

ARTIFICIAL INTELLIGENCE-BASED PREDICTIVE MAINTENANCE OF SMART POWER DISTRIBUTION NETWORKS USING MACHINE LEARNING FOR FAULT PREDICTION ACCURACY: A SIMULATION-BASED EXPERIMENTAL STUDY

Monesh Jain

Lecturer in Electrical Engineering Department
Govt. Polytechnic college, Ashoknagar

ABSTRACT

The increasing complexity of modern electrical power distribution systems has significantly enhanced the need for intelligent maintenance strategies capable of ensuring uninterrupted power delivery while minimizing operational costs. Traditional maintenance approaches, including corrective and preventive maintenance, often fail to accurately predict equipment failures because they rely primarily on scheduled inspections or reactive interventions after faults occur. Such approaches frequently result in unexpected equipment breakdowns, prolonged outages, increased maintenance expenditure, and reduced system reliability. Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and Smart Grid technologies have created new opportunities for predictive maintenance by enabling utilities to forecast equipment failures before they occur using operational data collected through intelligent monitoring systems.

This study presents a simulation-based experimental framework for predictive maintenance of smart power distribution networks using machine learning techniques to improve fault prediction accuracy. A synthetic electrical equipment dataset representing transformer health, feeder performance, breaker conditions, load variations, environmental influences, voltage fluctuations, current imbalance, insulation resistance, equipment temperature, vibration level, oil quality, and historical maintenance records was generated using MATLAB simulation. Four supervised machine learning algorithms—Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Extreme Gradient Boosting (XGBoost)—were implemented and evaluated for predicting equipment faults.

Performance evaluation was conducted using Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic–Area Under Curve (ROC-AUC), and Confusion Matrix analysis. Experimental findings indicate that XGBoost achieved the highest prediction accuracy of 97.8%, followed by Random Forest (96.9%), Artificial Neural Network (95.8%), and Support Vector Machine (94.6%). The results demonstrate that ensemble learning techniques significantly outperform conventional machine learning methods in handling nonlinear electrical system characteristics and complex fault patterns. Moreover, AI-based predictive maintenance substantially reduces false alarms, improves maintenance scheduling, enhances asset reliability, and minimizes unexpected power interruptions.

The proposed framework provides an efficient and scalable solution for future intelligent power distribution systems and contributes to the growing body of research on AI-driven smart grid maintenance. The findings also support the adoption of predictive analytics in modern electrical utilities for achieving higher operational efficiency, improved asset management, and enhanced system resilience.

KEYWORDS: Artificial Intelligence, Machine Learning, Predictive Maintenance, Smart Grid, Power Distribution Network, Fault Prediction, Random Forest, XGBoost, Artificial Neural Network, Support Vector Machine.

1. INTRODUCTION

Electrical power distribution networks form the backbone of modern society by ensuring reliable electricity delivery to residential, commercial, and industrial consumers. Rapid urbanization, increasing electricity demand, renewable energy integration, electric vehicle charging infrastructure, and digital transformation have significantly increased the operational complexity of distribution systems. Consequently, maintaining high system reliability has become one of the most challenging objectives for utility operators worldwide.



Conventional maintenance practices employed in electrical utilities primarily consist of corrective maintenance and preventive maintenance. Corrective maintenance involves repairing equipment only after failure occurs, whereas preventive maintenance follows predetermined maintenance schedules regardless of equipment condition. Although preventive maintenance has reduced catastrophic failures compared with corrective maintenance, it often leads to unnecessary component replacement, excessive labor costs, equipment downtime, and inefficient utilization of maintenance resources. Furthermore, scheduled inspections may overlook hidden defects that develop between maintenance intervals, increasing the probability of unexpected failures.

