Journal of Multidisciplinary Sciences and Innovations (ISSN: 2751-4390)

Received: 01 April 2026 | Accepted: 15 April 2026 | Published: 30 April 2026

RESEARCH ARTICLE

Intelligent Prognostic Models for Electrical Infrastructure Reliability Assessment

Md. Arif Hossain

Department of Electrical and Electronic Engineering, Bangladesh University of Engineering and Technology, Dhaka, Bangladesh

VOLUME: Vol.05 Issue 04 2026

PAGE: 960-967

Abstract

The reliability of electrical infrastructure has become a critical research and operational concern due to increasing system complexity, aging assets, growing energy demands, and the integration of intelligent monitoring technologies. Traditional reliability assessment methods primarily depend on periodic inspection, statistical failure analysis, and predefined maintenance schedules. Although these approaches have contributed significantly to infrastructure management, they often lack the capability to identify gradual degradation processes and predict future failure conditions. Intelligent prognostic models provide an advanced alternative by combining data-driven analytics, machine learning techniques, degradation modeling, and remaining useful life estimation to enhance reliability assessment and maintenance decision-making.

This research examines the development and application of intelligent prognostic models for electrical infrastructure reliability assessment through a comprehensive analytical framework based on predictive modeling principles. The study synthesizes concepts from reliability engineering, machine learning-based prognostics, degradation pattern analysis, and predictive maintenance methodologies. Existing research on data-driven prognostic approaches for aircraft systems, batteries, and electrical power systems is analyzed to establish theoretical foundations for applying intelligent models to electrical infrastructure.

The proposed framework integrates condition monitoring data acquisition, degradation feature extraction, prognostic model development, reliability prediction, and maintenance optimization. The research evaluates how advanced models can transform conventional maintenance practices by enabling early identification of abnormal conditions and estimation of asset remaining useful life. Machine learning-based predictive maintenance approaches demonstrate significant potential for improving electric power system reliability through continuous analysis of operational parameters and failure indicators (Philip, 2025).

KEYWORDS

Intelligent Prognostics; Electrical Infrastructure; Reliability Assessment; Predictive Maintenance; Remaining Useful Life Prediction; Machine Learning; Degradation Modeling; Condition Monitoring; Fault Prediction

INTRODUCTION

1.1 Background and Research Context

Electrical infrastructure represents one of the most essential components of modern society, supporting industrial operations, communication systems, transportation networks, and residential activities. The reliability of electrical assets directly influences economic stability, public safety, and energy security. However, electrical infrastructure is continuously exposed to operational stress, environmental variations, aging effects, and increasing demand fluctuations. These factors contribute to progressive degradation and increase the probability of unexpected failures.

Traditional reliability assessment approaches have historically focused on statistical failure analysis, scheduled maintenance, and corrective actions after equipment malfunction. While these approaches provide useful information regarding asset behavior, they often operate reactively rather than proactively. Modern electrical systems require more advanced strategies capable of identifying early degradation indicators and estimating future equipment conditions.

The emergence of intelligent prognostic models provides opportunities to address these limitations. Prognostics focuses on predicting future system health by analyzing current condition information and historical degradation patterns. Unlike conventional diagnostics, which identify existing faults, prognostic approaches estimate how and when failures may occur. This capability enables organizations to optimize maintenance planning, reduce operational interruptions, and extend equipment service life.

Electrical infrastructure generates large volumes of operational data through monitoring devices, sensors, protection systems, and automated control platforms. These datasets contain valuable information regarding asset health conditions. However, extracting meaningful reliability insights requires advanced analytical methods capable of processing complex relationships between operational variables and degradation behavior.

Machine learning and data-driven techniques have significantly expanded the capability of prognostic systems. Zhou et al. (2017) highlighted that machine learning approaches applied to big data environments create opportunities for discovering complex patterns and improving predictive decision-making. These capabilities are particularly relevant for electrical infrastructure, where asset degradation is often influenced by multiple interacting factors.

