Predictive Maintenance for Rotating Equipment Using Machine Learning

Mr. Rajesh B. Godase
Professor, Mechatronics Engineering Department,
Amrutvahini Polytechnic, Sangamner, India

Abstract: *Maintenance of rotating machinery is crucial for extending the lifespan and increasing the reliability of equipment on board ships. Presently, breakdown and preventive methodologies are used for the maintenance of equipment. Further, data loggers collect critical machinery parameters, and parameter data is used for real-time parameter monitoring. The availability of such extensive monitoring data has also led to the adoption predictive maintenance methodologies in the industry, wherein machine learning-based analysis of recorded data is used to predict impending defects and prompt required maintenance. In this paper, we propose a predictive maintenance system that records data through a network of sensors installed over multiple electrical motor pump sets on board the ship and uses statistical analysis to detect equipment degradation. Our system has been deployed on board a ship to undertake real-time predictive maintenance of electrical motor pump sets used in fireman, AC plants, stabilizers, steering pumps and other auxiliary engine room machinery.*

Keywords: Predictive maintenance system, vibration and current analysis, Naval ships, Unsupervised learning, Detecting performance degradation, Electrical motors

I. INTRODUCTION

In the last few decades, industrial systems maintenance has seen a shift from reactive to preventive and, most recently, predictive maintenance. Reactive maintenance, also known as a "run-to-failure" strategy, is based on fixing equipment after it fails. Although straightforward, it leads to unexpected downtime, increased repair costs, and safety hazards. Preventive maintenance, with its scheduled inspections and maintenance activities at fixed intervals, was developed to overcome these limitations. While this strategy minimises unplanned downtime, it may result in idle time and waste of resources. Predictive maintenance represents a major leap forward, powered by digital technologies and analytics. Predictive maintenance uses real-time monitoring and historical data to predict equipment failures and initiate actions to prevent them. This shift is in line with the concept of Industry 4.0, which prioritises the use of cyber-physical systems, automation, and smart data exchange in manufacturing processes.

Intelligent manufacturing systems leverage interconnected systems, sensors and analytical tools to drive smart and flexible manufacturing. Equipment like turbines, pumps, compressors and motors, collectively known as rotating machinery, is vital to the operations of many industries such as energy, manufacturing, oil and gas, and transport. These devices are typically exposed to demanding operating conditions and continuous use, which can lead to wear, misalignment, imbalance and other types of faults. Any breakdowns can result in substantial productivity losses, safety risks, and downtime. As such, maintaining the efficiency and effectiveness of rotating equipment is a critical concern for today's industries. Predictive maintenance integrated with Industry 4.0 offers a robust approach to monitor these assets and enhance efficiency (Ünlü & Söylemez, 2024; Shetty, 2025; Wu, 2026).

Fig. 1 Evolution of Industrial Maintenance towards AI-Driven Predictive Systems

The rotating machinery is the lifeline of ships, and specifically, electrical motor pump sets constitute a significant component of critical systems, namely, fireman, air conditioning, steering, stabilizers, propulsion, power generation (alternators) and various auxiliary pumps of circuits of fresh water, seawater and chilled water lines. The ship-board machinery is prone to defects due to exposure to sea climate, moisture and vibrations from the roll/pitch of the ship. Presently, Condition-based Monitoring (CBM) and Planned Preventive Maintenance (PPM) strategies are majorly adopted for the maintenance of equipment. However, these maintenance strategies are affected by more downtime (due to refit and maintenance periods) and are expensive (due to replacement of components) [22]. Predictive maintenance [13] (PdM) harnesses the potential of AI towards increasing the life span of equipment and enhances the reliability of machinery [14] PdM techniques analyze recorded sensor data of machinery to develop cognition for impending failures, and thereby, prompt required maintenance. Predictive maintenance within the shipping industry is in its early stages [5]. Recent research has been undertaken using supervised learning approaches over labelled data from simulated defects on machinery. Vibration analysis can detect abnormal vibration patterns, which may indicate potential machinery defects. PdM techniques using vibration analysis are helpful towards the identification of deviations from normal patterns and resolving issues before major breakdowns occur[18]. Study of vibration analysis [15] using Fast Fourier transform (FFT) has been undertaken by inducing defects in electrical motors. Vibration analysis of gearboxes [10, 2] of electrical motors has been undertaken using SVMs with experimental set-up and inducing defects using faulty bearings. Other than vibration analysis, PdM techniques may be implemented for ship-borne machinery using analysis of running current [1], thermography[4] and oil analysis [8]. In the absence of labelled (labels indicating operational and defective life), real-time datasets of a lifetime of motors and unsupervised learning approaches have also been attempted. Wescoat et al. describe vibration analysis of a paint dosing pump used for Condition Monitoring (CM) based maintenance using unsupervised learning [21]. The work majorly presents techniques to organize data using unsupervised approaches. In both supervised and unsupervised approaches, vibration analysis [16, 12] has been found of key importance for undertaking predictive maintenance of rotating machinery. Olesen et al. [3] review state-of-the-art techniques for applying PdM in thermal power plants and pump systems. The review describes various challenges concerning applying PdM for rotating machinery viz unavailability of run-to-failure labelled data set and restriction of state of the art techniques mostly to vibration analysis. Our work utilizes analysis of current parameters in addition to vibration analysis.