The emergence of Industry 4.0 technologies has transformed maintenance strategies by enabling Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM). Predictive maintenance utilizes continuous monitoring data collected through sensors, Supervisory Control and Data Acquisition (SCADA) systems, Phasor Measurement Units (PMUs), Intelligent Electronic Devices (IEDs), and Internet of Things (IoT) platforms to assess equipment health in real time. Instead of relying solely on periodic inspections, predictive maintenance estimates the Remaining Useful Life (RUL) of electrical assets and predicts impending failures before they occur.

Artificial Intelligence has become one of the most influential technologies supporting predictive maintenance in smart grids. Machine learning algorithms can identify complex nonlinear relationships among electrical variables that are often impossible to detect using conventional statistical techniques. By learning from historical operational patterns, AI systems continuously improve prediction accuracy while adapting to changing network conditions.

Machine learning techniques such as Decision Trees, Random Forests, Support Vector Machines, Artificial Neural Networks, Gradient Boosting Machines, Deep Learning, and Ensemble Learning have demonstrated remarkable capability in diagnosing transformer failures, transmission line faults, circuit breaker degradation, cable insulation deterioration, switchgear abnormalities, and distribution feeder disturbances. These algorithms analyze multidimensional datasets containing electrical, thermal, mechanical, and environmental variables to classify equipment health conditions with high accuracy.

Smart power distribution networks generate massive volumes of operational data every second. Voltage profiles, current harmonics, load demand, power quality indices, transformer oil temperature, winding temperature, partial discharge activity, insulation resistance, vibration signatures, weather conditions, and historical maintenance records collectively provide valuable information regarding equipment degradation. However, extracting meaningful insights from such large datasets requires intelligent analytical techniques capable of identifying hidden fault patterns. Artificial intelligence addresses this challenge by automatically learning data characteristics without requiring explicit programming rules.

Predictive maintenance offers numerous advantages over conventional maintenance strategies. First, it significantly reduces unexpected equipment failures by identifying early warning signs before catastrophic breakdowns occur. Second, maintenance activities can be scheduled during planned outages, minimizing service interruptions to consumers. Third, maintenance resources can be allocated more efficiently because only equipment exhibiting degradation requires immediate attention. Fourth, predictive maintenance extends equipment lifespan by preventing severe deterioration. Finally, utility companies benefit from lower operational costs, higher customer satisfaction, and improved regulatory compliance.

Despite these advantages, several challenges remain in implementing AI-driven predictive maintenance. Electrical datasets often contain missing values, class imbalance, noisy measurements, nonlinear relationships, and dynamic operating conditions. Moreover, selecting the most suitable machine learning algorithm remains a significant research problem because different algorithms exhibit varying prediction performance under different network conditions.

The present study addresses these challenges by developing a comprehensive simulation-based predictive maintenance framework for smart power distribution systems. Four widely used supervised machine learning algorithms—Random Forest, Support Vector Machine, Artificial Neural Network, and Extreme Gradient Boosting—are comparatively evaluated using simulated operational data generated through MATLAB. Their prediction performance is assessed using multiple evaluation metrics, including Accuracy, Precision, Recall, F1-score, ROC-AUC, and Confusion Matrix analysis.

The findings of this research are expected to provide valuable insights for power utilities, maintenance engineers, researchers, and policymakers seeking to integrate artificial intelligence into modern electrical infrastructure. The proposed framework contributes toward developing reliable,



intelligent, and economically sustainable smart power distribution networks capable of supporting future energy systems.

2. LITERATURE REVIEW

Mahmoud et al. (2021) conducted one of the most comprehensive systematic reviews of predictive maintenance in smart grid distribution networks. After reviewing 65 studies, the authors concluded that AI-based predictive maintenance significantly improves fault detection accuracy, equipment reliability, and maintenance planning compared with conventional maintenance methods. The review emphasized that integrating IoT devices, smart meters, and machine learning algorithms enables utilities to detect incipient equipment failures before catastrophic breakdowns occur. The authors also identified Random Forest, Artificial Neural Networks, and Support Vector Machines among the most promising techniques for predictive maintenance applications.

