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Artificial Intelligence-Driven Predictive Maintenance in Data-Scarce Environments: A Systematic Review

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ABSTRACT

The adoption of Predictive Maintenance (PdM) using Artificial Intelligence (AI) and Internet of Things (IoT) has been accelerated by Industry 4.0, however, it is still challenging to implement it for Small and Medium-sized Enterprises (SMEs) in data-scarce environments. This systematic review investigates the shift from reactive to proactive maintenance models, taking into account the particular limitations of small datasets. In contrast to current surveys that focus on big data analytics, this study evaluates the effectiveness of machine learning (ML) algorithms under data sparsity. We find that deep learning (DL) is the ideal approach for large datasets but classical algorithms such as Support Vector Machines (SVM) and Random Forests often provide better reliability for SMEs where historical failure data is limited. Moreover, we highlight low-cost sensor integration and federated learning as key enablers for SME digital transformation. The review ends with a roadmap for cross-machine model generalization and overcoming the socio-technical challenges to PdM adoption.

1. INTRODUCTION

The emergence of Industry 4.0 has introduced a new era of technological integration and industrial growth, setting the stage for more advanced manufacturing trends [1, 2]. Within this context, the industrial landscape is undergoing a fundamental shift from traditional reactive and preventive maintenance to intelligent Predictive Maintenance (PdM) [3]. Traditional strategies, despite their simplicity, can often lead to unplanned downtime or unnecessary maintenance costs due to rigid scheduling [4]. The emergence of Industry 4.0, which is defined by the integration of cyber physical systems (CPS), the Internet of Things (IoT), and Artificial Intelligence (AI), has provided the technical foundation for real-time equipment monitoring [5, 6]. PdM utilizes continuous streams of sensor data to predict equipment failures ahead of time, thus optimizing the Remaining Useful Life (RUL) of assets [7-9]. However, the "big data" assumption, which is dominant in the current literature, is not representative of the reality of many industrial sites, especially Small and Medium-sized Enterprises (SMEs) [10].

Such environments often have data scarcity due to legacy equipment, high costs of deploying sensors, and the rare occurrence of critical failures [11]. We present a systematic analysis of PdM strategies for data-deficient environments in this paper. We bridge the world of high-level Industry 4.0 concepts and the concrete implementation issues. In particular, we investigate the performance of AI algorithms trained on limited data, and we propose a socio-technical framework to allow SMEs to implement PdM without prohibitive upfront investments [12, 13].

Unanticipated equipment failures can lead to significant financial loss, safety risks and environmental damages, especially for SMEs with limited resources [14]. Industry 4.0, despite its potential to improve efficiency and productivity, often lacks a practical connection to the operational realities of smaller companies that face outdated infrastructure, limited capital for new technologies, and a lack of specialized technical expertise [15]. This review is not confined to fault detection, but also discusses the wider implications of PdM for operational optimization, resource allocation, and long-term sustainability [16]. This systematic review contributes uniquely to the literature by focusing on data-scarce environments and the specific needs of SMEs, differentiating itself from the existing surveys that mostly focus on data-rich industrial contexts [17]. Our work aims to provide actionable insights and a clear roadmap for SMEs to successfully implement AI-driven PdM solutions, fostering resilience and competitive advantage in the ever-changing industrial landscape.

2. SYSTEMATIC LITERATURE REVIEW METHODOLOGY

This review follows the Preferred Reporting Items for

Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency and reproducibility [18, 19].

2.1 Search strategy

Our study involved conducting a thorough search through various scientific database sources such as IEEE Xplore, ScienceDirect, Scopus, Web of Science, and ACM Digital Library. These database sources were chosen because of the huge volume of research papers that covered engineering, computer science, and industrial management literature with regard to Industry 4.0, AI, and PdM studies [18, 19]. The timeframe of the search is limited from January 2014 to December 2024 in order to ensure the most recent progress made in Industry 4.0 and AI-based PdM, consistent with the rapid changes in these domains, since the appearance of Industry 4.0 definitions [20]. The search query involved the use of Boolean operators to link the key terms associated with maintenance, technology, and data limitations:

(Predictive Maintenance OR PdM) AND (Industry 4.0 OR IIoT OR Smart Manufacturing) AND (AI OR Machine Learning (ML) OR Deep Learning (DL)) AND (Data Scarcity OR Limited Data OR Small Data OR SMEs).

