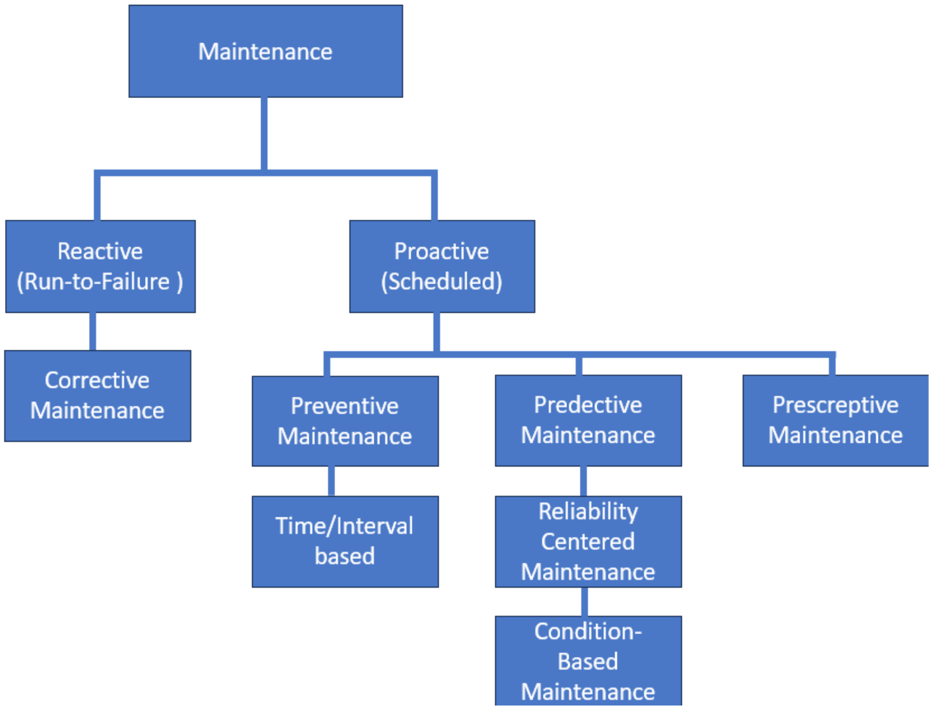

Figure 2. Different maintenance strategies (Shukla, Nefti-Meziani & Davis, 2022)

Within the context of Industry 4.0, prognosis pertains to estimating a machine's remaining useful life (RUL) by forecasting the predicted state of degradation of the machine or its components. Prognostics is viewed as a crucial service in the field of maintenance in the modern industry since it makes it possible to schedule actions, both short- and long-term, based on model projections that establish the RUL. Within this context, the literature discusses many methodologies, including knowledge-based, physics-based, and data-driven models. In order to handle more complicated situations, knowledge-based and physics-based models are frequently integrated with data-driven models, which may make use of statistical or machine learning techniques (Nunes, Santos & Rocha, 2023). These hybrid approaches can occasionally produce significant outcomes. In the literature, hybrid model-based predictive maintenance tasks are divided into series and parallel techniques. A hybrid model-based strategy combines physics-based and data-driven prognostics approaches in an effort to capitalize on the advantages from both categories. A physical model is first employed in a series method to establish prior knowledge about the manufacturing process under observation. Conversely, data-driven techniques capture unmeasured process factors by acting like a state estimator. When fresh data becomes available, data-driven approaches are used as an online parameter estimate methodology to continuously update the model parameters. A parallel strategy predicts residuals not explained by first principal models by leveraging the powerful computing power of data-driven models. To merge the results of physical model-based and data-driven methodologies, the majority of literature work use a fusion procedure (Cao, Zanni-Merk, Samet, Reich, De-Beuvron, Beckmann et al., 2022).

Figure 3 represents the different approaches used to attain Predictive Maintenance objectives. The term "Industry 4.0" refers to a wide range of data technology developments in the manufacturing sector, with a particular emphasis on the Internet of Things (IoT) and cyber-physical systems. These technologies are being utilized to collect information from a wide range of sources, including machines, gadgets, outside sensors, vision-based systems, and even people. Industry 4.0's smart factories use edge and/or cloud computing systems to view and analyze the acquired data to monitor physical processes, simulate the real environment, and make decentralized choices. Over the IoT, real-time communication and coordination between the cyber-physical systems and humans is possible. Machine and Deep learning are a data-driven techniques which can also be used to analyze the obtained data in order to automatically detect process and product fingerprints, improving production systems and guaranteeing that made parts meet the specified criteria (Farahani, Khade, Basu & Pilla, 2022).

As anomaly detection methods, data-driven approaches can be divided into two categories: statistical and machine learning. Numerous statistical models and methods are used to analyze PdM in the literature, including hidden Markov models (HMM), Wiener process models (WPM), gamma process models, proportional hazards models, and autoregressive-moving-average (ARMA) models. Among other things, ML approaches include ANN and its variants, support vector machines (SVM), random forests (RF), xGBoost, and self-organized maps (SOM) (Nunes, Santos et al., 2023).

The traditional machine learning methods have dimensionality and expressiveness problems. Deep learning methods have been created to extract structured data from data sets utilizing layered machine learning algorithms in order to address this issue. The industrial sector has profited over the past few decades from deep learning's rapid development and expansion. Manufacturing systems now operate more productively, efficiently, and reliably thanks to these deep learning techniques. Artificial neural networks (ANN) and deep neural networks (DNN) are the most traditional and often used deep learning models (Cao et al., 2022).

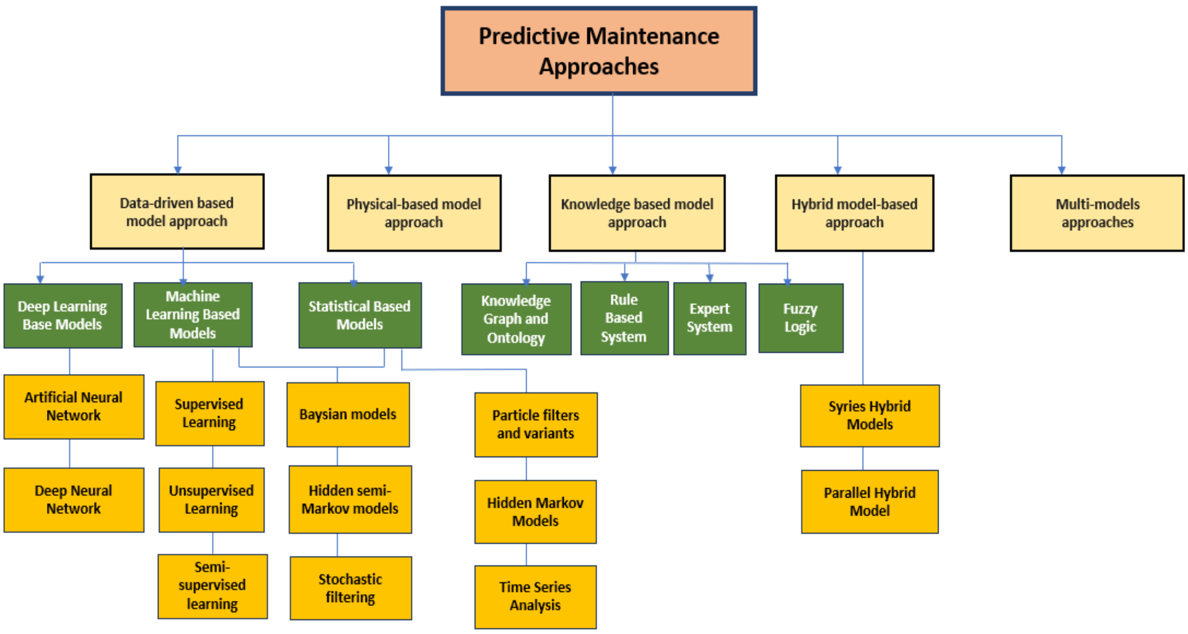

Figure 3. Different Predictive Maintenance Approaches (Cao et al., 2022)

Physics-based methods utilize mathematical models to describe physical processes that directly or indirectly affect how well equipment works. Physical models are widely utilized to characterize fatigue and fracture propagation in mechanical and structural components because they have been well studied in the literature. Similar to knowledge-based models, these techniques are domain-specific and need a thorough grasp of mathematics in addition to knowledge of the actual behavior of the parts of machinery. Additionally, they are expensive, time-consuming, and often deficient for most of the components (Nunes, Santos et al., 2023).

In practical engineering applications, it is typically challenging to generate precise mathematical models of the system being observed, which restricts the use of model-based prognostic techniques. Knowledge-based techniques are more promising than model-based ones because they don't need any models. Expert systems and fuzzy logic are two common examples of knowledge-based techniques among them (Hao, Jinsong, Ping & Xingshan, 2009).

A hybrid model-based approach combines physics-based and data-driven prognostics methods to take advantage of the best features of each group. A hybrid model-based predictive maintenance task can be categorized into series and parallel techniques in the literature (Cao et al., 2022).

The term "hybrid model" is associated with multi-model approaches. After knowledge-based, data-driven, and physics-based models, hybrid models are the fourth category of model types. There are numerous multi-model approaches, albeit they aren't usually classified as hybrid. The idea of a hybrid model evolves as one reads through the different texts. Following a thorough examination, it was determined that hybrid models are a kind of multi-model method in which two or more models are merged to fulfill a single predictive maintenance system functional requirement. To generate their outputs, the coupled models collaborate (Jimenez, Schwartz, Vingerhoeds, Grabot, & Salaün, 2020).

