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PREDICTIVE MAINTENANCE AND RELIABILITY-CENTERED APPROACHES IN MECHANICAL ENGINEERING SYSTEMS

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Abstract: Predictive maintenance and reliability-centred maintenance (RCM) are now two important strategies in modern mechanical engineering systems and provide a useful solution to minimize the number of unexpected failures, decrease the cost of maintenance, and increase operational reliability. Data used in predictive maintenance: Integrating data on real-time, condition monitoring, machine learning algorithms and predicting equipment failures prior to occurrence enables timely data-driven solutions. Conversely, RCM offers a formal methodology to determine what maintenance strategy is most suitable on the basis of the role and the importance of each piece. Combined, these methods are a move away from the traditional reactive and pre-emptive maintenance into intelligent and data-driven systems. Industry 4.0 has enhanced its use by incorporating technologies like the Internet of Things (IoT), artificial intelligence (AI) and deep learning to enable an accurate identification of faults, better decision making and maintenance routines being performed automatically. Such methodologies have proved to be effective in many different industries, such as manufacturing, transportation, energy, and aerospace, where the performance of the systems and uptime are crucial. The predictive and reliability-centred maintenance styles have also become very crucial in the growth of the mechanical engineering systems as industries focus on greater efficiency, safety, and sustainability.

Keywords: Predictive Maintenance, Reliability-Centered Maintenance (RCM), mechanical Engineering Systems, Machine Learning, Condition Monitoring.

1. INTRODUCTION

Mechanical systems apply to many industrial processes, including manufacturing, transport and energy production. It is imperative to ensure that they run smoothly to increase their overall productivity in an organization, reduce maintenance costs, and downtime [1]. In the conventional literature maintenance has always been classified into two maintenance strategies which are reactive maintenance as well as preventative maintenance. Reactive maintenance is maintenance practice where you wait until problems occur and it can be very costly and time consuming in fixing them. Preventive maintenance, however, is based on an inspection and replacement of parts on a regular basis to avert failure [2]. Although preventive maintenance presents an advancing on the reactive strategy, it has excessive parts replacements and the possibility of over-maintenance.

Predictive Maintenance (PdM) is a broad term used to refer to a wide variety of methods used to optimize the timing of maintenance based on the actual condition of equipment. They comprise thermographic surveys on electrical gear and vibration surveys of rotating equipment; these examples depict the versatility and applicability of PdM in several industrial areas [3]. The main concept of PdM is to constantly monitor mechanical conditions, operational efficiency, and many other important factors, and to maximize the time interval between the next set of maintenance routines and minimize unexpected outages caused by equipment malfunctions.

Machine learning (ML) stands in the framework of data science and artificial intelligence and is referred to some data mining based on the employment of statistics to find unknown patterns. The Deep Learning is identified as one of the prominent technologies in the field of machine learning, where the ability to learn happens by successive layers and is a new era of machine learning [4]. The introduction focuses on the shift of the industrial world into Industry 4.0 which is the data-driven world. It indicates the importance of large scale data analysis especially in predicting failures in order to save resources and time that are spent on reactive repairs [5]. The focus is on the demand for Predictive Maintenance (PdM) systems to prevent component failures, ensuring uninterrupted operations and impacting production quality and client satisfaction.

Reliability evaluation for the use of mechanical equipment to increase the reliability of equipment through condition-based maintenance and reduce costs has made it a prominent subject for studies on dependability and life prediction for mechanical equipment [6]. Predictive life also benefits from knowing how to evaluate dependability. The ability to evaluate dependability is also beneficial for life prediction and maintenance time [7]. Machine tool stability and overall production effectiveness are affected by performance deterioration, which is one of the most significant factors during machining and closely relates to product accuracy.

Maintenance has become a significant burden for corporations. As a result, contemporary businesses are looking for methods to improve maintenance at a higher level through various tactics. Reliability Centre Maintenance (RCM) has been a strategy for providing maintenance to many organizations for decades [8]. The concept of RCM was initially presented by the aviation industry in the 1960. For some equipment units, it is usual practice to identify the best kind and frequency of maintenance. The process of identifying the best maintenance practices is called RCM. It has been shown to be more successful in maintenance planning, which is the most crucial sustainability pillar.

