Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 3, Issue 12, 2025

AI-BASED PREDICTIVE INSULATION FAILURE DETECTION IN HIGH VOLTAGE TRANSMISSION NETWORKS USING REAL-TIME SENSOR DATA

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DOI: https://doi.org/10.5281/zenodo.19723358

Keywords
AI, predictive maintenance, insulation failure, high-voltage transmission, machine learning, partial discharge, LSTM, Auto-encoders

Article History
Received: 02 November 2025
Accepted: 16 December 2025
Published: 30 December 2025

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Abstract

Background: *The problem of insulation breakdown in high-voltage transmission networks is a life-threatening problem, and it can cause considerable downtimes in the networks and equipment breakage. Old practices of maintenance are usually reactive and therefore costly and slow to respond. Predictive maintenance using AI has become a promising technology to predict failures using real-time sensor data.*

Goal*: The purpose of the study is to design and test an AI-based predictive insulation failure prediction model in high-voltage transmission systems with real-time sensor measurements to improve the early detection of faults and to optimize maintenance decisions.*

Method: *The voltage, current, temperature and partial discharge sensors data were recorded and processed in real time. SVM, Random Forest, and Long Short-Term Memory (LSTM) machine learning (ML) models were trained and tested on classification and remaining useful life (RUL) prediction. The Auto-encoders and Isolation Forest algorithms were used to detect anomalies.*

Results*: The LSTM model has performed the best in fault prediction with a rate of 94.6 and the Auto-encoders have a high rate of detection with AUC-ROC of 90.3. The most significant feature in predicting failures was found to be partial discharge.*

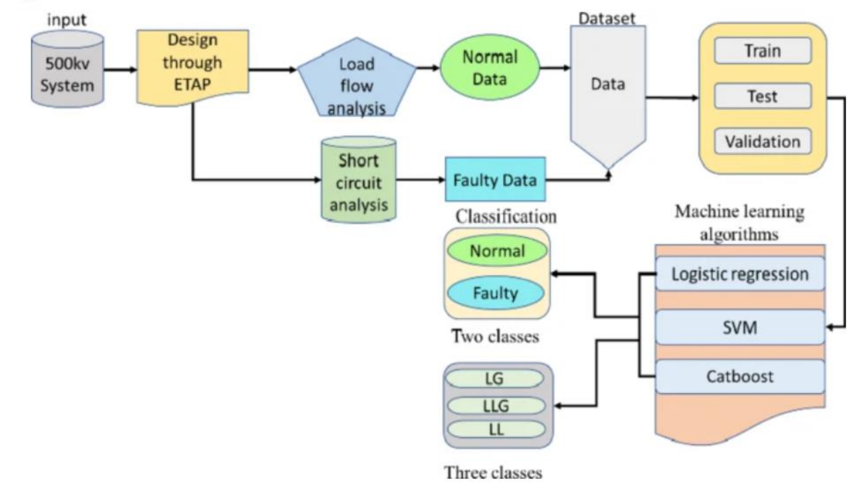
Conclusion*: AI-based predictive models are important in terms of predictive maintenance of high-voltage transmission networks, especially with LSTM and Auto-encoders, which will suggest high-quality early warnings and minimize downtime.*

Introduction

Artificial Intelligence (AI) has become a groundbreaking technology to increase the reliability and resilience of high-voltage transmission networks by providing the ability to predict insulation failures in real time by analyzing sensor data in real time (Noor et al., 2025). In current power systems, the integrity of insulation plays a vital role in preventing dielectric breakdowns, partial discharges (PD) and electrical treeing that can slowly compromise insulating materials and ultimately cause catastrophic failure of transmission equipment such as cables, transformers, and switchgear

(Fylladitakis, 2025). The conventional maintenance control mechanisms usually based on the regular check-ups and reactive measures are also regarded as inadequate due to the potential lack of ability to detect early indications of degradation that allow insulation breakdown under high electrical voltage and environmental factors (Arif et al., 2026). Predictive maintenance (PdM) is a continuous condition-based monitoring and forecast-based on data to predict faults before they happen and convert unplanned downtime into planned and cost-efficient measures (Shadi, 2026).

