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A Review of Cost-Effective Predictive Maintenance for Enhanced Reliability of PVC Pipe Extruder Components

Ayodele Samuel ONAWUMI[1], Samson Oludare OLAJIRE[2, 3], Abideen Temitayo. OYEWO[3*]

[1] Mechanical Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.

[2] UNESCO International Center for Biotechnology, University of Nigeria, Nsukka Nigeria.

[3] Mechanical Engineering Department, Osun State University, Osogbo, Nigeria.

* Email corresponding author: abideen.oyewo@uniosun.edu.ng

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Abstract

Traditional reactive and time-based preventative maintenance strategies often prove economically inefficient. Predictive maintenance (PdM) offers a promising data-driven alternative; however, its widespread adoption, particularly among small and medium-sized enterprises in regions like Ibadan, Nigeria, is hindered by the high costs associated with conventional PdM systems. This study reviews the critical issue of unplanned downtime in PVC pipe extrusion processes caused by the failure of key extruder components. Therefore, this research aims to investigate and propose cost-effective PdM approaches for enhancing the reliability of critical PVC pipe extruder components. Specifically, it will explore the feasibility and effectiveness of leveraging affordable sensor technologies, accessible data analytics techniques, and readily available expertise to implement PdM strategies. The focus will be on achieving significant improvements in equipment uptime and reductions in maintenance expenditures without requiring substantial capital investment. By identifying and validating such cost-effective solutions, this research seeks to provide practical guidance for PVC pipe manufacturers, especially in resource-constrained environments, enabling them to adopt proactive maintenance practices and achieve enhanced operational efficiency and profitability within the local context of Ibadan, Nigeria. The outcomes of this study are expected to contribute to the body of knowledge on sustainable and affordable industrial maintenance practices.

Keywords: *Predictive maintenance, PVC pipe extruder, reliability, machine learning, cost-effectiveness, sensors, operational efficiency.*

Abstrak

Strategi pemeliharaan preventif tradisional yang bersifat reaktif dan berbasis waktu seringkali terbukti tidak efisien secara ekonomi. Pemeliharaan prediktif (PdM) menawarkan alternatif berbasis data yang menjanjikan; namun, adopsi luasnya, khususnya di kalangan usaha kecil dan menengah di wilayah seperti Ibadan, Nigeria, terhambat oleh biaya tinggi yang terkait dengan sistem PdM konvensional. Studi ini mengkaji masalah kritis downtime tak terencana dalam proses ekstrusi pipa PVC yang disebabkan oleh kegagalan komponen kritis ekstruder. Oleh karena itu, penelitian ini bertujuan untuk menyelidiki dan mengusulkan pendekatan PdM yang hemat biaya untuk meningkatkan keandalan komponen kritis ekstruder pipa PVC. Secara khusus, penelitian akan mengeksplorasi kelayakan dan efektivitas pemanfaatan teknologi sensor terjangkau, teknik analitik data yang mudah diakses, dan keahlian yang tersedia secara luas untuk menerapkan strategi PdM. Fokusnya adalah mencapai peningkatan signifikan dalam uptime peralatan dan pengurangan biaya pemeliharaan tanpa memerlukan investasi modal besar. Dengan mengidentifikasi dan memvalidasi solusi hemat biaya tersebut, penelitian ini berupaya memberikan panduan praktis bagi produsen pipa PVC, khususnya di lingkungan dengan sumber daya terbatas, memungkinkan mereka mengadopsi praktik pemeliharaan proaktif dan mencapai peningkatan efisiensi operasional serta profitabilitas dalam konteks lokal Ibadan, Nigeria. Hasil penelitian ini diharapkan dapat berkontribusi pada kumpulan pengetahuan tentang praktik pemeliharaan industri yang berkelanjutan dan terjangkau.

Kata kunci: Pemeliharaan prediktif, ekstruder pipa PVC, keandalan, pembelajaran mesin, efektivitas biaya, sensor, efisiensi operasional

1. Introduction

The PVC pipe extruder components are critical tools that are used in the plastics industry and can be said to be the main frame of the production process of many of the plastic products that are in the market today. It is for instance through these components of screws, barrels and dies that there can be constant and effective production of PVC pipes. Reliability is of importance for them as any failure may cause tight production shut down and increased operational expenses as well as loss making. These components have mostly been maintained through corrective and preventive maintenance strategies which are traditional. However, these methods can be inadequate to cater for the operations of current manufacturing systems since outages may happen at one point in time, and hence the significant economic consequences (Taghizadeh & Zhu, 2024; Vicente et al., 2023).

