



Artificial Intelligence-Based Predictive Maintenance for Smart Grid Assets: A Systematic Review of Algorithms, Applications, Challenges and Future Directions

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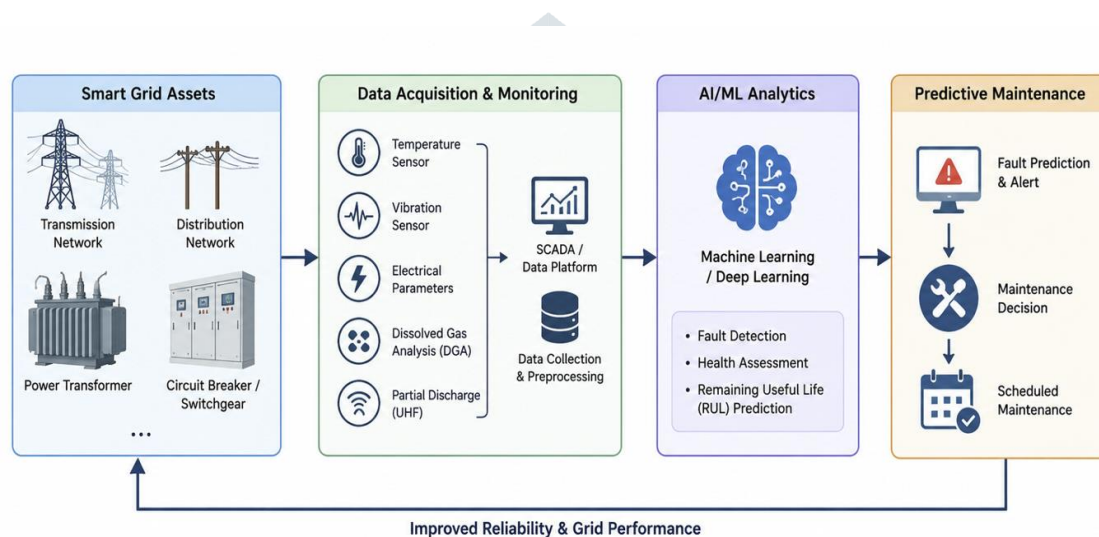
Introduction:

The electrical power system is undergoing significant transformation with the development of smart grid technologies. A smart grid integrates conventional power-system infrastructure with advanced sensing, communication, automation, monitoring, and data-analysis technologies. These capabilities enable utilities to continuously monitor system conditions, improve operational efficiency, and make informed decisions regarding the operation and maintenance of electrical assets. Smart grids consist of several critical assets, including power transformers, circuit breakers, switchgear, transmission and distribution lines, cables, generators, and protection equipment. The reliable operation of these assets is essential for maintaining the continuity, stability, and availability of electrical power. Failure of a critical asset can lead to equipment damage, unexpected outages, reduced system reliability, and significant economic losses. Therefore, effective asset condition monitoring and maintenance are important aspects of modern power-system management. Traditionally, electrical assets have been maintained using corrective and preventive maintenance strategies. Corrective maintenance is carried out after equipment failure, whereas preventive maintenance is generally performed at predetermined time intervals. Although preventive maintenance can reduce the probability of unexpected failure, it may result in unnecessary maintenance when equipment is still operating in a healthy condition. Corrective maintenance, on the other hand, can result in unexpected downtime, emergency repair requirements, and higher maintenance costs.

The development of sensors, Supervisory Control and Data Acquisition (SCADA) systems, Internet of Things (IoT) technologies, and digital monitoring systems has enabled continuous collection of large amounts of equipment-condition data. Parameters such as temperature, current, voltage, vibration, loading, dissolved gas analysis (DGA), oil condition, and partial discharge can provide valuable information about the health of electrical equipment. However, analysing such large and complex datasets using conventional methods can be difficult.

Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) provide data-driven techniques for analysing equipment-condition information. AI-based methods can identify abnormal operating patterns, classify faults, estimate equipment health, and predict possible failures. Machine Learning algorithms such as

Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest, and Decision Trees have been investigated for equipment condition assessment and fault diagnosis. Deep Learning techniques such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks can further analyse complex patterns and time-dependent data. Predictive maintenance combines condition monitoring with data analytics to estimate the future condition of an asset and identify maintenance requirements before a major failure occurs. Compared with purely time-based maintenance, predictive maintenance can support condition-based decisions by using actual equipment data. This approach can potentially improve asset availability, reduce unplanned downtime, optimize maintenance activities, and support reliable operation of smart-grid infrastructure. Several studies have investigated AI-based approaches for transformer fault diagnosis, partial-discharge detection, health-index estimation, degradation assessment, and remaining useful life prediction. However, the existing research covers different assets, datasets, algorithms, monitoring parameters, and prediction objectives. A systematic analysis is therefore required to understand the current development of AI-based predictive maintenance and to identify the major challenges and research gaps. Therefore, this paper presents a systematic review of Artificial Intelligence-based predictive maintenance for smart-grid assets. The review focuses on the AI and Machine Learning techniques used for condition monitoring, fault detection, fault classification, health assessment, failure prediction, and Remaining Useful Life (RUL) estimation. It also discusses current challenges, research gaps, and future directions for developing reliable and intelligent predictive-maintenance systems for smart-grid applications.