Predictive maintenance projects are designed using a life cycle that includes five essential elements (Achouch et al., 2022) The life cycle and workflow of a predictive maintenance project are shown in Figure 4:

Step 1: Determine the project's requirements:

Understanding the business aspects of the project, its challenges, and the obstacles that need to be overcome is the first step. This step requires a thorough understanding of the equipment and system that will be utilized to finish the project, as well as how they work. This includes choosing sensors, defining the actual quantities to be measured, and, if required, installing them. We also need to outline the many kinds of failures that could happen throughout this time.

Step 2: Data gathering, comprehension preparing:

The gathering of data Data can be collected by device sensors and stored in a database. Understanding entails selecting which data to analyze, assessing the quality of the data that is available, and connecting it to its meaning. Preparation includes things like identifying similar data, combining data through mixing datasets, cleaning and managing missing values by removing them or inputting them with related data, and managing inaccurate data by eliminating errors.

Step 3: Modeling the data:

Data modeling is widely acknowledged as the core of data analysis. The model generates the necessary output using the data that was generated in the preceding step (data preparation) as input. This step entails selecting the optimal algorithm for a clustering, regression, or classification problem. To create a model, a number of approaches are evaluated and parameterized.

Step 4: Evaluation and implementation:

A system Assessment: Lastly, we need to assess the model's relevance (does it answer the initial question?) and correctness (how effectively it functions, i.e., does it accurately reflect the facts). Additionally, we need to make sure that performance and generalization are well-balanced, which calls for a model that is both impartial and broadly applicable.

Deploy the model as follows: Finally, the evaluated model is supplied in the format and channel of choice. In the predictive maintenance life cycle, this is the final data-related stage.

Step 5: Making a decision:

The decision-making process, in general, aids operators in problem resolution by selecting the optimal course of action. A step-by-step plan is an excellent method for making meaningful, educated decisions that serve both short- and long-term objectives.

The first step is to make a decision. Recognizing the issue is the first step toward making the right decision. Various intervention scenarios with related repair times and prices of predictive maintenance are generated in this step, allowing us to improve future interventions.

Second Step: Actions: After identifying the potential scenarios, we select or combine them in order to discover the one with the lowest costs and delays. The repair days are determined by the availability of manpower and spare parts.

Step 3: Review: Because the predictive maintenance life cycle is recurring, this stage is crucial because it allows us to examine the efficacy of our decision.

Figure 4. Predictive Maintenance Workflow (Achouch et al., 2022)

4. Systematic Literature Review Results

The first step of our work as earlier mentioned was based on several articles starting from 2018 to 2024. This time frame was selected for this Systematic Literature Review to ensure the inclusion of recent and relevant studies that reflect the latest advancements in predictive maintenance, particularly the integration of hybrid approaches combining data-driven, physics-based, and knowledge-based models. This period captures the surge in Industry 4.0 adoption and provides a focused analysis of modern, high-impact research aligned with current industrial and scientific practices. Articles found based on our SLR review are articles treating Predictive maintenance topic, whereas other ones represent a specific application of Predictive Maintenance in Industry 4.0.

Figure 5 reveals a clear upward trajectory in research publications related to the topic, demonstrating significant growth from a single publication in 2018 to 14 publications by 2023, with continued strong presence in 2024. This seven-fold increase over the period suggests rapidly growing academic interest in the field. ELSEVIER emerges as the dominant publication platform, showing consistent growth and accounting for approximately 60% of all publications by 2022-2024. Google Scholar maintains a steady secondary presence with consistent contribution of 3-4 publications annually since 2019. The data indicates a potential research acceleration point in 2022, where publication numbers nearly doubled from the previous year. This inflection point could signal a critical mass of interest being reached or possibly reflects responses to industry developments during this period. The relatively minor contributions from IEEE and Springer suggest the research may be more aligned with disciplines typically published in ELSEVIER journals rather than those in engineering or computer science domains. This publication pattern analysis provides valuable context for understanding how research attention has evolved, potentially correlating with practical implementation or industry adoption of the concepts being studied.

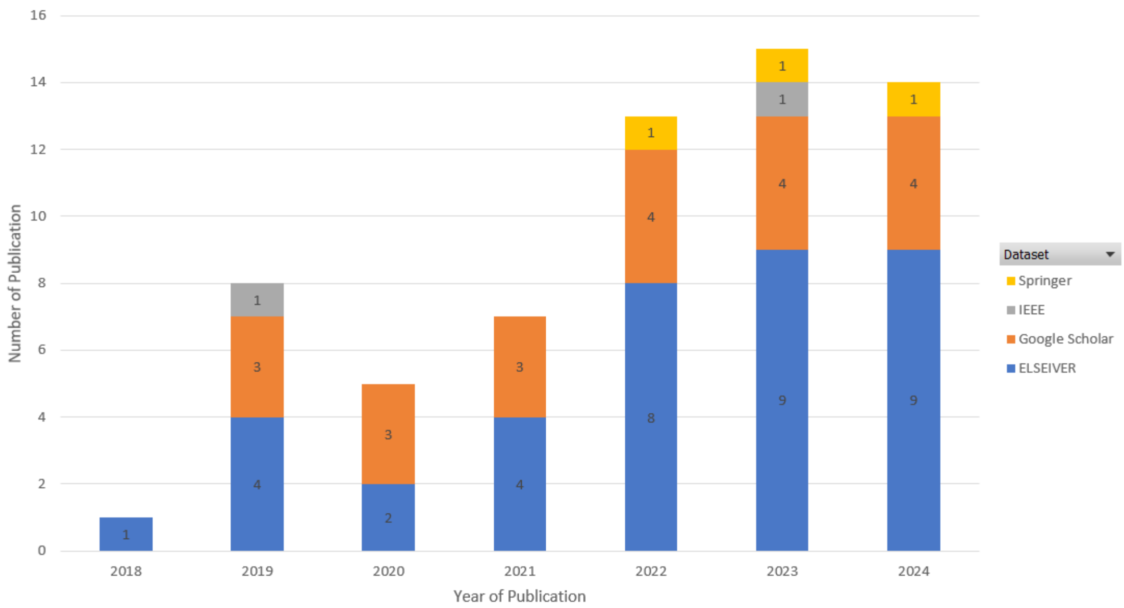

Figure 5. Number of Articles per year and databases based on our filter

While conducting our research we encountered some interesting review articles treating PdM whereas the other articles put a focus on a specific application related to one of PdM approaches, Table 1 gives an overview of all review articles mentioned in our review.

Article	Database	Description
Jimenez et al. (2020)	Elsevier	This systematic survey aims to present current trends in diagnosis and prognosis, with particular attention to multi-paradigm approaches, and to summarize current challenges and research opportunities. research related to predictive maintenance.
Nunes, Santos et al. (2023)	Elsevier	The primary challenges facing the creation of generalized data control systems for PdM are the existence of spurious or erroneous sensor data in an actual industrial setting and the requirement for fast data collection, transmission, and processing.
Van-Dinter, Tekinerdogan & Catal (2022)	Elsevier	In order to open the door for more research, this study gathers and synthesizes works that concentrate on predictive maintenance employing digital twins.
Es-Sakali, Cherkaoui, Mghazli & Naimi (2022)	Elsevier	The most common method for predicting future HVAC system failures is presented in this article along with an explanation of the benefits and limitations of the current algorithms for HVAC predictive maintenance application. This is accomplished through a thorough literature review of the topics.
Çınar, Abdussalam-Nuhu, Zeeshan, Korhan, Asmael & Safaei (2020)	Google Scholar	This paper attempts to provide a comprehensive review of the recent advancements of ML techniques widely applied to PdM for smart manufacturing in I4.0 by classifying the research according to the ML algorithms, ML category, machinery and equipment used, device used in data acquisition, classification of data, size and type, and highlighting the major contributions of the researchers.
Ran et al. (2019)	IEEE	They provide a thorough assessment of DL-based approaches while doing a brief review of knowledge-based and traditional ML-based approaches used in various industrial systems or components.