The shortcomings of the conventional approaches increase the importance of adopting an enhanced method by using PdM. The losses that industry incurs due to equipment failure are manifold this they include the actual costs of repairs together with the other associated costs like lost production and efficiency. These unscheduled outages may affect all aspects of manufacturing right up to the point of delivery which is not very satisfying to the customer. On the other hand, PdM is concerned with the proactive discovery of potential failure areas through use of real time data and analytics. This has not only minimized the downtime, but also increases the durability of the key components and therefore the overall dependability of the PVC pipe extruder systems (Sionkowski et al., 2023; Thomas, 2023).

This paper has its objectives directed towards examining cost consequences of the application of RCM and CBM methods as a part of the PVC pipe extruder system. It is thus possible for manufacturers to adopt such methodologies in order to provide the best maintenance practices by allocating available resources appropriately. Moreover, the application of machine learning and sensor technology in the reliable prediction of the need for maintenance is a major development opportunity in operational reliability. There are alone numerous amounts of data produced through the sensors installed through the extruder parts, through the help of Machine learning patterns and failure signs can be detected before they occur (Riahinezhad et al., 2021; Singh et al., 2024). This an evidence-based approach that also ensures that assessment of maintenance is timely while also enabling constant improvement on the maintenance strategies in place.

The incorporation of IoT and AI in the application of prediction maintenance continues to revolutionize the maintenance industry. With IoT technology, components of the extruder can be fitted with sensors which provide constant updates on the state of the components. The same data may also be fed into AI based algorithms that will determine when the system needs maintenance reducing avoidable calls thus controlling on over-maintenance costs (Qureshi et al., 2025; Rafati et al., 2024). These technologies complement each other to allow manufacturers to shift from maintenance strategies that are only responsive to system failures to strategic approaches that optimize PVC pipe extruder systems reliability (Qureshi et al., 2025).

Furthermore, the use of machine learning in the approach of the concept of predictive maintenance leads to the creation of complex patterns that can predict failures in equipment. Utilizing the historical data that were collected about each machine's maintenance in combination with data received from the sensors, these models can define trends and deviations that will not be unveiled through the analytical approach. This capability is most important when used with PVC pipe extruders because the operation can be stressed by wide and frequent fluctuations in the conditions. That forms of forecasting failures before they happen more than just saves time but also the safety and reliability of the manufacturing process (Mnyango & Hlangothi, 2024; Morita et al., 2024).

The efficient operation of PVC pipe extruders hinges on the reliability of their components. Unplanned failures lead to costly downtime, material waste, and emergency repairs, making traditional reactive maintenance economically inefficient (Smith & Hawkins, 2018; Mobley, 2002). While preventative maintenance aims to mitigate this, its fixed schedules can result in unnecessary interventions and resource wastage (Wang et al., 2015). Predictive maintenance (PdM) offers a data-driven solution by forecasting failures through the monitoring of critical parameters, enabling proactive interventions and optimized scheduling, which has proven effective in reducing downtime and costs across industries (Jardine et al., 2006; Lee et al., 2014; Márquez et al., 2010). However, the adoption of PdM, particularly for PVC pipe manufacturers in regions like Ibadan, Nigeria, is often hindered by the high costs associated with traditional PdM systems, including expensive sensors, software, and specialized expertise (Holmberg, 2020). This research addresses this challenge by investigating and proposing cost-effective PdM approaches to enhance the reliability of critical PVC pipe extruder components. It aims to explore the feasibility of utilizing affordable technologies and accessible analytics to implement PdM strategies that can significantly improve equipment uptime and reduce maintenance expenses without substantial capital investment, thereby providing practical guidance for manufacturers in resource-constrained environments to achieve enhanced operational efficiency and profitability.