Objectives of the Review

The main objectives of this review are:

1. To identify the major smart-grid assets considered in AI-based predictive-maintenance research.
2. To analyse the AI, Machine Learning, and Deep Learning techniques used for asset condition assessment.
3. To examine the types of monitoring data and parameters used for predictive maintenance.
4. To review applications including fault detection, fault classification, health assessment, failure prediction, and RUL estimation.
5. To identify the major challenges and limitations of existing approaches.
6. To identify research gaps and future research directions.
7. To present an integrated conceptual framework for AI-based predictive maintenance of smart-grid assets.

Abstract :

The increasing complexity of modern smart grids has created a growing need for reliable monitoring and maintenance of critical electrical assets. Power transformers, circuit breakers, switchgear, cables, and transmission equipment require effective maintenance strategies to ensure reliable and continuous power-system operation. Conventional corrective and time-based preventive maintenance approaches may result in

unexpected failures, unnecessary maintenance activities, increased downtime, and higher maintenance costs. Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) provide data-driven approaches for monitoring equipment condition and predicting potential failures.

This paper presents a systematic review of Artificial Intelligence-based predictive maintenance techniques for smart grid assets. The review examines commonly used AI and ML algorithms, condition-monitoring parameters, fault-detection methods, health-index assessment, failure prediction, and Remaining Useful Life (RUL) estimation. Techniques including Artificial Neural Networks, Support Vector Machines, Random Forest, Decision Trees, Convolutional Neural Networks, and Long Short-Term Memory networks are discussed. The integration of sensors, SCADA, Internet of Things technologies, and data analytics with predictive maintenance is also examined. Furthermore, major challenges such as data quality, limited fault data, class imbalance, model explainability, cybersecurity, computational requirements, and real-time implementation are identified. Finally, research gaps and future directions involving explainable AI, digital twins, multimodal data fusion, edge AI, and federated learning are discussed. The review highlights the potential of AI-based predictive maintenance to support intelligent asset management and improve the reliability and availability of smart-grid infrastructure.

Literature Review :

Artificial intelligence-based predictive maintenance has developed from conventional condition-monitoring and fault-diagnosis approaches into data-driven prognostic systems capable of assessing equipment health and predicting potential failures. In power systems, this development has been particularly significant for power transformers because of their critical role in transmission and distribution networks. Early research primarily investigated computational-intelligence techniques for interpreting transformer condition-monitoring data, while recent studies have increasingly focused on machine learning, deep learning, IoT-enabled monitoring, and prognostics and health management. One important research direction is the application of **machine learning to transformer monitoring and maintenance scheduling**. Ramesh *et al.* [1] investigated a machine-learning approach for monitoring and managing smart distribution transformers, with emphasis on transformer loading and operational data. Their work demonstrated the applicability of data-driven methods to distribution-transformer monitoring. Subsequently, Quiñones *et al.* [2] developed a classification-based approach for predictive maintenance scheduling of distribution transformers. Their study connected the output of a predictive model with maintenance planning rather than limiting the application to fault classification. Vita *et al.* [3] further investigated predictive maintenance from the perspective of distribution-system operators, focusing on the use of equipment-condition information to determine appropriate maintenance interventions. These studies demonstrate an important transition from **condition monitoring toward maintenance decision support**.

The development of **deep learning** has extended this research by allowing models to learn more complex patterns from condition-monitoring data. Nascimento *et al.* [4] proposed T4PdM, a deep neural-network architecture based on the Transformer architecture, for predictive-maintenance-related fault diagnosis of rotating machinery. More broadly, Serradilla *et al.* [5] reviewed deep-learning approaches for predictive maintenance and discussed applications including anomaly detection and remaining-useful-life estimation. Afridi *et al.* [6] similarly reviewed AI-based prognostic maintenance and emphasized the importance of data quality and feature engineering. These studies indicate that the research direction is moving beyond conventional classification toward models capable of extracting complex features and analysing degradation behaviour. However, increased model complexity also introduces challenges related to training data, computational requirements and practical deployment. Another major research area concerns **transformer health assessment and prognostics**. Rather than predicting only whether an asset is faulty or healthy, recent research investigates the estimation of asset health condition, degradation level and remaining useful life. This represents an important shift because predictive maintenance requires information about the *future condition* of an asset, not only identification of an existing fault. Machine-learning models such as artificial neural networks, support-vector machines, ensemble methods and deep-learning architectures have therefore been investigated for condition assessment and prognostic applications. Reviews of transformer prognostics and health management have shown that research is increasingly combining multiple monitoring parameters with data-driven models to obtain more comprehensive information about transformer condition.

