Predictive Maintenance Approaches in Industry 4.0: A Systematic Literature Review

Fidma Mohamed Abdelillah, Hamour Nora, Ouchani Samir, Sidi Mohamed Benslimane

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1st Fidma Mohamed Abdelillah
CECI Lineact
Villeurbanne, France
0009-0006-7187-1534

2nd Hamour Nora
CESI Lineact
Villeurbanne, France
0009-0001-1786-103X

3rd Ouchani Samir
CESI Lineact
Aix-en-Provence, France
0000-0002-7997-8225

4thSidi Mohamed Benslimane
LabRI-SBA Lab, ESI-SBA
Sidi Bel Abbes, Algeria
0000-0002-7008-7434

***Abstract*—The advent of industry 4.0 (I4.0) has brought about significant advancements in manufacturing processes, leveraging advanced sensing and data analytics technologies to optimize efficiency. Within this paradigm, predictive maintenance (PdM) plays a crucial role in ensuring the reliability and availability of production systems. There are several existing approaches for PdM in I4.0, each with its own advantages and disadvantages. In this paper, we review the state-of-the-art related to PdM approaches in the context of I4.0. Our systematic literature review encompasses a comprehensive analysis of recent research, focusing on the different AI-based techniques employed in PdM applications. Through this survey, we aim to provide valuable insights into the current landscape of PdM methodologies and foster future innovations in this rapidly evolving field.**

***Index Terms*—I4.0, industrial cyber-physical system, Prognostic and Health Management, PdM.**

I. Introduction

I4.0 has ushered in a new era of manufacturing, with advanced technologies such as IoT, AI, and big data analytics transforming the way factories operate. One of the key areas of focus in I4.0 is PdM, which leverages these technologies to enable companies to monitor the health of their equipment in real-time and predict when maintenance will be required [1].

In I4.0, PdM is becoming increasingly sophisticated, with the integration of sensors, data analytics, and AI algorithms enabling real-time monitoring and analysis of equipment performance [1]. This allows for more accurate and timely predictions of equipment failure, as well as the ability to prioritize maintenance tasks based on their urgency and impact on production. Despite the growing importance of PdM in I4.0, there remains a lack of comprehensive understanding and analysis of the existing approaches available. A multitude of techniques, ranging from statistical methods and machine learning (ML) algorithms to knowledge-based approaches, have been developed and implemented to address PdM challenges. Nevertheless, a systematic study and comparison of these approaches, along with an exploration of their requirements, are essential to determine their effectiveness, applicability, and limitations in diverse industrial contexts.This research aims to bridge this knowledge gap by conducting an in-depth study and comparison of the existing approaches for PdM in I4.0. Through a rigorous analysis and evaluation of the strengths and weaknesses inherent in various techniques, this survey will provide valuable insights into the effectiveness of diverse PdM strategies. Furthermore, it will identify the key factors that influence the selection and implementation of these approaches, including considerations like data availability, computational requirements, and interpretability.

In contrast to previous survey papers in the realm of PdM, this study aims to address some notable limitations present in existing literature:

- **Scope of Existing Surveys:** Most previous survey papers have primarily focused on reviewing specific approaches, often tailored to particular equipment. However, these surveys lack a comprehensive framework for guiding the selection of a holistic PdM system.
- **Novel Deep learning algorithms:** Given the rapid evolution of DL techniques, numerous novel Deep learning(DL)-based approaches have emerged in the field of PdM. As such, a fresh review is imperative to encompass the recent advancements in this field.

This survey paper is organized into four main sections. The introduction I establishes the importance of PdM in I4.0 and the necessity for a comprehensive review of existing approaches. The related work section II conducts a systematic literature review, comparing various PdM techniques and analyzing their strengths, weaknesses, and applicability within the I4.0 context. The discussion section III addresses the acquired insights and comparisons. Finally, the conclusion and future directions section IV summarizes the primary findings and underscores the significance of addressing the current gap in understanding PdM approaches .It also highlights potential research avenues and emerging trends for the future of PdM in the manufacturing sector.

