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# REINFORCEMENT LEARNING FOR IOT-BASED PREDICTIVE MAINTENANCE: APPLICATIONS, CHALLENGES, AND FUTURE DIRECTIONS

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**Abstract**
*This paper is our literature review to investigate the integration of RL and IoT in predictive maintenance of industrial systems. This review aims to summarize the significant applications, challenges, and prospects in this field according to 22 related peer-reviewed papers published from 2020 to 2023. Aggregating results from the literature, this study demonstrates the applications of both RL and IoT technologies, for example, in the manufacturing, energy and smart building domains, and aims to optimize maintenance schedules, predict equipment failure, and decrease operational downtime.*
*The paper also presents the major difficulties involved in the use of RL and IoT in predictive maintenance systems, in terms of data quality, computational bounds, privacy issues and integration with legacy systems. In contrast, the review highlights some of the potential future research areas, such as leveraging Federated Learning for privacy-preserving model training, exploiting Edge AI for real-time decision-making, the requirement for explainable AI (XAI) for gaining trust, and designing scalable RL models to address the large-scale industrial IoT setting.*
*This review offers an up-to-date perspective of where the RL and IoT stand with predictive maintenance, and an orientation of future research is offered, outlining the main bottleneck and frontiers that have to be addressed to improve the efficiency and scalability of these systems in actual industrial scenarios.*

## INTRODUCTION

### 1.1 Background

The combination of Reinforcement Learning (RL) and Internet of Things (IoT) is receiving utterly intensive attention in the last few years, particularly as applied to predictive maintenance in industrial plants. Predictive maintenance (PdM) has emerged from those classical maintenance types (e.g., reactive, preventive maintenance) and evolved to more data-based methods. Real-time data from IoT sensors in machines are being used to predict imminent machine failure, resulting in minimizing downtime and maintenance costs.

In the recent years, the converging of ML with IOT have brought in significant changes in the asset management for many industries. Reinforcement Learning (RL), a subfield of ML, has shown great potential in handling dynamic, uncertain environments, and is well suited for the optimization of predictive maintenance decision making. RL models reinforce their decision making over time, using explicit feedback such as rewards, as well as penalties for undesirable decisions. With the shift of industrial workplaces to Industry 4.0, the combination of RL and IoT in PdM can greatly improve the operational efficiency and mitigate maintenance cost.

### 1.2 Problem Statement

Even so, the full benefit of these technologies for predictive maintenance has not been gained. The practical application of RL based predictive maintenance systems is highly challenged by data quality, privacy and computational resources constraints and the integration with legacy systems. The absence of integrative overviews of the (fragmented) literature on these information systems results in limited knowledge for both practice and research on the current state of the art of these systems, and what we know and do not know until now.

To the best of our knowledge, no previous review identifies studies related to the use of RL and IoT for predictive maintenance; thus, the purpose of this work is to fill this gap able to perform a structured review and synthesizing the literature on the application of RL and IoT for predictive maintenance. We would like to provide comprehensive view to the reader by focusing on the following: i) identifying major areas of application, ii) challenges involved and iii) future research directions that may enable more effective and scalable predictive maintenance systems based on RL.

### 1.3 Objectives of the Study

**The main goals of this research are as follows:**

· To investigate and classify the uses of Reinforcement Learning (RL) in IoT-based predictive maintenance systems in various industries.

To discover and evaluate the problems during applying RL and IoT to predictive maintenance, including data privacy, computational resources and integration problem.

· To point out the future research and development directions of RL and IoT integration in the predictive maintenance, underlining the emerging trends like federated learning, edge computing, and explain ability of AI models.

### 1.4 Scope of the Study

In this paper we will only consider integration of RL and IoT for predictive maintenance. The scope ranges from a careful investigation of 22 peer-reviewed research papers from 2020 to 2023 (covering various RL and IoT techniques in predictive maintenance in manufacturing, energy, transportation, and building facilities). The project will not produce new models or conduct evaluations but rather it will integrate results available in the literature to increase what is known about the state of the art.

### 1.5 Research Questions

The following are the research questions that underpin the study: 1.

· What are potential usage of RL in IoT based predictive maintenance systems and how it is implemented across different industries?

What are the main difficulties of applying RL and IoT for the predictive maintenance, and how to cope with such complexities?

What are the future prospects of research for RL and IoT-based predictive maintenance, and what more recent technologies can be explored in this area?

