



A Review of Predictive Maintenance Methods for Electrical Machines Using Machine Learning Algorithms and Sensor Data

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Abstract

Induction motors serve as an integral part in industrial applications, where unexpected failures lead to huge financial losses. Predictive maintenance (PdM) has emerged as a key approach for early fault detection and machine health monitoring since demand for reliability and efficiency has been increased. This paper provides a structured analysis of data-driven predictive maintenance techniques for electrical machines, combining conclusions from traditional motor fault diagnosis methods and modern machine-learning-based approaches.

For detecting motor abnormalities such as broken rotor bars, bearing defects, and stator faults, traditional techniques such as Motor Current Signature Analysis (MCSA) and Park's Vector Analysis (PVA) have been widely used. Under different loading conditions, variations in current, voltage, slip, and vibration patterns serves as strong indicators of motor health. Support Vector Machines (SVM) and other supervised learning algorithms have been used for detecting motor faults with high precision.

Keywords: Predictive maintenance, machine learning models, downtime failure

I. Introduction

Electrical machines like motors, generators, transformers are very crucial for industries like manufacturing, energy transportation. It is estimated that unplanned failures in these assists can lead to significant losses in the country's economy. Around \$50 billion economic losses have been found in U.S. alone due to downtime failures.

The old method of maintenance is now found to be inefficient, often resulting in over maintenance or catastrophic breakdown. The method of predictive maintenance integrates the sensor data methods (vibration, temperature, current) with the various ML Algorithms to detect the fault probabilities. The rise of Industrial Internet of Things (Iao), edge computing, advanced ML has accelerated adoption with global predictive maintenance market projected to reach \$ 23.5 billion by 2028.



II. Literature Review

A progressive shift is noticed from traditional scheduled approaches of maintenance of electrical machines to intelligent, data-driven predictive systems. Various authors have highlighted the limitations of reactive and preventive maintenance which motivated industries to adopt Predictive Maintenance (PdM). The combination of PdM with advanced sensor technologies and AI-based analytical models have made it more effective.

Maximize uptime, minimize unplanned downtime, and reduce maintenance costs is the primary goal of PdM by identifying the potential equipment failures in advance. To analyze the actual health and condition of equipment in realtime, Condition-Based Maintenance (CBM) is the approach which is adopted that uses sensor data and monitoring.

Advancement of Maintenance Paradigm:

In the past, there were finite maintenance strategies and often ineffective, which provided the motivation for the growth of PdM.

Types of Maintenance:

1. Corrective maintenance / Reactive maintenance:

It is referred to as the maintenance tasks which are performed to restore damaged equipment to working condition. It leads to costly down time, possible safety hazards and production losses.

2. Preventive maintenance (PM):

This includes the maintenance tasks that are conducted at fixed time intervals to reduce failure risks. However, it can lead to unneeded servicing, raising operating costs irrespective of the equipment's conditions and wasting resources.

3. Asset management (AM):

Asset management combines life-cycle management of physical assets and risk-controlled optimization. It determines the best moment to maintain assets, reducing unnecessary maintenance and lowering outage costs by using operational data from cyberphysical systems.

4. Predictive maintenance (PdM):

It consist of a proactive maintenance strategy that uses Internet of Things (IoT), condition monitoring tools and machine learning (ML) algorithms to prevent the breakdown by knowing the possibility of occurring downtime and performing maintenance just in time.



Table I. Comparison Of Maintenance Methods

Maintenance Type	Downtime Impact	Cost Per Maintenance (USD)	Predictive Accuracy
Reactive maintenance	High	High	Low
Preventive Maintenance	Medium	Medium	Medium Low
Predictive Maintenance	Low	Low	High

A. Machine Learning Techniques for Fault Diagonosis in Predictive Maintenance of Electric Machines:

a) Machine Learning Algorithms:

ML algorithms provide many predictive solutions by learning from past data and identify patterns that are responsible for equipment failures.

b) Supervised Learning (SL):

Algorithms like Support Vector Machines (SVMs) and Decision Trees/Random Forests (RF) are used to structure predictive models. SL provides a more accurate and stable prediction and also is applied for classification tasks, like classifying equipment health status (e.g., "Healthy" or "Needs Preventive Maintenance" (PM)).