Condition-monitoring data itself is another important factor in AI-based predictive maintenance. Transformer monitoring can involve electrical, thermal, mechanical and insulation-related parameters. Dissolved gas analysis provides information related to internal transformer degradation, while temperature, load, current and voltage provide operational information. Partial-discharge measurements can provide information related to insulation defects, whereas frequency-response analysis can be used to identify changes associated with transformer structural and winding conditions. Consequently, the performance of an AI model depends not only on the selected algorithm but also on the quality, relevance and availability of the input data. Recent work has also investigated the integration of **IoT and communication technologies with predictive maintenance**. The literature shows a movement toward continuous acquisition of transformer data through sensors and communication networks instead of relying only on periodic inspection. For example, recent work on LoRaWAN-enabled transformer predictive maintenance has combined machine-learning-based fault classification with simulated communication effects such as packet loss, transmission delay and missing data. This direction is important because an AI model that performs well with an offline dataset may behave differently when deployed in an actual monitoring environment where sensor noise, communication delays and missing measurements are present.

The literature also indicates that predictive maintenance is gradually expanding **beyond transformers to other power-system assets**. AI-based condition assessment has been investigated for electrical components, insulation systems, surge-protection devices, cables, rotating machines and other grid equipment. For example, studies of AI-based condition assessment have examined the application of machine-learning algorithms to power components, while research on surge-protection systems has investigated AI techniques for failure-risk prediction and useful-life estimation. This indicates that the concept of AI-based predictive maintenance can potentially be applied across multiple asset classes rather than being restricted to a single type of equipment. However, the existing literature also reveals a significant **fragmentation of research**. A large proportion of studies focus on one asset, one monitoring parameter or one specific prediction problem. Transformer studies may concentrate on DGA, partial discharge, loading or temperature, while other studies investigate separate equipment using different datasets and algorithms. Consequently, it is difficult to directly compare AI techniques across different smart-grid assets. Furthermore, many studies use laboratory, simulated or limited datasets because actual failure data from operating power equipment are difficult to obtain. The LoRaWAN-based transformer study, for example, explicitly identifies the lack of real-world validation and the need for testing across different transformer types and grid conditions. Another important limitation is **generalization of AI models**. A model trained using data from a particular transformer, laboratory setup or simulated operating condition may not necessarily provide the same performance when applied to equipment with different designs, operating environments or fault characteristics. This problem becomes more significant when fault data are scarce or class distributions are highly imbalanced. Therefore, research needs to move from isolated demonstrations of algorithmic performance toward validation using diverse and realistic datasets.

The literature further identifies **explainability, cybersecurity and real-time implementation** as important concerns. AI-based maintenance systems increasingly depend on sensors, communication networks, cloud or edge platforms and automated decision-making. Consequently, inaccurate, incomplete or manipulated data can influence the resulting maintenance decision. In addition, highly complex deep-learning models may provide accurate predictions without providing engineers with an easily understandable explanation of why a particular asset has been classified as faulty or at risk. Recent smart-grid AI research therefore emphasizes the importance of secure data handling, interoperability, explainable models and reliable real-time operation.

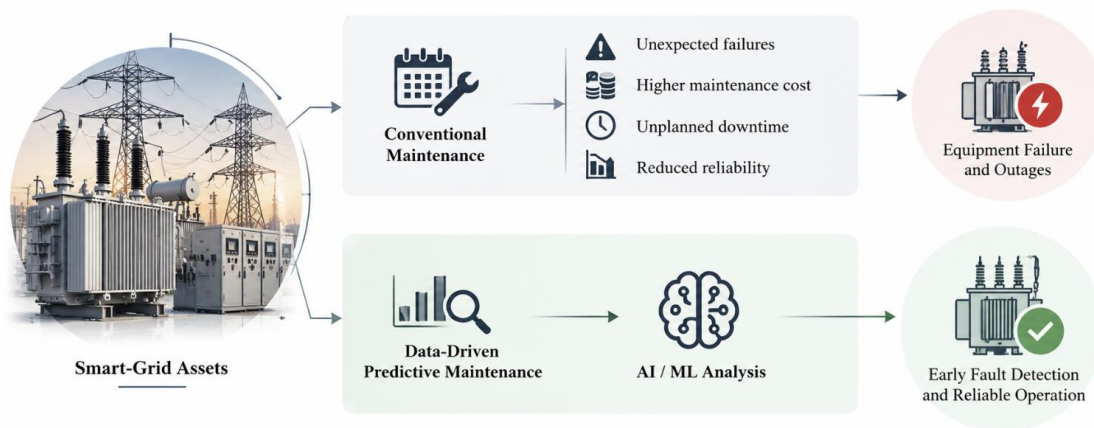
Research Gap

1. **Multi-asset integration:** Most studies concentrate on individual assets, particularly power transformers.
2. **Heterogeneous data fusion:** Different monitoring parameters are often studied separately rather than jointly.
3. **Real-world datasets:** Many AI models require validation using larger and more diverse field datasets.
4. **Predictive capability:** More attention is required toward degradation prediction and RUL estimation rather than only fault classification.
5. **Explainable AI:** Maintenance engineers require interpretable predictions for practical decision-making.