1.2 Problem Statement

The primary challenge addressed in this research is the difficulty of accurately assessing electrical infrastructure reliability under dynamic operating conditions. Electrical assets such as transformers, transmission components, batteries, and power system equipment experience gradual degradation processes that may not produce immediate failure symptoms.

Conventional reliability models often rely on simplified assumptions regarding failure distributions and equipment behavior. However, real-world degradation is frequently nonlinear, uncertain, and influenced by changing operational environments. Developing reliable prognostic models requires approaches capable of representing these complex degradation mechanisms.

Another major challenge is the transformation of collected monitoring data into actionable reliability predictions. Although modern electrical systems generate extensive operational information, raw data alone does not provide direct insight into future equipment health. Effective prognostic frameworks must identify relevant degradation features, model uncertainty, and generate reliable predictions.

Remaining useful life (RUL) prediction represents a particularly important aspect of this problem. Accurate RUL estimation enables maintenance teams to determine the appropriate timing for intervention before failure occurs. Research on degradation pattern learning demonstrates that intelligent models can improve RUL prediction by identifying hidden relationships within historical operational data (Zhao et al., 2017).

1.3 Research Relevance

The development of intelligent prognostic models is highly relevant due to the transition toward smart and data-driven electrical infrastructure. As power systems become increasingly interconnected and automated, reliability management requires continuous monitoring and predictive capabilities.

Predictive maintenance represents a major application area for intelligent prognostics. Instead of performing maintenance according to fixed schedules, predictive approaches use real-time condition information to determine when intervention is required. Such approaches improve maintenance efficiency by reducing unnecessary activities and preventing unexpected failures.

Recent research on machine learning-based predictive maintenance for electric power systems demonstrates that intelligent analytical models can support improved reliability assessment by identifying potential equipment degradation before critical failure occurs (Philip, 2025). These methods provide a foundation for integrating prognostic intelligence into electrical asset management strategies.

Furthermore, intelligent prognostic models contribute to sustainability objectives by extending equipment lifespan and optimizing resource utilization. Effective reliability assessment reduces material waste, minimizes operational disruptions, and improves the efficiency of infrastructure investments.

1.4 Research Objectives

This research aims to investigate the role of intelligent prognostic models in improving electrical infrastructure reliability assessment. The major objectives include:

The first objective is to examine the theoretical foundations of prognostic modeling and its relationship with reliability engineering principles.

The second objective is to analyze data-driven approaches for degradation modeling and remaining useful life prediction.

The third objective is to develop a conceptual framework integrating condition monitoring, machine learning, and reliability assessment processes.

The fourth objective is to evaluate the benefits, challenges, and limitations associated with implementing intelligent prognostic systems in electrical infrastructure.

The fifth objective is to identify future research directions for improving adaptive and scalable reliability prediction models.

1.5 Scope and Significance

The scope of this research focuses on intelligent prognostic methodologies applicable to electrical infrastructure reliability assessment. The study considers machine learning models, degradation analysis techniques, predictive maintenance strategies, and data-driven reliability frameworks.

The significance of this research lies in demonstrating how intelligent prognostic models can transform infrastructure management from reactive failure response toward proactive reliability optimization. By predicting degradation trends and estimating remaining useful life, organizations can improve maintenance planning and reduce the risk of unexpected failures.

The research also contributes to understanding the relationship between data-driven intelligence and traditional reliability engineering. Intelligent prognostics does not replace engineering principles but enhances them by providing additional analytical capabilities for complex systems.

LITERATURE REVIEW

2.1 Foundations of Prognostic Modeling and Reliability Assessment

Prognostic modeling has emerged as an important research area within reliability engineering due to the increasing need for predictive asset management. Unlike traditional reliability assessment methods that focus primarily on failure probability analysis, prognostic approaches aim to estimate future system behavior based on current health information.

Liu and Zio (2017) investigated system dynamic reliability assessment and failure prognostics, emphasizing the importance of considering system evolution over time. Their work highlights that reliability is not a static property but a dynamic characteristic influenced by degradation processes and operational conditions.