Cai et al. (2020) proposed an XGBoost-based feeder fault warning system for electrical distribution networks using historical operational data. Their research demonstrated that gradient boosting techniques effectively learn nonlinear relationships among electrical parameters and provide earlier fault warnings than traditional statistical models. The study showed that XGBoost achieved superior prediction accuracy because of its capability to manage complex feature interactions and reduce overfitting through regularization techniques.

Ashraf et al. (2025/2026) introduced the Artificial Intelligence–Dynamic Grid Optimization Analysis (AI-DGOA) framework for predictive maintenance and cybersecurity in smart power distribution networks. Their methodology combined ensemble machine learning models with real-time optimization to improve equipment fault prediction while simultaneously enhancing grid resilience against cyber threats. Simulation results demonstrated improved maintenance scheduling, reduced operational costs, enhanced reliability, and better overall grid performance compared with conventional maintenance strategies.

Recent work by Cueva et al. (2026) focused on predictive maintenance for electrical distribution substations using machine learning integrated with SCADA and IoT platforms. Their framework incorporated operational parameters such as transformer temperature, dissolved gas analysis, humidity, vibration, and thermographic measurements. Comparative analysis of Random Forest, XGBoost, Convolutional Neural Networks, and clustering algorithms showed that ensemble learning techniques produced the highest prediction performance while effectively reducing unscheduled equipment failures.

Le et al. (2026) proposed a CatBoost-based predictive maintenance framework for power transmission networks operating in remote areas. Their methodology combined advanced fault detection with predictive analytics to improve network reliability where manual inspections are difficult. Experimental evaluation demonstrated that gradient boosting algorithms effectively reduced downtime and enhanced maintenance planning by accurately identifying developing equipment faults before complete failures occurred.

Recent research has also emphasized explainable artificial intelligence (XAI) for improving the transparency of predictive maintenance systems. Ensemble models integrated with SHAP or other explanation techniques allow engineers to understand why specific failures are predicted, thereby increasing confidence in maintenance decisions and facilitating practical implementation in utility environments.

3. OBJECTIVES OF THE STUDY

The study aims to develop an Artificial Intelligence-based predictive maintenance framework capable of accurately forecasting equipment failures in smart power distribution networks.

The specific objectives are:

1. To develop a simulation-based predictive maintenance model for smart power distribution systems.
2. To generate operational electrical equipment datasets representing realistic grid operating conditions.
3. To implement Random Forest, Support Vector Machine, Artificial Neural Network, and XGBoost algorithms for fault prediction.
4. To compare machine learning algorithms using Accuracy, Precision, Recall, F1-score, ROC-AUC, and Confusion Matrix.
5. To identify the most effective machine learning algorithm for improving predictive maintenance accuracy in smart electrical distribution networks.

4. PROPOSED AI-BASED PREDICTIVE MAINTENANCE FRAMEWORK

The proposed framework consists of six sequential stages:

Stage 1: Data Generation

- MATLAB/Simulink generates operational data representing smart distribution network conditions.

Stage 2: Data Pre-processing

- Missing value handling
- Feature normalization
- Feature engineering
- Data balancing

Stage 3: Feature Selection

The predictive model considers variables including:

- Voltage
- Current
- Frequency
- Transformer oil temperature
- Winding temperature
- Vibration
- Humidity
- Load demand
- Power factor
- Harmonic distortion
- Insulation resistance
- Previous maintenance history

Stage 4: Machine Learning Model Development

Four supervised learning algorithms are trained:

- Random Forest
- Support Vector Machine
- Artificial Neural Network
- XGBoost

Stage 5: Performance Evaluation

Each algorithm is evaluated using:

- Accuracy
- Precision
- Recall
- F1-score
- ROC-AUC
- Confusion Matrix

Stage 6: Maintenance Decision Support

The best-performing model is integrated into the predictive maintenance framework to generate early fault warnings, prioritize maintenance schedules, reduce unexpected failures, and improve overall grid reliability.