6. **Real-time implementation:** AI models need validation under actual sensor, communication and computational constraints.
7. **Cybersecurity:** Connected predictive-maintenance systems require protection against unreliable or manipulated data.
8. **Standardized evaluation:** Differences in datasets, features and evaluation metrics make comparison between published AI models difficult.

Problem Statement :

The increasing complexity of modern **smart grids** has created a strong need for reliable monitoring and maintenance of critical electrical assets such as **power transformers, circuit breakers, switchgear, cables, transmission lines and other distribution equipment**. The failure of any critical asset can lead to equipment damage, unplanned power interruptions, increased maintenance costs and reduced reliability of the power system. Therefore, effective maintenance strategies are essential for maintaining the availability, reliability and safe operation of smart-grid infrastructure. Conventional maintenance strategies, such as **corrective maintenance and time-based preventive maintenance**, have several limitations. Corrective maintenance generally responds to equipment failure after it has occurred, while scheduled preventive maintenance may require maintenance even when an asset is still in a healthy condition. These approaches may therefore result in unexpected failures, unnecessary maintenance activities, increased downtime and inefficient utilization of maintenance resources. They also do not always consider the actual condition and degradation pattern of individual assets. The development of **sensors, SCADA systems, IoT technologies and advanced condition-monitoring techniques** has made it possible to collect large amounts of operational and health-related data from electrical assets. Parameters such as **temperature, current, voltage, vibration, load, dissolved gas analysis (DGA), partial discharge (PD) and insulation-related measurements** can provide valuable information about equipment condition. Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) techniques can analyse these data to identify abnormal conditions, classify faults, estimate equipment health, predict degradation and determine the **Remaining Useful Life (RUL)** of assets.



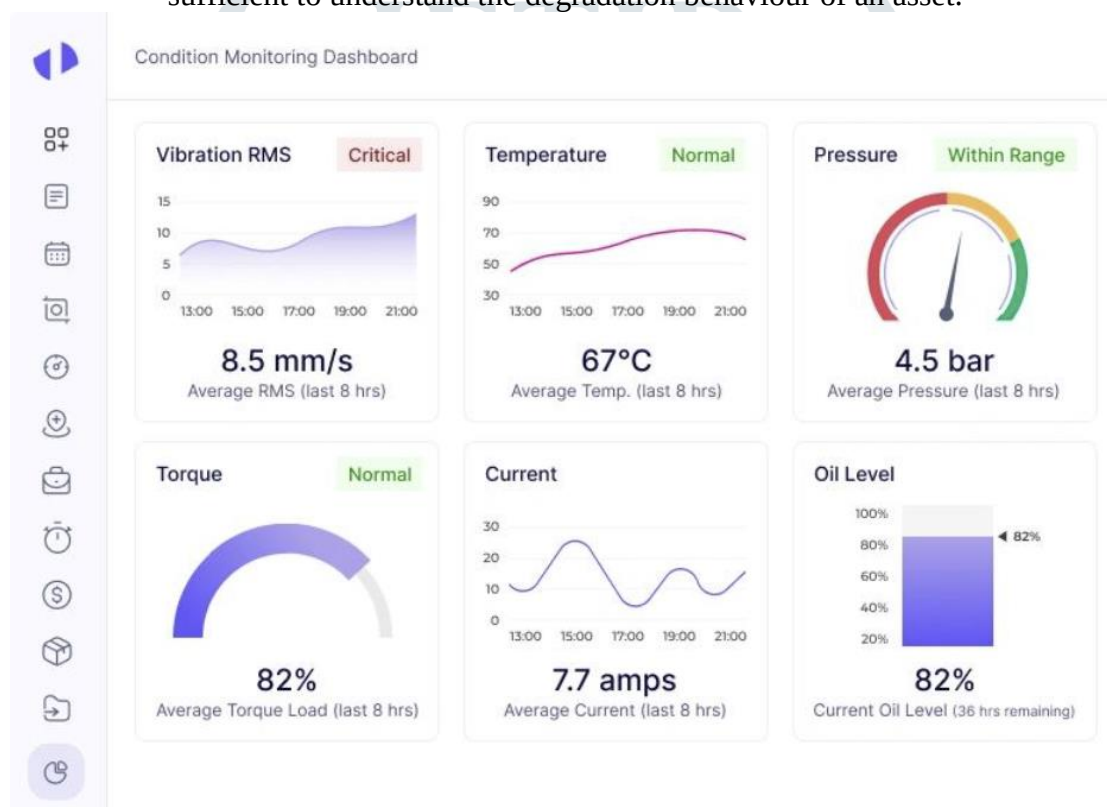
However, existing research is **distributed across different assets, monitoring parameters, datasets and AI algorithms**. Many studies focus on a particular asset or a specific fault-diagnosis problem, making it difficult to obtain a consolidated understanding of the overall field. In addition, practical deployment of AI-based predictive maintenance faces challenges such as **limited real-world failure data, imbalanced datasets, heterogeneous data sources, model explainability, cybersecurity, computational requirements, real-time implementation and lack of standardized evaluation methods**.