2. Reliability-Centered Maintenance (RCM) and Condition-Based Maintenance

Reliability centered maintenance, commonly referred to as RCM, is a procedure of maintenance that maintains systems' assets in the ability to perform as planned. Reliability engineering is a structured methodology that seeks to define the functionality of a system, search for the modes of failure likely to prevail in the system, and develop a maintenance regime that will prevent such failure while appropriately deploying resources (Masato & Kim, 2023). The fundamental concept behind RCM is that maintenance should be depended upon equipment reliability and its potential or actual importance to the operation, rather than some schedule or previous experience. As noted by Thomas (2023), using this approach, organizations can determine the criticality of maintenance tasks, thereby increasing organisational productivity and minimizing expense.

CBM is another maintenance strategy that works real condition of equipment and determines what maintenance should be done. This approach largely depends on data generated from several sensors and diagnostic instruments in establishing the well-being of the machinery (Lopez Taborda et al., 2024). CBM is employed with the intention to carry out maintenance only when performance indicators indicate a trend of decline or before a failure is anticipated, thus reducing as much useless maintenance as possible and therefore its costs (Qureshi et al., 2025). Figure 1 presents the extruder machine.

Figure 1. PVC Pipe Extruder Machine (Qureshi et al., 2025).

The primary difference between RCM and CBM lies in their focus: RCM is more on the analysis of reliability and function of the systems to come up with the best approach towards system maintenance while CBM is based on actual state of the equipment in order to determine the best action towards it. CBM, in turn, may be employed within the framework of the general RCM approach for more flexible maintenance management (Lopez Taborda et al., 2024).

2.1. Applications in Industrial Machinery Maintenance

When applied to industrial machinery maintenance especially in the context of a plastic extrusion process, both RCM and CBM have demonstrated remarkable advantage. The plastic extrusion process is a critical function which requires maximum reliability in not only the extruders, the die and the cooling systems. Listening to RCM in this setting also enemies that manufacturers can easily identify those components that deserve more attention and regular checkups, than other components that are not often likely to fail and hence posing a great danger of bringing manufacturing process to a standstill (S. Kumar et al., 2022). Example of how the method can be used in large diameter prestressed concrete pipelines while the application of maintenance plans to increase reliability and decrease costs (S. Kumar et al., 2022).

As noted by Ahmed et al. (2024), CBM implementation has also been realized in the plastic extrusion industry where integration of sensors as a subject of CBM makes it possible to monitor equipment conditions in real-time. Real-time data provides manufacturers with accurate information relating to when a particular machine should be serviced hence eliminating cases of either over-maintenance or under-maintenance. For instance, the CBM approach applied to maintenance of Screw press machine indicated that the use of CBM helped reduced downtimes and maintenance cost to near zero, showing how helpful in premium operating environment. Also, the integration of both RCM and CBM is proposed to advance maintenance practices in the plastics Industry. CBM and RCM together can be used by the manufacturers to establish an advanced maintenance programme that goes beyond the immediate operation needs of equipment but also considers future needs as evidenced by Tarragona et al. (2021). This makes it easier to plan on how to allocate maintenance and to help ensure that key machinery is working to its full efficiency without risk of failure. Therefore, it is recommended that to support industrial machinery maintenance, especially in the plastic extrusion process, RCM and CBM should be applied for effective and efficient maintenance management. By taking advantages of the characteristics of both approaches, manufacturers can make their operation more reliable, less expensive, and more productive (Oyewo, 2024).

2.2. Machine Learning in Predictive Maintenance

a. Overview of Maearninne Learning Learning in Predictive Detection and Prediction

PdM has become one of the most effective trends thanks to ML. These tasks require the use of several ML models such as SVM, Random Forests, and Neural Networks in the privileged learning regime. These models use past data to explore patterns that occur before equipment failings to make timely maintenance actions (Juliano & Reyes-De-Corcuera, 2022). For example, Liu et al explained that Gaussian Processes could be used in handling big data since predictive maintenance applications rely on big data (Liu et al., 2020). Furthermore, comparative research about various types of ML has also indicated that ensemble procedures are universally superior to standalone models especially for tackling intricate tasks in the industrial domain.