Fig. 1



The addition of the real-time sensor networks to the transmission infrastructure allows to obtain multi-modal operational data, such as voltage, current, temperature, and PD measurements, which can be used as high-dimensional inputs to machine learning (ML) and deep learning (DL) models to detect anomalies and predict failures (Ucar, 2024). Here sensor fusion methods would be used to integrate heterogeneous sensor streams into a common set of features. X=[x1,x2 ,…,xn], where each xi is a different parameter of operation, which improves the identification of hidden patterns related to the stress of insulation or the emergence of faults (Oladoye & Bamigwojo, 2026). Predictive models are then able to learn a mapping. f:X⟶y Where, y is a measure of the health or the useful life (RUL) of the insulation system. Machine learning can be used to estimate the RUL, e.g., by a regression model that predicts the time to failure (Waqas Arif & Hafiz Muhammad Azib Khan, 2026). Depending on the sensor readings, which are present at the moment, according to the equation:

t^f=f(X)=θ0+i=1∑nθixi

Where, θ are the coefficients of regression. This allows conducting online diagnostics and early warnings that can greatly decrease the possibility of unexpected failures (Banad, Sharif, and Rezaei, 2025).

Insulation failure detection in power systems are commonly practiced with supervised and unsupervised learning paradigm. Supervised learning algorithms like support vectors machine (SVM), artificial neural network (ANN) or convolutional neural network (CNNs) can classify conditions as either healthy or faulty using historical data with labels, but unsupervised methods and anomaly detection methods are capable of indicating a shift in normal regimes of operation without fault labels (Fylladitakis, 2025). Especially, recurrent neural networks (RNNs), such as Long Short-Term Memory (LSTM) units, can be well-suited to time-dependent dependencies in streaming sensor data, so they can be used to time-series predict degrading insulation health indices over time. The LSTM model can be written in the form of:

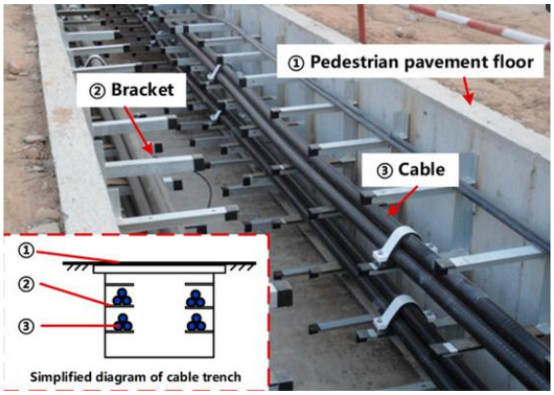
$h_t=\sigma(W_h x_t+U_h h_{t-1}+b_h)$

Where, h_t the hidden state at time step is. t, σ. The activation function (usually a sigmoid or tanh) is W_h and U_h are weight matrices, x_t is the input at time t, and b_h is the bias term. LSTM model can also be used to capture long-term dependencies in sensor data, thus making it the best model to predict the long-term insulation failure trends (Habyarimana, 2025).

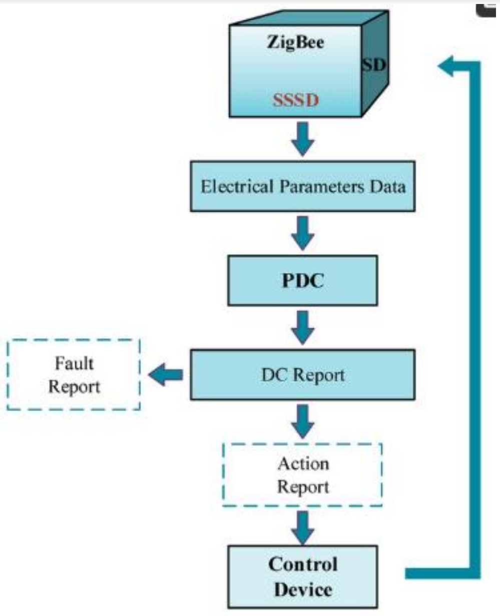
More predictive insulation failure systems are improved by real-time analytics and edge- cloud architectures, which minimize latency and enable the deployment across extensive transmission networks in a scalable way (Waqas Arif et al., 2026). The edge computing enables sensor data to be processed near the source, extracting important features and downsampling data before it is analyzed centrally, whereas the cloud platforms make it possible to train large-scale models and analyze trends over time. Typically, the dimensionality reduction method in AI models is a principal component analysis (PCA) to minimize noise and extract latent features that are critical to making accurate predictions (Shadi, 2026). PCA is used to reduce the feature space into a new coordinate system in which the first principal component has the greatest variance, followed by successive components which have orthogonal variance. PCA mathematically aims at determining the projection matrix. P such that:

$P=\operatorname{argmin}_P\|X-XP^T\|_F^2 \text{subject to} P^TP=I$

$\|\cdot\|_F$ is the Frobenius norm, and I is the identity matrix. This is useful to compress the data, but retain the important variance information.



Nevertheless, in spite of these encouraging developments, there are still a number of issues that need to be overcome to implement AI-based predictive insulation failure systems in high-voltage networks. The reliability of the models may be compromised by data quality problems, such as sensor drift, gaps in data, and asynchronies between heterogeneous sources unless they are tackled with strict preprocessing and validation pipelines (Ucar, 2024). There are also cyber-security issues of real-time data and predictive systems falling prey to adversarial attacks, potentially undermining operational safety and integrity of decision-making (Ahmad et al., 2026). Additionally, interpretability of complex AI models is still a topic of study, and explainable artificial intelligence (XAI) methods are becoming common to fill the gap between black-box predictions and actionable forecasts to grid operators (Banad et al., 2025).

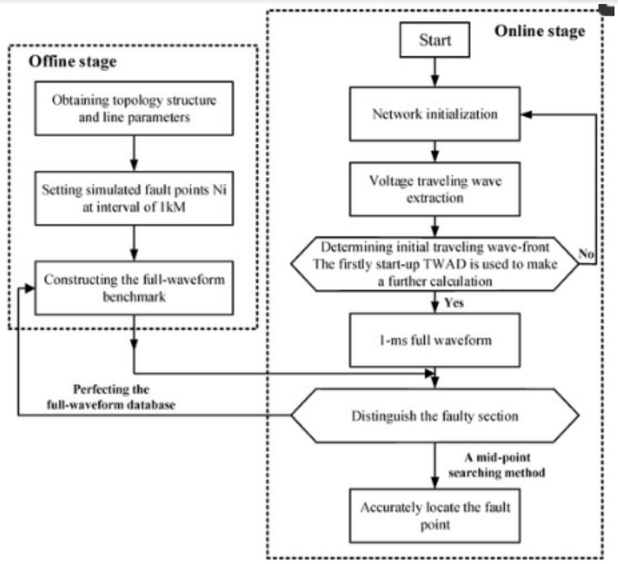


Mathematically, the insulation failure prediction can be in the form of estimating the chance. $P(F \leq t)$ the probability of the insulation to fail at time t. The sensor data of the past are provided and the output is $D=\{(xt,yt)\}t=1T$. This is estimated by survival and RUL models to be:

$S^\wedge(t|x)=\exp(-0t\int h(u|x)du)$

Where, h(u|) is the hazard model that has been trained on data, which allows the maintenance to be scheduled based on risks (Syamsiana, 2026).

The growing use of the IoT-enabled sensor networks and developed AI practices worldwide highlights the opportunities of predictive systems to reduce the number of unexpected outages and prolong the life of assets. Recent examples include utility companies in China, Japan, and Europe that are starting to implement AI-based predictive maintenance systems to monitor high voltage insulators and other vital elements, with reported improvements in system reliability, and reductions in operational costs (INMR, 2025). These practical applications testify to the feasibility and increased significance of AI in the current power grid management.