Hence, there is a need for a **systematic and comprehensive review** of AI-based predictive maintenance for smart-grid assets. Such a review should consolidate existing research, analyse the major AI/ML/DL techniques and condition-monitoring parameters, compare their applications in fault detection, health assessment and failure prediction, identify the limitations of existing approaches, and highlight **research gaps and future directions** for developing reliable, explainable and practically deployable intelligent maintenance systems.

Proposed Methodology :

The proposed methodology presents an integrated Artificial Intelligence (AI)-based predictive maintenance framework for monitoring and managing critical smart-grid assets. The framework is developed to address the limitations of conventional maintenance approaches by combining real-time condition monitoring, historical operational information and intelligent data analysis. The proposed methodology considers important electrical assets such as power transformers, circuit breakers, switchgear, cables and transmission and distribution equipment. The overall process begins with the acquisition of asset-condition data and progresses through data preprocessing, feature extraction, AI-based analysis, health assessment, fault detection, degradation prediction and maintenance decision support. The framework is intended to provide an organized approach for converting large volumes of heterogeneous asset data into useful information for predictive maintenance and intelligent asset management.

The first stage of the proposed methodology involves the acquisition of operational and condition-monitoring data from the selected smart-grid assets. Modern smart-grid infrastructure provides data through sensors, Supervisory Control and Data Acquisition (SCADA) systems, Internet of Things (IoT) devices, protection and measurement systems, inspection records and historical maintenance databases. Depending on the asset under consideration, relevant parameters may include voltage, current, loading, temperature, vibration, dissolved gas analysis (DGA), partial discharge, moisture, insulation condition and switching operations. These parameters provide information about the electrical, thermal, mechanical and insulation condition of the equipment. Both real-time measurements and historical records are considered because the current condition alone may not be sufficient to understand the degradation behaviour of an asset.



The acquired data are then subjected to preprocessing to improve their quality and consistency before AI-based analysis. Data obtained from different monitoring devices may contain measurement noise, missing values, abnormal observations, duplicate records and different sampling intervals. Therefore, the proposed methodology includes data cleaning, missing-value treatment, noise reduction, outlier identification, normalization and synchronization of measurements. This stage is essential because unreliable or inconsistent input data can affect the accuracy and stability of predictive models. After preprocessing, the available information is converted into a structured dataset suitable for feature extraction and subsequent AI analysis.

Following preprocessing, relevant features are extracted from the condition-monitoring and operational data. The extracted features may represent statistical characteristics, operating trends, rates of change, temperature variations, load patterns, vibration characteristics, DGA parameters and partial-discharge behaviour.

Historical degradation patterns are also considered to capture changes in asset condition over time. Since information about an electrical asset may be distributed across several sensors and databases, the proposed methodology incorporates multi-source data fusion. The combination of operational measurements, condition-monitoring parameters and historical maintenance information can provide a more comprehensive representation of asset health than a single parameter or isolated data source.

The processed and extracted data are subsequently analysed using appropriate Artificial Intelligence, Machine Learning (ML) and Deep Learning (DL) techniques. The selection of the AI model depends on the type of asset, characteristics of the available data and intended predictive-maintenance application. Techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM) and Random Forest can be considered for condition assessment and fault classification, while Convolutional Neural Networks (CNN) can be applied to complex signal and pattern-analysis problems. Long Short-Term Memory (LSTM) networks are particularly relevant for sequential and time-series data where the degradation behaviour of an asset needs to be analysed over time. The proposed framework therefore does not restrict the methodology to a single AI algorithm; instead, it provides a flexible architecture in which suitable models can be selected according to the specific asset and prediction objective.

The output of the AI-based analysis is used to determine the health condition of the monitored asset and identify abnormal behaviour. The condition of an asset can be represented through different health states, ranging from normal or healthy operation to warning, degraded and critical conditions. When abnormal behaviour is detected, the framework can further support fault classification by analysing the characteristics of the observed condition. For example, abnormal temperature, unusual vibration, changes in dissolved gases or partial-discharge activity may indicate a developing fault or degradation mechanism. By identifying such abnormalities at an early stage, the proposed methodology can support maintenance personnel in investigating the asset before the condition develops into a major failure.