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1.1. Structure of the Paper

The paper is organized as follows: Section 2 discusses predictive maintenance techniques and enabling technologies. Section 3 focuses on reliability-centered maintenance methods. Section 4 presents real-world applications in mechanical systems. Section 5 provides a literature review of recent studies. Section 6 concludes the paper and outlines future research directions.

2. PREDICTIVE MAINTENANCE (PDM): DATA-DRIVEN RELIABILITY

Predictive Maintenance (PdM), often referred to as Condition-Based Maintenance (CBM), focuses on forecasting the likelihood and timing of equipment failures. PdM converts operational data into actionable insights for reliability improvement by utilizing ML algorithms, sophisticated analytics, and real-time condition monitoring data. This data-driven method helps maintenance teams plan interventions in advance by accurately estimating Remaining Useful Life (RUL) and detecting early indicators of degradation. The ultimate goal is to strike an optimal balance between maintenance frequency and associated costs, thereby minimizing unplanned downtime, enhancing system availability, and extending equipment life (as illustrated in Figure 1).

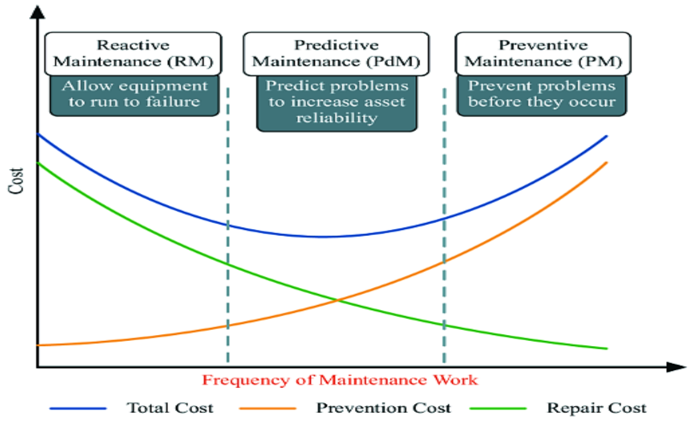

Figure 1: Comparison of RM, PM and Pdm on the Cost and Frequency of Maintenance Work

The idea behind PdM is to optimize O&M by using the real operating conditions of systems and components. The foundation of the predictive analysis is data collected from meters and sensors mounted on tools and machinery, such as vibration data, thermal imaging, ultrasonic data, operation availability, etc. Through the use of predictive algorithms, the predictive model analyses the data, finds patterns, and determines when equipment needs to be retired or repaired [9]. PdM helps businesses optimize their strategies by doing maintenance operations only when absolutely essential, as opposed to letting a piece of equipment or a component break down or replacing it when it still has usable life. PdM may reduce unneeded inventory, excessive maintenance costs, scheduled and unexpected downtime, and needless maintenance on operational equipment.

2.1. Enabling Technologies in PdM

PdM, supported by the industrial industries of machinery, electronics, autos, and aerospace, heavily relies on the ongoing development of network, database, and object-oriented technologies [10]. In addition to increasing employee productivity, it lowers engineering expenses, shortens product life cycles, reduces engineering change control time, and lessens the frequency of project revisions. Furthermore, PdM shortens the launch cycle of new products, lowers development costs, and enhances both product quality and service quality.

2.1.1. Condition Monitoring Techniques

A maintenance technique called condition monitoring keeps an eye on a machine's or structure's state over time to identify when maintenance is required [11]. Sensor devices are employed to collect real-time data from the system, which is then processed into actionable information. The best time to perform maintenance interventions is determined by applying decision-making techniques. The diagnostic center is a health control center that uses techniques to differentiate between complicated system defects and precisely identify fault circumstances. The maintenance plan is divided into three growth stages:

- **Breakdown maintenance:** Maintenance is performed only after equipment fails, often leading to unplanned downtime and higher repair costs
- **Preventive maintenance:** Scheduled maintenance is carried out at regular intervals to reduce the likelihood of failures and extend equipment life.
- **Predictive maintenance:** Uses real-time condition monitoring and Analyzing data to anticipate possible failures enables prompt and focused actions.

