

Survey on Predictive Maintenance of Electrical Machines

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Abstract: Predictive maintenance (PdM) of electrical machines has emerged as a key enabler for improving system reliability, reducing unplanned downtime, and minimizing maintenance costs in modern industrial and power systems. Unlike traditional time-based or reactive maintenance strategies, predictive maintenance relies on continuous condition monitoring and data-driven fault diagnosis to anticipate failures before they occur. This survey presents a comprehensive review of predictive maintenance techniques applied to electrical machines such as induction motors, synchronous machines, and transformers. The paper categorizes existing approaches based on signal acquisition methods, including vibration analysis, motor current signature analysis, thermal monitoring, acoustic emission, and infrared sensing. Furthermore, recent advancements in machine learning, deep learning, and IoT-based frameworks for fault detection, remaining useful life estimation, and decision-making are critically analyzed. Comparative insights into model-based, data-driven, and hybrid techniques are provided, highlighting their advantages, limitations, and application scenarios. Finally, key challenges such as data quality, sensor reliability, scalability, and real-time deployment are discussed, along with future research directions toward intelligent, autonomous, and edge-enabled predictive maintenance systems.

1. Introduction

Electrical machines such as induction motors, transformers, and generators are critical assets in industrial, transportation, and power system applications. Their continuous and reliable operation is essential for ensuring productivity, energy efficiency, and system stability. Traditionally, maintenance practices for these machines have relied on corrective or preventive strategies, which often fail to provide optimal reliability and cost efficiency. With the rapid advancement of sensing technologies, data analytics, and intelligent algorithms, predictive maintenance (PdM) has gained significant attention as an effective approach for early fault detection and condition-based decision-making.[1-6]

Corrective maintenance addresses failures only after they occur, leading to unexpected downtime, production losses, and potential safety hazards. Preventive maintenance, although scheduled at regular intervals, does not account for the actual health condition of the machine. As a result, components may be replaced prematurely or failures may still occur between maintenance cycles. [8] These approaches often increase operational costs, reduce equipment availability, and lack the capability to detect incipient faults at an early stage.

Predictive maintenance enables continuous monitoring of machine health using sensor data and intelligent diagnostic techniques. [17] By identifying early signs of degradation, PdM helps in minimizing downtime, extending equipment lifespan, and optimizing maintenance schedules. In electrical machines, early detection of faults such as bearing defects, insulation degradation, rotor faults, and overheating significantly improves system reliability and operational safety. Moreover, PdM contributes to cost reduction by preventing catastrophic failures and supporting efficient asset management in industrial and smart grid environments. [20]

This survey provides a comprehensive review of predictive maintenance techniques applied to electrical machines. The paper systematically analyzes condition monitoring methods, signal processing techniques, and data-driven approaches, including machine learning and deep learning models. Recent developments in IoT-enabled monitoring systems and hybrid diagnostic frameworks are also reviewed. The survey highlights comparative strengths and limitations of existing approaches, identifies research gaps, and outlines future directions for scalable, real-time, and intelligent predictive maintenance solutions. [22]

The remainder of this paper is organized as follows. Section 2 presents an overview of common faults and failure mechanisms in electrical machines. Section 3 reviews condition monitoring and feature extraction techniques. Section

4 discusses data-driven and intelligent diagnostic methods for predictive maintenance. Section 5 addresses implementation challenges and emerging trends. Finally, Section 6 concludes the paper and outlines potential future research directions.

2. Electrical Machines and Common Faults

Electrical machines are fundamental components in industrial automation, power generation, transportation, and renewable energy systems. Their operating conditions often involve mechanical stress, thermal loading, electrical disturbances, and environmental influences, which can lead to gradual degradation and eventual failure. Understanding the types of electrical machines and their typical fault characteristics is essential for designing effective predictive maintenance strategies.