This perspective is highly applicable to electrical infrastructure because equipment health continuously changes throughout its operational lifecycle. A transformer, battery system, or power component may operate normally for extended periods while gradually experiencing internal degradation. Prognostic models provide mechanisms for capturing these gradual changes and estimating future reliability states.

Theoretical prognostic frameworks generally involve three primary components: condition monitoring, degradation modeling, and prediction. Condition monitoring provides information about current equipment status, degradation modeling describes how system health changes over time, and prediction techniques estimate future conditions.

2.2 Data-Driven Prognostics and Machine Learning Applications

The advancement of machine learning has significantly influenced prognostic research by enabling models to learn complex relationships from operational datasets. Unlike traditional analytical models requiring predefined degradation assumptions, data-driven approaches identify patterns directly from historical observations.

Zhou et al. (2017) examined machine learning applications in big data environments and discussed both opportunities and challenges associated with large-scale predictive analytics. Their research demonstrates that machine learning models can discover hidden patterns within complex datasets, making them suitable for reliability assessment applications.

In electrical infrastructure, machine learning models can analyze variables such as temperature, voltage variation, current patterns, load conditions, and historical maintenance information. These models can identify relationships between operational behavior and future degradation risks.

However, machine learning-based prognostics also introduces challenges. Model performance depends heavily on data quality, availability, and representativeness. Electrical failures are often rare events, making it difficult to obtain sufficient failure examples for training accurate models.

2.3 Degradation Pattern Learning and Remaining Useful Life Prediction

Remaining useful life (RUL) prediction is one of the most important components of intelligent prognostic systems because it provides an estimation of how long an asset can continue operating before reaching an unacceptable degradation level. Accurate RUL prediction enables organizations to optimize maintenance schedules, allocate resources efficiently, and minimize unexpected system interruptions.

Zhao et al. (2017) investigated remaining useful life prediction of aircraft engines based on degradation pattern learning. Their research demonstrates the importance of identifying degradation trajectories from historical operational data. Instead of relying only on failure events, degradation pattern learning focuses on understanding gradual changes that occur throughout an asset’s lifecycle.

The principles of degradation pattern learning are directly applicable to electrical infrastructure. Many electrical assets do not fail suddenly; rather, they experience progressive deterioration caused by thermal stress, electrical loading, environmental exposure, and aging mechanisms. For example, insulation systems in transformers may gradually lose performance due to repeated thermal cycles. A prognostic model capable of identifying these degradation trends can provide early warnings before severe failures occur.

However, electrical infrastructure presents unique challenges compared with other industrial systems. Unlike controlled environments such as aircraft engines or laboratory-based systems, electrical networks operate under continuously changing conditions. Load variations, environmental influences, and operational disturbances introduce uncertainty into degradation behavior. Therefore, prognostic models must incorporate adaptive capabilities to handle changing operating conditions.

Wang et al. (2017) addressed this challenge through nonlinear-drifted Brownian motion modeling with multiple hidden states for remaining useful life prediction of rechargeable batteries. Their approach highlights the importance of representing uncertainty and hidden degradation mechanisms. The concept of hidden states is particularly valuable for electrical infrastructure because many degradation processes cannot be directly measured through conventional monitoring systems.

For instance, a power system component may exhibit normal external measurements while internal degradation progresses. By incorporating probabilistic degradation models and hidden condition estimation, prognostic systems can provide more reliable predictions under uncertain conditions.

2.4 Predictive Maintenance Applications in Electrical Power Systems

Predictive maintenance represents a practical application of prognostic modeling where reliability predictions are transformed into maintenance decisions. The objective is to perform maintenance activities based on actual equipment health rather than fixed schedules.

Traditional preventive maintenance approaches often replace or inspect equipment at predetermined intervals. While this reduces some failure risks, it may result in unnecessary maintenance when equipment remains in good condition. Conversely, excessive reliance on corrective maintenance may lead to unexpected failures and operational losses.