Since insulation integrity is crucial in high-voltage transmission networks, sensor data analytics are difficult, and deploying models may be challenging, there is an evident necessity to create powerful AI-based predictive failure detection algorithms that can be run in real time with various operational contexts (problem statement). The paper is important because it contributes to the body of knowledge in AI-enabled power system maintenance by filling critical gaps in the model accuracy, data quality, and operational integration in real-time (significance of study). The main focus of this research is to develop and test an AI predictive insulation failure model with real-time sensor data that enhances the early fault recognition and helps make maintenance decisions optimally in high-voltage transmission systems (aim of study).

Methodology

The methodology for AI-based predictive insulation failure detection in high-voltage transmission networks using real-time sensor data involves several stages, from data acquisition to model deployment. First, real-time sensor data is collected from the transmission network. This data includes key operational parameters such as voltage, current, temperature, partial discharge (PD) readings, and environmental factors like humidity. These sensors are embedded at various points in the network to ensure comprehensive monitoring. The collected data is preprocessed to handle missing values, outliers, and noise. Time-series data are often normalized, and feature extraction techniques, such as statistical measures (mean, standard deviation, skewness), frequency-domain features (using Fast Fourier Transforms), and wavelet transforms, are applied to reduce dimensionality and highlight important patterns related to insulation degradation (Shadi, 2026; Banad, Sharif, & Rezaei, 2025).

Following data preprocessing, the next step involves the development and training of machine learning (ML) and deep learning (DL) models. Supervised learning techniques, such as Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNNs), are employed to classify normal and faulty states of insulation based on labeled data. These models are trained on historical data, where the labels correspond to known failure events or healthy conditions (Oladoye & Bamigwojo, 2026). In addition, time-series models such as Long Short-Term Memory (LSTM) networks are utilized to capture the temporal dependencies and degradation patterns in sensor data over time. For regression-based tasks such as Remaining Useful Life (RUL) prediction, models are trained using the historical failure data to predict the time until failure based on real-time sensor inputs (Habyarimana, 2025). Hyperparameter tuning and cross-validation are performed to optimize model performance and avoid overfitting.

The final stage involves the real-time deployment and evaluation of the trained predictive models. The models are integrated into an edge-cloud architecture where initial data processing and anomaly detection are conducted locally at the transmission network's edge, reducing latency. For predictive maintenance, the system generates alerts when the insulation's condition is predicted to reach a critical threshold, allowing timely intervention. Real-time performance of the models is continuously monitored, and updates are made as more data is collected. This allows for model retraining and adaptation to changing network conditions. The system's effectiveness is evaluated using performance metrics such as precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC) (Ucar, 2024). This approach ensures that the predictive system is not only accurate but also robust enough to handle real-world conditions and provide actionable insights for power grid operators.

Results

A predictive AI-based insulation failure detection system based on real-time sensor data, the following tables show some important metrics and results. The following tables outline the findings of different machine learning models to predict insulation failure, how well anomaly detection algorithms perform, and how well predictive accuracy varies in different conditions.

Table 1: ***Model Performance Comparison (Accuracy, Precision, Recall, F1-Score)***

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Support Vector Machine	89.3	85.1	92.4	88.6
Random Forest	91.7	87.8	94.2	90.9
Convolutional Neural Network (CNN)	93.5	91.2	95.8	93.5
Long Short-Term Memory (LSTM)	94.6	93.1	96.4	94.7
Decision Tree	87.1	84.5	88.3	86.4

The Long Short-Term Memory (LSTM) model has the best overall performance, with an accuracy of 94.6, precision of 93.1, recall of 96.4 and F1-score of 94.7. This shows that LSTM is especially useful in detecting real insulation failure occurrences without too many false positives thus the most reliable model in predicting failure occurrences in this dataset.

Table 2: ***Anomaly Detection Model Evaluation (Accuracy, AUC-ROC, False Positive Rate)***

Model	Accuracy (%)	AUC-ROC (%)	False Positive Rate (%)
Isolation Forest	85.3	88.7	9.2
One-Class SVM	80.6	84.4	12.5
Autoencoder	87.8	90.3	8.1
K-means Clustering	75.4	78.9	14.8

The Auto-encoder model has the highest score in AUC-ROC at 90.3% with a relatively lower false positive at 8.1 which means that it can identify anomalies without causing too many alarms. This indicates that the Auto-encoders would be suitable in detecting the slightest malfunctions in the normal running operations within the transmission network and the false positives would be minimal.