2.2 PRISMA flowchart and selection process

The selection process was based on four steps: identification, screening, eligibility, and inclusion.

1. Identification: An initial search resulted in 425 references (Figure 1 and Table 1).

2. Screening: After eliminating duplicates and screening titles and abstracts, 112 articles were left.

3. Eligibility: The full-text review helped to exclude 66 articles that either did not deal with the topic of data-scarce environments or lacked empirical validation of AI.

4. Inclusion: In total, there were 46 articles used for the final synthesis, in addition to 14 important studies from 2020 to 2025 [21].

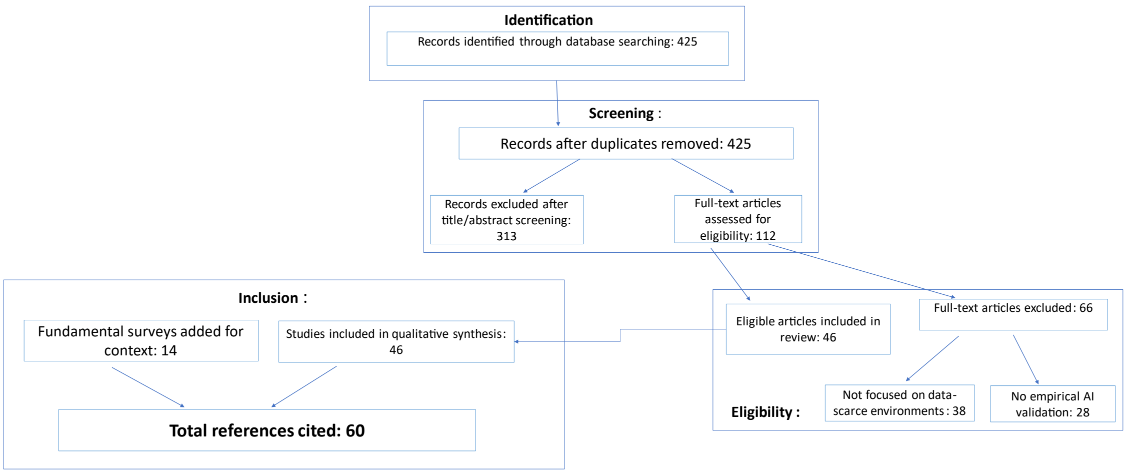

Figure 1. PRISMA flow diagram of the systematic literature review (SLR) process

Table 1. Core literature analysis

Ref.	Core AI Algorithms	Key Findings / Contribution
[22]	SLR / Multiple	Comprehensive review of PdM in Industry 4.0.
[23]	CPS / AI-based Systems	Human-centered design in Industry 4.0 environments.
[24]	AI + Blockchain	Using pre-trained Blockchain integration in Industry 4.0 systems.
[25]	ML / Data Analysis	Economic and social impact of Industry 4.0.
[26]	AI / Trustworthy AI	AI impact on sustainability in Industry 4.0.
[27]	AI-based Decision Support	Low-power Strategic roadmap for Industry 4.0 transformation.

Note: ML = machine learning; SLR = systematic literature review; PdM = Predictive Maintenance; AI = Artificial Intelligence; CPS = cyber physical system.

3. INDUSTRY 4.0-ENABLING TECHNOLOGIES AND DATA ISSUES

Industry 4.0 does not refer to simply having tools, but rather to a transformation towards an age where connectivity leads to intelligence and seeks to form smart factories through integrating CPS, IoT, and AI [28]. Nevertheless, the evolution from one state to another faces challenges, particularly the "data rich but information poor" paradox [29]. The paradox indicates the presence of large volumes of data in industrial settings, which need to be converted to insights to inform decision-making.