Intelligent predictive maintenance addresses these limitations by continuously analyzing equipment condition and predicting future performance. Philip (2025) demonstrated the potential of machine learning-based predictive maintenance approaches for electric power systems, emphasizing that data-driven models can identify abnormal operational patterns and support early intervention.

The integration of predictive maintenance into electrical infrastructure requires coordination between monitoring technologies, analytical models, and maintenance management systems. Data collected from electrical assets must be transformed into reliability indicators that maintenance personnel can interpret and use effectively.

A practical example involves monitoring large transformer populations in a utility network. Instead of inspecting all transformers according to the same schedule, a predictive system can classify assets according to health conditions. Equipment showing accelerated degradation can receive immediate attention, while healthy assets can continue operating without unnecessary intervention.

Despite these advantages, predictive maintenance implementation requires addressing several limitations. The effectiveness of predictions depends on the availability of accurate historical data and appropriate model training. Additionally, maintenance decisions in critical infrastructure require high confidence because incorrect predictions may create safety risks or operational disruptions.

2.5 Comparative Analysis of Existing Prognostic Approaches

The reviewed studies demonstrate different perspectives on intelligent prognostic development. Each reference contributes a specific theoretical or practical foundation for reliability assessment.

Baptista et al. (2017) conducted a comparative case study involving life usage and data-driven prognostics techniques using aircraft fault messages. Their research emphasizes the importance of evaluating prognostic methods through practical operational data. The study highlights that data-driven approaches can improve failure prediction but require careful consideration of data characteristics and application context.

Liu and Zio (2017) focused on dynamic reliability assessment and failure prognostics. Their contribution emphasizes the importance of modeling systems as evolving processes rather than static structures. This perspective supports the development of adaptive prognostic models suitable for electrical infrastructure.

Wang et al. (2017) contributed by addressing uncertainty in degradation processes through nonlinear stochastic modeling. Their work provides theoretical support for handling unpredictable degradation behavior, which is highly relevant for electrical assets operating under variable conditions.

Zhao et al. (2017) emphasized degradation pattern learning for remaining useful life prediction. Their approach demonstrates that identifying historical degradation trends can improve future condition estimation.

Zhou et al. (2017) examined machine learning within big data environments, highlighting both opportunities and limitations of data-driven approaches. Their work establishes the importance of scalable learning techniques while recognizing challenges related to data complexity and model reliability.

Philip (2025) extends these concepts toward electrical power systems by demonstrating how machine learning-based predictive maintenance can support improved reliability management in energy infrastructure.

Together, these studies indicate that intelligent prognostics requires integration between reliability theory, statistical modeling, machine learning, and practical maintenance strategies.

METHODOLOGY

3.1 Research Design and Framework Development

This research adopts a conceptual framework development methodology to analyze intelligent prognostic models for electrical infrastructure reliability assessment. The methodology integrates concepts from reliability engineering, machine learning, degradation modeling, and predictive maintenance.

The framework is designed to represent the complete lifecycle of intelligent reliability assessment, beginning with data acquisition and ending with maintenance decision optimization. The approach emphasizes how different analytical components interact to transform operational data into reliability predictions.

The proposed methodology consists of six interconnected stages:

1. Condition monitoring and data acquisition
2. Data preprocessing and feature extraction
3. Degradation behavior modeling
4. Intelligent prognostic model development
5. Reliability and remaining useful life prediction
6. Maintenance decision optimization

Each stage contributes to improving the accuracy and practical value of reliability assessment.

3.2 Condition Monitoring and Data Acquisition

The first stage involves collecting operational information from electrical infrastructure components. Modern electrical systems generate continuous data through monitoring devices, intelligent sensors, and control systems.

The quality of prognostic predictions depends significantly on the reliability of collected information. Data sources may include:

- electrical measurements,
- equipment operating conditions,
- temperature variations,
- load profiles,
- historical maintenance records,
- environmental factors.

The purpose of data acquisition is not simply to collect large amounts of information but to capture meaningful indicators related to asset health.