2.1.2. Sensors and Data Acquisition Systems

Undergraduate experiments in Mechanical Engineering (ME) laboratories often focus on implementing simple data acquisition programs that students can easily operate and instructors can customize based on specific objectives [12]. Sensors play a critical role

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in these setups by collecting real-time physical data from experiments [13]. The use of electronic spreadsheet add-ins has proven effective in optimizing time and improving the depth, quality, and clarity of laboratory work. Tools like Measure have been integrated into software such as Lotus 1-2-3 and Excel, enabling direct communication and data acquisition from sensors and various instruments into the spreadsheet environment.

2.1.3. Signal Processing and Feature Extraction

Feature extraction in condition monitoring involves analyzing signal derivatives such as velocity $x^{(1)}$, acceleration $x^{(2)}$, higher-order derivatives $x^{(3)}$, $x^{(4)}$, and fractional-order derivatives $x^{(a)}$ where $\alpha \in R$. These signals are often obtained from acceleration measurements through numerical or analogue integration and differentiation. Vibration analysis, which focuses on the dynamic aspects of the signal, aims to detect faults at an early stage. In long-duration signals, the mean of the velocity and acceleration will usually be taken as zero, that is, at steady measurement points such as bearing housings. On this assumption the standard deviation of the fractional derivative $x^{(a)}x^{(\propto)}$, under the assumption, is equal to its root mean square (RMS), which can be easily calculated, and is a useful statistical property in fault detection and condition evaluation.

2.2. Machine Learning and Artificial Intelligence Techniques in Predictive Maintenance

Machine Learning (ML) and Artificial Intelligence (AI) are increasingly becoming a part of predictive maintenance (PdM) systems, which allows analyzing large datasets and predicting equipment breakdowns with more accuracy and efficiency [14]. Such technologies can be used to help shift the paradigm of traditional maintenance towards a more proactive, data-driven one. Under predictive maintenance, the ML and AI methods will be especially employed in analyzing the sensor data and identifying trends and forecasting potential malfunctions even before they happen. Some of the important ML and AI methods commonly used in predictive maintenance of mechanical systems are outlined below.

- Supervised Learning Techniques
- Unsupervised Learning Techniques
- Reinforcement Learning
- Knowledge-Based Systems and Expert Systems

2.3. Deep Learning Methods for Predictive Maintenance

The more often used PdM methods are DL-based methods as they can address the heterogeneity in the data set, including vibration signals, acoustic emissions, and sensor readings [15]. The latest developments in deep learning applications for predictive maintenance. According to the authors' state-of-the-art analysis of the use of DL models in predictive maintenance, CNNs and RNNs produce much better results than conventional ML models. However, lightweight deep learning models for edge real-time predictive maintenance are not included in this work [16]. It can also go over deep learning methods for health forecasting, since years of study have shown that these methods have a lot of promise. However, given that most practical approaches are modelled in such severe data-centric problems, this is not feasible in small enterprises.

3. RELIABILITY-CENTERED MAINTENANCE (RCM)

The concept of Reliability-Centred Maintenance (RCM) originated in the aircraft industry and has been successfully applied for over 20 years across various sectors, including military forces, nuclear power, offshore oil and gas, and numerous other industries [17]. These domains' experiences show that preventative maintenance (PM) expenses may be significantly decreased while preserving or even improving system availability [18]. RCM is the best combination of proactive, condition-based, time- or interval-based, and reactive maintenance techniques. Figure 2 shows how each method is fundamentally applied. Instead of being implemented separately, these primary maintenance techniques are combined to capitalize on their unique advantages, increasing facility uptime and equipment dependability while lowering life-cycle expenses.