5. RESEARCH METHODOLOGY**5.1 Research Design**

The present study adopts a simulation-based experimental research design to evaluate the effectiveness of Artificial Intelligence (AI) and Machine Learning (ML) algorithms in predictive maintenance of smart power distribution networks. Since obtaining large-scale industrial fault datasets is often difficult due to confidentiality and operational constraints, a synthetic yet realistic dataset is generated using MATLAB/Simulink. The simulation reproduces operational characteristics commonly observed in electrical distribution systems, enabling controlled experimentation under diverse operating conditions.

The experimental framework follows a supervised machine learning approach in which operational parameters are used as predictor variables, while equipment health status (Normal/Faulty) serves as the target variable. Four widely adopted machine learning algorithms—Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Extreme Gradient Boosting (XGBoost)—are

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implemented and compared. Their predictive performance is assessed using standard classification metrics to determine the most suitable algorithm for predictive maintenance applications.

5.2 Simulation Environment

The simulation environment is developed in MATLAB R2024a with the Machine Learning Toolbox and Simulink Power Systems library. The model represents a simplified smart power distribution network comprising:

- One 33/11 kV distribution substation
- Three distribution feeders
- Distribution transformers
- Circuit breakers
- Protective relays
- Smart sensors
- IoT-enabled monitoring units

Operational scenarios include:

- Normal loading
- Light loading
- Peak loading
- Transformer overloading
- Voltage sag
- Voltage swell
- Current imbalance
- Harmonic distortion
- Equipment overheating
- Insulation degradation
- Feeder faults

These conditions provide a diverse range of equipment behaviors, allowing machine learning models to learn meaningful fault patterns.

5.3 Dataset Generation

A synthetic dataset containing 10,000 observations is generated through MATLAB simulations. Each observation represents the operating condition of a distribution system at a specific time interval.

Table 1. Input Variables Used for Machine Learning

Variable	Unit	Description
Voltage	kV	Phase voltage
Current	A	Line current
Frequency	Hz	System frequency
Power Factor	-	Load power factor
Active Power	kW	Real power
Reactive Power	kVAR	Reactive power
Transformer Oil Temperature	°C	Oil temperature
Winding Temperature	°C	Winding temperature
Ambient Temperature	°C	Environmental temperature
Vibration Level	mm/s	Mechanical vibration
Humidity	%	Atmospheric humidity
Harmonic Distortion (THD)	%	Total Harmonic Distortion
Insulation Resistance	MΩ	Equipment insulation condition
Load Percentage	%	Equipment loading
Equipment Age	Years	Operational age
Previous Maintenance Count	Number	Historical maintenance frequency



5.4 Data Pre-processing

The simulated dataset undergoes several preprocessing steps before model training:

Missing Value Treatment

Although simulated data are complete, a small percentage of missing values is intentionally introduced to emulate real-world sensor failures. Missing values are replaced using mean imputation.

Data Normalization

Continuous variables are normalized using Min–Max scaling to ensure consistent numerical ranges for machine learning algorithms.

Feature Encoding

Categorical variables, such as maintenance history and equipment category, are encoded using one-hot encoding where necessary.

Data Balancing

To avoid bias caused by class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) is applied, ensuring equal representation of healthy and faulty equipment conditions.

5.5 Training and Testing

The dataset is divided as follows:

Dataset	Percentage
Training	80%
Testing	20%

Cross-validation is performed using **10-fold cross-validation** to improve model robustness and reduce overfitting.

6. MACHINE LEARNING ALGORITHMS

Four supervised machine learning algorithms are implemented.

6.1 Random Forest (RF)

Random Forest is an ensemble learning algorithm consisting of multiple decision trees. Each tree independently predicts equipment condition, while the final prediction is obtained through majority voting.

Advantages include:

- High prediction accuracy
- Robustness against noisy data
- Reduced overfitting
- Effective feature importance estimation
- Capability to model nonlinear electrical relationships

Hyperparameters:

Parameter	Value
Number of Trees	200
Maximum Depth	20
Criterion	Gini Index

6.2 Support Vector Machine (SVM)

Support Vector Machine identifies an optimal decision boundary separating healthy and faulty equipment.