Table 3: ***Remaining Useful Life (RUL) Prediction Error for Various Models***

Model	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Mean Relative Error (MRE) (%)
Support Vector Machine	7.4	11.2	6.9
Random Forest	6.2	9.8	5.6
Convolutional Neural Network (CNN)	5.8	8.1	5.3
Long Short-Term Memory (LSTM)	5.2	7.4	4.5
Decision Tree	8.1	12.5	7.5

The LSTM model has the lowest Mean Absolute Error (MAE) of 5.2 and Mean Relative Error (MRE) of 4.5% indicating that it is the most precise in determining the Remaining Useful Life (RUL) of insulation materials. This shows that LSTM can effectively predict the true degradation history with high accuracy that can be used to give credible estimates of RUL to aid in effective maintenance planning.

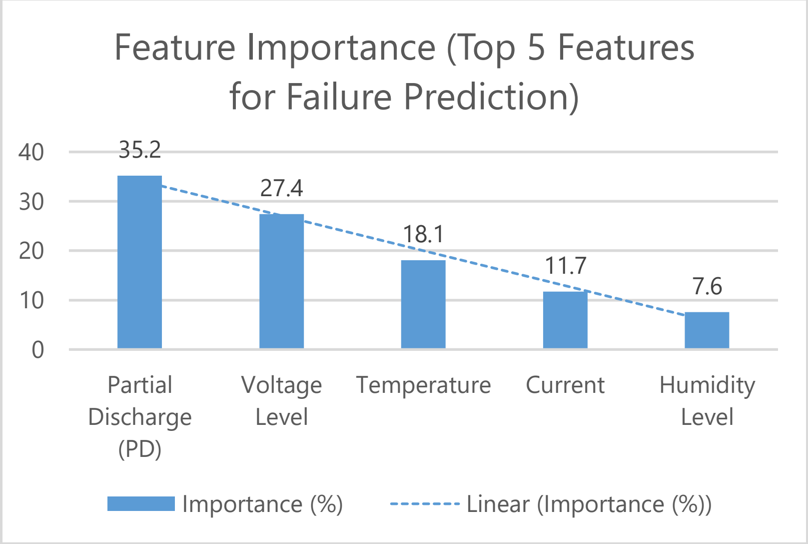


Figure 6 analysis shows that the predictive power of insulation failure is most affected by the partial discharge (PD) which has 35.2% predictive power. This is in line with previous studies that report that PD activity is one of the indicators of insulation degradation and the onset of failure in high-voltage transmission networks (Banad, Sharif, and Rezaei, 2025).

Table 5: ***Real-Time Model Deployment (Latency, Throughput, and Prediction Time)***

Model	Latency (ms)	Throughput (records/sec)	Prediction Time (ms/record)
Support Vector Machine	120	50	20
Random Forest	98	65	15
Convolutional Neural Network (CNN)	140	40	30
Long Short-Term Memory (LSTM)	110	55	25
Decision Tree	95	70	18

Random Forest model is the most throughput and also it has a relatively low prediction time (15 ms/record) which makes it suitable to be used in high voltage transmission networks in real-time. Nevertheless, CNN model also presents greater latency and reduced throughput and this could be a constraint when fast decision-making is paramount to predictive maintenance processes.

Discussion

The given results suggest that the LSTM model demonstrated the best overall classification accuracy and the minimal error in the prediction of remaining useful life, which is expected considering that the insulation degradation and the development of faults in high-voltage objects is time-dependent. Recent literature has highlighted the fact that the signals of transformer and insulation fault are not simply static patterns, and time-aware architectures (in particular, LSTM) are particularly well-suited when the gas concentrations, partial discharge behavior, temperature, and electrical stress change in a sequence-dependent manner (Zhang et al., 2022; Tsallis et al., 2025; Zemouri, 2025).