Article	Database	Description
Zonta, da-Costa, da-Rosa-Righi, de-Lima, da-Trindade & Li (2020)	Elsevier	This survey examines the current challenges and limitations in predictive maintenance and proposes a new taxonomy to classify this area of research in accordance with Industry 4.0 specifications. They concluded that computer science, particularly the areas of distributed computing and artificial intelligence, is becoming more prevalent in an area where engineering used to be the primary area of competence in order to properly meet Industry 4.0.
Wen, Rahman, Xu & Tseng (2022)	Elsevier	To aid researchers and practitioners in developing a thorough understanding of the field, this review's main goals are to categorize the body of existing literature and report on the most recent research developments and directions. The basic methodologies for data-driven approaches to predictive maintenance are initially summarized in this study. The paper then performs a thorough analysis into the many domains in which machine prognostics is used. To wrap up this work, a review of the difficulties, possibilities, and potential directions of predictive maintenance is provided.
Carvalho, Soares, Vita, Francisco, Basto & Alcalá (2019)	Elsevier	The purpose of this work is to give a thorough literature review of ML approaches used to PdM, highlighting those that are being researched in this area and the effectiveness of the most advanced ML methods at the moment. This review, which is focused on two scientific databases, offers an important background on machine learning techniques, their key findings, obstacles, and prospects. It also promotes future research projects in the PdM sector.
Pech, Vrchota & Bednář (2021)	Google Scholar	The authors proposed Intelligent and Predictive Maintenance (SIPM) based on full-text assessments of relevant papers. The paper's primary contribution is a summary and overview of recent advancements in intelligent sensors, which are utilized in smart factories to do preventive maintenance.
Durbhaka (2021)	Google Scholar	This article will discuss wind turbine prognostics and diagnostics, machine learning approaches, determining interdependency within subsystems, and accessible digital solutions for suitable data handling in predictive maintenance plans.
Arena, Collotta, Luca, Ruggieri & Termine (2021)	Google Scholar	This study provides an organized assessment of the literature on statistical inference techniques, AI methods, and stochastic methods for predictive maintenance in the automobile industry. It summarizes these methods, highlights their key findings, discusses obstacles and possibilities, and encourages more studies on vehicle predictive maintenance.
Mallioris et al. (2024)	Elsevier	In order to offer tailored insights from academic and operational perspectives, the primary goal of this research is to thoroughly examine sophisticated predictive maintenance applications in a number of industrial sectors. A comparative decision support map is one of the results. To categorize predictive maintenance solutions by industrial sector, the research makes use of sophisticated software tools, applied algorithms, input characteristics, expected variables, assessment metrics, and standard methodology.
Andrianandrianina-Johanesa, Equeter & Mahmoudi (2024)	Google Scholar	This study examines current advancements in AI-driven predictive maintenance (PdM), emphasizing reliability, essential elements, and emerging patterns. It addresses the integration of AI in practical applications, human-robot interaction, ethical concerns, testing and validation, and state-of-the-art approaches, difficulties, and prospects. Prospective fields of study encompass digital twins, the metaverse, blockchain, trustworthy AI, generative AI, collaborative robotics, and the Industrial Internet of Things (IIoT).

Article	Database	Description
Arafat, Hossain & Alam (2024)	Elsevier	This work proposes future research directions for improving predictive maintenance in microgrid operations, focusing on machine learning approaches for real-time fault detection, component health monitoring, and sustainability, while also reviewing current techniques and identifying challenges.
Hector & Panjanathan (2024)	Google Scholar	This study examines statistical inference methodologies, stochastic methods, and AI techniques for predictive maintenance in the automobile industry, addressing their outcomes, obstacles, and prospects, and recommending further research in vehicle predictive maintenance.
Ucar, Karakose & Kırımça (2024)	Google Scholar	This paper explores AI-based Predictive Maintenance (PdM) techniques, challenges, and opportunities, focusing on real-world applications, human-robot interaction, ethical issues, and policy testing. It suggests potential areas for future research, including digital twins, metaverse, generative AI, and IIoT.
Hurtado, Salvati, Semola, Bosio & Lomonaco (2023)	Elsevier	Deep learning has revolutionized engineering, especially in Predictive Maintenance (PdM). Continual Learning (CL) helps models adapt to changing environments. However, real-world application remains challenging. This work reviews CL's current state, discusses challenges, and proposes future directions for improvement.
Azari, Flammini, Santini & Caporuscio (2023)	IEEE	The review defines transfer learning in predictive maintenance, discusses current advances, challenges, open-source datasets, and future directions from theoretical and practical perspectives
Tran, Sharma, & Nguyen (2023)	Google Scholar	This review article examines the application of digital twin technology in internal combustion engines (IC) to enhance real-time monitoring, diagnostics, and predictive modeling. This article examines how digital twins can improve innovation, creation, and efficiency, leading to increased reliability, lower downtime, and reduced emissions through case studies and innovations.

Table 1. Articles Review related to Predictive Maintenance Topic

While numerous review articles have explored Predictive Maintenance (PdM), as detailed in Table 1, most of them concentrate on a single dimension of the field whether it be data-driven techniques such as machine learning and deep learning (Çınar et al., 2020; Ran et al., 2019), domain-specific applications like HVAC or automotive (Es-Sakali et al., 2022; Arena et al., 2021), or emerging technologies like digital twins and continual learning (Van-Dinter et al., 2022; Hurtado et al., 2023). While these works offer valuable insights, there remains a notable gap in reviews that compare and integrate multiple paradigms of PdM. Our article addresses this gap by proposing novel hybrid architecture that brings together knowledge-based models, physics-based models, and data-driven models. This multi-perspective approach not only reflects the complexity of real-world industrial environments but also enables more robust, explainable, and context-aware predictive maintenance solutions. By bridging these traditionally distinct approaches, our work contributes a unique and integrative perspective that is currently lacking in literature.

Moreover, our article places strong emphasis on the integration of knowledge-based, physics-based, and data-driven models within a unified predictive maintenance framework. In addition to proposing hybrid architecture, we conduct a targeted review of how each of these three approaches has been applied individually and in combination across various PdM applications in the literature. This dual focus on both integration and application provides valuable insights into the strengths, limitations, and complementarities of each model type, serving as a practical reference for researchers and practitioners aiming to implement more comprehensive and intelligent maintenance strategies.

4.1. RQ1: What Are Predictive Maintenance Fields of Application and the Type of Approaches Used?

Now let's move on to have a look at the different applications of Predictive maintenance starting from 2019. Table 2 will give an overview that will permit future researchers to bear in mind all applications PdM try to solve in the context of Industry 4.0.

Article Title	Type of Article	Database	Field of Application	Type of Models used in article
Rosati, Romeo, Cecchini, Tonetto, Viti, Mancini et al. (2023)	Journal	Springer	Industry 4.0	Knowledge Based Models & Data-Driven Based Models
Cao et al. (2022)	Journal	Elsevier	Smart Manufacturing	Knowledge-Based Models
Werner, Zimmermann & Lentes (2019)	Conference	Elsevier	Production Machines	Physics Based Models
Aivaliotis, Arkouli, Georgoulias & Makris (2021)	Journal	Elsevier	Industrial robots	Physics Based Models
Aivaliotis, Georgoulias, Arkouli & Makris (2019)	Conference	Elsevier	Industrial robot	Physics Based Models
Zhong, Xia, Zhu & Duan, (2023)	Journal	Google Scholar	Manufacturing Industry	Physics Based Models
Kunzer, Berges & Dubrawski (2022)	Journal	Google Scholar	Manufacturing Industry	Physics Based Models and Data-Driven Based Models
Aivaliotis, Georgoulias & Chryssolouris (2019)	Journal	Google Scholar	Manufacturing Industry	Physics Based Models
Pagano (2023)	Journal	Elsevier	Manufacturing Industry	Data-Driven Based Models
Wang, Liu, Liu, Ling & Zhang (2023)	Journal	Elsevier	Industrial Robots	Data-Driven Based Models & Knowledge-Based Models
Farahani et al. (2022)	Journal	Elsevier	Manufacturing Industry	Data-Driven Based Models
Florian, Sgarbossa & Zennaro (2021)	Journal	Elsevier	Manufacturing Industry	Data-Driven Based Models
Torim, Liiv, Ounoughi & Yahia (2022)	Journal	Google Scholar	Manufacturing Industry	Data-Driven Based Models & Knowledge-Based Models
Massaro, Selicato & Galiano (2020)	Journal	Google Scholar	Monitoring of Bus Fleet	Data-Driven Based Models
Lee, Wu, Yun, Kim, Jun & Sutherland (2019)	Journal	Elsevier	Manufacturing Industry	Data-Driven Based Models
Nunes, Rocha, Santos & Antunes (2023)	Conference	Elsevier	Injection molds	Data-Driven Based Models
Lambán, Morella, Royo & Sánchez (2022)	Journal	Elsevier	Industry 4.0	Data-Driven Based Models
Abidi, Mohammed & Alkhalefah (2022)	Journal	Google Scholar	Manufacturing Industry	Data-Driven Based Models
Liu, Zhu, Tang, Nie, Zhou, Wang et al. (2022)	Journal	Elsevier	Manufacturing Industry	Data-Driven Based Models
Leohold, Engbers & Freitag (2021)	Conference	Elsevier	Manufacturing Industry	Data-Driven Based Models
Von-Birgelen, Buratti, Mager & Niggemann (2018)	Conference	Elsevier	Manufacturing Industry	Data-Driven Based Models
Abbas, Chasparis & Kelleher (2024)	Journal	Elsevier	Manufacturing Industry	Data-Driven Based Models
Lee & Mitici (2023)	Journal	Elsevier	Aircraft Maintenance	Data-Driven Based Models
Rodriguez, Marti-Puig, Caiafa, Serra-Serra, Cusidó & Solé-Casals (2023)	Journal	Google Scholar	Wind turbines	Data-Driven Based Models