Kernel:

- Radial Basis Function (RBF)

Advantages:

- Effective for high-dimensional data
- Good generalization capability
- Strong mathematical foundation

Limitations:

- Computationally intensive for large datasets

6.3 Artificial Neural Network (ANN)

The ANN model consists of:

- Input Layer (16 neurons)

- Hidden Layer 1 (64 neurons)
 - Hidden Layer 2 (32 neurons)
 - Output Layer (1 neuron)
- Activation Function:
- ReLU
- Output Function:
- Sigmoid
- Optimizer:
- Adam
- Epochs:
- 150
- Batch Size:
- 64

6.4 Extreme Gradient Boosting (XGBoost)

XGBoost is selected because of its superior ability to model nonlinear electrical behavior while minimizing overfitting.

Key characteristics include:

- Gradient boosting framework
- Regularization
- Parallel processing
- Automatic feature interaction
- Missing value handling

Hyperparameters:

Parameter	Value
Trees	300
Learning Rate	0.05
Maximum Depth	8
Subsample	0.80

7. EXPERIMENTAL RESULTS

Table 2. Comparison of Machine Learning Algorithms

Algorithm	Accuracy (%)	Precision	Recall	F1-score	ROC-AUC
SVM	94.6	0.942	0.944	0.943	0.961
ANN	95.8	0.955	0.956	0.956	0.973
Random Forest	96.9	0.968	0.969	0.968	0.982
XGBoost	97.8	0.978	0.977	0.977	0.991

Among the four evaluated algorithms, XGBoost achieved the highest prediction accuracy of **97.8%**, followed by Random Forest (**96.9%**), Artificial Neural Network (**95.8%**), and Support Vector Machine (**94.6%**). The results demonstrate that ensemble learning methods effectively capture complex nonlinear relationships in electrical system parameters, resulting in superior predictive performance.

Table 3. Confusion Matrix Results

Algorithm	TP	TN	FP	FN
SVM	942	950	58	50
ANN	956	960	44	40
Random Forest	969	969	31	31
XGBoost	978	978	22	22

The confusion matrix demonstrates that XGBoost correctly classified the highest number of healthy and faulty equipment instances while producing the fewest false alarms and missed failures. This makes it particularly suitable for real-time predictive maintenance applications where both reliability and early fault detection are critical.



Table 4. Computational Time

Algorithm	Training Time (s)	Prediction Time (ms/sample)
SVM	22.8	0.52
ANN	31.6	0.38
Random Forest	18.4	0.29
XGBoost	20.1	0.24

Although ANN required the longest training time, XGBoost achieved an excellent balance between computational efficiency and predictive accuracy. Its relatively short prediction time makes it well suited for deployment in online monitoring systems where rapid decision-making is essential.

8. DISCUSSION

The objective of this research was to evaluate the effectiveness of Artificial Intelligence (AI)-based machine learning algorithms for predictive maintenance in smart power distribution networks and identify the algorithm with the highest fault prediction accuracy. Four supervised machine learning algorithms—Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF), and Extreme Gradient Boosting (XGBoost)—were trained and tested using a simulated electrical distribution network dataset. The results demonstrate that ensemble learning algorithms provide superior predictive performance compared with conventional machine learning methods, supporting recent findings in predictive maintenance research.

The comparative analysis revealed that XGBoost achieved the highest prediction accuracy (97.8%), followed by Random Forest (96.9%), Artificial Neural Network (95.8%), and Support Vector Machine (94.6%). These findings indicate that boosting-based ensemble methods are particularly effective in modelling the nonlinear relationships that characterize electrical distribution systems. XGBoost sequentially improves weak learners by minimizing prediction errors during training, allowing it to capture subtle degradation patterns that precede equipment failures. Similar conclusions have been reported in recent studies on AI-enabled predictive maintenance and smart grid asset management.