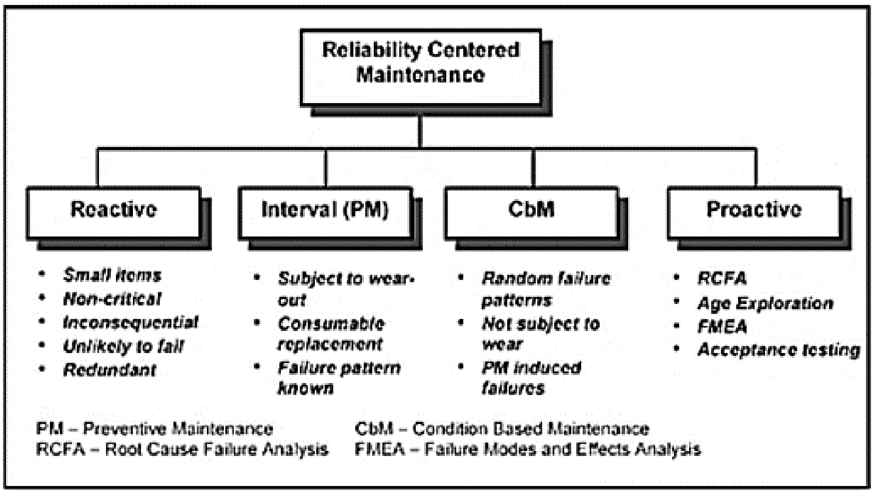

Figure 2: RCM Components

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3.1. Failure Mode and Effects Analysis (FMEA)

An FMEA produces two important results. To help identify high-priority failure modes, the related risk ranking comes first. The related mitigating approach comes in second. FMEAs and criticality assessment have been used by methodologies like RCM to create cost-effective maintenance plans. RCM weighs the cost of redesign or preventive maintenance against the risk and expense of failure [19]. Then, using this comparison, cost-effective mitigation techniques are identified. Failure modes should always incorporate some kind of mitigation where safety is an issue. Although some of the already available literature reviews the FMEA process and looks into possible reasons of error, there is a serious dearth of research-based validation of the FMEA's usefulness and efficacy as well as specific recommendations for process improvement incorporating the human element. To measure the validity and reliability of FMEA as a risk analysis approach, some work has been done in the healthcare industry, which formerly depended heavily on retroactive risk management.

3.2. Step of RCM Method

The Reliability-Centered Maintenance (RCM) method involves several key steps: identifying system functions, determining potential failure modes, analyzing the effects of failures, and selecting appropriate maintenance strategies [20]. This structured approach ensures maintenance decisions enhance system reliability, safety, and cost-effectiveness.

- **System Selection:** The system selection process and information gathering. To ensure that the system under evaluation is not overly expensive, elections would be held in one of these phases.
- **Explain the system:** The system's explanation aims to maintain the overlap between the two systems.
- Explanation system and block diagram function: The study's system is detailed in depth as opposed to using a block diagram function. In this stage, the system work breakdown structure for the study system will also be developed.
- **FMEA analysis:** Early in the process of preparing an FMEA, a matrix is developed that links equipment and their potential functional failures. This matrix is created by combining the system work breakdown structure (SWBS) with information about possible function failures. The FMEA process includes calculating the Risk Priority Number (RPN) according to evaluations for detection, incidence, and severity.
- **LTA:** The purpose of the LTA's preparation is to give each mode precedence in terms of its total destruction and evaluation of its operation and functions up until the point at which there are reports of damage or injuries in that mode that are not related to that mode.

3.3. RCM Category & Classification

The most effective approach for creating failure management policies at the moment to maintain the operational performance of our physical assets is RCM [21]. In spite of its name, it encompasses operational, engineering, procedural, process, and training results in addition to maintenance. If it makes use of tangible assets, it may touch on a variety of business topics, and these days.