Article Title	Type of Article	Database	Field of Application	Type of Models used in article
Mandala (2020)	Journal	Google Scholar	Automotive Industry	Data-Driven Based Models
Yıldız & Soylu (2023)	Journal	Elsevier	Manufacturing Industry	Physics Based Models & Data-Driven Based Models
De-Luca, Ferraro, Galli, Gallo, Moscato & Sperli (2023)	Journal	Google Scholar	Industry 4.0	Data-Driven Based Models
Zhuang, Xu & Wang (2023)	Journal	Elsevier	Aircraft Maintenance	Data-Driven Based Models
Arena, Florian, Sgarbossa, Sølvsberg & Zennaro (2024)	Journal	Elsevier	Industry 4.0	Data-Driven Based Models
Brahimi, Hadroug, Iratni, Hafaifa & Colak (2024)	Journal	Elsevier	Gas turbines	Data-Driven Based Models
Qureshi, Umar & Nawaz (2024)	Journal	Google Scholar	Solar Farms	Data-Driven Based Models
Wang, Zhu & Zhao (2024)	Journal	Elsevier	Aircraft Maintenance	Data-Driven Based Models
Giannoulidis, Gounaris, Naskos, Nikolaidis & Caljouw (2024)	Journal	Google Scholar	Manufacturing Industry	Data-Driven Based Models
Elkateb, Métwalli, Shendy & Abu-Elanien (2024)	Journal	Elsevier	Textile industry	Data-Driven Based Models
Meriem, Nora & Samir (2023)	Conference	Elsevier	Industry 4.0	Hybrid Approaches
Kamariotis, Tatsis, Chatzi, Goebel & Straub (2024)	Journal	Elsevier	Aircraft Maintenance	Data-Driven Based Models
Kavasidis, Lallas, Gerogiannis, Charitou & Karageorgos (2023)	Conference	Elsevier	Pharmaceutical Manufacturing	Data-Driven Based Models
Shoorkand, Nourelfath & Hajji (2024)	Journal	Elsevier	Manufacturing Industry	Data-Driven Based Models

Table 2. Predictive Maintenance Applications in Literature

Table 2 presents an overview of the various fields in which Predictive Maintenance has been applied since 2018. While the initial version of this table served a purely descriptive purpose, we now provide a structured grouping and an analytical discussion to enhance its value.

To better understand the landscape of PdM applications, we grouped the articles into the following categories:

- Manufacturing Industry: Most dominant field with over 20 articles, including Farahani et al. (2022), Liu et al. (2022), and Shoorkand et al. (2024). This reflects high PdM relevance due to complex machinery and production lines.
- Industrial Robots: Covered in Aivaliotis et al. (2021) and Wang et al. (2023), where precision and automation make predictive strategies essential.
- Aircraft Maintenance: Seen in Lee & Mitici (2023), Zhuang et al. (2023), Kamariotis et al. (2024), and Wang et al. (2024), indicating a growing focus on safety-critical applications.
- Industry 4.0: Includes Rosati et al. (2023), Lambán et al. (2022), and Arena et al. (2024). These works focus on PdM in highly digitized environments with IoT, big data, and automation.
- Other Specific Domains: Gas turbines (Brahimi et al., 2024), Solar farms (Qureshi et al., 2024), Textile industry (Elkateb et al., 2024), Automotive industry (Mandala, 2020), Pharmaceutical manufacturing (Kavasidis et al., 2023), Public transport fleet monitoring (Massaro et al., 2020).

This diversity shows that PdM is increasingly being adopted in both traditional industrial settings and more domain-specific applications.

We categorized the articles based on the modeling approach:

Approach Type	Number of Articles	Representative References
Data-Driven Models	26	Farahani et al. (2022), Abbas et al. (2024), Lee et al. (2019)
Physics-Based Models	5	Aivaliotis, Georgoulias, Arkouli et al. (2019), Zhong et al. (2023), Werner et al. (2019)
Knowledge-Based Models	1	Cao et al. (2022)
Hybrid Models (Two approaches)	5	Meriem et al. (2023)
Hybrid Approaches	1	Meriem et al. (2023)

Table 3. Types of Models Used in PdM Research and Notable References

Based on Table 3 it is evident that Data-Driven Models dominate the landscape. This trend aligns with the growing availability of sensor data, IoT systems, and machine learning tools.

Physics-Based Models are used in more structured and mechanical domains where physical laws are well understood (e.g., robotics, production systems).

Knowledge-Based Models appear less frequently, but are often used in combination with data-driven or physics-based models to leverage domain expertise.

Only one article explicitly proposed a hybrid architecture, though more such combinations are expected in the future as systems become more complex.

Summary and Interpretation:

- Dominant Field: Manufacturing remains the core domain for PdM research, reflecting its economic importance and operational complexity.
- Dominant Approach: Data-driven models are most frequently used, enabled by the explosion of industrial data.
- Emerging Trend: There is increasing interest in hybridizing approaches to overcome limitations of individual model types.
- Gap Identified: Few articles leverage fully integrated hybrid models (Data, Physics, Expert knowledge), indicating a promising research direction.

4.2. RQ2: What Are the Different Models Applied in Predictive Maintenance and their Perspective?

Predictive Maintenance calls for a variety of models and approaches to anticipate equipment breakdowns and enhance maintenance practices. This section highlights the range of approaches that have been used, focusing on their results and considering possible future directions in order to assess their potential for fostering innovation in PdM.

To address RQ2, we conducted a comprehensive literature review and presented a detailed summary Table 4 that captures a wide spectrum of predictive maintenance (PdM) approaches. These approaches were assessed and grouped into four primary categories, each representing a distinct modeling paradigm:

Regarding Data-Driven Models**,** this group comprises traditional machine learning and deep learning methods widely adopted in PdM:

- Machine Learning (ML): Algorithms such as Random Forest (RF), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Gradient Boosting, and Decision Trees are used for failure classification, Remaining Useful Life (RUL) prediction, and anomaly detection. These models often rely on labeled sensor data and feature engineering.

- Deep Learning (DL): More recent studies leverage Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Bi-LSTM, and Autoencoders to handle high-dimensional time-series data and learn patterns automatically.

Article	Approach Used	Results	Future work
Rosati et al. (2023)	Random Forest (RF)	By putting a real-world industrial use case that involves sophisticated processing and measuring equipment as its primary focus, this paper seeks to introduce and test a Decision Support System (DSS) for handling PdM tasks. Data gathering, feature extraction, predictive modeling, cloud storage, and data analysis are the main building blocks of the proposed DSS.	The authors plan to implement automated incremental learning, utilizing cloud-stored data to improve machine learning performance across various systems and processes.
Cao et al. (2022)	Chronicle Mining Rule Based	The study introduces KSPMI, a system for automating predictive maintenance in Industry 4.0 that uses a combination of statistical and symbolic AI. Machine learning and chronicle mining produce deterioration models, whereas domain ontologies and logic rules execute ontological reasoning. KSPMI detects irregularities and predicts future occurrences using SWRL rules and ontologies, which have been evaluated on synthetic and real-world data.	KSPMI's traditional ontological reasoning for failure prediction is insufficient for immediate decision-making in manufacturing. Stream reasoning, combining Semantic Web and CEP technologies, will replace it.
Werner et al. (2019)	Data-driven Models Digital Twin	This research proposes a predictive maintenance plan based on historical and simulated data. A structured process map assists firms in incorporating predictive maintenance. The digital twin concept is proposed to interact with measured, estimated, and simulated data, hence improving data-driven prediction models for better Remaining Useful Life (RUL) estimations.	Future work based on this study should involve data modeling and physics-based simulation. Mathematical models and data transfer interfaces need verification using real-world examples. Current integrated software solutions are not yet optimal for hybrid modeling methodologies.
Aivaliotis et al. (2021)	Digital Twin Degradation Curve integration	In this paper, a strategy for incorporating degradation curves into physics-based models for proactive maintenance was provided. A case study for the prediction of a robot's RUL used the four steps in this approach with success.	Future projects include modeling gear friction and backlash, investigating complex deterioration curves, and revisiting the Coulomb-viscous friction model. The authors also intend to create accelerated tests to verify their approach and collect actual data for validation.
Aivaliotis, Georgoulias, Arkouli et al. (2019)	Digital Twin	The study proposes a framework for sophisticated physics-based modeling to help with digital twin (DT) maintenance applications. The methodology is focused on enabling Digital Twin and developing digital models. To evaluate this method for predictive maintenance applications, a digital model of an industrial robot was created.	The authors hope to include the suggested approach into a predictive maintenance framework, which will analyze machine health, schedule repair, and validate the procedure across several machines in production settings. They also want to improve model accuracy, properly tweak parameters, and enable real-time data interchange for web applications.