During our study, we developed and deployed an AI-based predictive maintenance system onboard a ship to predict the degradation of electrical motor pump sets using a comparative approach. Our contributions are as follows:

- **Data Collection and Exploratory Data Analysis (EDA)** – Dataloggers were installed over one ship to collect data on 16 motors of different ship-borne systems. EDA techniques were used to get insights into patterns of machinery usage and understand the data for further application towards predictive maintenance.
- **Pre-Processing Techniques** – Real-time data received from dataloggers installed on electrical motors may have erroneous values, view accidental grounding of sensor equipment, malfunctioning of sensors or power fluctuations. Our work proposes pre-processing techniques to learn machinery exploitation patterns and segregate erroneous readings. We have used a decision tree-based classifier [7] in our model for filtering erroneous readings.
- **Prediction of Performance Degradation** – To undertake a regression-based analysis of Remaining Useful Life (RUL) [23], we require lifetime data of a motor, i.e. from the installation of a new motor till such time, the motor gets faulty. However, data collection for such rule-based analysis requires recording the parameters of motors for over two years. Our approach circumvents the need to record the parameters of an electrical motor for its lifetime, as we present a methodology for statistical and comparative analysis of motors of similar types, which may be in different stages of their lifetime. Our model determines the Gaussian distribution of data, compares the Gaussian distribution of similar machines and uses empirical rules to predict the degradation of machinery. Lastly, we demonstrate the efficacy of our system on real-world deployment onboard Naval Ships. We propose future work that can be undertaken to enhance our solution.

A. Problem Statement:

Despite the rapid development of predictive maintenance systems in Industry 4.0, we still have major issues with industrial downtime in areas like manufacturing, energy, and transport. Unexpected equipment breakdowns continue to impact production, efficiency and maintenance costs. Although conventional maintenance practices have shifted towards more advanced predictive maintenance, the expected downtime reduction hasn't been fully achieved in many industrial applications. This gap points to fundamental issues with the deployment and scalability of existing predictive maintenance systems. Artificial intelligence (AI) models have shown great promise in enhancing fault detection, failure prediction, and maintenance planning. Yet their use in the industrial sector is patchy at best. Data silo is a major challenge. Data in industrial applications may reside in a variety of systems, such as legacy systems, IoT systems, and enterprise databases. This makes data integration, normalization, and accessibility difficult, impacting the accuracy and efficiency of AI models. Lacking standardized and quality datasets, predictive models are unable to produce reliable insights. Integration also adds to the challenge. Existing industrial systems may not be compatible with these new AI-based solutions. It takes technical skills, financial resources,and change management to incorporate AI-based predictive maintenance systems into these systems. Integration of various hardware and software components may cause delays, higher costs, and inefficiency. Consequently, companies may hesitate to adopt AI-driven predictive maintenance over conventional maintenance techniques.