c) Deep learning:

It mimic the complex decision-making power of the human brain by using multi-layered neural networks, called deep neural networks. There are different kinds of neural networks like Convolutional neural networks (CNNs or Convent's) and recurrent neural networks (RNNs).

d) Unsupervised Learning (UL):

Clustering and anomaly detection methods are implemented for the identification of abnormal behaviour and irregularities in sensor data. Normal behavior of electrical equipments is represented by Gaussian Mixture Models (GMMs) .

e) Predictive Analytics:

Based on past data, it predicts the future events and outcomes with the use of statistical modelling and data mining techniques. Therefore, it helps in prioritizing the maintenance tasks.

f) Natural Language Processing (NLP):

It collects useful information and insights from the analysis of unstructured text data, like maintenance logs, inspection reports, and equipment manuals to take the maintenance decisions.

g) Reinforcement Learning:



With the use of trial-and-error methods, it trains agents to interact with an environment and learn

effective methods to improve maintenance scheduling and resource distribution tasks.

B. Sensor Fusion and Data Acquisition for Predictive Maintenance:

Multi sensor data enhances fault detection accuracy in electrical machines by providing a broader perspective of electrical machine health. These sensor does not depend completely on single data stream- such as vibration or temperature- integrated inputs from various sources including acoustic signals, current signatures, and thermal profiles. Therefore, these layered information assists various machine learning models to analyse and detect the patterns and correlations which might be missed in isolated datasets. For example, temperature rise coupled with abnormal vibration can indicate bearing wear more effectively than alone signal. By integrating various sensor modalities, predictive maintenance systems have become more robust and resulting in reducing false alarms.

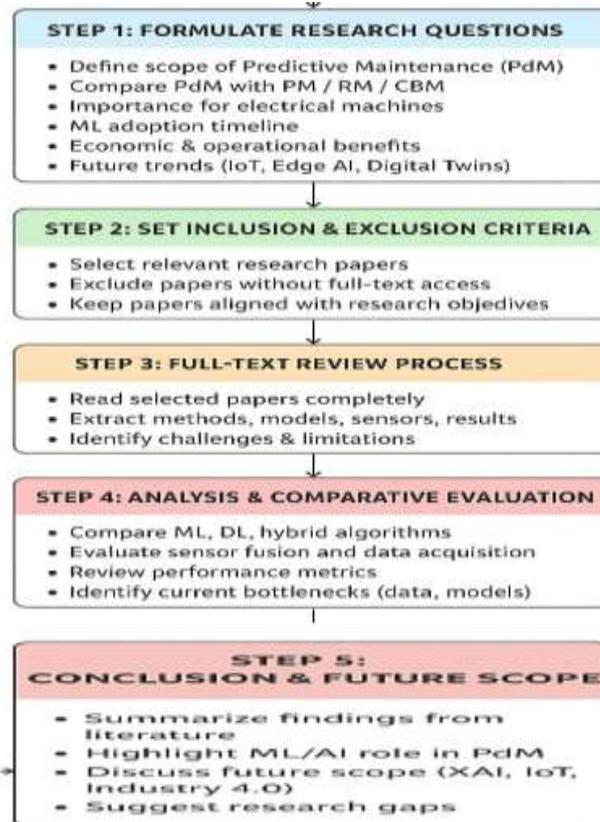
III. Methodology

The review aimed to do the investigation of the current state of maintenance of electrical machines, its challenges, limitations, root cause of downtime failures and solutions with the help of predictive maintenance using ML algorithms. To formulate the research questions was the first step of our review paper, which we use to shape the study scope and guide the review process.

Our research questions are:

- What is Predictive Maintenance?
- How it is different from Preventive, Reactive and Condition Based Maintenance?
- Why is PdM particularly important for electrical machines (e.g., motors, generators, transformers) in industries like transportation?
- How has the adoption of ML in PdM evolved over time?
- What are the economic and operational benefits of using ML for PdM in electrical machines, such as reducing downtime, extending equipment life, or improving safety?
- What emerging trends could shape the future of ML in PdM for electrical machines (e.g., integration with IoT, edge AI, federated learning, or digital twins)?