For example, a transformer monitoring system may record temperature trends, load fluctuations, and operational stress indicators. These measurements provide valuable information regarding potential degradation processes.

The collected data forms the foundation for subsequent analytical stages. Inadequate or inconsistent data may reduce model accuracy and create unreliable predictions.

3.3 Data Preprocessing and Feature Extraction Framework

After collecting operational information, the next stage involves preparing data for intelligent prognostic analysis. Raw data obtained from electrical infrastructure monitoring systems often contains noise, missing values, measurement errors, and inconsistent sampling patterns. Therefore, preprocessing is essential to ensure that the analytical model receives reliable and meaningful input.

Data preprocessing includes normalization, filtering, synchronization, and anomaly removal. Normalization ensures that different measurement parameters can be analyzed together despite differences in their numerical ranges. For example, voltage measurements, temperature values, and load indicators may have different scales; converting them into comparable representations improves model performance.

Feature extraction represents another critical step because not all collected variables contribute equally to reliability prediction. The objective is to identify parameters that provide meaningful information regarding degradation behavior. Relevant features may include rate of temperature increase, load stress patterns, voltage instability indicators, and historical failure-related characteristics.

Machine learning approaches depend strongly on effective feature representation. Zhou et al. (2017) emphasized that large-scale machine learning applications require appropriate data processing strategies to transform complex information into useful predictive representations. In electrical infrastructure applications, feature extraction bridges the gap between raw monitoring data and reliability-oriented intelligence.

The extracted features can be categorized into three groups:

The first category includes operational features representing current system behavior. These may include electrical loading conditions, operating hours, and environmental influences.

The second category includes degradation features representing changes over time. These features capture trends such as increasing thermal stress, declining performance, or abnormal operational patterns.

The third category includes historical reliability features derived from previous failures, maintenance records, and equipment lifecycle information.

Combining these feature categories enables prognostic models to understand both current conditions and long-term degradation patterns.

3.4 Degradation Modeling Approach

The central objective of a prognostic system is to model how equipment health changes over time. Electrical infrastructure degradation is rarely a simple linear process. Instead, deterioration often involves nonlinear behavior influenced by multiple uncertain factors.

The proposed methodology incorporates degradation modeling techniques capable of representing gradual health changes and uncertainty. A degradation model establishes the relationship between observed operational conditions and future equipment states.

Wang et al. (2017) demonstrated the importance of considering nonlinear degradation behavior and hidden states when predicting remaining useful life. Their approach highlights that equipment deterioration may involve internal processes that are not directly observable through external measurements.

For electrical infrastructure, hidden degradation mechanisms may include internal insulation aging, material deterioration, contact degradation, or thermal stress accumulation. Although these processes may not be directly measurable, their effects may appear through indirect indicators.

The degradation model therefore performs two functions:

First, it estimates the current health condition of the equipment based on available observations.

Second, it predicts future degradation progression to estimate remaining operational capability.

A hypothetical example can be considered for a high-voltage transformer. Continuous monitoring may reveal increasing operating temperature over several months. A simple threshold-based system may only generate an alarm after temperature exceeds a critical value. However, an intelligent degradation model can analyze the rate of increase, historical patterns, and operating conditions to predict whether the transformer is approaching a failure state.

This predictive capability enables maintenance actions before severe damage occurs.

3.5 Intelligent Prognostic Model Architecture

The proposed intelligent prognostic architecture combines statistical reliability concepts with machine learning capabilities. The architecture is designed to continuously learn from operational data and improve prediction accuracy over time.

The model consists of four major components:

Health State Estimation

The first component evaluates the current condition of electrical assets. It converts monitoring data into a health indicator representing equipment condition.

For example, a health indicator may represent the degree of transformer insulation degradation or battery capacity reduction. This indicator provides a simplified representation of complex physical processes.

Degradation Trend Analysis

The second component analyzes historical health information to identify degradation patterns. This stage determines whether equipment condition is stable, gradually deteriorating, or approaching failure.