2.1 Types of Electrical Machines

2.1.1 Induction Motors

Induction motors are the most widely used electrical machines in industrial applications due to their simple construction, robustness, and low cost. They are commonly employed in pumps, compressors, conveyors, and manufacturing systems. Despite their reliability, induction motors are susceptible to faults such as bearing defects, stator winding insulation failures, rotor bar breakage, air-gap eccentricity, and thermal overload. Their widespread usage makes induction motors a primary focus of predictive maintenance research. [22], [27]

2.1.2 Synchronous Machines

Synchronous machines are extensively used in power generation, large industrial drives, and grid-connected applications due to their constant speed operation and high efficiency. These machines include synchronous generators and motors with field windings or excitation systems. Common faults in synchronous machines include rotor winding faults, excitation system failures, stator insulation degradation, and mechanical misalignment. Early detection of these faults is critical, as failures in synchronous machines can significantly impact power system stability. [20], [22]

2.1.3 Permanent Magnet Machines

Permanent magnet (PM) machines have gained increasing attention in recent years due to their high power density, superior efficiency, and compact size. They are widely used in electric vehicles, wind energy systems, robotics, and aerospace applications. Typical faults in PM machines include demagnetization of permanent magnets, stator winding faults, bearing wear, and inverter-induced electrical stresses. The high cost of permanent magnets and sensitivity to thermal conditions make predictive maintenance particularly important for these machines. [23], [27]

2.1.4 DC Machines

DC machines, although less common in modern industrial systems, are still used in specific applications requiring precise speed control and high starting torque. Common faults in DC machines include brush and commutator wear, armature winding faults, and mechanical imbalance. Due to their relatively simple structure, DC machines are often briefly discussed in predictive maintenance surveys, primarily for historical relevance and comparative analysis. [22]

2.2 Common Faults in Electrical Machines

Electrical machines are subjected to continuous electrical, thermal, and mechanical stresses during operation, which can lead to various types of faults over time. These faults often develop gradually and, if not detected early, may result in severe damage or catastrophic failure. Predictive maintenance aims to identify such incipient faults at an early stage by analyzing deviations in electrical and mechanical parameters. [22], [27]

2.2.1 Stator Faults

Stator-related faults are among the most critical failures in electrical machines, accounting for a significant percentage of machine breakdowns. Inter-turn short circuits occur due to insulation degradation caused by thermal aging,

overvoltage, contamination, or mechanical vibration. If left undetected, these faults can evolve into phase-to-phase or phase-to-ground failures, leading to extensive damage. Monitoring stator current, voltage, temperature, and insulation resistance plays a vital role in the early detection of stator faults.

2.2.2 Rotor Faults

Rotor faults commonly include broken rotor bars, cracked end rings, and rotor eccentricity, particularly in induction motors. Broken rotor bars introduce asymmetry in the rotor circuit, resulting in torque pulsations, increased losses, and abnormal current harmonics. Rotor eccentricity, caused by uneven air-gap distribution, leads to unbalanced magnetic pull and excessive vibration. Predictive maintenance techniques such as motor current signature analysis (MCSA) and vibration monitoring are widely used to detect rotor-related anomalies. [22], [27]

2.2.3 Bearing Faults

Bearing faults are one of the most frequent causes of electrical machine failure, often responsible for a large proportion of motor breakdowns. These faults include defects in the inner race, outer race, rolling elements, and cage. Bearing degradation is typically caused by poor lubrication, contamination, misalignment, or electrical discharge effects. Early-stage bearing faults generate characteristic vibration and acoustic emission signatures, making vibration analysis and envelope detection effective tools for predictive maintenance. [9], [14], [22]

2.2.4 Air-Gap Eccentricity

Air-gap eccentricity occurs when the rotor is not concentrically aligned with the stator, resulting in an uneven air-gap. It can be classified as static, dynamic, or mixed eccentricity. This fault leads to unbalanced magnetic forces, increased vibration, noise, and localized heating. Persistent air-gap eccentricity accelerates bearing wear and rotor damage, making its early detection essential. Techniques based on current, vibration, and magnetic flux analysis are commonly employed to identify eccentricity-related faults. [22], [27]

2.2.5 Mechanical Faults

Mechanical faults such as shaft misalignment, rotor imbalance, looseness, and mechanical wear significantly affect machine performance and reliability. These faults often result in increased vibration levels, noise, and mechanical stress on bearings and couplings. Although mechanical faults may not initially impact electrical parameters, prolonged operation under such conditions can induce secondary electrical failures. Predictive maintenance strategies integrate vibration, thermal, and speed analysis to detect mechanical anomalies and prevent cascading failures.