II. I4.0 PDM CENTERED APPROACHES

In the I4.0 era, substantial research efforts have been dedicated to automating and enhancing smart manufacturing processes. Among the plethora of approaches, AI-based methods have shown promising results, particularly in the domain of PdM for I4.0 tasks. In this subsection, we categorize the existing AI-based PdM approaches into four distinct groups: data-driven approaches II-A, physical model-based approaches II-B, knowledge-based approaches II-C2, and hybrid model-based approaches II-D. Our categorization presented in 1 serves to provide a structured framework for understanding these approaches.

Following this hierarchical classification, We illustrate the range of approaches that have already been employed and conduct a comparative analysis to ascertain their relative effectiveness in various scenarios.

A. Data-driven approaches

In big data era, data-driven approaches have emerged as a significant solution for smart manufacturing and PdM. IWSNs, Cyber-Physical Systems, and Internet of Things (IoT) technologies are employed together to collect and intelligently process big industrial data, aiding in decision-making.The exponential growth in data volume (Big Data) and the rapid advancement of data acquisition technologies have led to increased attention on data-driven methods for PdM of industrial equipment [2]. These methods can be categorized into three main groups: ML methods, DL methods, and Statistical Learning-Based Models.

1) ML methods: A multitude of ML algorithms have been created to address real-world issues. These high-performance algorithms have played a significant role in digitizing and automating the manufacturing industry. [2] These models and algorithms can be roughly divided into three areas:supervised, unsupervied and semi-supervied.

- **Supervised learning :** In the context of PdM, this involve using historical sensor data to train a model to predict when a piece of equipment is likely to fail. The labeled data would include information about the state of the equipment at the time of failure.
  In [3], Federico Guedea-Elizalde and Marco Macchi proposed a cost-effective and straightforward cyber-physical system architecture. The architecture aimed to measure temperature and vibration variables during the machining process in a Haas CNC turning center. The collected data was stored in the cloud, and a Recursive Partitioning and Regression Tree model wasused to predict the rejection of machined parts based on a quality threshold.The authors proposed predictive models in [4] that leverage tree-based classification techniques to predict maintenance needs, activity types, and trigger statuses of railway switches.
- **UnSupervised learning :** In PdM, this involve using clustering algorithms to group similar pieces of equipment together based on their sensor data. This will help identify equipment that is likely to fail based on its similarity to other equipment that has failed in the past. In this study [5], the authors have explored the suitability of unsupervised learning for model building. They selected a straightforward dataset consisting of vibration data collected employing various unsupervised learning algorithms to assess their accuracy, performance, and robustness in analyzing this dataset.
- **Semi-Supervised learning :** In the context of PdM, this could involve using labeled data from equipment failures to train a model, and then using unsupervised learning techniques to identify patterns in the unlabeled data that could indicate impending equipment failures.

This study [6] introduces a data-driven Bayesian network approach coupled with a spatiotemporal fragility model to predict lightning-related failures in high-speed railway overhead contact lines. It combines a probabilistic lightning model, spatiotemporal OCL fragility model, and Bayesian network for risk prediction. This approach outperforms alternatives, offering accurate predictions even with imbalanced and noisy lightning data.