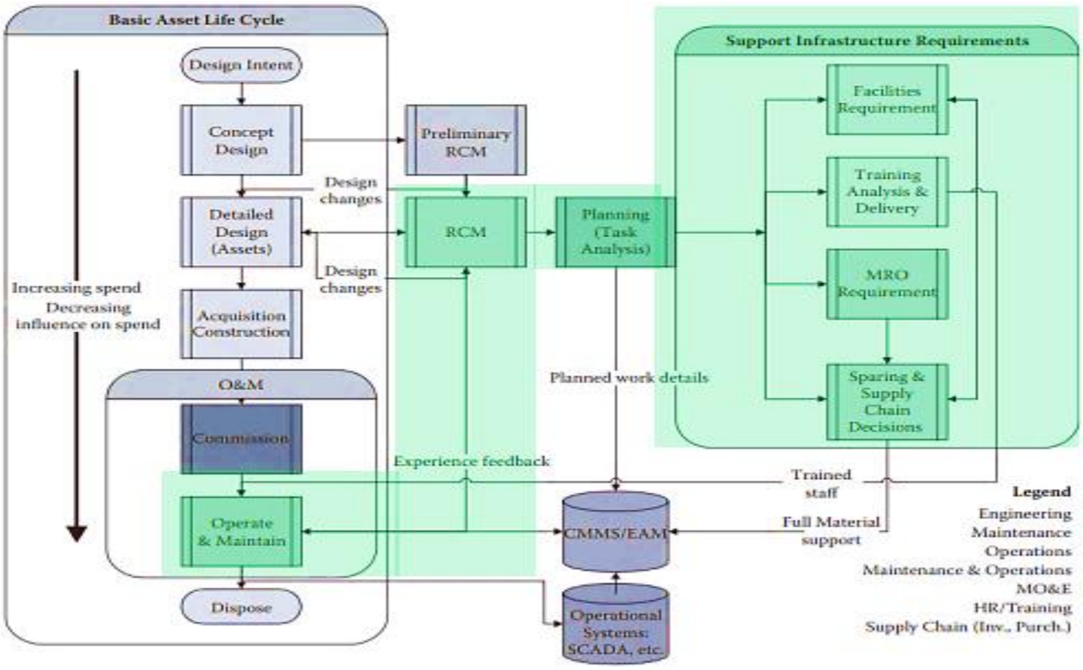

Figure 3: RCM Implementation in Asset Life Cycle

Referring to the categories and classifications of the asset life cycle sourced from ISO 55001, it can be understood that the implementation of RCM must have started from the design phase to operation & maintenance (green highlight), as clearly seen in the flow diagram in Figure 3.

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4. APPLICATIONS IN MECHANICAL ENGINEERING SYSTEMS

Predictive Maintenance (PdM) and Reliability-Centered Maintenance (RCM) are widely applied in mechanical engineering systems to improve reliability and reduce downtime [22]. In manufacturing, they monitor equipment like motors and conveyors to detect wear or failures early. In automotive and aerospace sectors, PdM ensures safety and performance by tracking components such as engines and actuators. Power plants use these approaches to monitor turbines and generators for efficient operation [23]. HVAC systems benefit from improved energy efficiency and reduced operational costs. Heavy machinery in construction and mining relies on condition-based monitoring to prevent unexpected failures. These applications highlight how PdM and RCM support cost-effective, data-driven maintenance strategies across industries, aligning with Industry 4.0 goals for smarter and more efficient asset management.

4.1. Manufacturing and Production Equipment

The application of mechanical engineering concepts to thoroughly investigate the production process landscape in the framework of mechanical engineering [24]. This approach facilitated a holistic understanding of how techniques and technologies are harnessed to drive innovation, efficiency, and sustainability across various industries:

4.1.1. Material Processing Techniques

Material processing techniques are foundational to the field of mechanical engineering, encompassing a range of methods that transform raw materials into functional components. This section delves into the intricacies of cutting processes, forming and shaping techniques, and surface treatment methods, highlighting their significance in modern manufacturing.

4.1.2. Advanced Cutting Technologies

Recent advancements in cutting technologies have expanded the capabilities of material processing. Waterjet cutting employs high-pressure water or abrasive materials to erode workpiece material, enabling precise and intricate cuts. Laser cutting utilizes focused laser beams to vaporize or melt material, providing clean and accurate cuts. Electrical discharge machining (EDM) employs controlled electrical discharges to erode material, making it suitable for complex shapes and hardened materials.

4.1.3. Computer Numerical Control (CNC) Machining

The use of computer numerical control (CNC) has transformed the cutting process. A CNC machining system refers to the computerization of cutting tools by the use of programmed instructions, making this process more precise and repeatable. CAD/CAM systems allow the user to design and simulate machining processes, generate and optimize tool paths and establish the machining process. CNC machining is widely used in industries requiring high accuracy and intricate part geometries.

4.2. Mechanical Engineering Principles in Electric Vehicle Design

The design and performance of electric vehicles (EVs) are being shaped by mechanical engineering, which is becoming more and more important as the automotive industry transitions to sustainable transportation [25], the complex mechanical engineering concepts that propel advances in electric vehicle design, with an emphasis on energy management systems, electric drivetrain technologies, and battery technology [26]. The battery is the central component of any electric vehicle, and mechanical engineering research has focused on the development of battery chemistries. Many battery chemistries, each with its own set of benefits and drawbacks, have been investigated over time. One of the first batteries used in electric cars were lead-acid ones, but their weight and energy density restrictions led to the hunt for substitutes [27]. An improvement was provided by nickel-metal hydride (NiMH) batteries, which have a lesser environmental effect and a better energy density. But a paradigm change was brought about with the introduction of lithium-ion (Li-ion) batteries.