Without the proper analytical skills, however, the amount of data generated, in addition to its heterogeneity, velocity, and veracity, makes it difficult to exploit for complex applications such as PdM [30]. In general, there are six basic principles that govern the concept of Industry 4.0 and allow for the creation of smart factories [31]:

Interoperability: Ability of CPS, people, and smart factories to network [32]. Essential for PdM to ensure data flow among PdM components.

Virtualization: The development of virtual models of the physical environment, such as machines, products, and manufacturing processes, using sensors and digital twins [33]. It provides for monitoring and predicting possible failure scenarios.

Decentralization: The ability of CPS to act independently, minimizing the dependence on centralized control and increasing the speed of reaction to possible failures [34].

Real-Time Feature: Collecting and analyzing data immediately, making it possible to recognize problems and take action in PdM [35].

Service-Oriented Approach: Providing services (internal and external) via cloud computing technologies to develop a flexible and scalable solution for PdM, especially for SMEs [36].

Modularity: The ability to add and remove separate modules when required to create customizable PdM solutions for various manufacturing settings [37].

However, despite all the basic tenets of Industry 4.0, its implementation within already established infrastructures poses many obstacles. Many factories run on outdated machinery that does not support any kind of digital connection, hence making the process of obtaining and integrating data quite problematic [38]. Lack of standardization, cybersecurity problems, and high capital outlays further aggravate the situation [39] (Table 2).

Furthermore, the emphasis laid by the concept of Industry 4.0 on Big Data is not relevant to smaller companies and data-deficient contexts, where the amount of data available is always limited [40].

Table 2. Key enabling technologies in Industry 4.0 for PdM

Technology	Role in PdM	Strategic Benefit	Ref.
Artificial Intelligence (AI)	Core predictive engine (ML, DL, Reinforcement).	Improves RUL prediction accuracy and maintenance decision-making.	[40]
Cyber-Physical Systems (CPS)	Integration of physical assets with digital twins.	Enables real-time monitoring for ML/DL-based PdM systems.	[41]
Internet of Things (IoT)	Network of sensors for real-time data acquisition.	Provides high-quality data for RUL estimation and failure prediction.	[42]
Big Data Analytics	Processing large-scale heterogeneous datasets.	Supports ML/DL models for detecting complex failure patterns.	[43]
Cloud & Edge Computing	Infrastructure for data storage and local processing.	Enables scalable and low-latency deployment of PdM models	[44]
Digital Twin	High-fidelity virtual replica of industrial assets.	Enhances RUL prediction through simulation and real-time updates.	[45]

Note: ML = machine learning; DL = deep learning; RUL = Remaining Useful Life; PdM = Predictive Maintenance

4. BRIDGE BETWEEN INDUSTRY 4.0 AND PREDICTIVE MAINTENANCE

An important gap noticed in existing literature [46] is the absence of an appropriate bridge between generic technologies of Industry 4.0 and concrete demands of PdM technology. Here, IoT and Cloud Computing form the sensory and nervous systems, while AI forms the brain system. For SMEs, the issue with such a bridge is that it remains difficult due to exorbitant costs involved in the use of gold standard sensors. Thus, virtualization and modularity should be focused upon [47].

5. AI ALGORITHMS AND THEIR EFFICIENCY IN PREDICTIVE MAINTENANCE

The choice of AI algorithm is the most vital step in developing a PdM system. Although currently, DL is preferred, it relies heavily on vast amounts of labeled data, which are not always available in most industrial settings [48].

5.1 Comparison between classical ML and DL methods

“Data-scarce” cases generally favor classical ML models over deep neural networks. Specifically, algorithms like SVM and RF have shown remarkable performance on small datasets owing to their resistance to overfitting and reduced computational cost [49]. In this regard, SVM is especially effective in high-dimensional spaces with a few data points because it can find an optimal hyperplane separating faulty states from healthy ones using only a few support vectors [49]. On the other hand, the use of ensemble methods in RF has enabled the algorithm to reduce variance and be robust in its predictions, making RF ideal for small datasets that contain either limited features or instances [49]. Gradient Boosting Machine (GBM) and Extreme Gradient Boosting (XGBoost) are other examples of such algorithms with outstanding performance in “data-scarce” cases.