3. Maintenance Strategies

Maintenance strategies play a crucial role in ensuring the reliable and efficient operation of electrical machines. Over the years, maintenance practices have evolved from reactive approaches to intelligent, data-driven strategies. This section reviews the major maintenance strategies applied to electrical machines and highlights the advantages of predictive maintenance over traditional approaches. [14], [17]

3.1 Corrective Maintenance

Corrective maintenance, also known as reactive or breakdown maintenance, involves repairing or replacing machine components only after a failure has occurred. Although this approach requires minimal planning and low initial cost, it often results in unexpected downtime, production losses, and increased repair expenses. In electrical machines, corrective maintenance can lead to catastrophic failures, secondary damage to associated components, and serious safety risks. [20], [22]

3.2 Preventive Maintenance

Preventive maintenance is based on scheduled inspections and servicing performed at predefined time intervals, regardless of the actual condition of the machine. This approach reduces the likelihood of sudden failures compared to corrective maintenance; however, it does not account for varying operating conditions or load profiles. As a result, components may be replaced prematurely or faults may still develop between maintenance intervals, leading to inefficiencies and increased operational costs. [20], [22]

3.3 Condition-Based Maintenance (CBM)

Condition-based maintenance relies on periodic or continuous monitoring of machine health parameters such as vibration, temperature, current, and voltage. Maintenance actions are initiated when monitored parameters exceed predefined thresholds, indicating abnormal behavior. CBM improves maintenance efficiency by considering the actual condition of the machine, but it often depends on rule-based thresholds and expert knowledge, which may limit its ability to detect complex or early-stage faults. [17], [20]

3.4 Predictive Maintenance (PdM)

Predictive maintenance represents an advanced maintenance strategy that utilizes historical and real-time data to predict future machine behavior and estimate the remaining useful life (RUL) of components. PdM employs signal processing, statistical analysis, and artificial intelligence techniques such as machine learning and deep learning to detect incipient faults before they become critical. In electrical machines, predictive maintenance enables early fault diagnosis, optimized maintenance scheduling, reduced downtime, and enhanced operational safety. [1–6], [8], [17], [20]

3.5 Comparison of Maintenance Strategies

A comparison of different maintenance strategies reveals that corrective and preventive approaches are limited by their reactive and time-based nature, respectively. Condition-based maintenance offers improved reliability by monitoring machine health but lacks strong predictive capability. Predictive maintenance outperforms other strategies by providing early fault detection, accurate prognosis, and data-driven decision support. Consequently, PdM is increasingly adopted in modern industrial systems, smart grids, and Industry 4.0 environments. [17], [20]

4. Predictive Maintenance Framework

A predictive maintenance (PdM) framework for electrical machines typically follows a systematic, multi-stage process that transforms raw sensor data into actionable maintenance decisions. This framework integrates sensing technologies, signal processing, data analytics, and intelligent algorithms to enable early fault detection, accurate diagnosis, and reliable prognosis. [2], [19], [21], [25]

4.1 Data Acquisition and Sensing

Data acquisition is the foundation of any predictive maintenance system. Electrical machines are monitored using various sensors that measure electrical, mechanical, and thermal parameters. Commonly used sensors include current and voltage sensors, accelerometers for vibration monitoring, temperature sensors, acoustic emission sensors, and magnetic flux sensors. Advances in IoT-enabled wireless sensor networks and edge devices have enhanced real-time data collection, scalability, and remote monitoring capabilities in industrial environments. [3], [9], [15]

4.2 Signal Preprocessing

Raw sensor data often contain noise, outliers, and non-stationary components due to operating condition variations and environmental disturbances. Signal preprocessing techniques are therefore applied to enhance data quality and reliability. Common preprocessing steps include filtering, normalization, resampling, noise reduction, and trend removal. Time–frequency analysis methods such as short-time Fourier transform (STFT) and wavelet transforms are widely used to handle non-stationary signals in electrical machines. [9], [15]

4.3 Feature Extraction

Feature extraction aims to transform preprocessed signals into informative representations that capture machine health characteristics. Features can be extracted in the time domain (e.g., mean, RMS, kurtosis), frequency domain (e.g., spectral peaks, harmonics), and time–frequency domain. Advanced techniques such as wavelet packet decomposition, empirical mode decomposition, and deep feature learning are increasingly employed to improve fault sensitivity and reduce reliance on handcrafted features. [7], [8], [11]

4.4 Fault Detection and Diagnosis

Fault detection involves identifying abnormal operating conditions, while fault diagnosis focuses on determining the type and severity of the fault. Traditional approaches rely on threshold-based rules and statistical analysis, whereas modern PdM systems utilize machine learning and deep learning algorithms such as support vector machines, random forests, convolutional neural networks, and recurrent neural networks. These methods enable accurate classification of faults in electrical machines, even under varying load and speed conditions. [6], [11], [27]