Another key issue is the trustworthiness of AI models. Many predictive maintenance models, especially those incorporating sophisticated machine learning and deep learning techniques, are "black boxes", offering little insight into the reasoning behind predictions. This opacity not only complicates the interpretation and verification of model results but also hampers trust and confidence in using them for maintenance planning. This can be a critical issue in high-risk industrial settings, where trust and reliability are crucial. As a result, while AI has been demonstrated to be effective in predictive maintenance applications, these issues (data siloed, integration problems, and trust) still hold back its adoption. Overcoming these challenges is crucial to closing the gap between the potential and implementation of AI technologies and to delivering significant improvements in industrial downtime reduction (Shamim, 2024; Okirie & Ejomarie, 2025; Soliman, 2025).

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Fig 2. Industrial Challenges in Traditional Maintenance System

II. LITERATURE REVIEW

There are already several applications of predictive maintenance in different industries, but this work is focusing on applications on rotating machineries. According to their review, Naive Bayes classifier, k-NN, ANN and SVM algorithms are most used machine learning algorithms. The k-NN (k-Nearest Neighbours) algorithm belongs to the instance-based learning category. It postpones the process of induction or generalization until after classification. Unlike k-means, which computes overall data, k-NN only focuses on nearest neighbours. This approach reduces training time compared to eager-learning algorithms like ANN (Artificial Neural Networks) and Bayes nets, albeit demanding more computation time during classification (Ruonan Liu 2018). In contrast, the Naive Bayes algorithm operates on a probabilistic approach, distinguishing itself from other AI models. It assigns probabilities to an instance belonging to each class, instead of a straightforward classification. SVM (Support Vector Machine) excels in generalization and can even perform well with limited training data. Using kernel functions, it achieves appropriate nonlinear mapping, enabling the separation of data from multiple categories using a hyperplane. This characteristic empowers SVM to high classification accuracy achievement in tasks like fault diagnosis and condition monitoring of rotating machinery. ANN, modelled after the human brain's structure. This architecture allows it to approximate intricate non-linear functions with multiple inputs and outputs. By adapting its structure, ANN demonstrates commendable fault diagnosis capabilities in various rotating machinery applications (Das, Das and Birant 2023). Deep learning emerges as a potent technique for automatic feature learning across multiple abstraction levels. It facilitates the direct learning of complicated input-to-output functions, eliminating the need for independent feature extractors. This quality is particularly advantageous for fault diagnosis of industrial rotating machinery. In broad terms, ANN, SVM, and deep learning techniques execute well where data frequently presents a high level of dimensionality and continuous characteristics. In contrast, naive Bayes and k-NN algorithms showcase superior performance when dealing with discrete features (Roberto M. Souza 2021).

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III. SYSTEM OVERVIEW

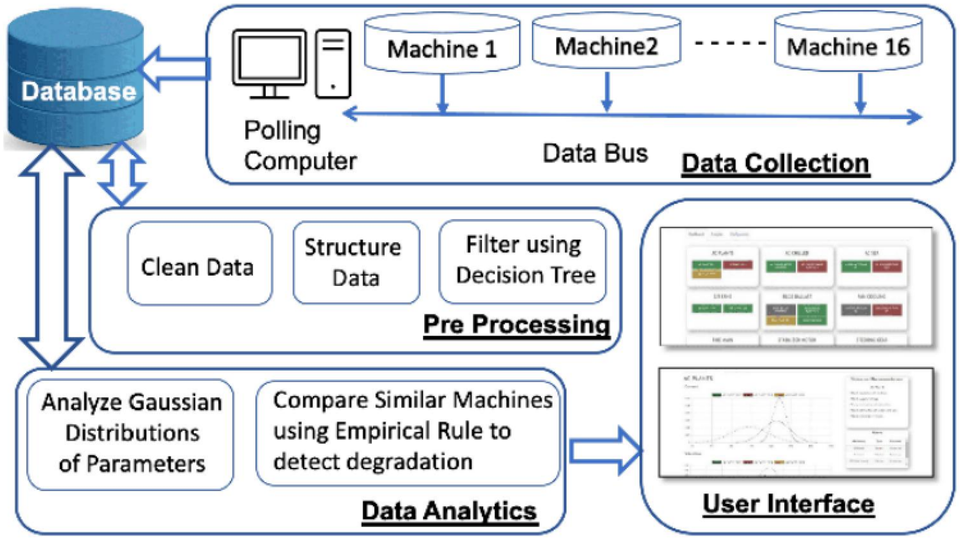

Fig 3: Architecture of Predictive Maintenance System

A. Application Overview

The application architecture is shown in Fig. 1. The system consists mainly of four modules: real-time data collection, pre-processing, data analytics and user interface. During the development of the application, firstly, we used a data collection module to collate data. After that, we used EDA techniques to understand the data. Based on the results of EDA, we developed pre-processing and comparative analytics modules (used for degradation prediction). Subsequently, we deployed the complete application and user interface onboard the ship for real-time predictive maintenance of electrical motor pump sets. In this paper, we briefly explain the data collection module, followed by the results of our EDA techniques. Further, we explain techniques used for pre-processing and prediction of degradation.