On the contrary, DL architectures, like Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTMs), need thousands of failure samples to capture the degradation patterns and generalize well [50]. Being complicated in nature with lots of parameters, DL models are extremely prone to overfitting, especially when the available training dataset is very small. For many SMEs, a machine may experience just one or two failures in a year, hence it would be impractical to build a DL model from scratch without performing massive amounts of data augmentation or generating new data, which poses another challenge [51]. Moreover, the computation power required for training such algorithms is not always feasible for SMEs that do not have adequate IT resources. To solve this problem, Transfer Learning techniques have been developed. With Transfer Learning, one can adapt the model trained in a rich data environment (e.g. a similar machine from another factory or public dataset) by applying the data available in the target SMEs through fine-tuning [51]. Examples of such applications can be found in the work [51]. In addition to the aforementioned methods, other approaches to PdM such as the One-Class SVM and Isolation Forest can be effectively employed in conditions where there is a lack of data, since they rely on learning about healthy cases and detecting any anomalies as possible defects, bypassing the necessity of having substantial data on failures.

5.2 Performance metrics for low-data environments

In addition to accuracy, performance of PdM solutions in SMEs also needs to be assessed in terms of their reliability and intelligibility [52]. An operator would trust an easy-to-understand decision tree that provides reasoning behind a decision to perform maintenance better than a “black box” neural network. According to recent studies, hybrid methods using both physics and ML are most effective in data-scarce environments [53].

5.3 Effective strategies and solutions for Small and Medium-Sized Enterprises

The abstract mentions "effective strategies for transition"; however most approaches are still conceptual. In the case of SMEs, the key obstacles are high costs of initial investment, lack of expertise in AI technologies, and the need for replacement of their existing infrastructure [54].

5.4 Low-cost solution framework

We suggest that the three-level strategy is suitable for overcoming these problems, and each step has its own advantages, although there are some obstacles to be overcome as well:

1. Low-Cost Sensors Implementation: Instead of making expensive upgrades and purchasing new equipment, SMEs may use retro-fitting solutions based on the "plug-and-play" sensors. Technologies like Micro-Electro-Mechanical System (MEMS) accelerometers, acoustic sensors, thermal cameras in conjunction with Low-Power Wide-Area Network (LPWAN), such as Long Range Wide Area Network (LoRaWAN) and Narrowband Internet of Things (NB-IoT) allow to send data without the necessity of creating complex infrastructure [55]. Moreover, using such sensors may result in reducing hardware costs up to 70% when compared to standard industrial devices. Nevertheless, the issue of ensuring data quality becomes crucial.

2. Cloud-based SaaS Models (PdMaaS): The cloud-based SaaS solution, referred to as PdM as a Service (PdMaaS), gives SMEs access to advanced AI algorithms and powerful cloud infrastructure that hosts the system. Using the cloud-based model, the SMEs do not require any huge upfront investment towards hardware and AI professionals since SMEs are paying for the use of this service via monthly subscriptions [56]. Some notable strengths of the PdMaaS include the ability to scale, less burden on operations, and availability of state-of-the-art AI systems. However, the risk of losing data privacy, vendor lock-in, and unreliable internet connection must be considered.

3. Federated Learning: Federated learning is an advanced distributed learning method where multiple SMEs can collectively build one model based on the data from all the SMEs. In federated learning, the data from SMEs are never shared, but the model parameters (weight parameters) from each local model are combined together for better performance of the global model. This is known as knowledge pooling, which helps to resolve the issue of individual lack of sufficient data. However, federated learning poses challenges in terms of aggregating models and managing communication overhead and fairness.

5.5 Socio-technological integration

PdM implementation requires more than just mastering technology; it is a major organizational issue. Small organizations should develop a corporate culture of decision-making based on data analysis, which implies a radical change of mentality and operation processes [57]. In particular, it is important to ensure the existence of training programs that will provide maintenance personnel with relevant digital skills for cooperation with AI. The main task is not to create a fully automated system, but to enable people with the ability to independently verify the results of the work of AI, using their extensive experience and intuitive awareness of the machinery [58]. Management practices play an important role in overcoming any resistance to changes associated with new technologies and smooth integration of PdM with them into current processes [59].