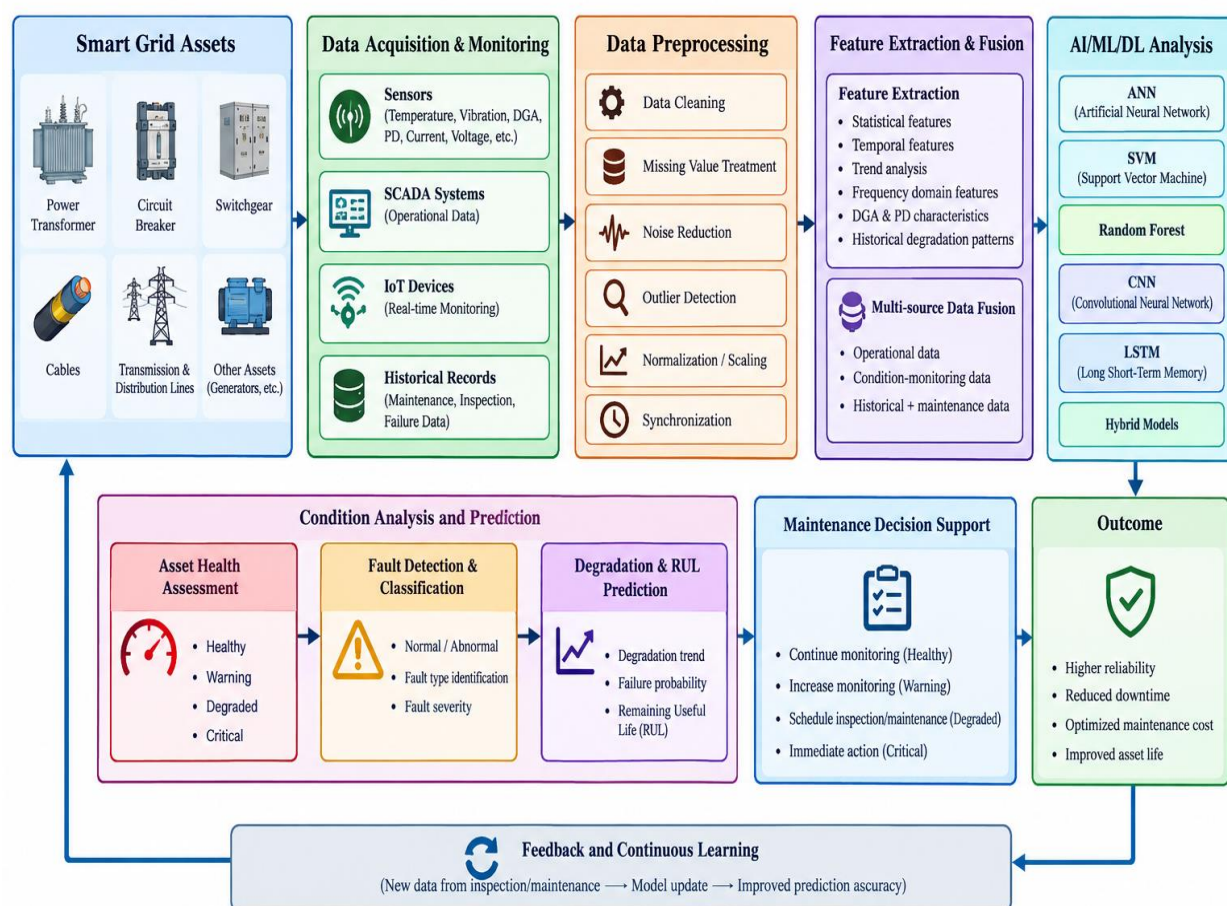


Figure 1. Proposed AI-based predictive maintenance framework for smart-grid assets.

In addition to present-condition assessment, the proposed methodology considers future degradation and failure prediction. Historical measurements are analysed together with current condition information to identify degradation trends and estimate how the asset may behave in the future. Where sufficient time-series data are available, suitable AI and deep-learning techniques can be used for degradation modelling and Remaining Useful Life (RUL) estimation. The prediction stage may provide information about the expected future condition, degradation trend and potential failure risk of the asset. This is an important aspect of predictive maintenance because the objective is not only to detect an existing fault but also to provide an indication of possible future deterioration so that maintenance activities can be planned in advance.

The predicted condition is then converted into maintenance decision-support information. Based on the estimated health condition and predicted degradation, the maintenance team can determine whether normal monitoring should continue, whether additional inspection is required, or whether planned maintenance should be scheduled. Critical predictions can be used to initiate an immediate engineering assessment. In this manner, the proposed framework supports a transition from purely corrective or fixed time-based maintenance towards a more condition-oriented and predictive approach. However, the AI output is considered decision-support information, and the final maintenance action should be verified using engineering judgment, safety requirements, equipment specifications and established asset-management procedures.