4.5 Fault Prognosis and Remaining Useful Life Estimation

Fault prognosis extends beyond diagnosis by predicting future machine degradation and estimating the remaining useful life (RUL) of critical components. Prognostic models can be physics-based, data-driven, or hybrid in nature. Data-driven approaches, including regression models, deep neural networks, and survival analysis, have gained prominence due to their ability to learn complex degradation patterns from historical data. Accurate RUL estimation supports timely maintenance actions and prevents unexpected failures.

4.6 Decision-Making and Maintenance Planning

The final stage of the predictive maintenance framework involves translating diagnostic and prognostic outputs into actionable maintenance decisions. Decision-making modules consider factors such as fault severity, RUL estimates, operational constraints, maintenance costs, and safety requirements. Intelligent decision support systems enable optimized maintenance scheduling, resource allocation, and spare parts management. Integration with industrial management systems and digital twins further enhances the effectiveness of predictive maintenance strategies. [2], [6], [19]

5. Sensing and Data Acquisition Techniques

5.1 Electrical Measurements

Electrical measurements are among the most widely used signals in predictive maintenance of electrical machines due to their non-intrusive nature, low implementation cost, and availability in most industrial systems. Parameters such as stator current, voltage, and power provide valuable insights into the operational and health condition of machines and are effective for detecting both electrical and mechanical faults. [22], [27]

5.1.1 Stator Current Analysis

Stator current analysis is a popular and effective technique for condition monitoring and fault diagnosis in electrical machines, particularly induction motors. Faults such as broken rotor bars, air-gap eccentricity, bearing defects, and stator winding faults introduce characteristic frequency components and amplitude variations in the stator current. Motor Current Signature Analysis (MCSA) leverages these fault-related harmonics to identify abnormal conditions without requiring additional sensors. Due to its non-invasive implementation and suitability for online monitoring, stator current analysis is extensively adopted in industrial predictive maintenance systems. Recent studies also integrate machine learning and deep learning models with current signal features to enhance fault detection accuracy under varying load conditions. [2], [9]

5.1.2 Voltage and Power Signals

Voltage and power signals offer complementary information for assessing machine health and operational efficiency. Abnormalities in voltage waveforms may indicate insulation degradation, supply imbalance, or inverter-related issues, while power-related parameters such as active power, reactive power, and power factor reflect changes in load behavior and fault progression. Monitoring voltage and power signatures enables early detection of electrical faults and helps in evaluating the impact of faults on energy consumption. When combined with current measurements, voltage and power analysis improves diagnostic reliability and supports comprehensive predictive maintenance frameworks. [20], [22]

5.2 Mechanical and Physical Sensors

Mechanical and physical sensors play a crucial role in capturing degradation-related signatures that are not always observable through electrical measurements alone. These sensors are particularly effective in detecting mechanical faults and thermal abnormalities at an early stage, thereby enhancing the reliability of predictive maintenance systems.

5.2.1 Vibration Sensors

Vibration sensors, typically accelerometers, are widely used for condition monitoring of electrical machines. Mechanical faults such as bearing defects, rotor imbalance, shaft misalignment, and looseness generate characteristic vibration patterns. Frequency-domain and time-frequency analyses of vibration signals enable accurate identification of fault types and severity. Due to their high sensitivity to mechanical anomalies, vibration sensors are considered a benchmark technology in predictive maintenance applications. [9], [14]

5.2.2 Acoustic Emission Sensors

Acoustic emission (AE) sensors capture high-frequency stress waves generated by crack initiation, friction, and material deformation within machine components. AE monitoring is particularly effective for detecting early-stage bearing faults and insulation degradation, often before noticeable changes appear in vibration or current signals. Although AE sensors offer high fault sensitivity, their deployment is limited by susceptibility to ambient noise and higher system complexity. [14]

5.2.3 Temperature Sensors

Temperature sensors are commonly used to monitor thermal conditions in stator windings, bearings, and machine housings. Abnormal temperature rise is often associated with insulation degradation, excessive friction, overload conditions, or cooling system failure. While temperature monitoring alone may not identify specific fault types, it provides valuable complementary information for fault diagnosis and remaining useful life estimation in predictive maintenance frameworks. [20], [22]