6. RESEARCH DIRECTIONS FOR THE FUTURE

As more advanced AI-based PdM models are developed, a number of issues will need to be addressed to ensure that their use becomes widely accepted within the industry as a whole.

Dealing with Concept Drift: Since industrial processes change continuously (for instance, changes in material composition, temperature, and machinery wear), the development of effective AI models must account for concept drift, changes in environmental conditions that do not necessitate complete retraining [59].

Cross-Machine PdM: Another issue that prevents the broad application of PdM is the inability of current models to generalize across machines (regardless of brand). Therefore, one potential direction of future research could be finding ways to train universal failure predictors that would apply to multiple brands and models of machinery [60].

Sustainability & Green PdM: Besides its economic value, PdM plays an essential part in ensuring industrial sustainability. It is important for researchers to find out how the use of PdM can lead to less CO_2 emissions and a reduction in energy waste, making the manufacturing process more sustainable by utilizing resources better and increasing the life cycle of machines. This also involves the study of the environmental effects of using AI-based models.

7. CONCLUSIONS

In any case, this systematic review has shown an evident discrepancy between the idea of Industry 4.0 and real-life problems experienced by a majority of SMEs. While a "Big Data" approach is considered a prerequisite for intelligent manufacturing and PdM, it should be borne in mind that many SMEs are forced to work in circumstances where there is a lack of data, financial limitations, and a deficiency of expertise in digitalization. Therefore, solutions tailored to large-scale enterprises with large amounts of data and digital technologies cannot always be applied in a smaller industrial context.

According to the results of this review, it is clear that PdM can function perfectly without the need to collect huge amounts of data. In this regard, classical ML models like SVM are still quite relevant because of their effectiveness, high interpretability, and performance even when working with small amounts of data. Moreover, new trends in ML such as Transfer and Federated Learning provide great potential in terms of solving a data-scarce problem while maintaining privacy and data ownership.

Furthermore, the review highlights the significance of cost-efficient technological infrastructures. Affordable sensors, edge computing and low-cost Software-as-a-Service (SaaS) platforms dramatically lower costs associated with deploying PdM practices by making it possible to benefit from advanced analysis and AI-assisted maintenance techniques without the need for considerable spending on hardware equipment, computing power, and qualified specialists. Thus, the democratization of digital innovations is necessary to bring the advantages of Industry 4.0 to the benefit of small and medium-sized enterprises.

Moreover, besides considering technology, this research highlights the fact that the implementation of PdM requires a holistic transformation which encompasses both technical and social aspects. AI should serve as an instrument that helps to make better decisions but not as something that replaces human experience altogether. Humans are needed to evaluate and interpret the results obtained during model execution, validate the maintenance decisions made according to the data collected and manage any abnormal situations.

The adoption of intelligent maintenance systems is the final aspect in which SMEs can benefit from opportunities that lie ahead in adopting PdM. The implementation of such systems will lead to greater reliability of equipment, reduced downtime, improved optimization of maintenance costs, and greater environmental sustainability due to improved resource management. Research in the future should be focused on the development of lighter AI models, standardized approaches to data sharing, and explanations of AI systems, all of which can help SMEs in their needs.

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NOMENCLATURE

PdM	Predictive Maintenance
AI	Artificial Intelligence
IoT	Internet of Things
SMEs	Small and Medium-sized Enterprises
CPS	Cyber-Physical Systems
RUL	Remaining Useful Life
ML	Machine Learning
DL	Deep Learning
SVM	Support Vector Machines
RF	Random Forests
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
CNNs	Convolutional Neural Networks
LSTMs	Long Short-Term Memory Networks
GBM	Gradient Boosting Machine
XGBoost	Extreme Gradient Boosting
MEMS	Micro-Electro-Mechanical Systems
LPWAN	Low-Power Wide-Area Network
LoRaWAN	Long Range Wide Area Network
NB-IoT	Narrowband Internet of Things
PdMaaS	Predictive Maintenance as a Service