Zhao et al. (2017) demonstrated that degradation pattern learning can improve remaining useful life prediction by identifying hidden trends within operational data.

Remaining Useful Life Prediction

The third component estimates the expected remaining service duration of equipment. RUL prediction allows maintenance teams to determine the appropriate timing for intervention.

The prediction process considers current health state, degradation rate, historical behavior, and operational conditions.

Reliability Decision Support

The final component transforms predictions into maintenance recommendations. The objective is not only to predict failures but also to support practical decision-making.

For example, if multiple transformers are monitored simultaneously, the system can prioritize maintenance activities based on failure risk and operational importance.

3.6 Machine Learning Integration Framework

Machine learning serves as the intelligence layer of the proposed prognostic framework. Different machine learning approaches may be applied depending on data characteristics and reliability requirements.

Supervised learning methods can be used when historical failure data is available. These models learn relationships between input variables and known failure outcomes.

Unsupervised learning methods are valuable when failure examples are limited. These approaches identify unusual patterns and detect potential anomalies without requiring extensive failure labels.

Hybrid approaches combine physical reliability knowledge with machine learning capabilities. Such integration is particularly useful for electrical infrastructure because engineering principles provide valuable information about equipment behavior.

Philip (2025) demonstrated the effectiveness of machine learning-based predictive maintenance approaches for electric power systems, showing that intelligent models can improve early detection of abnormal conditions and support proactive maintenance strategies.

However, machine learning integration requires careful model validation. A highly accurate model under laboratory conditions may not perform effectively in real operational environments. Therefore, continuous evaluation and updating are necessary.

RESULTS

The analysis of intelligent prognostic models for electrical infrastructure reliability assessment reveals several significant findings. First, data-driven prognostic approaches provide improved capability for identifying degradation patterns compared with traditional reliability assessment methods. By analyzing historical and real-time operational information, intelligent models can detect gradual changes that may indicate future failures.

Second, the integration of machine learning techniques enhances the accuracy of reliability predictions. Machine learning models can identify complex relationships among multiple operational parameters, enabling more comprehensive assessment of equipment health. These capabilities are particularly valuable in electrical infrastructure where failures are influenced by multiple interacting factors.

Third, remaining useful life prediction emerges as a critical component of intelligent maintenance strategies. Studies on degradation pattern learning demonstrate that understanding equipment deterioration trends improves prediction capability (Zhao et al., 2017). Similar approaches can support electrical asset management by estimating when intervention is required.

Fourth, uncertainty modeling improves the reliability of prognostic predictions. Electrical infrastructure operates under variable conditions, and degradation behavior cannot always be represented through deterministic models. Approaches incorporating hidden states and nonlinear degradation characteristics provide better representation of real-world conditions (Wang et al., 2017).

Fifth, predictive maintenance applications demonstrate practical value by enabling proactive decision-making. Machine learning-based approaches for electric power systems have shown potential for reducing unexpected failures and improving maintenance efficiency (Philip, 2025).

However, the findings also identify important limitations. Model performance depends heavily on data quality, computational resources, and appropriate validation procedures. Furthermore, successful deployment requires balancing predictive accuracy with interpretability and operational trust.

Overall, the findings indicate that intelligent prognostic models provide a valuable framework for improving electrical infrastructure reliability assessment. Their effectiveness depends on combining advanced analytics with engineering knowledge and practical implementation strategies.

DISCUSSION

The development of intelligent prognostic models has significantly improved the reliability assessment of electrical infrastructure by enabling early fault detection, predictive maintenance, and data-driven decision-making. Traditional reliability assessment approaches mainly depend on periodic inspections and historical failure analysis, which may not accurately predict unexpected equipment degradation. In contrast, intelligent models based on artificial intelligence, machine learning, deep learning, and advanced data analytics can analyze large volumes of operational data to identify hidden patterns and predict potential failures before they occur.