After formulating the research questions, we established criteria to determine which research articles to include or exclude. Through this process, we removed various papers due to them not having full-text access online. We examined the remaining papers in a full-text review process for this study and finally completed our review paper.



IV. Results And Discussion

A. Key Performance Findings:

The practical findings from the reviewed studies consistently emphasize that AI based predictive maintenance systems surpass traditional, time-based maintenance approaches in providing diagnostic performance and operational outcomes. The main conclusions stress the effectiveness of specific Machine Learning (ML) architecture and the critical role of data integration in maximizing fault detection accuracy.

1) Comparative Performance of Traditional ML

Classifier:

Various studies shows the clear distinguishing factors in performance while comparing standard ML algorithms like Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees for fault diagnosis in electrical machines. Validation of these algorithms with synthetic and historical datasets, highlights that more sophisticated models attain significantly better precision and recall in classification tasks. The comparison focusses greater ability of network-based approaches in processing non-linear fault signatures:

Table II. Comparative Performance of Traditional ML Classifier:

Model	Accuracy (%)	Precision (%)	Recall (%)
ANN	96.5	95.8	97.1
SVM	>95.0	N/A	N/A
Decision Tree	92.4	N/A	N/A

The ANN model showed the highest performance (96.5% accuracy), attested its appropriateness for complex datasets which involve fault categories such as phase imbalance, single-phasing, short circuits, and bearing wear. While the Decision Tree offered clarity and faster detection times, it displayed a lower accuracy of 92.4%. Also, models like the Random Forest algorithm consistently showed high accuracy in analysing complex, non-linear relationships characteristic of motor failures because their inherent robustness prevented over fitting.

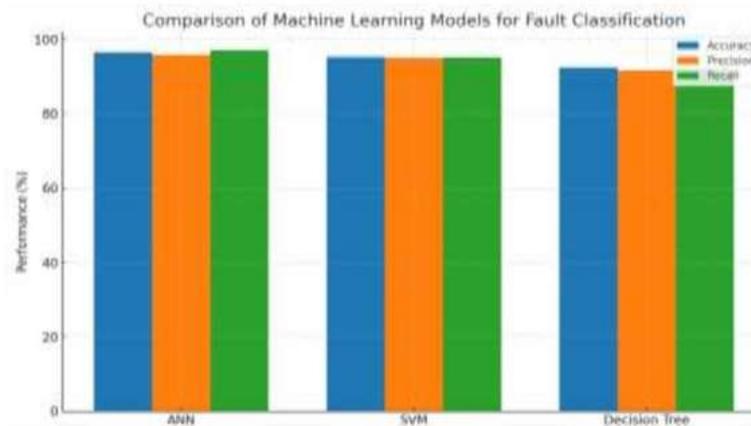


Fig. 1. Comparison of Machine Learning Models for Fault Classification

2) Deep Learning and Multi-Modal Fusion Superiority

Deep Learning (DL) architectures like Long ShortTerm Memory (LSTM) networks are essential for highly complex time-series data and for predicting the Remaining Useful Life (RUL). The issue of maintaining model robustness is being increasingly tackled through advanced fusion methods.

Research reveals that combining information from multiple sensors (multi-sensor fusion) and different data representations (multi-modal learning) drastically improves reproducibility. This involves merging unprocessed time domain data with derived frequency-domain data, such as time-frequency images generated through the Short-Time Fourier Transform (STFT). The type of data we use greatly influences in how accurately the system can find problems in a machine’s bearings is the key finding of this experiment.

TABLE III. Comparison of Deep Learning models with Sensor Data Modality (Accuracy, Mean ± Standard Deviation)

Method	PU Dataset Accuracy (%)	ESOGU Dataset Accuracy (%)
Multi sensor time and time frequency domain (4 inputs)	97 ±1.45	100
Vibration time and time frequency domain (2 inputs)	84 ±0.5	100
Only current time domain	61 ±7.68	77 ± 7.63

The data definitely shows that the use of four inputs (vibration time, vibration STFT, current time, and current STFT) produced the highest accuracy in both the publicly available Paderborn University (PU) dataset (97.10%) and the in house ESOGU dataset (100% success in all trials).