B. Analysis using DBSCAN

Density-Based Spatial Clustering Application with Noise (DBSCAN) [17] algorithm and parameters' timeline charts were used over the dataset to undertake EDA. The results of DBSCAN clustering over PCA [11] transformed dataset for one motor are shown in Fig. 4.1 and explained as follows:

The red and blue clusters indicate data points considered normal values by the DBSCAN algorithm, and black dots correspond to anomalies detected by DBSCAN. • The presence of two clusters was further analyzed in the dataset using timeline plots of current and vibration readings, as shown in Fig. 4.2. Further, the colours (red and blue) of vibration values and current in Fig. 4.2 were mapped with colours of data points in Fig. 4.1 for appreciation of affiche acy of DBSCAN clustering. It was found that zero-valued current readings were grouped in blue clusters, and data points with non-zero values were largely clustered in red clusters. As the motor does not draw current in switched OFF state, it was observed that the red cluster consisted of data points in the ON state of machinery, and the blue cluster indicated the OFF state of machinery. • Further, it was also observed that anomalies observed by the DBSCAN algorithm were about exceptionally high current values during state transition from OFF state to ON state. It is essential to mention that the datalogger recorded current values at a sampling rate of one data point per minute, and therefore, exceptionally high current values were starting current values captured during state transition. It was inferred that though the DBSCAN algorithm detects these points as anomalies, these data points were not anomalous as starting current is consistently higher than the running current during regular operation of the motors. It was also inferred that DBSCAN could not detect graceful degradation, as during a graceful degradation, values will iteratively increase slowly to higher values; therefore, all these density-reachable values would be clustered together.

IV. MAINTENANCE

This section delves into traditional maintenance models, highlighting their merits and limitations. Maintenance practices involve the assessment of equipment conditions and functionalities. Maintenance can be categorized into several distinct approaches, including preventive maintenance, condition-based maintenance, predictive maintenance and corrective maintenance.

A. Preventive maintenance

Even while equipment is operational, certain functions remain dormant until emergency scenarios arise. Consequently, it becomes imperative to assess the functionality of these features during maintenance routines. This genre of maintenance is termed "preventive maintenance," which is commonly complemented by routine maintenance procedures. Typically, an annual preventive maintenance schedule is instituted to ascertain the functionality of equipment without necessitating the dismantling or inspection of internal components. For more comprehensive evaluations, preventive maintenance cycles spanning intervals of three, five, six years, and so forth, are strategically planned within corporate frameworks. These temporal benchmarks often align with recommendations provided by manufacturers and documented manuals. Periodically, engineers might propose extensions or contractions of these cycles based on their observations of failures and perceived risks during routine maintenance activities. In rare instances, the execution of periodic maintenance might be postponed or rescheduled to accommodate production continuity. However, this decision is usually contingent upon a meticulous analysis conducted by both operational and maintenance personnel, with safety and risk considerations at the forefront of the decision-making process.

B. Corrective maintenance

Typically, preventive maintenance primarily focuses on upkeep tasks rather than extensive repairs, especially if the repair is intricate or substantial. Nevertheless, in instances where abnormal situations are detected during preventive maintenance activities, these occurrences are documented within maintenance systems as instances of "corrective maintenance." True to its name, corrective 10 maintenance pertains to the rectification of malfunctioning equipment functions. This necessitates supplementary planning and requisitioning of materials if components require replacement. Furthermore, corrective maintenance can be requisitioned at any point if anomalies or failures manifest during the production process. Ordinarily, the initial step in corrective maintenance involves an inspection aimed at verifying the equipment's functionality. Following this assessment, maintenance personnel scrutinize the operational status and subsequently propose either repairs or the replacement of equipment, contingent upon the nature of the identified issue.