## 1. LITERATURE REVIEW

### 2.1 Introduction

As industrial systems become more sophisticated and the desire to lower maintenance costs and unplanned downtime increases, Predictive Maintenance (PdM) has become an essential solution. Recent research exploits data, AI/ML, IoT, edge/fog computing, decentralized learning frameworks toward increasing accuracy, scalability, and privacy as well as cost effectiveness.

2.2 Reinforcement Learning & transformer-like methods we first start with more related works to language, including Reinforcement Learning (RL) & transformer-based techniques.

TranDRL: Transformer Driven Deep RL (Zhao et al. )

Zhao et al. introduce TranDRL, a Transformer-designed RL-based hybrid model for better maintenance scheduling and failure prediction. The Transformer model is responsible to capture long-range dependencies from the time-series data, whereas the RL agent can change the maintenance actions over each time-step. Experiments showed TranDRL outperforming significant traditional Q-learning or Policy Gradient in test accuracy and cost-efficiency.

Hierarchical HHMMRL (Abbas, Chasparis, Kelleher)

Abbas et al. propose an HMM-based RL approach to model the latent and observable states simultaneously. Hierarchical design allows multi-level decision making in a dynamic operational environment. Demonstrated on industrial pump data, it provides better predictive performance with as well as cost savings over rule-based and simpler RL models.

Challenges: RL frameworks benefit real-time maintenance decision making; the use of sequence models (Transformers or HMMs) increases context-aware and adaptability.

**2.3 Federated & Privacy Preserving Learning**

Federated Auto encoder (Becker et al.)

In the context of edge computing, Becker et al. train a federated auto encoder for anomaly detection retaining privacy by keeping the sensor data only at local without transmitting the synchronous model updates. Their scheme minimizes central data transmission and maintain good accuracy in IoT sensor setting.

Federated Learning for PdM & Quality Inspection (Pruckovskaja et al.)

Pruckovskaja et al. investigate federated learning in the training process of PdM models (not sharing raw data across multiple machines/hospitals or even factories). They use federated architecture that combines local updates into global model, which can provide better generalization and robustness in prediction of RUL, but also guarantee data privacy and reduce the time spent on maintenance.

**Hybrid FL: 1DCNN and BiLSTM (Ahn et al.)**

Ahn et al. introduce a decentralized anomalous event detection approach leveraging 1DCNN (for spatial features extraction) and BiLSTM (for temporal relations). Federated learning guarantees local training on pumps, while sharing only changes in the model. This structure provides efficient detection with data privacy protection and reduced communication.

Themes: Decentralized frameworks (federated and edge-based) are high-performing in terms of predictive maintenance and anomaly detection, without sacrificing privacy and infrastructure.

**2.4 Deep RL for Resource Scheduling**

**DRLIS: DRLBased-IoT Scheduler [ W16]**

Wang et al. propose DRLIS, a novel scheduler for fog computing networks based on Deep RL that efficiently allocates resources and schedules tasks for IoT devices. Formulated as an MDP, DRLIS is elastic to fluctuating workloads, and achieves significantly energy efficiency, lower latency, and more balanced resource allocations, compared to static schedulers.

**Theme:**

Reinforcement learning, goes beyond maintenance to a general IoT/fog resource optimization, and provides scalable, adaptive scheduling.

2.5 Classical ML Driven PdM Approach In recent years, many research papers are found discussing ML in predictive maintenance but when we talk about ML Informed styled PdM the literature is relatively sparse.

**(3) Machine Learning Models (Smith et al.**

Smith et al. examine clas- sical ML techniques (regression, classification, clustering) when used to predict PdM, with a focus on the tradeoff in selecting an appropriate model – i.e., accuracy versus com- mutational cost. Case studies have demonstrated significant maintenance cost reduction, and improved uptime from the hip application of ML.

Data Mining in Manufacturing (Johnson, et al.)

Johnson et al. s extensive review includes clustering, classifiers, and association rule mining in manufacturing PdM. They conclude that algorithms for data mining help predict and operate more accurately and efficiently than traditional methods.

AI in IoT \& Cost Optimization (Wang et al.

In this review, we find how AI/ML analytics lower Total Cost of Ownership (TCO) in IoT. Anomaly detection and RUL models based IOT sensors and Big Data have been discussed in the work by the authors, which prove reduction in unplanned downtime and maintenance costs pertaining to various industry domains.

Topics: "Classic" ML and data mining are also fundamental in PdM, particularly of (structured) sensor data; more general analytics of IoT systems allows for even more cost savings and less wear and tear in operations.