5.2.4 Flux and Magnetic Field Sensors

Flux and magnetic field sensors measure variations in air-gap magnetic flux, providing insights into electromagnetic abnormalities. These sensors are effective in detecting faults such as rotor bar breakage, air-gap eccentricity, and demagnetization in permanent magnet machines. Flux-based monitoring offers a non-invasive approach to fault detection, although sensor placement and calibration remain challenging in practical implementations. [22], [27]

5.3 Emerging and Non-Intrusive Sensors

Recent advancements in sensing and communication technologies have led to the development of emerging and non-intrusive monitoring solutions for predictive maintenance. These approaches enhance scalability, flexibility, and real-time monitoring capabilities in modern industrial environments. [16], [19], [25]

5.3.1 Wireless Sensors

Wireless sensor networks reduce installation complexity and enable flexible deployment in hard-to-access locations. They support real-time data acquisition without extensive cabling, making them suitable for large-scale industrial systems. Challenges such as power consumption, data reliability, and communication latency are actively addressed through energy-efficient protocols and edge processing. [6], [19]

5.3.2 IoT-Based Monitoring

IoT-based monitoring systems integrate sensors, communication networks, cloud platforms, and data analytics to enable continuous and remote condition monitoring. In predictive maintenance of electrical machines, IoT frameworks facilitate real-time fault detection, historical data analysis, and centralized asset management. The combination of IoT with machine learning algorithms enhances scalability and supports Industry 4.0 applications. [7], [12]

5.3.3 Digital Twins

Digital twins represent virtual replicas of physical electrical machines that continuously update their state using real-time sensor data. By simulating machine behavior under different operating conditions, digital twins enable advanced fault diagnosis, prognosis, and maintenance optimization. Their integration with predictive maintenance systems provides enhanced decision support, although challenges remain in model accuracy, computational complexity, and real-time synchronization. [6], [18]

6. Data-Driven and Model-Based PdM Techniques

Predictive maintenance techniques can be broadly classified into model-based and data-driven approaches. Each category offers distinct advantages depending on system complexity, data availability, and application requirements.

6.1 Model-Based Approaches

6.1.1 Physics-Based Modeling

Physics-based approaches rely on mathematical models derived from the electrical, mechanical, and thermal principles governing machine operation. These models describe normal system behavior and enable fault detection by analyzing deviations between measured and estimated parameters. Physics-based methods offer strong interpretability and robustness; however, their effectiveness depends on accurate modeling and parameter identification, which can be challenging for complex or aging machines. [5], [17]

6.1.2 Observer-Based Fault Detection

Observer-based techniques utilize state observers, such as Luenberger observers, Kalman filters, and sliding-mode observers, to estimate unmeasured system states. Faults are detected by evaluating residuals generated from discrepancies between observed and measured signals. These approaches are effective for real-time fault detection and isolation but may suffer from sensitivity to modeling uncertainties and noise. [6], [21]

7. Fault Prognosis and Remaining Useful Life (RUL) Estimation

Fault prognosis aims to predict the future health state of electrical machines and estimate the remaining useful life of critical components, enabling proactive maintenance planning.

7.1 Degradation Modeling

Degradation modeling captures the progressive deterioration of machine components over time using health indicators derived from sensor data. Linear, nonlinear, and exponential degradation models are commonly used to represent wear mechanisms in bearings, insulation systems, and rotating components. [6], [27]

7.2 Stochastic and Probabilistic Methods

Stochastic approaches, such as hidden Markov models, particle filters, and Bayesian inference, account for uncertainty in degradation processes and measurement noise. These methods provide probabilistic RUL estimates, enhancing decision-making reliability in uncertain operating environments. [6], [17]

7.3 Deep Learning-Based RUL Prediction

Deep learning techniques, including convolutional neural networks, recurrent neural networks, and long short-term memory networks, have demonstrated strong performance in RUL prediction. These models automatically learn complex degradation patterns from large datasets and are particularly effective for non-linear and multi-sensor data. However, their deployment requires sufficient labeled data and computational resources. [11], [23], [27]

7.4 Uncertainty Quantification

Uncertainty quantification is essential for reliable RUL estimation and risk-aware maintenance decisions. Techniques such as Monte Carlo simulation, ensemble learning, and probabilistic deep learning are used to quantify confidence intervals and prediction uncertainty in prognostic models. [17], [18]

8. Performance Evaluation and Benchmarking

Robust evaluation and benchmarking are critical for assessing the effectiveness of predictive maintenance techniques.