C. Condition monitoring

It serves as a fundamental predictive maintenance paradigm that, while not directly involved in executing maintenance decisions, assumes a pivotal role in precluding equipment failures. This model centres on the systematic acquisition of data through a diverse array of sensors, meticulously tracking equipment health and expeditiously alerting operators in anticipation of potential malfunctions. Embracing the principles of Industry 4.0, the proposed predictive maintenance model integrates seamlessly into the broader landscape of fully automated industrial ecosystems. Within this paradigm, condition monitoring transcends its traditional role, becoming an integral component in the symbiotic relationship between machines and the Internet of Things (IoT). The systematic acquisition of data through a myriad of sensors aligns with the tenets of Industry 4.0, where the interconnectedness of machines facilitates the seamless flow of information. This interconnectedness allows for real-time data aggregation and analysis, enabling predictive maintenance decisions based on a broad understanding of equipment health. In this thesis not only underscores the importance of condition monitoring but also positions it as a key enabler for the predictive maintenance strategies essential for the evolving landscape of Industry 4.0. Operationalizing this approach entails a carefully orchestrated interplay between data aggregation, analysis, and decision-making. The data stream, garnered via an assortment of sensors, is channelled to a central controller, which undertakes the continuous scrutiny of this incoming information. Notably prominent within this suite of sensors are those dedicated to monitoring vibration, temperature, and pressure – a trinity of paramount parameters that form the foundational basis for evaluating equipment health (Eleonora, Fabio and Ilenia 2021)

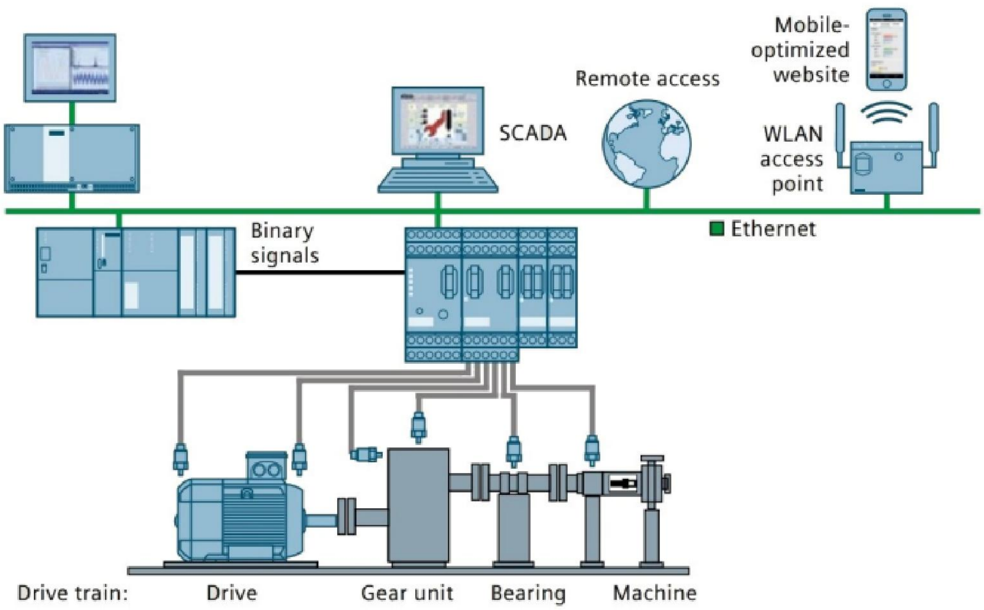

Fig 4: Condition Monitoring System (Siemens 2016)