3) Real Time Deployment and Anomaly Detection

The utility of PdM is achieved by implementation strategies that facilitate real-time monitoring and anomaly detection. This process is frequently made more efficient by the use of edge computing technologies. The success in implementation of an anomaly detection algorithm in a predictive maintenance system is evaluated by the continuous monitoring of a machine health index. The criteria, known as the “similarity index,” quantifies the deviation of real-time sensor data from the established normal operating profile (trained data).

B. Challenges and Limitations in Predictive Maintenance:

The implementation of large-scale PdM systems presents profound difficulties. Data management, technical constraints, operational complexity, and AI-specific requirements are the major challenges in the implementation of Predictive Maintenance approaches.

a) Data Complexity and Integration:

Sensors, meters, SCADA systems, and maintenance records generates variety of sensor data like sheer volume ,velocity ,etc. are the major challenges in data management. Incorporation of the data from heterogeneous industrial systems still remains a key hurdle. Since, different devices and infrastructures use unique data packet formats and communication standards, so compatibility solutions are needed .

b) Data Quality and Completeness:

The quality and completeness of the data results in the effectiveness of ML models . The efficiency of Machine Learning is degraded due to the incomplete, noisy, or unbalanced data and can result in unreliable data outcomes. Since, supervised learning algorithms require classified datasets (e.g., determining a machine’s condition as "Healthy" or "Needs Maintenance"),so this challenge is complicated by the fundamental lack of labelled data. As, the historical fault data is scarce, obtaining these required labels becomes a severe limitation.



c) Model Accuracy and Reliability:

The main obstacles in achieving accurate and reliable predictions are the problems like overfitting of models, data quality problems, and skewed sample selection (towards failure cases) .

d) Complexity of Patterns:

Machine Learning models should be good at dealing with complex, non-linear patterns to provide successful prediction of motor failures.

V. Conclusion

The evolution of the maintenance methods for electrical machines and power networks has been presented in this review paper. The shift in maintenance strategies from reactive and preventive approaches to data driven, intelligent Predictive Maintenance framework.

PdM uses IoT based sensor data, real time condition monitoring and advanced machine learning algorithms to detect early on about possible equipment failures. It also helps us avoid unnecessary servicing and therefore reduces working cost.

Machine Learning algorithms, particularly unsupervised learning, supervised learning along with deep learning play a crucial role in deriving tangible insights from archival and real-time data. Other tools like predictive analytics, NLP and reinforcement learning improve the decision-making capabilities within PDM systems.

The incorporation of IoT architectures, edge computing, and standardized communication protocols has significant contribution in the development of modern PdM. The advancement in PdM demonstrates its effectiveness in improving reliability, efficiency, and safety of electrical systems. Future developments may focus on enhancing the accuracy, reliability and adaptability of ML algorithm further improving PdM.

VI. Future Scope

Advancements in automation, real-time capability, and integration with broader digital initiatives is heavily focussed in the future of AI – based PdM.

A. Key Trends Include:

1) Edge Computing and IoT Integration:

IoT devices and sensors are used in this technology for the analysis of the data right where it is generated—at the network edge. Communication delay is greatly reduced with the shifting of the real-time processing closer to the machine, thus making the system less dependent on the cloud. Therefore, it aids organizations to respond swiftly to equipment anomalies.

2) Advanced ML and DL

More accurate fault detection and diagnosis is possible with the further studies of deep neural networks (DNNs) and complex DL architectures.

3) Digital Twins and Simulation:

This technology plays a significant role in simulation-based modelling, allowing organizations to analyze equipment behavior and simulate different maintenance scenarios by creating the virtual replicas or models of physical assests . To predict the impact of interventions, by enabling the optimization of maintenance strategies to maximize asset performance and reliability is the core function of this technology.



4) Integration with Industry 4.0 Initiatives:

Predictive maintenance will facilitate seamless data exchange and real-time monitoring through technologies like cyber-physical systems and so it will become an integral component of Industry 4.0.

5) Explainable AI (XAI):

As AI solutions become more common there will be a growing need to understand the functioning of AI, why it makes certain decisions. This understanding is important for building trust.

6) Ethical AI Practices:

Organizations must address concerns regarding data privacy, bias, fairness, and accountability.

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