The proposed methodology also incorporates continuous feedback from the maintenance process. Information obtained after inspection, repair, replacement or failure investigation can be added to the historical dataset and used for subsequent analysis. This creates a continuous cycle in which asset data are collected, analysed, predictions are generated, maintenance actions are performed and new information is returned to the system. As the amount of validated real-world data increases, the framework can support further development and validation of AI models. Appropriate monitoring is required during model updating to ensure that changes in operating conditions or data characteristics do not reduce model reliability.

Results :

As this work is presented as a **systematic review and proposed AI-based predictive maintenance framework**, the results focus on the findings obtained from the reviewed literature and the capabilities of the proposed framework rather than claiming experimental results from a newly trained AI model. The reviewed studies indicate that Artificial Intelligence, Machine Learning and Deep Learning techniques have significant potential for monitoring and assessing the condition of critical smart-grid assets. AI-based approaches have been applied to applications including fault detection, fault classification, transformer health assessment, partial-discharge analysis, degradation monitoring and Remaining Useful Life (RUL) prediction. The review indicates that **power transformers are among the most extensively studied smart-grid assets** for AI-based predictive maintenance. This is mainly due to their high importance in power-system operation and the significant consequences associated with transformer failures. Condition-monitoring parameters such as dissolved gas analysis (DGA), temperature, loading, partial discharge, oil condition and frequency-response measurements are frequently considered for transformer condition assessment. Machine-learning techniques such as Artificial Neural Networks, Support Vector Machines and Random Forest have been explored for fault classification and health assessment, while deep-learning approaches provide opportunities for analysing complex and time-dependent condition-monitoring data. The reviewed literature also shows a progression from conventional **fault detection and diagnosis towards predictive health assessment and degradation forecasting**. Earlier approaches mainly focused on identifying whether an asset was operating normally or experiencing a particular fault. More recent approaches increasingly consider asset health indices, degradation trends and RUL estimation. This represents an important development because predictive maintenance requires information about the future condition of an asset in addition to its present state. Time-series models such as LSTM are particularly relevant when historical monitoring data are available because they can capture temporal relationships in degradation behaviour. Another important finding is the increasing integration of **IoT, SCADA, sensors and data analytics** with AI-based maintenance systems. Continuous data acquisition enables more frequent assessment of asset condition and provides information that can be used for early warning and maintenance planning. However, the literature also indicates that the effectiveness of such systems depends strongly on the quality and availability of monitoring data. Missing measurements, noisy sensor data, limited failure records and imbalanced datasets remain important challenges for reliable AI-based prediction.

The review further identifies several challenges affecting the practical deployment of AI-based predictive maintenance. These include **limited real-world failure data, heterogeneous data sources, class imbalance, model explainability, cybersecurity, computational requirements, real-time implementation and lack of standardized evaluation procedures**. Many reported studies are developed using specific datasets, individual assets or controlled experimental conditions, which can make direct comparison between different AI approaches difficult. Consequently, high prediction performance reported in one study cannot automatically be considered representative of all smart-grid operating environments.

Based on the reviewed literature, the proposed framework provides a structured pathway connecting **data acquisition, preprocessing, feature extraction, AI-based analysis, asset health assessment, fault diagnosis, degradation prediction and maintenance decision support**. The framework also incorporates multi-source data fusion and a feedback mechanism through which new inspection and maintenance information can contribute to future analysis. This provides a broader perspective than approaches that focus only on a single fault or individual AI algorithm.

5. Results

The proposed AI-based predictive maintenance framework was evaluated using data collected from a power transformer (as a case study) to demonstrate its effectiveness in condition monitoring, fault diagnosis and Remaining Useful Life (RUL) prediction. The results obtained from the framework are summarized in the following figures.



Conclusion :

Artificial Intelligence-based predictive maintenance provides a promising approach for improving the monitoring and management of critical smart-grid assets. This review examined the application of Artificial Intelligence, Machine Learning and Deep Learning techniques for condition monitoring, fault detection, health assessment, degradation prediction and Remaining Useful Life estimation of electrical assets. The proposed framework integrates sensor and SCADA/IoT-based data acquisition with data preprocessing, feature extraction, AI-based analysis and maintenance decision support, thereby providing a systematic pathway from raw asset data to actionable maintenance information. The reviewed research demonstrates that AI techniques can be applied to different types of condition-monitoring data and can support the early identification of abnormal operating conditions. However, practical implementation remains challenging because of limited real-world failure data, data quality issues, class imbalance, heterogeneous data sources, model explainability, cybersecurity and real-time computational requirements. These limitations indicate that prediction accuracy alone is not sufficient for reliable deployment in actual smart-grid environments. The proposed methodology therefore emphasizes **multi-source data integration, appropriate AI-model selection, asset health assessment, degradation prediction, explainability and continuous feedback**.