8.1 Evaluation Metrics

Commonly used evaluation metrics include accuracy, precision, recall, and F1-score for fault diagnosis tasks, as well as root mean square error (RMSE), mean absolute error (MAE), and prognostic horizon for RUL estimation. These metrics enable objective comparison of different PdM approaches. [9], [15]

8.2 Public Datasets and Test Benches

Publicly available datasets and experimental test benches play an important role in benchmarking PdM algorithms. Datasets derived from bearing test rigs, motor drives, and industrial equipment enable reproducibility and comparative analysis, although they may not fully capture real-world operating variability. [3], [9], [27]

8.3 Comparison of Methods

Comparative studies highlight trade-offs between model-based and data-driven approaches in terms of accuracy, interpretability, data requirements, and computational complexity. Hybrid approaches increasingly demonstrate superior performance by combining physical insights with data-driven learning. [5], [17]

8.4 Challenges in Real-World Deployment

Despite promising results, real-world deployment of PdM systems faces challenges such as varying operating conditions, sensor noise, data imbalance, and integration with legacy systems. Addressing these challenges is essential for industrial-scale adoption. [17], [20], [26]

9. Industrial Applications and Case Studies

Predictive maintenance has been successfully applied across various industrial sectors, demonstrating its practical value and effectiveness.

- **Manufacturing Plants:** In manufacturing environments, PdM is widely used for monitoring motors, conveyors, and robotic systems. Early fault detection reduces unplanned downtime and improves production efficiency. [1], [2], [8]
- **Power Generation and Renewable Energy Systems:** PdM techniques are applied to generators, wind turbine drives, and solar inverters to enhance reliability and ensure stable power generation. Condition monitoring of electrical machines is particularly critical in renewable energy systems due to their variable operating conditions. [20], [25]
- **Transportation Systems:** In transportation applications, including electric vehicles and railway traction systems, predictive maintenance improves safety, energy efficiency, and asset utilization. Monitoring traction motors and power electronics enables early detection of faults under dynamic load conditions. [10], [23]
- **Aerospace and Marine Applications:** Aerospace and marine systems require high reliability and safety standards. Predictive maintenance of electrical machines in these sectors supports mission-critical operations and reduces maintenance-related downtime. [24]

10. Challenges and Open Research Issues

- **Data Scarcity and Labeling:** The availability of high-quality labeled fault data remains a major challenge, particularly for rare failure modes. Semi-supervised and unsupervised learning methods are emerging as potential solutions.
- **Generalization and Transfer Learning:** PdM models trained under specific operating conditions often struggle to generalize across different machines or environments. Transfer learning and domain adaptation techniques are critical research areas to improve model robustness.
- **Scalability and Real-Time Implementation:** Deploying PdM systems at scale requires efficient data processing, real-time analytics, and edge computing solutions. Balancing accuracy and computational efficiency remain an open challenge.
- **Sensor Reliability and Cost:** Sensor failures, calibration issues, and installation costs can limit the effectiveness of PdM systems. Research into low-cost, robust, and self-diagnostic sensors is essential for widespread adoption. [17], [20], [26], [28]

11. Conclusion

This survey highlights that predictive maintenance significantly outperforms traditional maintenance strategies by enabling early fault detection, accurate diagnosis, and remaining useful life estimation for electrical machines. Electrical, mechanical, and emerging non-intrusive sensing techniques provide complementary information for effective condition

monitoring. Data-driven approaches, particularly machine learning and deep learning models, demonstrate superior fault classification and prognostic accuracy, while model-based methods offer better interpretability and physical insight. Hybrid frameworks combining both approaches show strong potential for robust and scalable predictive maintenance systems. The review reveals a growing trend toward IoT-enabled monitoring, edge intelligence, and digital twin integration for real-time predictive maintenance. Public datasets and benchmarking frameworks have accelerated research progress, although gaps remain between laboratory results and real-world deployment. Handling data uncertainty, operating variability, and limited labeled fault data are critical factors influencing system performance. Predictive maintenance represents a transformative approach for intelligent asset management of electrical machines. Continued research focusing on generalizable models, uncertainty-aware prognosis, and cost-effective sensing solutions will be essential to achieve reliable and widespread industrial adoption.

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