The integration of real-time monitoring systems, sensor networks, and intelligent algorithms enhances the capability of prognostic models to evaluate the health condition of critical electrical components such as transformers, transmission lines, generators, and distribution systems. These models provide improved accuracy in estimating remaining useful life (RUL), reducing unplanned outages and improving overall system availability.

However, the implementation of intelligent prognostic models also faces several challenges. The quality and availability of data, model interpretability, cybersecurity risks, and computational requirements remain important concerns. In addition, variations in operating conditions and aging patterns of electrical assets can affect model performance. Therefore, continuous improvement in data collection techniques, hybrid modeling approaches, and explainable artificial intelligence methods is required to increase reliability and practical adoption.

Overall, intelligent prognostic models represent a promising approach for transforming conventional maintenance strategies into predictive and condition-based maintenance frameworks. Their application can contribute to safer, more efficient, and more resilient electrical infrastructure.

CONCLUSION

Intelligent prognostic models provide an effective solution for assessing the reliability and health condition of modern electrical infrastructure. By utilizing artificial intelligence, machine learning techniques, and real-time operational data, these models enable accurate prediction of equipment failures and support proactive maintenance planning. The ability to forecast degradation trends and estimate remaining useful life helps reduce maintenance costs, minimize downtime, and improve the reliability of power systems.

Although challenges related to data management, model transparency, and system integration still exist, continuous advancements in intelligent algorithms and monitoring technologies are expected to overcome these limitations. Future research should focus on developing more adaptive, scalable, and explainable prognostic models that can operate effectively under diverse electrical system conditions.

In conclusion, intelligent prognostic approaches are essential for achieving a reliable, sustainable, and smart electrical infrastructure capable of meeting the increasing demands of modern energy systems.

Intelligent prognostic models provide a powerful framework for improving the reliability assessment of electrical infrastructure by enabling accurate fault prediction, condition monitoring, and preventive maintenance planning. The integration of artificial intelligence, machine learning, and data-driven techniques allows electrical systems to move from traditional reactive maintenance approaches toward predictive and intelligent maintenance strategies.

These models enhance the capability to detect early signs of equipment degradation, estimate remaining useful life, reduce unexpected failures, and improve the overall availability and safety of power systems. Despite challenges related to data quality, computational complexity, model interpretability, and cybersecurity, continuous advancements in intelligent technologies are creating new opportunities for more reliable and efficient electrical infrastructure management.

Future developments should focus on creating adaptive, scalable, and explainable prognostic models capable of handling complex operating environments and large-scale power networks. Overall, intelligent prognostic models represent a key technology for achieving resilient, sustainable, and reliable electrical infrastructure in modern energy systems.

REFERENCES

1. Baptista, M., I. de Medeiros, J. Malereb, C. Nascimento Jr., H. Prendinger, and E. Henriques. "Comparative case study of life usage and data-driven prognostics techniques using aircraft fault messages," Computers in Industry, vol. 86, pp. 1–14, 2017.

2. Liu, J., and E. Zio. "System dynami. c reliability assessment and failure prognostics," Reliability Engineering System Safety, vol. 160, pp. 21–36, 2017.

3. Philip, P. G. (2025). Predictive Maintenance Approach for Electric Power Systems Using Machine Learning. The American Journal of Interdisciplinary Innovations and Research, 7(09), 145–160. Retrieved from https://theamericanjournals.com/index.php/tajiir/article/view/ml-predictive-maintenance-power-systems

4. Wang, D., Y. Zhao, F. Yang, and K-L Tsui. "Nonlinear-drifted Brownian motion with multiple hidden states for remaining useful life prediction of rechargeable batteries," Mechanical Systems and Signal Processing, vol. 93, pp. 531–544, 2017.

5. Zhao, Z., B. Liang, and X. Wang. "Remaining useful life prediction of aircraft engine based on degradation pattern learning," Reliability Engineering System Safety, vol. 164, pp. 74–83, 2017.

6. Zhou, L., S. Pan, and J. Wang. "Machine learning on big data: Opportunities and challenges," Neurocomputing, vol. 237, pp. 350–361, 2017.