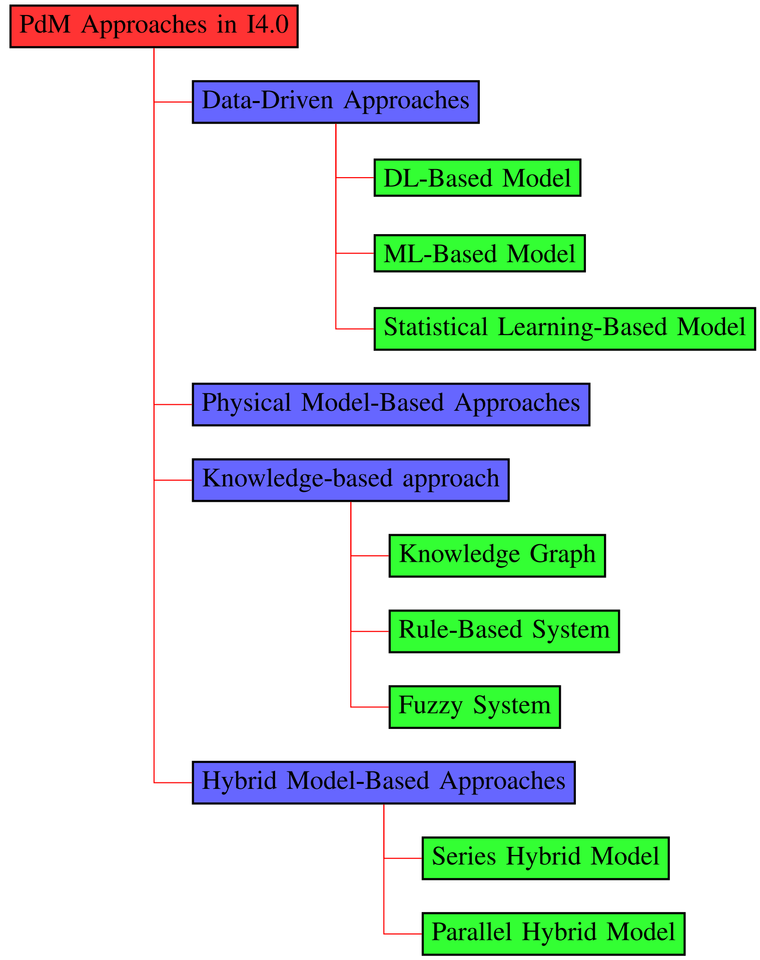

Fig. 1. Classification of PdM Approaches according to [7], [8], [1].

2) DL methods: Traditional ML algorithms have limitations when it comes to expressing complex relationships between variables and can struggle when dealing with high-dimensional datasets [9].To address this issue, DL techniques have been developed, employing layered ML algorithms to extract structured information from datasets. This advantage makes artificial neural networks (ANNs) highly applicable for handling non-linear and stochastic data. Consequently, this approach is particularly well-suited for managing intricate and expansive systems [10].

Wang in [11] addresses the need for integrated PdM planning models by combining data-driven Remaining Useful Life (RUL) prognostics and maintenance scheduling. Convolutional Neural Networks with Monte Carlo dropout estimate

RUL distribution, while Deep Reinforcement Learning guides maintenance actions. Applied to aircraft turbofan engines, the approach reduces total maintenance costs of unscheduled maintenance and optimizes engine life. In this work [12], the authors present an innovative DL-based approach for PdM tasks. They utilize a highly efficient architecture with a multi-head attention (MHA) mechanism, achieving superior results in terms of RUL estimation while maintaining a compact model size. Experimental results on the NASA dataset demonstrate the approach's effectiveness and efficiency compared to prevalent state-of-the-art techniques.

3) Statistical learning based model: This method is rooted in statistical models and relies on the analysis of the degradation of random variables in order to establish a correlation with operational time or other non-random variables that describe the system's lifecycle. In order to determine prognostics, Regression analysis is used to identify the relationship between random variables and the system's lifecycle. [1].

Statistical learning-based model approaches can be classified into three sub-classes: Particle filters and variants, Hidden Markov models and Time Series analysis:

- **Particle filters and variants:** Particle filtering is a technique that utilizes a group of particles to represent the posterior distribution of a stochastic process given noisy or partial observations.
  In [13], the researchers have introduced a novel approach by combining the whale algorithm with regularized particle filtering (RPF). This combination was employed to address the issue of particle degradation and, specifically, for predicting the RUL of valves. The study also delved into the analysis of valve crack propagation, utilizing the RPF approach with the Paris Law as a condition function.
- **Hidden Markov models :** is a statistical approach that is frequently used for modeling event sequences. When presented with a sequence of inputs, such as words, an HMM will output a sequence of the same length.
  In this paper [14], an automated feature subset selection method is introduced, employing a genetic algorithm. The complete feature set is generated by considering various sliding windows that capture different time shifts based on statistical metrics from measurement data. Subsequently, the fitness function for the genetic algorithm is designed, leveraging the initial fitting of a hidden Markov model (HMM) on the chosen subset of features and the assumed machine conditions found in the training data.
- **Time Series analysis :** Time series analysis is a specific way of analyzing a sequence of data points collected over an interval of time. In time series analysis, analysts record data points at consistent intervals over a set period of time rather than just recording the data points intermittently or randomly.
  An approach combining time series analysis methods with ML techniques was presented in [15]. The method aimed to forecast predictor variables and predict RUL using SVM. The predictor variables were estimated using an ARIMA model, and the results were fed as input to the SVM model, with RUL as the response variable.

B. Physical model-based approaches

Physical models are models that utilize physical laws, often from first principles, to quantitatively characterize the behavior of a failure mode. Such models typically employ mathematical representations of the physical behavior of a machine's degradation process to calculate the RUL of the machinery. The mathematical representation captures how the monitored system responds to stress on both the macroscopic and microscopic levels [16]. Compared to other types of models, physical models offer the most precise and accurate estimation of RUL .

Sheng in [17] presents an application of Gaussian Process Regression (GPR), a significant Bayesian ML method, for bearing features tracking. The GPR model incorporates variance around its mean prediction, enabling the representation of associated uncertainties in evaluation and prediction. Three GPR models with distinct covariance functions are explored for feature tracking and RUL evaluation. Another work [18] in which the focus lies on predicting the RUL of lithium-ion batteries to enhance the reliability and safety of battery-powered systems. This research utilizes an empirical degradation model followed by the particle filter (PF) algorithm for online parameter updates. Then,Vianna and others [19]propose a methodology for optimizing predictive line maintenance of redundant aeronautical systems under multiple wear conditions. This approach involves estimating degradation trends and future wear values through an extended Kalman filter technique using a multiple model approach. The optimization of planning aims to minimize operational costs, encompassing factors like dispatch requirements, delays, cancellations, and equipment expenses, thus catering to various aspects of the aviation industry.

C. knowledge-based approaches

A system based on knowledge uses a knowledge base to store a computational model's symbols in the form of domain statements and performs reasoning by manipulating these symbols . These systems determine appropriate decisions by measuring the similarity between a new observation and a databank of previously described situations . Knowledge-based approaches are categorized into three sub-classes: rule-based, knowledge graph and fuzzy system.

1) Rule-based system: The knowledge in this approach is represented by rules in the form of "IF-THEN" statements. It consists of a knowledge base that contains a set of rules, a facts base that stores inputs, and an inference engine that applies the rules to the facts base to derive new knowledge. The inference engine uses an iterative process that is repeated until the end of the reasoning process, following the rules specified in the knowledge base. In [20], a novel maintenance strategy was introduced with a twofold objective. Firstly, it centers on the anticipation of component failures through the utilization of association rule mining. Secondly, it aims to enhance the plant's overall reliability by optimizing the selection of components for repair, all while considering time and budget constraints. To validate these innovative approaches, an experimental campaign was conducted using a real-life case study involving an oil refinery plant.

2) Knowledge graph and ontology: The term "knowledge graph" is often used interchangeably with **"ontology"**. In computer science, an ontology is defined as "an explicit specification of a conceptualization for a domain of interest" [21], where specification refers to a precise description or identification. This necessitates the use of formal logic to clearly define concepts and relationships in ontologies.Furthermore, ontologies provide reasoning capabilities that enable the inference of new knowledge.

Konys and al in [22] provided formal, practical, and technological guidance to a knowledge management-based approach to sustainability assessment. They proposed ontology as a form of knowledge conceptualization and, using knowledge engineering and make gathered knowledge publicly available and reusable, especially in terms of interoperability of collected knowledge.