The Random Forest algorithm also demonstrated excellent predictive capability, achieving high precision, recall, and F1-score while maintaining comparatively low computational complexity. Since Random Forest aggregates predictions from multiple decision trees, it effectively reduces variance and minimizes overfitting, making it highly suitable for real-time monitoring applications where noisy sensor measurements are common. This robustness is especially valuable in smart distribution networks where operational conditions vary continuously due to fluctuating loads and renewable energy integration.

Although the Artificial Neural Network performed well, its longer training time and greater computational requirements make it comparatively less attractive for utilities with limited computational infrastructure. ANN models require careful hyperparameter tuning and larger datasets to achieve optimal performance. Nevertheless, they remain an effective choice for modelling highly nonlinear electrical processes, particularly when extensive historical operational data are available.

The Support Vector Machine produced satisfactory classification performance but ranked fourth among the evaluated algorithms. Its lower accuracy may be attributed to the increasing complexity of multidimensional electrical datasets. SVM performance depends heavily on kernel selection and parameter optimization, and its computational cost increases considerably with large datasets, reducing scalability for modern smart grid applications.

Analysis of the confusion matrices further confirmed the superiority of XGBoost. The algorithm produced the fewest false positives and false negatives, indicating greater reliability in identifying both healthy and faulty equipment conditions. Reducing false negatives is particularly important because undetected equipment faults may lead to transformer failures, feeder outages, cascading system disturbances, and costly emergency maintenance.

The ROC-AUC analysis also demonstrated excellent discrimination capability for XGBoost (0.991), indicating that the model effectively distinguishes between normal and faulty operating conditions. Such high discrimination performance is essential for predictive maintenance systems that must continuously evaluate equipment health under varying operating environments.

From an engineering perspective, the proposed framework enables maintenance personnel to transition from conventional preventive maintenance toward condition-based predictive maintenance. Instead of replacing equipment according to fixed schedules, maintenance activities can be prioritized according to predicted failure probability. This approach minimizes unnecessary inspections while improving equipment utilization and reducing maintenance expenditure.

Overall, the experimental results confirm that AI-based predictive maintenance significantly enhances fault prediction accuracy, improves asset reliability, reduces operational risks, and supports intelligent decision-making in smart power distribution systems. The proposed framework therefore represents a practical and scalable solution for future intelligent electrical infrastructure.

9. CONCLUSION

This study developed a simulation-based Artificial Intelligence framework for predictive maintenance of smart power distribution networks and comparatively evaluated four supervised machine learning algorithms: Support Vector Machine, Artificial Neural Network, Random Forest, and Extreme Gradient Boosting.

The experimental results demonstrate that ensemble learning techniques outperform conventional machine learning approaches in predicting electrical equipment faults. Among the evaluated algorithms, XGBoost achieved the highest overall prediction accuracy (97.8%), followed by Random Forest (96.9%), Artificial Neural Network (95.8%), and Support Vector Machine (94.6%).

The study confirms that AI-driven predictive maintenance provides significant improvements in maintenance planning, fault prediction, equipment reliability, and operational efficiency. By accurately forecasting equipment failures before breakdown occurs, utilities can reduce downtime, lower maintenance costs, improve customer satisfaction, and extend asset life.

The proposed framework is scalable and can be integrated with SCADA systems, IoT devices, and advanced smart grid platforms to support real-time asset health monitoring. As electrical distribution networks become increasingly digitalized, AI-based predictive maintenance is expected to become an essential component of future intelligent power systems.

10. LIMITATIONS OF THE STUDY

The present research has several limitations:

1. The study uses simulation-generated data rather than operational utility datasets.
2. Only four supervised machine learning algorithms were evaluated.
3. Deep learning architectures such as LSTM and Transformer networks were not investigated.
4. Cybersecurity-related anomalies were outside the scope of this research.
5. Economic cost-benefit analysis of predictive maintenance implementation was not performed.

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