4.3. Components of A Flywheel Energy Storage

The components of FES include a flywheel, a flywheel housing, bearings, a motor-generator system, and a motor control system. Because mechanical friction is the cause of energy loss in flywheel energy storage, the type of bearings utilized in a flywheel is crucial. Because they require continual lubrication and maintenance, mechanical bearings are not the best option for FES. Magnetic bearings are used in place of mechanical bearings in contemporary FES. By making the shaft levitate, they can lessen the effects of friction and the requirement for lubrication [28]. An FES's motor-generator unit serves two purposes. When there is an excess of electricity being produced, it can function as a motor to acquire kinetic energy. It functions as a generator, transforming the flywheel's stored kinetic energy into electrical energy when power is needed. FES housing creates a vacuum in which FES may be positioned. The casing ensures that air friction won't cause any energy loss.

5. LITERATURE REVIEW

This literature Summary provides a comprehensive examination of recent advancements in predictive maintenance strategies, emphasizing ML and DL approaches, their applications across various industries, challenges in data accessibility and implementation, and future research directions, including transfer learning and SME integration.

Lins et al. (2025) an approach to predictive maintenance (PdM) for commercial vehicles that focuses on the turbocharger, a crucial but sometimes overlooked part. The study shows how data-driven DL approaches may reliably anticipate impending problems by

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integrating sensor inputs, workshop maintenance logs, and technical requirements. In order to identify patterns and capture temporal relationships that traditional methods and merely onboard monitoring can miss, Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) architectures were specifically used [29].

Akyaz and Engin (2024) a data-driven method for using sensor data to identify industrial equipment issues. The approach is to maximize system performance, which will reduce maintenance expenses and energy usage. As part of the strategy described in this study, a PdM system for yarn manufacturing machines equipped with ML techniques is established. The precise selection of ML techniques is essential to the efficacy of PdM applications. For predictive modelling, this study looks at four ML algorithms as well as one DL method [30].

Azari et al. (2023) a thorough assessment of the literature that focusses on predictive maintenance and addresses related studies. By presenting a particular taxonomy based on pertinent viewpoints, the review aims to provide a definition of transfer learning within the predictive maintenance framework. From a theoretical and practical standpoint, it can also discuss the most recent advancements, challenges, open-source datasets, and possible directions for predictive maintenance transfer learning applications. New paradigms and digital technologies are now widely used in industrial production and manufacturing processes as a result of Industry 4.0. Using more efficient data-driven predictive maintenance techniques, such as machine learning-based ones, was also suggested by the goal of simplifying industrial operations monitoring [31].

Alvarez-Alvarado et al. (2022) a thorough and methodical analysis of the most recent developments in power system maintenance and their implications for the field of power system dependability. This paper's primary contributions include a taxonomy of the various maintenance techniques, an examination of the most important turning points in the history of power systems adequacy and security improvement, as well as a systematic review of the existing literature. This includes describing current approaches for power system maintenance planning as well as providing detailed definitions, models, methods, and aspects of maintenance policy. The evaluation also includes the most significant standards utilized in the field of power system maintenance. Lastly, in order to guide industry practice and encourage more research, topics that need more study are noted alongside new developments in power system maintenance [32].

Khan et al. (2022) In order to help academics, scientists, and developers understand the potential of PdM systems, as well as their limitations, unique features, and best practices in SMEs, the topic of predictive maintenance from a SME viewpoint is being explored. Four research questions—key problems, distinguishing features, best practices for predictive maintenance in SMEs, and demographic data—form the basis of our study. In the SME arena, they have discovered that the existing literature on PdM is lacking, particularly in the area of ambiguity around the financial aspect. PdM has a lot of promise in SMEs to create cost models and concentrate on barriers to data availability. PdM and trained staff management and oversight are also insufficient [33].