Article	Approach Used	Results	Future work
Zhong et al. (2023)	Digital Twin CNN (Conventional Neural Network) LSTM (Long Short-Term Memory)	The research emphasizes the relevance of digital twins in predictive maintenance, contrasting them with conventional methods. It examines PdMDT adoption in various industries and recent advances. It also presents a manufacturing sector framework that includes equipment maintenance and an industrial robot example, as well as considerations for limits and opportunities.	Digital twin models for maintenance and life prediction face challenges due to lack of a standardized platform for building physical models. Establishing a broad foundation for PdMDT development is crucial for overcoming this challenge.
Kunzer et al. (2022)	Digital Twin	This article investigates the word "digital twin" by looking at its origins and original context in several fields. It proposes a concept of a minimum feasible digital twin framework and provides a brief overview of digital twin applications across industries. It focuses on digital twin architecture for predictive maintenance and its expansion, which include machine learning and physics-based modeling.	Challenges of Digital Twin Implementation: Sensor Issues: Addressing offline sensors, missing or poor-quality data, and assuring sensor system reliability. Adoption in the Workplace: Investigating the integration of Digital Twin frameworks into existing workplace processes and systems. Safety Protocols: Ensuring that safety protocols are followed within digital twin environments.
Aivaliotis, Georgoulias & Chryssolouris (2019)	Digital Twin Physics-Based Modelling	The paper presents a method for forecasting the remaining useful life (RUL) of mechanical equipment in industrial resources using Prognostics and Health Management methodologies and the Digital Twin idea, enabling non-intrusive monitoring without traditional predictive maintenance procedures.	The authors plan to integrate their proposed methodology into a predictive maintenance framework, focusing on equipment health assessment and maintenance scheduling. They aim to improve RUL computation accuracy through machine component modeling, real-time tests, and degradation models.
Pagano (2023)	LSTM Bayesian inference	The study presents a predictive maintenance strategy for an industrial facility that uses Long Short-Term Memory (LSTM) neural networks and Bayesian inference, evaluating the compatibility of time-evolving industrial data with LSTM output.	The study applies a predictive maintenance technique to various time-evolving systems but has limitations due to potential sensitivity issues and data noise causing substantial posterior probability fluctuations.
Wang et al. (2023)	LSTM Knowledge Graphs (KG)	This work used data and knowledge to create a predictive maintenance (PdM) technique for industrial robots (IRs). An LSTM-based model identified future running states using previous and present data. The k-nearest neighbor method connected state features to possible faults for predicting. PdM strategies are developed using knowledge graphs (KGs) that have been updated with predictions. The method was tested with welding robots in an automotive welding workshop.	The proposed PdM technique and model can help improve smarter machines and IoT-enabled industrial systems. Future studies on complex intelligent manufacturing systems (IMS) should improve data-driven and knowledge-based techniques by adding transfer learning and few-shot learning to increase productivity. In addition, research should enhance knowledge graph reasoning and ontology knowledge.

Article	Approach Used	Results	Future work
Farahani et al. (2022)	The principal component analysis (PCA)	This paper proposes a predictive maintenance framework for injection molding using cloud and edge computing. A case study demonstrates its effectiveness in detecting cooling problems by monitoring process parameters not directly related to mold temperature.	Future work includes integrating vision-based measurement systems with data sources for precise predictive maintenance, establishing real-time communication between shop-floor employees and business information systems, and exploring proactive and reliability-centered maintenance strategies for root cause identification.
Florian et al. (2021)	Machine Learning	This study presents a mathematical model that considers investment costs and measures machine learning performance using defects detection likelihood. It includes an error matrix and a cost-based strategy, optimizing decision thresholds and guiding predictive maintenance deployment.	To test the proposed framework's robustness for the following CBM approaches: RUL estimation, multi-fault diagnosis, and condition indicator estimation.
Torim et al. (2022)	Python stumpy Matrix Profile library rule-based	The study proposes a smart monitoring system for equipment maintenance, combining predictive maintenance with anomaly detection to prevent damage and ensure adaptable solutions.	This work needs to be applied in a real case in manufacturing industry in order to test its performance.
Massaro et al. (2020)	K-means algorithm Multilayer perceptron artificial neural network (MLP-ANN)	The article discusses the development of a compact ECU for monitoring a bus fleet, utilizing SAE J1939 and ODB-II standards. It uses an artificial intelligence engine to predict maintenance based on driver behavior and tests the model on a dataset.	The work could be more investigated by applying more approaches.
Lee et al. (2019)	SVM ANNs RNN CNN	In this article, AI-based predictive maintenance algorithms are presented and applied to monitor two important elements of machine tool systems cutting tool and spindle motor. Data-driven modeling will be described and used to study tool wear and bearing failure.	To attain high accuracy, the study could include more algorithms and conduct comparisons to decide which is the most accurate and efficient. This strategy would strengthen the findings and provide useful insights into the performance of various algorithms in the context of the study's aims.
Nunes, Rocha et al. (2023)	Fault Tree Analysis	The study uses GFT methodology for predictive maintenance of injection molds at OLI, a plastic component manufacturer. It incorporates a cost-saving training method and isolation forest anomaly detection technique.	GFT model, unlike machine learning, uses actual data distributions for failure probability calculation. It's computationally inexpensive but may increase complexity with more variables.
Lambán et al. (2022)	CPS implementation	The research explores the use of 4.0 technologies to tackle predictive maintenance challenges, specifically focusing on real-time data processing and maintenance indicators, utilizing a machine tool for accurate machine status information.	This work implemented KPIs using a machine tool for research, but future work could involve real cases and consider additional Cybernetic CPS and new indicators to broaden KPIs.

Article	Approach Used	Results	Future work
Abidi et al. (2022)	Support Vector Machine (SVM) Jaya algorithm Sea Lion Optimization (SLnO) Recurrent Neural Network (RNN) KNN (K-Nearest Neighbors Algorithm)NN	This paper presents a PdM planning model using five stages: data cleaning, data normalization, optimal feature selection, decision-making for the prediction network, and prediction. The model uses a mix of Jaya algorithms and Sea Lion Optimization to eliminate redundant data, a support vector machine (SVM) to pinpoint the network for prediction, and a Recurrent Neural Network (RNN) to make predictions. The model accurately forecasts future component state for maintenance planning.	The model presented in this work requires further generalization for various industrial cases, which could greatly benefit scientific literature.
Liu et al. (2022)	CNN-LSTM Augmented reality	The research proposes a multi-service architecture for intelligent predictive maintenance for machine tools, using Convolutional Neural Network and Long Short-Term Memory for defect prediction. Deep reinforcement learning is used for production control and scheduling repair workers. Augmented reality is used for guidance and remote expert service for unforeseen failures. Comparative tests with real-world case studies show the technique is efficient and workable.	The proposed approach is suitable for larger IoT-enabled manufacturing platforms, accommodating diverse machines like robots and AGVs. To improve maintenance efficiency, multi-agent reinforcement learning techniques should be considered, with future features adding flexibility to the state space.
Leohold et al. (2021)	Data-driven Based Models Physics-based models	The paper proposes a general forecast approach for maintenance system design, simplifying method changes and enhancing efficiency. It provides an explanation of topology and models for forecasting maintenance tasks.	The study suggests adding more advanced model selection methods to the system that doesn't need a lot of expert knowledge and accurate rating metrics. This would give users more control over the processes.
Von-Birgelen, et al. (2018)	Self-organizing map (SOM)	This study showed an unsupervised method based on SOM for finding and localizing anomalies in CPPS data as well as using it for condition tracking and preventive maintenance.	Future research focuses on evaluating a system's remaining useful life using regression analysis and Holt Winters forecasting, as these models are deemed unsuitable for estimating the system's useful life.
Arena et al. (2024)	Various Machine Learning algorithms	The objective is to present a set of guidelines and ideas for figuring out which machine learning techniques are most likely to yield useful outcomes for certain tasks or data sets.	Comprehensive ML vision should consider human roles, societal interactions, and technology integration, with defining requirements for ML procedures being a crucial aspect.
Wang et al. (2024)	CNN Bi-LSTM	We suggest a deep learning ensemble approach as part of a dynamic predictive maintenance strategy to forecast the remaining usable life (RUL) of a system. Using CNN and a Bi-LSTM together, this technique accurately predicts RUL. In addition to order, stock, and maintenance decisions, the strategy takes uncertain system mission cycles into account. The results of our experiments with the NASA turbofan engine dataset demonstrate the superiority of our approach over current ones.	Future research will develop dynamic predictive maintenance strategies for different turbofan engine mission cycles. We will explore decision-maker preferences regarding maintenance cost and reliability trade-offs. Additionally, we aim to enhance Remaining Useful Life (RUL) predictions by using heuristic algorithms to optimize network hyperparameters

Article	Approach Used	Results	Future work
Kamariotis et al. (2024)	LSTM	The study proposes a metric to evaluate prognostic algorithms' impact on Predictive Maintenance decisions, estimating long-term maintenance costs, and evaluating their performance with PdM policies, using a simulated turbofan engine.	Future research focuses on training prognostic algorithms to learn PdM policies using monitoring data, requiring extensive training data to calibrate these policies to cost models and deterioration processes.
Shoorkand et al. (2024)	CNN LSTM	The paper discusses the integration of tactical production planning and predictive maintenance using a rolling horizon approach. It introduces a hybrid deep learning method combining CNN and LSTM to improve Remaining Useful Life prediction accuracy. The approach reduces total production and maintenance costs through imperfect maintenance.	The study focused on a single machine, but future research should investigate multiple machines and develop more accurate dynamic learning methods for system health conditions.
Elkateb et al. (2024)	IoT Machine Learning	The study introduces a predictive maintenance system using AdaBoost for knitting machines, achieving 92% accuracy in classifying six types of stops through pre-processed data from IoT devices	This study could significantly impact on the textile industry by increasing manufacturer revenue, extending machine life, and improving product quality, with further work to address errors and various machinery types.
Meriem et al. (2023)	Hybrid Approaches	This paper discusses the challenges in implementing predictive maintenance (PdM) in Industry 4.0, focusing on machine learning, knowledge representation, and semantic reasoning applications.	The literature review identifies three primary PdM challenges: defining PdM objectives, ensuring system architectures satisfy industry standards and easily interact with developing methodologies, and customizing fault diagnostic and prognosis approaches to particular issues.
Giannoulidis et al. (2024)	Deep Learning	The study explores evaluation methods for predictive maintenance, addressing misconceptions and limitations, and proposes an extension of range-based anomaly detection for PdM purposes. It also explores pre-processing, distance metrics, domain expertise, and deep learning.	Future challenges include using historical data for KPIs to dynamically modify setups, influencing maintenance scheduling with sparse or continuous alarm data, and improving predictive maintenance plans by combining multiple strategies.
Qureshi et al (2024)	Logistic Regression Decision Trees Support Vector Machines	The study discusses the use of machine learning in predictive maintenance (PdM) for solar farms, highlighting its importance in enhancing infrastructure reliability and performance. It discusses key components, challenges, and ML algorithms used for real-world deployment.	The study on predictive maintenance in solar farms has limitations due to a single dataset and focus on equipment reliability. Future research should explore advanced machine learning techniques.
Brahimi et al. (2024)	ANFIS LSTM	The study introduces an intelligent monitoring system for MS5002C gas turbines, using ANFIS and LSTM algorithms for real-time anomaly detection and predictive maintenance, enhancing turbine longevity and performance optimization.	The authors emphasize the need for further research to expand the applicability of the proposed framework beyond MS5002C gas turbines, emphasize the importance of rigorous evaluation, and explore alternative AI algorithms.