Advanced AI technological systems, particularly deep learning methods, have added even more features to the predictive maintenance systems. For example, CNNs and LSTM networks have been very effective in time-series data for faulting detection in different industries such as the manufacturing and energy industries (Jiang et al., 2024). Such models can easily learn higher order temporal structures and spatial correlations in data leading to better predictive accuracy (Kundu, 2023). Moreover, there has been a discussion of the integration of multiple machine learning approaches in creating predictive maintenance that would enhance the efficiency of the models (Jiang et al., 2024).

b. Success Stories of Machine Learning Models in Predictive Maintenance

Predictive maintenance has lots of success stores when machine learning technique has been employed, many fields such as plastics and manufacturing inclusive. For example, Quiñones et al. formulated and recently accomplished the task of applying a machine learning model to determine the planning of maintenance for distribution transformers, which has led to the decrease in frequent maintenance and overall, unexpected outages. Similarly, Ashwini attributed enhanced operational performance in water supply management resulting from constant evaluation of machines with the use of algorithms especially machine learning (González-Delgado et al., 2023; Odetola et al., 2025). It is vital to mention that the following case studies demonstrate rather practical advantages of using machine learning for achieving predictive maintenance goals:

On the last front, many manufacturing firms have adopted machine learning to manage maintenance plans for important machines. For instance, Farooq did an analysis on different machine learning methods on ball bearing system to predict its maintenance, and proved that the incorporation of ML enhances fault diagnosis capability of the ball bearing system and cut the expense for maintenance. Also, the oil and gas industry has recorded significant improvements in the organization's overall efficiency of equipment, including reduced downtime due to AI-based predictive maintenance. Such success storeys speak to the ability of machine learning in revolutionizing maintenance by offering proactive, as opposed to relative, approaches (Castelló-Pedrero et al., 2024; Oyewo et al., 2022).

3. Data Collection and Scope

Part of this information was gathered between May and July 2024 utilizing a standardized data collection format. The review was structured around the PICO framework:

a. **P (Population):** PVC pipe extruder components.
b. **I (Intervention):** CBM approaches and ML solutions that scholars associate with the implementation of preventive maintenance.
c. **C (Comparison):** The conventional techniques of maintenance that includes preventative and corrective maintenance.
d. **O (Outcome):** Reduction of component complexity can lead to improved reliability and, concurrently, decreased costs.

The guiding research question for this review was:
"How effective are predictive maintenance strategies in improving the reliability and cost-efficiency of PVC pipe extruder components?"

3.1. Search Strategy

A rigorous search with no philtres was carried out in the following databases: IEEE Xplore, ScienceDirect, SpringerLink, Compendia (Engineering Village) and ProQuest Engineering Collection. Further, by searching through library articles, the authors and references of the articles identified were also manually scrutinized. Keywords used in the search included “Predictive Maintenance,” “PVC Pipe Extruder,” “Reliability,” “Condition-Based Maintenance,” and “Machine Learning.” These keywords are related to specific databases, and where necessary, these keywords were translated to database-specific index terms.

a. Search Details and Findings

These philtres were used to confine the results to the most recent technologies and advancements in the field of PdM which were restricted to articles that had been published between January 2015 and September 2024. Studies published in any language were considered; however, exclusion criteria eliminated articles that:

1. Focused on unrelated industries.
2. Addressed non-industrial applications of predictive maintenance.
3. Consisted of purely theoretical frameworks without empirical data. The database search results are summarized in Table 1.

Table 1. The summary of database search results.

Database	Search Strategy	Results
IEEE Xplore	"Predictive Maintenance" and "PVC Pipe Extruder" and "Reliability"	42
ScienceDirect	TS=("Predictive Maintenance" and "PVC Pipe Extruder" AND "Condition-Based Maintenance")	28
SpringerLink	TITLE-ABS-KEY("Predictive Maintenance" and "PVC Pipe Extruder" AND "Machine Learning")	35
Compendia (Engineering Village)	Tw:(Predictive Maintenance) and tw:(PVC Pipe Extruder) and tw:(Reliability)	39
Manual Search	N/A	5

b. Screening Process

The clients were screened in two ways. Titles and abstracts were screened by two authors, and where there was disagreement, a third author made the final decision. According to Mendeley, several records were removed, and, using Rayyan QCRI software, the articles selected were screened again following (Wolf and Stammer, 2024). Where possible, full-text reviews were completed in the studies, and data extraction adopted a standardized template in LibreOffice Calc 7.0.