**2.6 Domain Specific Applications**

PdM in the Building services (Bouabdallaoui et al.

Such work like [53] applies auto encoder and LSTM for anomaly detection in building systems including HVAC. Trialed at a sports venue in Paris, the system successfully forecast failures two days in advance. Although promising, the authors point to false positives, data sparsity, and transferability between different facility types as limitations.

DSS builts for Industry 4.0 (Rosati et al., 2023)

Rosati et al. introduce an IoT–Big Data–ML-empowered DSS for PdM in Industry4.0. Employing Random Forest models and cloud-based learning, they obtained excellent prediction accuracy ($R^2$ ≈0.868) and low response time (~2.35s per batch of 400 samples), thus confirming the system usability for real industrial applications.

**Block chain Backed IIoT (Peruthambi et al.)**

In this manuscript, we review several ML algorithms for IIoT PdM: Random Forest, XGBoost, CNN, LSTM and we introduce a block chain-supported FL framework. XGBoost achieved top accuracy (~96.1%). Other techniques such as Koop man observables and DMDc decrease the computational expense by 35%. The work highlights the scale issues and the importance of edge AI and RL affecting next developments.

Highlights: Practical application focuses on ML-based DSS in the real-world; privacy/security using block chain and federated learning; and scalable, interpretable models in a variety of industrial domains.

**2.7 Synthesis & Emerging Trends**

· Reinforcement Learning with Sequence Modeling: Innovative classes of combinations (Transformers, HMM) allow for fine-grained scheduling and failure prediction.

· Federated & Edge Paradigms: Privacy-preserving is executed without major data transfer towards a data-consuming party.

Hybrid ML Strategies: CNNBiLSTM hybrids, Random Forests, XGBoost lead in accuracy with scalability and explain ability.

• System Efficiency: System-level integration of IoT, Big Data, cloud-edge paradigms, and block chain enable real-time decision systems with low latency.
• Cost A cross Domains: Models implemented in pumps, buildings, and general Industry4.0; cross- asset-type generalization is still challenging.

### 2.8 Gaps & Future Directions

Model Interpretability – Transformer/RL approaches provide high efficacy but are less explainable than simpler ML models. Explainable RL solutions are what's needed.

Scalability/ Heterogeneity: Several works are concentrated on certain assets or in pilot projects. More broad and diverse deployment of such systems across multiple industries has yet to be explored.

Long-Term Deployment Perspective: Research work in literature constitutes of mainly simulation-based or short term validations. Challenging, high-dimensional, longitudinal real-world studies are required, particularly in federated and edge environments.

Hybrid Architectures: More investigations are required to integrate federated learning, RL, edge AI and block chain as a in a holistic PdM system.

Humans interaction in PdM (Industry 5.0) : Majority of the techniques are algorithm-focused. Future generation's systems need to be embedded in human-in-the-loop mechanisms for operational safety and efficiency.

### 2.9 Conclusion

The literature surveyed also indicates the development of predictive maintenance towards more intelligent, adaptable and distributed systems. Hybrid RL Transformer and HMM based architectures, federated learning, CNN/BiLSTM models, and even real world Industry4.0 platforms are developed and implemented in progress to optimize the operational efficiency maintaining privacy, minimize the computational burden and to expand over different types of assets. Future research could emphasize interpretability, real-life validation, and also incorporate human-centered frameworks in order to ground sustainable practical PdM solutions.

## 2. METHODOLOGY

### 2.1 Research Design

In this paper, we take a systematic literature review on the application, challenge of RL and IoT integration for predictive maintenance in industrial systems. This study aims to draw together findings from existing studies to obtain an overview of the current state of the field.

The analysis is based on 22 peer-reviewed articles (published between 2020 and 2023). These papers were chosen because they were related to the RL technology and IoT in the scope of predictive maintenance. Rather than to build new models, this review attempts to discover what are the common and consistent themes, problems and trends occuring in the mutual use of RL and IoT to PM.

### 2.2 Paper Selection Criteria

The research papers included in this work have been selected according to the following criteria:
• On the topic: Papers were chosen that were about use of RL in IoT-based predictive maintenance systems, or that were about IoT systems using machine learning for maintenance optimization.
• Regency: Only papers published from 2020 to 2023 were included so that the reported results are recent and related to state-of-the-art technology.
• Industry coverage: Papers from different industries (manufacturing, energy, transportation, building systems, etc.) were included to provide a diverse perspective to applications of RL and IoT for predictive maintenance.