Article	Approach Used	Results	Future work
Zhuang et al. (2023)	Bayesian neural network	The proposed integrated predictive maintenance framework combines prognostics and maintenance decision-making for complex industrial systems. It uses a Bayesian deep learning model to generate a predictive RUL distribution, updating maintenance and spare-part ordering decisions dynamically. The framework's effectiveness was validated using the C-MAPSS turbofan engine dataset.	The proposed prognostics-driven dynamic PdM framework can be applied to condition-monitored complex systems across various industries, requiring adaptations like industry-specific constraints and using some realistic data like Deep Reinforcement and Active Learning
De-Luca et al. (2023)	Deep attention-based model	The authors propose a DL approach for PdM task, utilizing a multi-head attention mechanism for high RUL estimation and low memory model storage requirements, allowing direct implementation on equipment hardware.	Future research should focus on the attention mechanism in PdM applications and explore the model's learning process using explainable artificial intelligence (XAI) technologies for explanation.
Yıldız & Soylu (2023)	Weibull Analysis Machine Learning Algorithms	The study uses a machine learning algorithm to predict failure types, analyzing its performance under various scenarios and parameter settings, revealing its marginal utility and providing planners with multiple choices.	Future research could apply this approach to various maintenance problems, incorporate selective maintenance strategies, and use machine learning to predict decision-maker actions based on multiple examples.
Mandala (2020)	XGBoost Random Forest Isolation Forest Local Outlier Factor Elliptic envelop	The paper explores strategies for the automotive industry using AI systems for maintenance and supply chain optimization, highlighting their potential and the importance of these solutions, predicting their imminent necessity in the industry.	The first step to discover in predictive maintenance involves expanding optimization models for dynamic and stochastic formulations, covering inventory control and scheduling. The second approach to be attacked integrates AI with operations research for real-world effects. Empirical validation via industry case studies is needed for market penetration.
Rodriguez et al. (2023)	K-means	Wind turbine failures can be identified or predicted by machine learning; however, this is made more difficult by problems with labeled data, such as ambiguous fault associations and label imbalance. We investigate K-means clustering and boxplot representations for six tests in order to address these problems. By identifying anomalies and abnormal behaviors in wind turbines, these techniques help experts enhance predictive maintenance.	This study limited its scope by using a single clustering technique, which could be enhanced with feed-forward neural networks, self-organizing maps, or fuzzy C-means algorithm, and only tested a few feature types.
Lee & Mitici (2023)	Deep Reinforcement Learning	The proposed framework integrates data-driven probabilistic RUL prognostics into predictive maintenance planning, reducing total maintenance costs by 29.3%, preventing 95.6% unscheduled maintenance, and limiting wasted engine life to 12.81 cycles, using sensor data collection and Deep Reinforcement Learning.	As a future work authors intend to extend the suggested DRL technique for multiple component predictive maintenance in subsequent works. Furthermore, they take into account more practical inputs and limitations related to aircraft maintenance, such as hangar space limitations, spare component logistics, and dynamic flight circumstances.

Article	Approach Used	Results	Future work
Shoorkand et al. (2024)	Deep Transformer models	The study introduces ManuTrans, a deep learning model for tracking raw sensor data in pharmaceutical production lines, assessing state, and forecasting failures. It uses deep transformer models for pattern extraction, classification, and regression, and shows promising results on real datasets.	Further research is required to incorporate automated techniques like XAI approaches into the model authors developed and to locate the predicted function failure precisely, which would provide even more benefits for preserving production lines.

Table 4. Different approaches used for each application

Future Directions from Literature: Several authors suggest extending these models by incorporating transfer learning, reinforcement learning, and self-supervised learning to reduce dependence on labeled data. Others propose real-time implementation on edge devices for latency-sensitive applications.

Physics-Based Models**,** these models are built upon fundamental physical principles describing machine degradation, such as fatigue, thermal dynamics, and wear mechanisms. Some works embed these models into Digital Twin (DT) architectures to simulate real-world behavior.

Future Directions from the Literature: a common limitation is the need for domain expertise and precise system knowledge. As such, many studies recommend developing hybrid physics-informed ML models that blend first-principles with learning to improve adaptability and scalability. Others emphasize integrating these models into cloud-based DT platforms for simulation and predictive testing.

Hybrid Approaches, Hybrid models combine data-driven learning with physics-based reasoning or rule-based logic. These models strive to achieve high accuracy while retaining physical interpretability, which is especially crucial in industrial contexts.

Future Directions from the Literature: many authors foresee the rise of federated hybrid models, where different components (ML, simulation, and expert knowledge) interact in real time. Others advocate for embedding hybrid models into autonomous maintenance frameworks for proactive decision-making and self-healing systems.

As of Knowledge-Based and Semantic Models, this category includes approaches based on expert systems, ontologies, semantic reasoning, and rule-based frameworks like SWRL or Fault Tree Analysis. These models support explainability and human-centered reasoning, facilitating PdM in complex systems or knowledge-scarce environments.

Future Directions from the Literature: numerous papers highlight the importance of developing dynamic rule-based systems that evolve with data and context. The integration of these models with semantic IoT infrastructures, digital threads, and context-aware agents is also proposed to improve industrial interoperability and real-time fault diagnosis.

Across all categories, literature suggests a strong move toward:

- Real-time, Edge, and Cloud Integration: Shifting models from static analysis to real-time predictive services via edge computing and cloud platforms.
- Explainable and Transparent AI: Especially in regulated industries, there is a growing need for explainable PdM systems to support trust and validation.
- Human-Machine Collaboration: Models should enable human-in-the-loop mechanisms to combine automated insights with expert validation.
- Generalization and Transferability: A number of works advocate for models that generalize across different machines, systems, and industrial sectors, with domain adaptation techniques playing a key role.

4.3. RQ3: What Are the Data Used to Apply PdM?

Predictive maintenance (PdM) data differs depending on the particular environment and study goals. For instance, data from sensors on welding robots in a new energy automobile welding facility is used in (Wang et al., 2023). A Li-ion battery database and an aircraft engine database were used in (Abidi et al., 2022). In order to gather machine data, the study in (Werner et al., 2019) used Internet of Things sensing technology, especially the Message Queuing Telemetry Transport (MQTT) protocol. The data from sensors mounted on an actual robot was used by the authors of (Aivaliotis et al., 2021). PdM data collection is usually carried out by specialist systems, such OSA-CBM (Jimenez, Schwartz, Vingerhoeds, Grabot & Salaün, 2020), that follow certain guidelines and standards. Data was taken straight out of Vehicle On-Board Diagnostics in (Massaro et al., 2020).

4.4. RQ4: Which Type of Approaches Are the Most Optimal to Respond to Predictive Maintenance Goals?

This question is specifically addressed in (Jimenez et al., 2020) which reviews the advantages of combining different types of models. The multi-model approach that integrates knowledge-based, data-driven, and physics-based models offers a powerful strategy for predictive maintenance by leveraging the strengths of each model type. Knowledge-based models can incorporate expert insights to enhance the results of data-driven models in diagnostic and prognostic tasks, while also improving the accuracy of physics-based models. Although the integration of knowledge-based and physics-based models is less explored in scientific literature, this combination can yield significant benefits, as demonstrated in studies like (Swanson, 2001) which merge fuzzy knowledge-based systems with physics-based models for mechanical parts. Data-driven models are increasingly popular due to their compatibility with physics-based models for deterioration modeling, making this approach the most commonly used in recent research, as categorized in (Wang, Li, Gao, Zhang, 2022). The comprehensive integration of all three model types —knowledge-based, data-driven, and physics-based— captures the complexity of each individual model while also addressing the challenges of system design and result integration, highlighting a promising yet underexplored area for future research.