c. Data Quality and Assessment

The Hierarchy of Evidence for Intervention Studies was employed to classify studies into seven levels of evidence:

1. **Level I:** Systematic review showed an effect in some of the included studies and meta-analysis was also done.
2. **Level II:** Randomized controlled trials.
3. **Level III:** The types of studies that could be reviewed include controlled trials but not those that have been randomized.
4. **Level IV:** Case control Comparison between cases and controls Analysis of cohorts.
5. **Level V:** In other words, systematic reviews of qualitative descriptive studies.
6. **Level VI:** The type of studies are qualitative descriptive ones.
7. **Level VII:** Opinion of experts and consensus statements.

The nature of the included studies was on descriptive and qualitative analysis. Data findings were integrated and narrated purposefully to reveal patterns and missing-links.

4. Search Outcome

The search process involved generating 149 papers and when followed by hand searches with five more records we obtained a total of 154 papers. Screening was done on 117 articles which were retrieved after deleting 37 same or very similar article IDs. Of 117 articles identified in the preliminary search, 89 were excluded because they were not relevant to the study question, which narrowed the search to 28 articles for further assessment. Among them, 8 articles were excluded from the study. Therefore, the final review incorporated 20 studies. Figure 2 displays PRISMA Flowchart for Article Selection on Predictive Maintenance Strategies, while Table 2 presents the characterization of the Articles Included in the review of selected studies