3) Fuzzy system: Fuzzy-knowledge-based models utilize fuzzy logic, which employs a similar format of IF-THEN rules as rule-based systems. Fuzzy logic is a collection of traditional Boolean logic that can handle partial truth values that lie between true and false values. It describes the degree of truth or falsity of a statement, and is closely related to human perceptions.

The authors in [23] introduce a sophisticated thermography approach for PdM in electric railways, employing a complex fuzzy system. It addresses the need for a complex fuzzy approach due to the influence of various factors like seasonal conditions, environmental variables, daylight, and periodic effects, such as train speed, on maintenance estimations in rail systems. The study also highlights the heightened sensitivity of both the rail surface and the pantograph catenary system to thermal fluctuations. Consequently, diagnosing faults using image processing and monitored systems requires substantial effort to account for these thermal changes.

D. Hybrid model-based approaches

A hybrid model-based approach involves combining the strengths of different methodologies, such as physical models, data-driven techniques, and knowledge-based systems. These approaches aim to leverage the benefits of each individual method to enhance predictive accuracy and flexibility.A hybrid model-based PdM task can be classified into two main subclasses: series hybrid model and parallel hybrid model based on the integration approach and the interplay between these methodologies.

1) Series hybrid model: The series hybrid approach refers to an approach that combines more than one approach in a sequential manner. it aims to capitalize on the accuracy of physics-based understanding for example while benefiting from the adaptability and real-time insights offered by data-driven techniques [24], resulting in improved predictions and maintenance strategies. The work [25], discusses the initial work on developing a data-driven algorithm for forecasting the discharge endpoint of Li-ion batteries. It focuses on using data from constant load experiments and outlines the difficulties encountered when implementing these algorithms for variable load profiles. In [26],Cao and al introduced a new approach that combines fuzzy clustering and semantic technologies to understand the significance of failures and predict the timing and criticality of these failures . A domain ontology is developed to model PdM knowledge, and a set of SWRL predictive rules is presented to reason about the timing and criticality of machinery failures.The approach has been optimized in [8], and it has shown promising results using SECOM datasets.

2) Parallel hybrid model: Involving the simultaneous application of both approaches, the hybrid model combines the strengths of both methods in parallel to enhance the accuracy and effectiveness of decision-making.

In [27],The authors propose a new method for reliable PdM of Computer Numerical Control Machine Tools (CNCMT) using a hybrid approach driven by Digital Twin (DT) technology. This approach combines DT model-based and DT data-driven methods. They demonstrate the effectiveness of their approach through a case study on predicting the lifespan of cutting tools. In [28], Zhou has proposed ML pipelines for quality monitoring in Resistance Spot Welding, incorporating sophisticated feature engineering strategies supported by domain knowledge. The interpretation of ML analysis results is carried out intensively to derive insightful engineering insights. In the same context, Klein in [29] integrated expert knowledge about class or failure mode dependent attributes into SNN. Additionally, they present an attribute-wise encoding of time series based on 2D convolutions, enabling the sharing of learned knowledge in the form of filters between similar data streams.

III. Discussion

The systematic literature review of PdM approaches within the context of I4.0 reveals a diverse landscape of techniques, each offering its own unique strengths and limitations.

Data-driven methods exhibit adaptability and provide real-time insights. ML techniques offer high classification and prediction accuracy and excel at approximating nonlinear functions. However, they may require significant computational resources, are prone to overfitting and their effectiveness heavily depends on data quality and volume., lack physical interpretability, and lack standardized approaches for network structure determination. DL, a subset of ML, demonstrates superior feature learning, fault classification, and prediction capabilities, yet it may suffer from the curse of dimensionality and demands extensive data and computational power.

Physical model-based approaches ensure accurate predictions but require expert knowledge and validation. These approaches are domain-specific and necessitate an in-depth understanding of mathematics and the physical behavior of machinery components. Nevertheless, acquiring such expertise can be costly, time-consuming, and challenging for many components.