4.5. RQ5: What Are the Current Challenges Facing Predictive Maintenance?

In the area of anomaly identification, which is part of PdM with prognostics models, there are a lot of things that could go wrong. This is a big problem. These can be mistakes in the transmission, problems with the machine, stops in therapy, changes in working conditions, sensor problems caused by hard weather, and more. There is also a lot of theory behind statistical methods, but they use known distributions for parameters, such as Weibull, exponential, and others, instead of real distributions. This means that the results may only give a rough idea of how things really work. Moreover, models of fatigue or fracture failure that have been established for certain components but whose methodology is not applicable to other industrial assets are frequently the basis for statistical processes. On the other hand, machine learning techniques may represent incredibly diverse and non-linear models; but, in order to train the models, they need enormous quantities of data and powerful computers. Data-driven systems, for all their advantages, need a lot of data, and because there isn't enough data to predict the less common types of failure, they usually overlook them (Nunes, Rocha et al., 2023).

When there is a lack of actual data on the usual and aberrant behavior of the equipment, and when there is no operating experience with new technologies. Owing to this situation, companies can start second-guessing their choice to spend money on PdM solutions (Compare, Baraldi & Zio, 2019). The publication (Achouch et al., 2022) separates Pdm Challenges into four primary categories (Figure 6): limits in the deployment of industrial predictive maintenance models, limitations in data sources, financial and organizational constraints, and machine repair activity limits:

- Financial and Organizational Limits: In order to set up predictive maintenance companies should be willing to harness huge resources and costs, some companies avoid that depending on its vision and strategy.
- Data Source Limits: When the required confidence in the data is not maintained, for example, when sensors, controllers, or other data sources deliver erroneous or inaccurate measurements, the business employing predictive maintenance techniques may encounter difficulties. This may lead to inaccurate forecasts, overlooked maintenance needs, and erroneous alerts. The fact that sensors now have a tendency to function offline and not contribute to online data is another obstacle for sensor technology.

Furthermore, sensors are vulnerable to noise, instrument deterioration, downtime, and sensor failure. In order to forecast the real world and avoid skewing the outcomes, it is crucial to clean the data before using the predictive maintenance algorithm.

- Machine Repair Activity Limits: Maintenance schedules can be planned by estimating a component's remaining life, however real component maintenance still has difficulties because of the dependance to human interaction and low self-maintenance. Moreover, the deterioration and prediction model, along with all the data required to make predictive maintenance choices, would be dispersed and accessible at the component level, as contrast to a central system managing one or more assets. Then, machinery can schedule its own maintenance. Nonetheless, industrial machines do not currently possess this degree of self-awareness or self-maintenance.
- The use of industrial predictive maintenance models is limited by the following: The development of intelligent failure prediction models usually involves three difficult steps: updating, monitoring, and integration. Because it is usually managed by an information technology (IT) team that is distinct from the research and development team that developed the predictive maintenance models, model integration is challenging in the industry. Building an IT infrastructure to support the data pipelines can take a lot of time, and project planning usually ignores this. Part of the monitoring method is making sure that the model is up to date. Adding a feedback loop to the model adds new data that can be used to teach the model new things. The results are less reliable because the forecast models have to be trained over and over again. Actually, there is no guarantee that the data being used is correct or up-to-date during manufacturing. This means that mistakes can be made and estimates end up being wrong. Lastly, it is very important to keep machine learning models from falling into the problem of mental drift when updating them. The company needs to make changes to the data, the model, and the code all at the same time in order to update the prediction models. This cycle of making predictive maintenance models better is a lot more complicated than regular software changes for businesses.

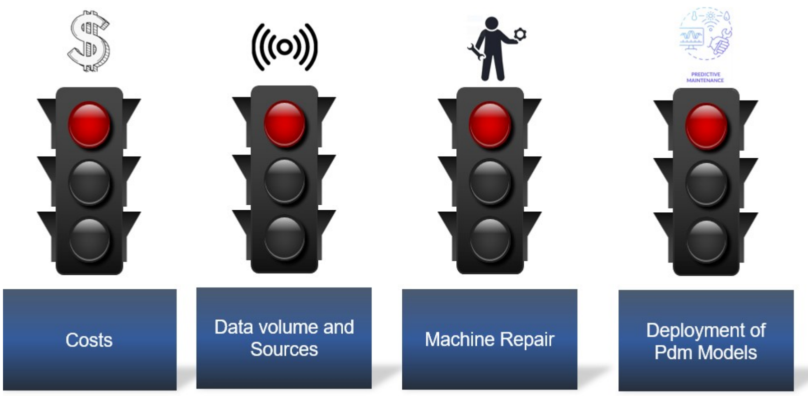

Figure 6. Challenges of Predictive Maintenance

5. Proposed Approach

This article proposes a novel hybrid predictive maintenance (PdM) architecture that systematically combines data-driven physics-based, and knowledge-based approaches to improve the accuracy, interpretability, and robustness of failure predictions. This architecture is structured into three distinct but interconnected phases, each contributing a complementary perspective to the prediction and decision-making process. The design aligns with the call for hybrid and explainable models in PdM, as highlighted by Jimenez et al. (2020), Cao et al. (2022), and Van-Dinter et al. (2022).

5.1. Phase 1: Data-Driven Model for Initial Prediction

The architecture begins with a data-driven model based on machine learning (ML) or deep learning (DL), which performs the initial failure prediction. Input features may include for example temperature, torque, rotational speed, tool wear, and other operational parameters derived from sensor data. This component draws on proven strategies described in the literature, such as convolutional neural networks (CNNs) for anomaly detection (Çınar et al., 2020) or gradient boosting algorithms (Wen et al., 2022) for failure classification. These models learn patterns from historical datasets and provide a probabilistic prediction regarding the machine's health status.

However, as data-driven approaches are typically black-box models and may not generalize well across operating conditions, their predictions are passed on to the next module for validation.

5.2. Phase 2: Physics-Based Model for Validation and Consistency Checking

To overcome the limitations of purely statistical models, the second phase incorporates physics-based modeling to validate whether the predicted failure pattern is physically plausible. This model is designed based on engineering principles and degradation laws. In our case, the physics-based component uses relationships between torque, rotational speed, temperature differences, and tool wear to simulate mechanical behavior under real-world operating conditions.

This approach is consistent with the vision presented by Van-Dinter et al. (2022), who emphasize the value of physics-based modeling within digital twin systems for maintenance. Similarly, Kothamasu et al. (2006) underscore the role of analytical models in enabling better generalization and interpretability, especially in complex industrial settings. The objective here is not to replace the data-driven model, but to ensure that its prediction aligns with known physical constraints, thereby reducing false alarms or implausible alerts.

5.3. Phase 3: Knowledge-Based Model for Contextual Reasoning

The final phase introduces a knowledge-based system, which applies domain-specific rules to contextualize and interpret the validated predictions. This layer incorporates expert knowledge, maintenance history, and logical rules in the form of IF–THEN statements, decision trees, or fuzzy logic systems. Knowledge-based systems help bridge the gap between prediction and action, ensuring that recommendations are aligned with operational realities.

For example, Cao et al. (2022) propose the Knowledge-Based Smart Predictive Maintenance Implementation (KSPMI), which integrates domain knowledge with predictive analytics to guide maintenance decisions. Likewise, Nunes, Rocha et al. (2023) demonstrate the utility of expert systems in formalizing reasoning processes that are difficult to capture through ML models alone. The knowledge-based layer ensures that predictions and physics-based outputs are considered within the broader context of system behavior, usage constraints, and business rules.

5.4. Integration and Novelty of the Proposed Architecture

The strength of this hybrid architecture lies in the sequential integration of three modeling paradigms:

Aspect	Data-Driven	Physics-Based	Knowledge-Based
Role	Failure prediction	Validation & interpretability	Decision contextualization
Input	Historical sensor data	Physical parameters & laws	Expert knowledge, rules
Output	Probability of failure	Physical consistency check	Final decision/recommendation

Table 5. Aspects of each type of PdM models

While previous studies have combined two approaches (e.g., data-driven with knowledge-based or physics-based), our proposed model integrates all three in a modular, layered structure. This ensures greater robustness, accuracy, and explainability, aligning with recommendations from Jimenez et al. (2020) and Van-Dinter et al. (2022), who call for more comprehensive hybrid frameworks in PdM.

5.5. Positioning as a Theoretical Contribution

This contribution is primarily theoretical, serving as a structured framework for future implementation. Unlike previous works that apply hybrid models to specific use cases, our goal is to present a generalizable architecture that combines the best aspects of current PdM strategies. As emphasized by Kothamasu et al. (2006), true prognostic systems require a synthesis of multiple data sources and reasoning layers. By formalizing this integration, our architecture offers a new path forward for the design of more reliable and intelligent maintenance systems.