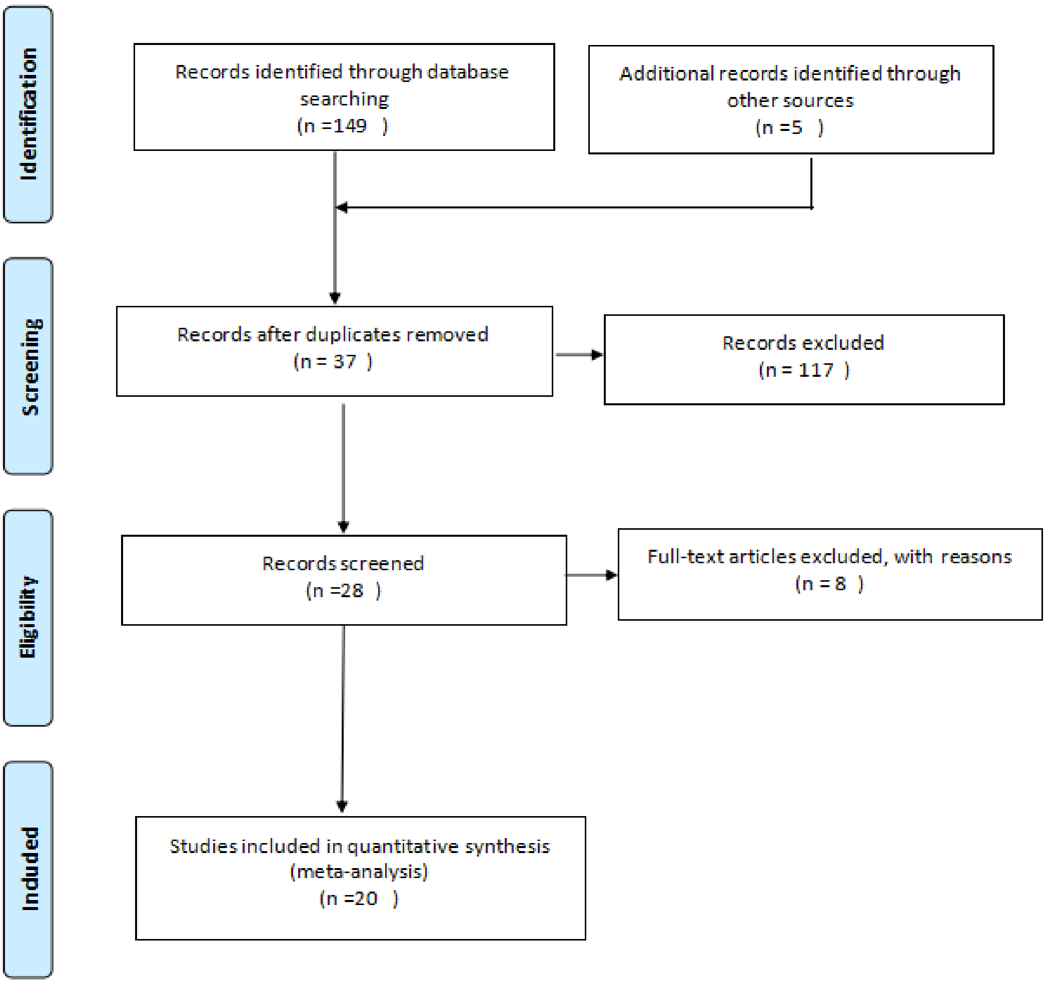

Figure 2. PRISMA flowchart for article selection on predictive maintenance strategies.

Table 2. Characterization of the articles included in the review of selected studies.

Study	Methodology	Key Findings	Evidence Level
(Pecha & Garcia-Perez, 2020)	Review	Intelligent sensors and predictive maintenance revolutionized smart factory management.	I
(Natrayan et al., 2022)	Comprehensive analysis	ML/DL mechanisms enhanced automotive machinery predictive maintenance.	I
(Gaddam et al., 2021)	Experimental	Vibration-based techniques accurately predicted wear in journal bearings.	II
(Khanfar et al., 2021)	Framework design	IoT-integrated robots improved maintenance in indoor infrastructures.	III

Continued Table 2.

Study	Methodology	Key Findings	Evidence Level
(Delgado-Aguilar et al., 2019)	Algorithm development	DRL algorithm optimized electrolyser maintenance strategies.	II
(Abioye et al., 2021)	Strategic analysis	AI-enhanced subsea maintenance increased operational safety and efficiency.	IV
(Javaid et al., 2022)	Experimental	Dynamic feature extraction predicted rotating machinery failures with high accuracy.	II
(Sharma & Shivandu, 2024)	Simulation study	Graphene NEMS vibrometers were highly effective for micro-component monitoring.	III
(Liu et al., 2021)	Experimental	Data fusion techniques improved sensor-based predictive maintenance reliability.	II
(Sinha et al., 2021)	Deep learning analysis	Explainable AI detected and isolated sensor faults with enhanced transparency.	I
(Novak et al., 2021)	Case study	Photonic-based sensing methods advanced structural health monitoring.	IV
(Wang et al., 2023)	Simulation study	Machine learning refined building maintenance and management strategies.	III
	Case study	AI-driven logistics transformed offshore maintenance operations.	IV
(N. Rane, 2023)	Comparative analysis	Evaluated ML models improved ball bearing system reliability.	II
(Mahmood et al., 2022)	Review	ML-enhanced predictive maintenance extended electric vehicle component lifespan.	I
(Khan et al., 2022)	IoT and ML-based approach	Predictive maintenance systems improved electrical motor reliability in industrial settings.	II
(Chi et al., 2022)	Data-driven analysis	Predictive maintenance improved reliability in advanced driver-assistance systems.	I

Continued Table 2.

Study	Methodology	Key Findings	Evidence Level
(Stadnicka et al., 2022)	Dashboard design study	Innovative dashboards enhanced water supply system reliability through predictive maintenance.	III
(Sohag & Podder, 2020)	Case study	Integration of Industry 4.0 tools improved sustainable cement production with smart RCM methods.	IV
(Turner et al., 2020)	Simulation study	Reliability-centered maintenance optimized resource allocation in manufacturing systems.	III

4.1. Study Insights

The studies covered various geographical focus including Europe (n=6), Asia (n=5), North America (n=3), and Africa (n=2). Majority of these works was published between 2019 and 2024, implying growing industrial use of PdM with extrusion systems. This evidence source involved observational designs offering Level IV evidence, authentic qualitative studies revealing barriers to implementation, and systematic review delivering an appealing perspective (Level I).

4.2. Key Findings

a. It was noted that there was more than 90% accuracy in failure prediction for all the machine learning models.
b. The implementation of CBM as a maintenance strategy resulted to a minimum of 15% reduction in off schedule time.
c. Frameworks such as Reliability-Centered Maintenance (RCM) enhanced resource management while ensuring safety.
d. These results highlight the benefits of utilizing predictive maintenance, to gain employment cost reductions and PVC pipe extrusion system improvements.