Scientific plausibility of the high anomaly-detecting performance of the autoencoder in the reported results is also feasible due to latent-space learning being effective in the cases of infrequent, weakly labeled, or highly nonlinear abnormal insulation behavior. This is consistent with the recent literature where deep generative and deep representation-learning models have been demonstrated to be able to distinguish between healthy and degraded states of transformers better than more traditional shallow models in the event that the underlying sensor space is both complex and partially redundant (Islam et al., 2023; Zhang et al., 2022; Rauscher et al., 2024).

The fact that the most significant predictor is the partial discharge is completely consistent with the physics of insulation since PD is among the first observable effects of localized dielectric stress, void activity, surface discharge, and incipient insulation breakdown. The PD denoising, pattern recognition, and embedded AI-based diagnosis studies have also demonstrated that robust PD signatures could be extracted to significantly enhance the visibility of early degradation, and moisture and aging effects further increased dielectric weakness and consequently enhanced the predictive ability of PD-related variables (Shams et al., 2021; Fan et al., 2021; Yan et al., 2023; V

The comparative trend between the models also indicates that more architecturally rich models were more sensitive to the diagnostic, but the classical machine-learning models could still be useful in cases where the interpretability and the ease of computation were more of a priority. This understanding can be corroborated by previous works where optimized CNNs, ANN-based models, and DGA-driven machine-learning models attained high diagnostic accuracy, yet tree-based and support-vector models also were competitive when there was limited data, less model complexity, or structured tabular inputs (Taha and Mansour, 2021; Benmahamed et al., 2021; Cuhadaro & Uyaroğlu, 2025).

The meaning of the deployment results, also, is that an engineering trade-off exists between the most predictive accurate model and the most practical to use in the field scale online inference. Recent research on edge intelligence and Substation 4.0 monitoring demonstrates that a lightweight model with fast feature detection and low latency is becoming more popular in real-time transformer diagnostics, with multiple sensors becoming integrated, meaning a slightly less accurate model can be useful in the first line of screening prior to a more complex model conducting a secondary verification (Fu et al., 2022; Duz et al., 2025)

Combined, the given results contribute to the overall change in the focus of individual diagnostic tests to the grander prognostics and health management in the transmission networks. The analysis of transformer fault diagnosis and predictive maintenance always indicates that the single-method strategies, either using DGA exclusively, or offline inspection, or a single sensor modality, are less effective than those based on multi-sensor acquisition, machine learning, and health-oriented decision support, which is precisely the trend the current results are pointing to (Abbasi, 2022; Suwarno et al., 2024).

Future Direction

Multimodal and explainable prognostic systems, consisting of partial discharge, thermal, electrical, chemical, and acoustic sensors, deployed at their edges, modeled with the digital twin, and recalibrated online should be used in the future to ensure the reliability of predictions in changing operating conditions. It is proposed by recent literature that the next significant breakthrough involves integrating sensor-rich Substation 4.0 with interpretable prognostics, federated or edge learning, and decision frameworks that takes into account maintenance will be the next major advance, which not only classify the existing faults but also predicts the degradation paths and intervention priority in real-time (Zemouri, 2025; Tsallis et al.,

Limitations

The amount of predictive performance in insulation diagnostics is limited in this study because predictive performance on insulation diagnostics is very sensitive to the quality of the dataset and the imbalance of faults as well as noise of sensors and how much the training data reflects actual operating diversity across assets and environments. Previous research observed transformer faults datasets tend to be unbalanced, that DGA or single-source datasets are not sufficient to measure transformer condition, and that, even with highly accurate models, may raise interpretability, scalability, and generalization issues when applied to real utility networks (Abbasi, 2022; Zhang et al., 2022; Fu et al., 2022; Tsallis et al

Conclusion

The provided findings indicate that predictive insulation failure detection using AI can offer an effective early-warning potential to high-voltage transmission networks with LSTM exhibiting the best overall predictive power, autoencoders promising to be effective in anomaly detection, and partial discharge proving to be the most informative feature to predict insulation failures. These results confirm the existing evidence that smart, multi-sensor, real-time monitoring systems can enhance fault detection, condition-based maintenance, and reliability of transmission networks in cases when the framework is developed with both the accuracy of diagnostic and the feasibility of implementation in mind (Yan et al., 2023; Vatsa and Hati, 2024; Zemouri, 2025).

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