• Methodological quality: Reputed journals or conferences have published the included studies, indicating high quality research sound with sound methodological.

### 2.3 Data Collection

In this documentary, we obtained data by a systematic search of academic databases (IEEE Xplore, Google Scholar, ScienceDirect). The selection of applicable articles followed this procedure:

• Search Strategy: We identified papers using keywords like "Reinforcement Learning," "IoT," "predictive maintenance," and "industrial applications."

• Inclusion and Exclusion Criteria:

• Selection: Works that explicitly 'mentioned the topic under consideration', that is, RL applied to the IIoT in predictive maintenance or that addressed challenges associated with these technologies.

• Exclusion: Papers that were not targeted towards predictive maintenance or that did not addressed integration of IoT and RL.

**• Data Points Extracted:**

• Applications: Application of RL in IoT predictive maintenance such as the industrial systems and operational context.

• Challenges: Data quality, privacy, computational bottlenecks, scalability in the applied those of RL and IoT.

• Future Directions: Recommended remedies and new trends regarding the application of RL and IoT to predictive maintenance, including federated learning, edge computing, and model explain ability.

### 2.4 Analysis Methodology

The findings of the selected papers were systematically analyzed by means of thematic content analysis. The analysis involves the following steps:

Categorization of Applications:

• The papers about RL, IoT and predictive maintenance were classified according to the industry of interest. These categories include:

• Manufacturing and Industrial Equipment: Predictive maintenance of in-factory equipment, robotics and production lines.

• Energy and Utilities: RL and IoT for predicting component failure from power grids and renewable energy systems.

• Smart buildings and infrastructure - Predictive maintenance for HVAC, elevators, and other building systems.

**Identification of Challenges:**

• Themes The barriers identified in the papers were grouped under the following themes:

• Data quality and availability: Problems with noisy, incomplete, or inconsistent sensor data.

• Computational Bound: Computation limitations of IoT devices in employing complex RL models due to scarcity of resources.

• Legacy Integration: The difficulty of integrating RL predictive maintenance systems to legacy industrial systems.

• Privacy and Security: The data protection and privacy issues are increasingly becoming a concern and have a particular significance in IoT enabled environment.

**Extraction of Future Directions:**

• The identified future directions in the papers were categorized according to the following rising trends:

• Federated Learning (FL) : Train models on decentralized devices preserving data privacy.

• Edge computing: Processing data and making decisions in real time on local IoT devices for lower latency and better system performance.

• Explain ability of RL Models: The requirement for understandable decision making in order to promote trust in RL-based predictive maintenance systems, particularly when dealing with safety-critical applications.

• Scalability: Understanding how to scale RL based predictive maintenance across large industrial systems.

**2.5 Evaluation Criteria**

The relevance and quality of the selected papers were assessed based on the following criteria:

• Relevant Degree: How relevant each paper is with respect to RL and IoT in predictive maintenance, mainly to the industrial field.

• Innovativeness: The originality of the methods/algorithms/frameworks, proposed in each paper, for RL-based predictive maintenance.

• Practicality of Future Directions - The practicality of future research suggestions (e.g., the impact of emerging technologies such as federated learning, edge AI on Predictive Maintenance).

• Performance of Models: There were no novel models developed in this study, however, performance of models that were referenced in the papers were reviewed including accuracy, decrease in downtime, and saving in cost.

**2.6 Limitations**

**The principal limitations of this study are:**

Range of Literature: Literature covered in the review is based on 22 papers published from 2020 to 2023. Although this is a way to get a broad perspective, it doesn't necessarily include all the studies in the field that are pertinent.

• No Primary Research: This work is an analysis based on literature review alone, hence no primary experiments and no development of new models.

• Generalization: The results of this study may not be completely transferable to all industries, since predictive maintenance requirements can differ widely between industries.

**2.7 Conclusion**

The objective of this research was to establish a comprehensive systematic review of the current research about the amalgamation of Reinforcement Learning (RL) with the Internet of Things (IoT) for predicting preventive maintenance. The literature survey gathered in a total of 22 papers, which are analyzed to find out main application domains, challenges and research directions and to give a comprehensive review of the current state and the new trends in the discipline.

## 3. RESULTS AND DISCUSSION

### 3.1 Applications of RL and IoT on Predictive Maintenance

Insights from the 22 selected research papers, several critical uses of Reinforcement Learning (RL) in IoT-based predictive maintenance systems were recognized. These use cases cut across different sectors, highlighting the generalizability and applicability of integrating RL and IoT.