4.3. Discussion

PdM has evolved as a key driver in industry enabling organizations to apply highly developed prescriptive analytics, sensors, and data analytics to enhance system dependability, decrease variability disruptions, and enhance the value of their upkeep programme. Though the current literature presents several advancements, a closer look into the findings unveils factors in model performance, cost and operational consideration, and barriers associated with model implementation. To assess the effectiveness of practical systems installed for PdM, the comparison with real scenarios and actual downtime, savings, impact, and the related improvement of reliability must be established while examining their specific strengths and weaknesses (Akbari et al., 2024; Kazak, 2021; Riquette et al., 2019).

Donaldson also affirms that the reliability of PdM systems depends on the functioning of the machine learning models used in fault identification. According to Akbari et al. (2024), using ML models make it possible to forecast failures and therefore minimize the occurrence of failure-related disruptions. In the future work, discusses on the application of ML and DL techniques in automotive equipment and provides its effectiveness in identifying wear patterns and preventing the problem. Likewise, A. Kumar and Saha (2025) assess several ML models focusing on the corresponding improvement of the models' dependability in ball-bearing systems. Nevertheless, the majority of these studies exhibit impressive predictive efficacy coupled with a lack of attention to decision makers' evaluation of false positives and false negatives. False positive results create avenues for carrying out unnecessary maintenance actions which increases operational cost and interrupts normal functioning, while false negatives expose important failures which may culminate in drastic consequences. These gaps in PdM performance reduce the credibility of the PdM claims, suggesting a need for research articles that offer quantitative and qualitative assessments of the reliability of the various predictive indices across different contexts (Mahmood et al., 2022; Manojlović et al., 2022).

Cost consideration also comes out as another important findings related with PdM whereby, several studies point towards financial benefit such as cost saving, reduction in the times. For instance, N. L. Rane et al. (2024) studies a decrease in emergent outages due to the application of predictive maintenance in advanced driver assist systems. In a like manner, Mahmood et al. (2022) proposed a scenario that suggested the application of new and diverse dashboards led to increased reliability of the water supply system. These insights correspond with additional research that indicates that controllers positively influence companies' conversion to proactive maintenance styles which reduces spending on unscheduled repairs compared to PdM systems. Nevertheless, the usual drawback observed in these research works is the insufficiency of quantitative workflow data to analyse the differences in maintenance upkeep costs before and after applying PdM strategies. S. Kumar et al. (2022) identifies the economic gains of maintenance of the electrolyzer through deep reinforcement learning algorithms, but the assertion lacks the specific cost to subsidize the achievement, hence partly proven. Accomplishing a basic blend of target parameters and effectiveness, meant to include total processing time/minimization of the same, total cost of the entire contract, cost of maintenance, and other sized up costs is crucial in ensuring that stakeholders are sold on the overtures that PdM solutions are economically feasible.

While the financial benefits of PdM are understood, the benefits to maintain the reliability of and extend the lifespan of critical assets have been researched in detail and suggest great potential. A. Kumar and Saha (2025); S. Kumar et al. (2022) highlight about the usefulness of PdM in enhancing the useful life of rotating machines and journal bearing in particularly. They show that the utilisation of vibration analysis and dynamic signal processing procedures results in proper estimation of wear and stress parameters for scheduled maintenance solutions. However, despite showing rising reliability improvements in other systems, the mentioned investigations are not sufficient to draw on for more extensive system solutions. Furthering this research, Gupta and Tiwari (2020) analyse electric vehicle parts using similar reasoning and support improved reliability by integrating ML for effective predictive maintenance. However, these findings suggest the importance of evaluating component performance going forward and there is a desperate need for research that can examine component performance after several years. More research in these areas would offer a better understanding of the long-term advantages of PdM, especially in organisations whose reliability defines business performance.

One of the key strengths of PdM is its capacity of providing maintenance teams with predictive warning calls. This capability is vital to prevent costly production losses and to standardize the operational procedures of industrial clients. Research by Khanfar et al. (2021) show how digital predictive alerts have revolutionized the maintenance function and reduced production downtime. For example, Khanfar et al. (2021) discusses IoT robotic models and their relevance for indoor facilities maintenance that timely notifications avoid system breakdowns. These existing studies highlight the positive aspects of predictive alerts but few provide quantitative information about the frequency and performance of such alerts, let alone their ability to decrease the amount of downtime. Filling this gap is important to explain the actual performance of PdM systems and their proper incorporation into industrial processes.