V. LIMITATION

While the technological progress and proven success of AI-based predictive maintenance systems, there are still some limitations that hinder their adoption and performance in industry. Perhaps the most significant limitation is poor data quality. To develop and test machine learning models, predictive maintenance systems use a vast amount of data collected from sensors. But in practice, this data can be noisy, missing or inconsistent due to sensor failure, environmental factors, calibration issues or communication problems. Moreover, gaps in data and non-uniform sampling frequencies can also degrade model performance, resulting in poor predictions and lack of confidence. Ultimately, data quality affects the generalisation capability of AI systems across various operating conditions and equipment. The cost of implementing predictive maintenance using AI is also a significant limitation. Setting up these systems can be costly in terms of investing in IoT infrastructure, advanced sensing, data storage and analytics infrastructure to power these systems. Furthermore, they need to invest in software and system integration, as well as training their employees, to implement and manage such systems. This can be a significant barrier for small and medium-sized businesses, which may struggle to adopt AI-based predictive maintenance from their existing maintenance practices. Even for larger enterprises, the payback period for investing in AI systems may be lengthy, and this may impact on the rate of adoption. The lack of explainability is also a major challenge in using AI models for predictive maintenance. Many sophisticated techniques, such as deep learning, are "black-box" models that offer little information about how the predictions are made. As a result, it is hard for maintenance engineers to interpret the basis of fault predictions or risk analysis. This can lead to a lack of trust in AI systems and uncertainty in decision-making in safety-critical applications, such as energy, oil and gas, and manufacturing. While efforts are underway to create explainable AI solutions, their adoption in industrial applications is still in its infancy and not yet widely established. In summary, the issues with data quality, cost of implementation and lack of explainability indicate the need for more research and development to enhance the reliability, affordability and explainability of predictive maintenance systems based on AI (Sinnah, 2025; Abdelhafid et al., 2026).

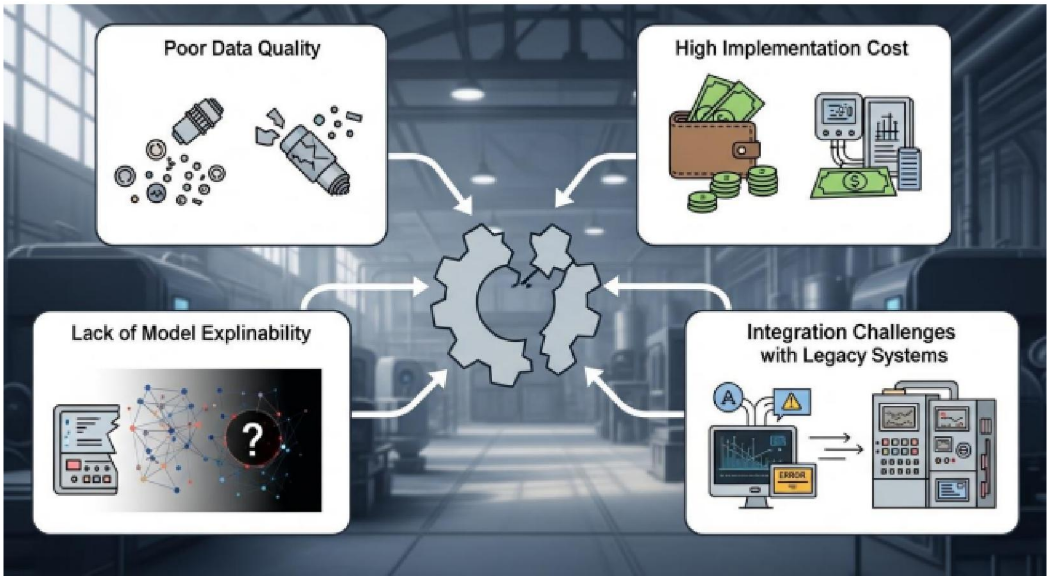

Fig 5: Key Limitations of AI-Driven Predictive Maintenance Systems in Industry

VI. CONCLUSION

We have developed a technique to process sensor data from various electrical motor pump sets fitted onboard ships, recorded by a network of sensors. Our application involves pre-processing techniques for cleaning, structuring and filtering data. EDA has allowed us to understand the dataset for its application for predictive maintenance. Further, we incorporated machine learning techniques and empirical rules to perform comparative analytics of data of similar machines [6, 9]. A complete application along with GUI was developed and deployed onboard a ship by combining pre-processing techniques, EDA, and comparative analysis module.

Future Work:

Our application may be enhanced by integrating knowledge of the design parameters of machinery for comparing the design and observed parameters. Further, the application can facilitate the collection of more maintenance data by providing functionalities to record details of maintenance routines, downtime of equipment, spares consumed during maintenance and similar data. The availability of detailed maintenance data would facilitate using other AI and ML algorithms for predictive maintenance.

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