**Manufacturing and Industrial Equipment:**

A large number of the considered papers addressed the application of RL to optimize predictive maintenance in manufacturing systems. RL was used for failure prediction in production lines, robots and industrial machinery. These systems leveraged real time IoT sensor data (vibration, temperature, pressure, etc.) to predict potential failures and optimize when best to send in the maintenance crew.

Key Finding Studies demonstrated that RL algorithms, in particular DQL, enabled a reduction in unscheduled downtime and enhanced maintenance efficiency by making maintenance decision through data-guided information on when maintenance actions should be taken.

**Energy and Utilities:**

Other studies combined RL and IoT in the energy context (in the context of predictive maintenance related to power grids, transformers, and wind turbines). RL algorithms have been applied for degradation forecasting for the remaining useful life (RUL) of key components that make it possible to optimize maintenance intervals and minimize the influence on operations.

**Smart Buildings and Infrastructure:**
Another prominent application domain was the predictive maintenance of smart buildings through IoT. RL models were utilized to forecast failures in HVAC, elevator, and lighting systems. These have been the recipients of real-time sensor data to change the maintenance schedules and optimize the use of resources.
Key Result: A study indicated that the RL-based PD system in smart buildings contributed to enhancing energy efficiency, overcoming high maintenance costs and reducing energy consumption to the advantage of environmental sustainability and operational performance.
3.2 The hardships of RL and IoT applied to Predictive Maintenance
From the reviewed papers, it also became apparent that there were a number of remaining challenges with the deployment of both RL and IoT for predictive maintenance systems. These issues were similar throughout industries and must be resolved to help exploit the potential offered by these technologies.

**Data Quality and Availability:**
The issue of data quality was a common problem in almost all the papers reviewed. Most of the IoT sensors in industrial applications give noisy, incomplete or inconsistent data. This damages the performance of RL models that rely on good quality data to make good predictions.
Key Finding: Multiple studies recommended that data preprocessing methods, including cleaning, normalization, and selection of features ought to be used to improve the quality of data on which RL models are trained to address this issue.

**Computational Constraints:**
High computation complexity of most RL models in IoT devices because few IoT devices (sensors & actuators) have powerful resources. As for the computational resource, the edge device is incapable of dealing with the processing from large sensor data to atomic event on the fly.
Findings: The results of the study cited the possibility that energy hungry computations being offloaded to the edge for processing might be a way to lower latencies and help support real-time decision making in IoT.

**Integration with Legacy Systems:**
A major challenge identified in the literature was how to integrate the RL-based predictive maintenance system with legacy industrial systems. There are quite a few sectors where older machinery and infrastructure are still in place which are not capable of letting in modern IoT technologies.
Key Finding: To overcome this issue a number of papers suggested to employ hybrid methods that mix traditional maintenance concept with the state of the art reinforcement learning, which results in a smoother transition and the better synergy.

**Data Privacy and Security:**
Since IoT networks gather a lot of sensitive data, privacy and security were focal in many of the studied papers. One of the recurring problems was how to enable data sharing for model training in an effective way, without risking industrial data being misused.
Key Finding: The potential use of Federated Learning to train RL models on decentralized devices without exposing raw data was proposed for preserving data privacy and security.

### 3.3 Future Work in RL and IoT for Predictive Maintenance

Several future directions were also identified by the papers reviewed in this paper to enhance the cur-rent integration of RL and the IoT in predictive maintenance systems. Remarks are also made in these areas regarding new technologies and methods that could help them in the face of current limitations and in maintaining and improving their effectiveness.

Federated Learning for Privacy Preserving Model Training:

(FL) was recognized as an important trend in the future by some papers. FL enables local training of models and transmission of model updates (not raw data) for IoT devices, which is beneficial for data privacy when model learning is still being performed.

Key finding: FL is especially suitable for industries with consideration for privacy protection, for example, healthcare, energy, and manufacturing. It may provide a powerful tool for mitigating challenges relating to data sharing and privacy.

**On-Chip AI for Real-Time Processing and Decision:**

Future work was focused on the use of Edge AI for real-time decision-making. RL models can act faster and more efficiently if data is processed by edge devices, which minimizes the burden on the cloud for continuous communication.

Key Finding: Edge AI adoption will enhance the agility of predictive maintenance systems and minimize latency, critical for time-sensitive applications in manufacturing and energy.

What do we really know about interpretability in RL?