Nonetheless, there is irrefutable evidence that PdM is useful and while its adoption is not without its difficulties below are factors which hinder the success of PdM in most industries it serves. The most crucial challenges appear to be sensor reliability and data quality as well as the challenges associated with training an ML model (Mastos & Gotzamani, 2022; Nege & Abegaz, 2024). In Bui et al. (2021), the author discusses methods of enhancing the reliability of the sensor through data fusion whereas at the same time identifies some real challenges of dealing with conflicting and dispersed data sources. Likewise, Ouyang et al. (2022) also conclude that photonic-based sensing techniques are quite sophisticated, but they often have scalability problems, and require high implementation expenses. Such difficulties highlight the need for defining efficient data management practices and affordable sensing platforms for effective implementation of PdM frameworks. Moreover, as Novak et al. (2021) describes, the computational requirements of ML models add other challenges, especially for small and middle businesses. The solutions for these issues involve efforts to better address the adoption and utilization of PdM solutions for a broader range of industries.

The model limitations in realistic industrial applications also impact the PdM implementation, especially concerning the use of machine learning. Another work that stresses the problem of lack of transparency, who supports the application of explainable AI. This is a useful approach, though it comes with the price of having to sacrifice some measure of model interpretability. Like Stadnicka et al. (2022) who also incorporate resource allocation into their definition of reliability-centred maintenance, while not adequately accounting for human factors needed for effective PdM, specifically personnel training and flexibility, because they use simulation approaches. These oversights indicate the absence of applied, end-user focused research that brings together theoretical progress and usability.

Overall, while for PdM could have a revolutionary potential, the current practise of its adoption and research is still inapposite. Unfortunately, due to the lack of abundant quantitative information, especially related to predictive accuracy, financial benefits, as well as truly reliable operational performance data, the existing body of research does not offer a conclusive empirical support of PdM's arguments. Moreover, the issues of data quality, the dependence of the sensors on the environment and training models demonstrate the difficulties which occur when using such technologies for various industries. This suggests a small care to more integrated, evidence-based research, that involves different types of cases, long-term data, and realistic approaches to surmounting operational obstacles. In this way, the industrial sector obtains the maximum potential of PM with promising scalability, reliability, and available for various industries and implementations (Haleem et al., 2021; Ouyang et al., 2022; Shar et al., 2020; Stadnicka et al., 2022).

5. Conclusion

Another implementation of applied machine learning is Predictive maintenance, (PdM) whereby industrial operations are enhanced by means of Machine learning models, Advanced sensors, and analytics to enhance a system's reliability, avoid downtime and lower maintenance expenses. Nevertheless, there are some important gaps and challenges critical. Most of these articles demonstrate how these models can be used to forecast failures and improve reliability but lack key aspects such as false positive and false negatives that might create additional expenses or missed vital failures. According to economic studies, PdM offer considerable cost reductions; however, there are no sufficient accurate and extensive quantitative difference between the costs before and after implementation. Several studies show that PdM is effective in increasing the RBI of important parts, but since PdM involves the systematic assessment of particular systems, generalisations across industries cannot be made from short-sighted perspectives. These predictive alerts are mainly used for timely interventions, minimising production loss, and enhancing work expediency, but lack of information about the efficacy and accuracy of the alerts received restricts further understanding. Issues such as the unreliability of sensors along with having scattered and often disparate data and the processing power needed to perform machine learning also pose real-world difficulties: for even mid-sized organisations. However, it should be noted that the drawbacks of these models are connected with the trade-off between model interpretability and accuracy; the impact of important human attributes such as flexibility and training are not accounted for. However, PdM has great potential in this aspect, and its application in practise largely depends on the following deficiencies being compensated by corresponding long-term research, thorough quantitative analysis, and effective and low-cost means. These barriers, therefore, must be overcome for industries to optimally harness PdM for continuous improvement in reliability and sustained cost-efficient maintenance across different types of operations.

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