Liu et al. (2021) a new method of predictive maintenance (PDM) based on the improved deep adversarial learning (LSTM-GAN). The generative adversarial network's (GAN) mode collapse and vanishing gradient issues can be resolved by the long-short-term memory (LSTM) network. In addition to preventing GAN mode collapse, the method enables the identification of aberrant data on its own. The predictive maintenance model consists of one maintenance decision model and two prediction models. The prediction models might also anticipate the machine's flaw and its particular state beforehand. Thereafter, maintenance plan and staff will be allocated through the maintenance decision model [34].

As Table 1 presents, recent studies in predictive maintenance can be contrasted and compared in terms of various machine learning methods, major findings, current limitations, and future research avenues in the fields of mechanical and industrial engineering.

Table 1: Summary of A Study on Predictive Maintenance and Reliability-Centered Approaches in Mechanical Engineering Systems

Author	Study On	Approach	Key Findings	Challenges	Future Directions
Lins et al. (2025)	Predictive maintenance for turbochargers in commercial vehicles	Deep learning using LSTM and BiLSTM, multi-source data (sensor, logs, specifications)	Deep learning models effectively detect failures overlooked by traditional and onboard systems.	Monitoring under-utilized components like turbochargers	Enhance component-level monitoring with improved sensor integration
Akyaz & Engin (2024)	Fault detection in yarn production machines	Data-driven PdM using ML and DL algorithms	Machine learning improves system performance and reduces costs (energy, maintenance).	Selecting appropriate ML models for domain-specific use	Broaden PdM applications to more industrial domains with model optimization
Azari et al. (2023)	Transfer learning in PdM	A comprehensive assessment of the literature that includes a taxonomy of transfer learning techniques	Provides a framework to understand TL in PdM; identifies datasets, challenges, and use cases.	Lack of open-source datasets and standardized TL applications	Define benchmarks and domain-specific TL strategies

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Alvarez-Alvarado et al. (2022)	Power system maintenance and reliability	State-of-the-art review: taxonomy of strategies, planning models, and standards	Comprehensive mapping of maintenance strategies, definitions, and policies in power systems.	Limited practical implementation and lack of standardization	Establish unified standards and research emerging technologies
Khan et al. (2022)	PdM in Small and Medium Enterprises (SMEs)	Empirical study based on research questions	Highlights the PdM potential in SMEs; identifies lack of financial models, skilled personnel, and proper data access.	Data availability, cost models, and workforce skills	Develop SME-focused cost-effective PdM models and data access infrastructure
Liu et al. (2021)	Improved predictive maintenance using LSTM-GAN	Deep adversarial learning with LSTM and GAN	Predicts machine state and faults while addressing GAN mode collapse and enabling abnormal data detection.	Complexity in model integration and real-world deployment	Real-time integration of predictive and decision-making models

6. CONCLUSION AND FUTURE WORK

The predictive maintenance and reliability-based methods have become fundamental concepts in the development of contemporary mechanical engineering systems to ensure equipment reliability, spare parts usage, and operational efficiency. These techniques mean the abandonment of time-based and reactive practices that relied on inspections and waiting to be discovered in favor of data-driven condition-based practices. Predictive maintenance uses sensor technologies, machine learning, and real-time monitoring, which help foresee potential failures so that appropriate interventions can be made in time. In the interim, reliability-centred maintenance (RCM) is an ordered pattern that allows identifying the best maintenance operations on the basis of the performance and the importance of the elements. The effectiveness and accuracy of these strategies have additionally been improved by the integration of Industry 4.0 technologies, including the IoT, AI and deep learning. They have a wide application area in the manufacturing sector, aerospace, transport and energy sectors. But one should take into account limitations. The difficulty in gathering quality data in many small- and medium-sized industries and the prohibitive cost of implementing predictive systems can act as barriers to widespread adoption.

Future research ought to focus on the development of real time, lightweight prediction models that are suitable in SMEs, where processors and budgets are scarce. Beliefs Note: Enhanced integration of edge computing, digital twins, and explainable AI have the potential to increase the transparency and scalability of PdM systems. Furthermore, standardizing data formats, sharing open-access industrial datasets, and improving interoperability between monitoring devices and software platforms are necessary for widespread adoption. Addressing human factors in FMEA and refining RCM methodologies to reduce subjectivity will also improve decision-making. Continued interdisciplinary collaboration will be key in advancing predictive maintenance and reliability-centered approaches across evolving mechanical engineering applications.

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