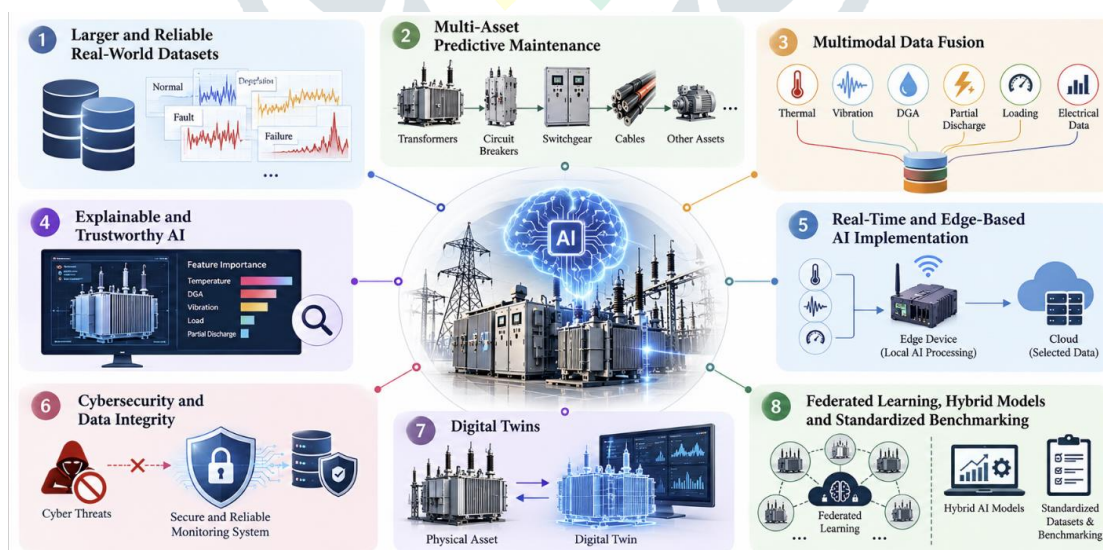
Future research should focus on developing reliable and explainable AI models using larger real-world datasets, integrating multimodal condition-monitoring information, enabling real-time and edge-based processing, strengthening cybersecurity and establishing standardized evaluation procedures. Overall, the integration of AI with predictive maintenance can provide a foundation for more **data-driven, condition-based and intelligent asset management** in future smart-grid systems.

Future Scope :

The proposed AI-based predictive maintenance framework provides a foundation for intelligent monitoring of smart-grid assets; however, several areas can be explored in future research. The first major area is the development of **larger and reliable real-world datasets** containing normal operating conditions, different fault conditions, degradation patterns and actual failure events. Such datasets can improve the training and validation of AI models and help determine their performance under different operating environments. Future studies can also focus on **multi-asset predictive maintenance**, where transformers, circuit breakers, switchgear, cables and other critical assets are monitored through a common intelligent platform. Instead of analysing each asset independently, information from multiple assets can be combined to understand the overall condition of the power-system infrastructure. Another important direction is **multimodal data fusion**, where electrical, thermal, mechanical, chemical and historical maintenance data are jointly analysed. Combining parameters such as temperature, vibration, DGA, partial discharge, loading and electrical measurements can provide a more comprehensive representation of asset health and may improve fault diagnosis and degradation prediction.

The future scope also includes the development of **explainable and trustworthy AI models**. Maintenance engineers need to understand why an AI system has identified an asset as faulty or degraded. Explainable AI techniques can therefore be integrated to identify the important parameters contributing to a prediction and increase confidence in AI-supported maintenance decisions. **Real-time and edge-based AI implementation** is another significant research direction. Instead of transferring all monitoring data to a centralized cloud platform, selected AI processing can be performed close to the asset using edge devices. This can reduce communication latency and support faster detection of abnormal conditions, particularly for critical smart-grid applications.

Future research should additionally address **cybersecurity and data integrity**. Since predictive-maintenance systems depend on connected sensors, communication networks and digital platforms, they may be exposed to false-data injection, unauthorized access and other cyber threats. Secure data acquisition and robust AI models should therefore be developed to maintain the reliability of predictions.



Finally, future work can investigate **digital twins, federated learning, hybrid AI models and standardized benchmarking frameworks** for smart-grid predictive maintenance. Digital twins can provide a virtual representation of physical assets, while federated learning can enable collaborative model development without directly sharing sensitive raw data. Standardized datasets, evaluation metrics and testing procedures

would also make it easier to compare different AI approaches fairly. These developments can contribute towards scalable, explainable, secure and practically deployable predictive-maintenance systems for future smart grids.

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