Knowledge-based systems, leveraging domain expertise, enhance reasoning capabilities. Ontologies, in particular, provide a means to integrate, share, and reuse contextual knowledge of a system, but they often require integration with other reasoning methods to achieve effective PdM. Rule-based approaches prove valuable when substantial experience exists but insufficient detail is available to develop precise quantitative models.

In this landscape, hybrid models emerge as a powerful option, offering a balance between accuracy and flexibility. Hybrid approaches, which combine multiple single approaches, often demonstrate superior performance and can overcome certain limitations.

Ultimately, the selection of the most suitable PdM approach hinges on the specific industrial context, underscoring the necessity of tailored strategies to optimize PdM within the framework of I4.0.

Table I provides a concise summary of the multidimensional nature of decision-making processes in PdM and illustrates the interplay between various approaches, along with their associated advantages and limitations. Researchers and practitioners can strategically select and combine these approaches to create tailored solutions that effectively address the unique challenges within their domains.

IV. Conclusion and Future directions

This study has provided a ystematic literature review of the existing approaches for PdM in I4.0. Through a thorough review of literature and comparative analysis, the strengths and weaknesses of different approaches have been identified, shedding light on their applicability and effectiveness in various industrial contexts. Therefore, companies need to carefully evaluate their needs and consider a combination of approaches to develop a tailored PdM strategy.

Furthermore, we've identified common challenges including the limited availability of labeled failure data in manufacturing, the complexities of uncertainty management, the absence of a structured strategy for building PdM systems, and the need to adapt pre-existing solutions to intricate systems featuring numerous components and their respective faults. Overcoming these challenges entails adeptly harnessing the power of hybrid approaches by amalgamating various methods, managing diverse data sources, incorporating external influence data, exploring and designing of hybrid network architectures for achieving exceptional performance in complex applications and formalizing & sharing knowledge.

Looking ahead, several promising avenues for future research and development in PdM for I4.0 can be identified. Firstly, exploring the integration of PdM approaches with other I4.0 technologies such as **digital twins**,**augmented reality**, and **autonomous systems** could lead to enhanced maintenance strategies and decision-making processes. Secondly, investigating **the implementation of PdM in complex and interconnected industrial systems**, including supply chains and networked environments, would be valuable.

However, there is a need for further research on **standardization** and **interoperability** of PdM solutions to ensure seamless integration and data exchange between different systems and equipment. Moreover, continuous advancements in data analytics algorithms and techniques should be monitored and evaluated to improve the accuracy and efficiency of PdM models.

In conclusion, this study not only advances our comprehension of PdM approaches but also underscores the need for flexibility and customization within the evolving landscape of I4.0.

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TABLE I
COMPARATIVE TABLE OF DIFFERENT APPROACHES

Approaches	Advantages	Limitations
Data-driven	• No prior knowledge needed [30] • High classification and prediction accuracy [31] • Few parameters to treat with [31]	• Model can't be reused under different contexts [30] • The lack of expressiveness and defect of dimensionality [32] • Some algorithms may be very complex in terms of computation [30]
Physical model-based	• Reusability of model [33] • Provides high accuracy [34]	• Require a huge mathematics knowledge [33] • Real-life systems are often too stochastic and complex to model [33] • Changes in structural dynamics and operating conditions can affect the mathematical model [35]
Knowledge-based	• Uniform knowledge representation of physical resources [8] • Easy to integrate, share, and reuse knowledge [36] • Estimate human intelligence by automating rules for PD [37]	• Lack of reasoning [38] • Acquire complete knowledge to build a reliable rule-based system / describe system components [26] • Expensive and time-consuming for implementation [37]
Hybrid Model-Based	• Combines strengths of different approaches for enhanced accuracy [28] • Flexible and adaptable to various scenarios [27] • Can handle complex, real-world systems by leveraging both data-driven and physical models, data-driven and knowledge-based approach [8] • Offers robustness and improved fault tolerance [27]	• Complexity in integrating multiple approaches [28] • May require significant computational resources [27] • Difficult to interpret due to the complexity of combining different modeling paradigms [15]

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