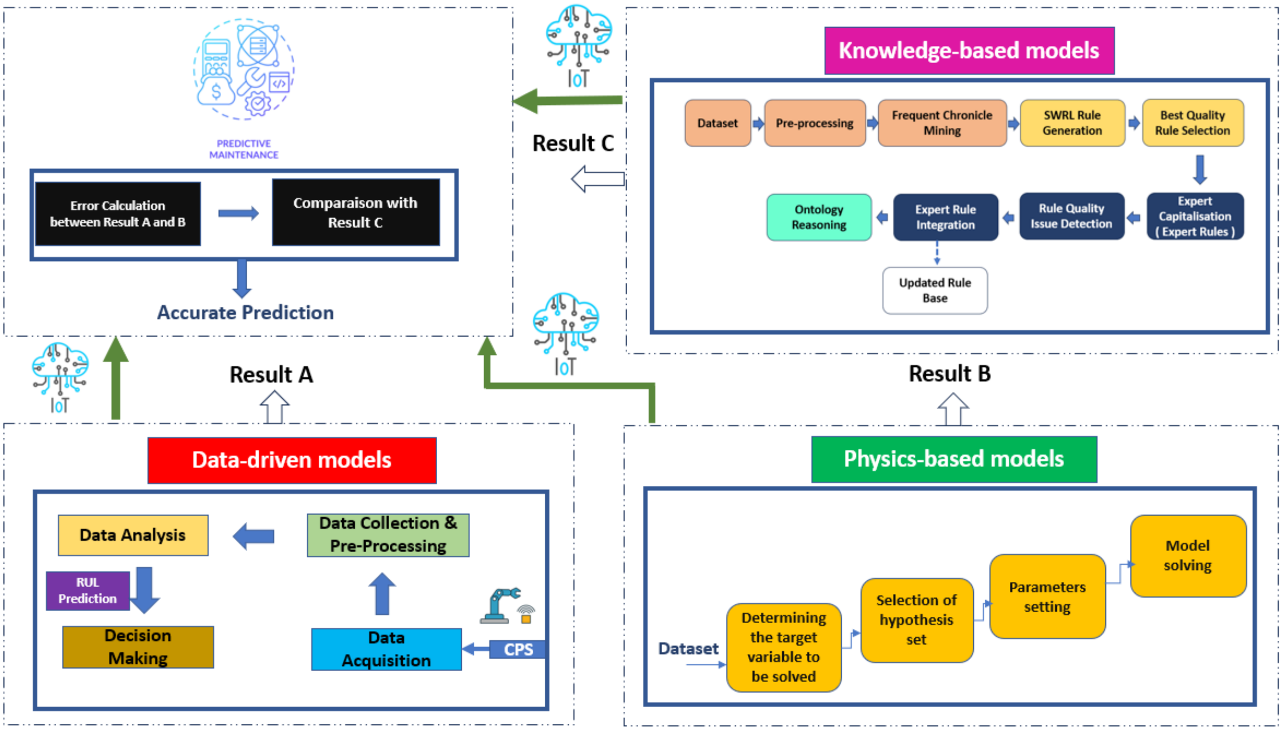

Figure 7. Predictive Maintenance Architecture

6. Discussion

The several Predictive Maintenance (PdM) models and techniques were investigated in this systematic literature review (SLR), which also emphasized the range of uses for PdM in academic literature. According to the analysis, a lot of applications have a tendency to combine two techniques or make use of many algorithms within one approach (Jimenez et al., 2020). Applications that combine all three strategies are uncommon, though. We provide an architecture that takes advantage of the outputs from every method and compares them to yield a precise failure time prediction based on the findings of our SLR.

The majority of applications pertain to smart manufacturing settings, suggesting a strong connection between industrial areas and maintenance. Manufacturers are driven to implement advanced maintenance technologies in order to overcome the constraints of reactive or preventative maintenance, as asset shutdowns result in large expenditures (Molęda, Małysiak-Mrozek, Ding, Sunderam & Mrozek, 2023).

PdM algorithms are mostly derived from knowledge-based models, physics-based models, and artificial intelligence. The volume and availability of data, type of industry, and context all influence the choice of algorithms.

It is imperative that researchers concentrate on fusing knowledge- and physics-based models with AI techniques. Regrettably, the current approach frequently overlooks the integration of other models in favor of applying machine learning and deep learning algorithms (Jimenez et al., 2020). Outcomes that are less accurate may arise from this oversight. We can improve the precision and dependability of Predictive Maintenance (PdM) predictions by highlighting a more comprehensive strategy that combines AI, physics-based, and knowledge-based models. By utilizing the advantages of each model type, this all-encompassing approach guarantees that we can make maintenance decisions that are more accurate and practical in the long run.

The reluctance to fully integrate knowledge-based, physics-based, and data-driven approaches reveals a significant theoretical gap in the field of Predictive Maintenance (PdM). This hesitation likely stems from several underlying factors: the siloed nature of expertise across these domains, the computational complexity of unified models, and the organizational challenges of cross-disciplinary collaboration (Lee, Azamfar & Singh, 2020). Our proposed architecture (Figure 7) addresses these limitations by creating a synergistic framework where each approach compensates for the others' weaknesses. The comparative analysis between Results A, B, and C demonstrates how this integration transcends the traditional trade-offs between model interpretability and predictive power. This integration has profound theoretical implications for advancing PdM beyond its current state challenging the field to move from algorithm-centric approaches toward holistic system thinking. As Zonta et al. (2020) argue, successful PdM implementation requires not just technical integration but also organizational and knowledge management strategies that bridge disciplinary boundaries. The resistance to integration observed in current literature suggests that the PdM field may be experiencing a paradigm shift, where established methodological boundaries are being reconsidered in favor of more comprehensive frameworks that can better address the multifaceted nature of industrial maintenance challenges in the Industry 4.0 era.

7. Conclusion

We conclude our SLR by putting up a strategy that will enable the full utilization of the three widely employed PdM techniques.

We studied predictive maintenance in-depth and discussed every kind of strategy that may be applied in a predictive maintenance setting in this work. Our paper aimed to address five concerns and is based on SLR as a scientific research approach. First, in order to give future readers a thorough understanding of this topic, our research has introduced a number of terminologies linked to PdM. Additionally, our PdM study has produced a number of intriguing reviews that address the subject. Moreover, a number of applications have been studied with their methods and by application domain, for every paper, we attempted to extrapolate the necessary future work to emphasize the amelioration axis that researchers should target. It was also crucial to list the difficulties PdM encountered so that they might be discussed and kept in mind while using any strategy.

Our systematic review of 68 articles published between 2018 and 2024 reveals several significant findings. First, we identified a clear dominance of data-driven approaches (26 articles) over physics-based models (5 articles) and knowledge-based models (1 article), with only 5 articles attempting to combine two approaches and just 1 article proposing a comprehensive hybrid framework. This distribution highlights a critical gap in the literature: despite the theoretical advantages of integrated approaches, most research remains siloed within individual modeling paradigms [Doc 1]. Second, our analysis demonstrates that manufacturing remains the primary application domain for PdM, followed by emerging applications in aircraft maintenance, industrial robotics, and specialized sectors such as pharmaceutical manufacturing and renewable energy. This indicates both the maturity of PdM in traditional industrial settings and its expanding relevance across diverse domains.

The primary contribution of this work is our novel hybrid architecture that systematically integrates knowledge-based, physics-based, and data-driven models within a cohesive predictive maintenance framework. Unlike previous approaches that typically leverage only one modeling paradigm or loosely combine two, our architecture creates a structured pipeline where each model type contributes complementary insights while compensating for others' limitations. This integration enhances not only prediction accuracy but also interpretability and robustness —critical factors in industrial deployment contexts. Additionally, our comprehensive mapping of PdM applications, approaches, and challenges provides researchers and practitioners with a valuable reference for understanding the current state of the field and identifying promising research directions.

Our study has several limitations that should be acknowledged. First, despite our rigorous methodology, the review was constrained to articles published between 2018 and 2024, potentially missing relevant earlier foundational works. Second, our proposed hybrid architecture, while theoretically sound, remains conceptual and requires empirical validation across diverse industrial settings to demonstrate its practical efficacy and implementation challenges. Third, our analysis of data sources (RQ3) was limited by the inconsistent reporting of data characteristics across the reviewed literature, making it difficult to draw comprehensive conclusions about optimal data requirements for different PdM approaches. Fourth, the predominance of manufacturing applications in our review may limit the generalizability of our findings to other domains with different operational characteristics and failure modes. Finally, while we identified integration challenges between modeling paradigms, our work does not fully resolve technical issues such as uncertainty propagation, temporal alignment between models, and computational efficiency in real-time industrial deployments.

Future research should focus on several promising directions. First, empirical validation of hybrid architectures like the one we propose is essential, particularly through case studies that quantify the performance improvements over single-model approaches across different industrial contexts. Second, researchers should explore adaptive integration mechanisms that dynamically adjust the weight given to each model type based on contextual factors such as data availability, failure criticality, and operational conditions. Third, more attention should be directed toward knowledge-based models and their integration with data-driven and physics based approaches, as this combination remains underexplored despite its potential to address data scarcity issues in many industrial settings. Fourth, standardized frameworks for evaluating PdM performance are needed, as our review revealed inconsistent metrics and evaluation approaches across studies. Finally, research on explainable AI for PdM deserves greater emphasis to enhance trust and adoption in safety-critical applications, particularly as regulatory requirements for AI transparency increase across industries.

By addressing these research directions, the field can move beyond the current fragmented approach to PdM modeling and toward more holistic, robust, and industrially viable solutions that fully realize the promise of predictive maintenance in the industry 4.0 era.

Nomenclature and Symbols

PdM Predictive Maintenance
AI Artificial Intelligence
ANFIS Adaptive Neuro-Fuzzy Inference Systems
SLR Systematic Literature Review
CPS Cyber Physical System
PBM Physics Based Models
KBM Knowledge Based Models
DT Digital Twin
IoT Internet of Things
SWRL Semantic Web Rule Language
ML Machine Learning
PHM Prognostics and Health Management
RUL Remaining Useful Life
GFT Generalized Fault Trees

Declaration of Conflicting Interests

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