Because RL models are typically "black-box" systems, one of the identified requirement is towards explainable AI (XAI) in the literature. These industries with safety-critical work processes need clear and understandable decision-making processes to ensure confidence in AI based systems.

Key Finding: Future work is needed to develop methods that explain the rationale for decisions by the RL models to the human operators, especially in high-risk industries.

**Scalability and Deployment of RL Models in Large-Scale IoT Systems:**

With the growth of IoT systems, scalability of RL models is a key issue. Several studies indicated that RL models must be adapted to the large-scale industrial IoT system where thousands of devices produce large volumes of data.

Key finding: Studies related to distributed RL and multi-agent reinforcement learning (MARL) can help to make RL models more scalable to manage large scale IoT deployments.

### 3.4 Summary of Findings

The present study show case the potential of Reinforcement Learning (RL) and Internet of Things (IoT) implemented in predictive maintenance for diverse industries. The found literature applications contribute largely to maintenance planning, predict of failures, and costs reduction. However, issues of the quality of data, constraints of computing power, and system integration are still in place.

The promise of RL and IoT in predictive maintenance will largely depend on how these challenges will be solved with various cutting-edge technologies, such as Federated Learning, Edge AI, and scalable RL models. Furthermore, the further development of explainable AI is also likely to facilitate the acceptance of RL-based systems, especially in fields that require a high level of trust and safety.

## 4. CONCLUSION

The aim of this paper is to discuss the consolidation of RL and IoT in predictive maintenance by exploring 22 research papers through the systematic review published between 2020 and 2023. By consolidating the results of these papers, this paper seeks to uncover target applications, as well as the challenges among the adoption of RL and IoT, and suggest future research that can mitigate inadequacies of these systems.

**Key Findings**

Applications: Studies reviewed showed that the RL in context with IoT provides considerable benefits for predictive maintenance across multiple domains such as manufacturing industry, energy industry, transportation and smart building. RL techniques, in particular Deep Q-Leaning (DQN), have been used to predict machinery failure, to schedule maintenance, and to minimize breakdowns. They demonstrated cost and efficiency benefits compared to the existing ones, thereby enhancing the system reliability for industrial applications.

Challenges the convergence of RL and IoT in predictive maintenance systems is, however, not a straight-forward task, and numerous challenges need to be addressed:

Data Quality and Availability: A lot of IoT systems are affected by noisy, incomplete and inconsistent sensor data, making the performance of traditional RL models difficult.

Computational Limitations: The low-level computational capability of most IoT devices hinders the ability of deploying state-of-the-art, and often complex, RL models/ algorithms in real-time.

Integration of legacy products: Current industrial systems are generally not compatible with new technologies based on IoT and RL, and the integration of such products is non-trivial.

Privacy & Security: Privacy issues arise in the gathering and analytics processing of sensitive industrial data.

**Future Directions:**

The study revealed the following key future directions to advance RL and IoT in the area of predictive maintenance:

Federated learning: To mitigate concerns for data privacy, federated learning enables decentralized training of models so that data can be maintained locally to achieve higher privacy guarantees without sacrificing model quality.

Edge AI: By processing data locally on IoT devices with Edge AI, decisions can be made in real-time, which reduces latency and results in more responsive systems.

Explain ability of RL Models: It is important to have transparent decision-making process in RL models, especially useful in safety-critical applications requiring operators to have trust towards the decisions of the AI systems.

Scalability: With the increasing complexity of industrial IoTs, scalable RL model studies and distributed learning techniques (e.g., Multi-Agent Reinforcement Learning) will be necessary for efficiently handling large-scale systems.

**Contribution to the Field**

In this context, this work aims at offering a complete state of art about the topic of the integration of RL and IoT for PM. By consolidating literature findings, the paper provides new perspectives on how such techniques are being used, reasons why their uptake is less than might be expected, and future potential for the research field of predictive maintenance systems.

**Research Gaps and Future Work**

The current study, despite contributing useful insights, also revealed some research gaps during the literature review that need to be considered in future research:

Deployment Studies: The majority of the studies are simulations over short-terms, case study with small scale data. Long-term deployment studies need to be carried out in order to confirm the applicability of RL-based predictive maintenance in practical industrial scenarios over long periods.

Real-world Scenarios: Most of the work is performed in hypothetical or simulated environment. A larger set of industrial case studies is necessary to determine how well RL and IoT systems function in real-time, industrial scenarios as well as to address the real-world challenges associated with deploying at scale.

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