

# Fault Detection and Isolation in Smart Grids Using IoT and Edge Computing

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**Abstract-** The dynamic nature of smart grids requires more advanced maintenance techniques in addition to traditional reactive and time-based preventive techniques, which are frequently to blame for inefficient resource use, unnecessary downtime, and delayed problem discovery. Existing platforms are not particularly dependable these lack real-time analytical and forecasting capabilities. A predictive maintenance framework built on the Internet of Things (IoT) and Machine Learning (ML) is provided as a solution to the preceding issues. The proposed system uses a combination of real-time sensor data, a Long Short-Term Memory (LSTM) network for Remaining Useful Life (RUL) prediction, Isolation Forest for anomaly detection, and Random Forest for fault categorization. In these ways, it facilitates condition-based maintenance, intelligent decision-making, and early fault detection. Compared with existing systems, detective accuracy, precision, and recall improved to 92.6%, 90.8%, and 91.2%, respectively, with ephemeral recordings. When the average downtime was lowered from 6 hours to just 1.9 hours, it demonstrated that smart grid maintenance was more responsive, efficient, and reliable.

*Keywords: Predictive Maintenance, Smart Grid, Fault Detection, Asset Management, Condition Monitoring, Grid Reliability, Data Analytics.*

## I. INTRODUCTION

A technological improvement of traditional power networks, smart grids combine dispersed energy resources, real-time monitoring, and contemporary communication technologies. The complexity of energy systems and rising power consumption have made smart grid energy efficiency and dependability a real problem. Rapidly evolving grid circumstances have rendered traditional maintenance procedures, which are primarily reactive or time-based preventive techniques, obsolete. It cannot anticipate the possibility of a malfunction or deterioration in performance because of their incapacity and rigidity. Unexpected equipment breakdowns, protracted downtime, and costly cogs and gears are still the

results. Real-time data collection and smart failure prediction are two new ways that the IoT and ML are improving smart grid maintenance techniques. It requires more information, precision, and response time than people can now supply in order to increase fault detection and maintenance capabilities. Existing conventional reactive techniques result in costly outages and customer loss due to unanticipated outages; preventive strategies are expensive and fail to account for real-world substitution scenarios. In addition to being time-consuming, manual grid infrastructure monitoring is also prone to errors. These limitations show how urgently an intelligent system that can detect the issue before it manifests itself is needed in order for the utility provider to take preventative measures. An IoT- and ML-based fault predictive maintenance system can transform grid operations by comparing real-time sensor data with previous fault patterns. These will improve the lifespan of electrical components integrated into the grid and lower maintenance costs and risk. By combining ML algorithms with IoT sensing, the study seeks to develop and evaluate a predictive maintenance framework for smart grid infrastructure. In addition to fault classification, anomaly detection, and continuous operating parameter monitoring, the proposed system is built to estimate the RUL of essential grid components, such as circuit breakers and transformers. As a result, it provides early defect identification, lowers the likelihood of unplanned malfunctions, and facilitates prudent maintenance planning decisions. Instead of using a reactive or even schedule-based approach to grid management, the goal is to transition to a condition-based, data-driven system that incorporates optimal performance and operational cost management. In the field of smart grid maintenance, the paper provides a number of significant contributions. IoT-based sensors, cloud-based analytics, and edge computing are used to first present a multi-layered architecture for

anticipating system repair. Second, it provides a collection of ML models, including Random Forest for fault classification, Isolation Forest for anomaly detection, and LSTM for RUL prediction, together with the use of these ML techniques for comprehensive equipment health analysis. An effective fusion of equipment time-to-failure prediction results based on the constituent models, as well as satisfactory equipment fault state categorization and anomaly detection, are demonstrated by the results, demonstrating the practical usability of the proposed system. Third, it performs better than the existing approaches with reduced delay time, quicker reaction time, and higher precision. It provides much more, including enabling continuous learning through model retraining with new data and providing visualization dashboards for real-time insights into operations. Such an all-encompassing ecosystem guarantees smart grid system monitoring and intelligent management. The following describes the structure of the rest of the paper: In Section II, related work in fault prediction systems and smart grid maintenance is compiled. Section III outlines the workflow, components, and system architecture of the proposed system, including the sensor network, data processing techniques, and ML models. Experimental results and comparisons with existing structures are shown in Section IV. Section V concludes the research by summarizing the key conclusions and providing a few possibilities for enhancing smart grid predictive maintenance.

## II. RELATED WORK

The rapid development of renewable energy integration and demand-side management has accelerated the application of big data and ML technology to smart grid predictive maintenance. Real-time analytics solutions use several sorts of sensor data, such as voltage, temperature, vibration, and load profiles, to assess the grid's health. These methods enable smart diagnostics and predictive maintenance. Neural networks, decision trees, and regression Model ML technique applications include renewable energy resource management and component failure prediction [6]. Similar to building infrastructure, predictive maintenance models based on ML have demonstrated potential. Anomalies are found, and equipment degradation is predicted using data from environmental sensors and previous maintenance logs. These systems can also

host applications, so the organizational model might possibly influence smart grid maintenance by including ML models that adapt to contextual infrastructure elements [7]. IoT and fog computing are another possible avenue for predictive maintenance. Decentralizing data processing near the source minimizes latency and improves real-time responsiveness. At the edge, ML models can detect early indicators of malfunction and send out alerts before these arise [8]. These encourages numerous industrial verticals to employ IoT-ML hybrid frameworks for monitoring and maintaining heavy machinery. In such cases, time-series data is utilized to train anomaly detection models as part of predictive maintenance frameworks, allowing the detection of far more subtle (and smaller) patterns that lead to failures. The application of the idea to smart grids yields comparable predictive capabilities for components such as circuit breakers, transformers, and energy meters [9]. One of the cornerstones of smart grid reliability is condition-based grid monitoring that employs signal processing and ML. Sensors convert information into raw data, which is subsequently preprocessed using a variety of approaches (signal processing techniques such as Fourier and wavelet transformations) before being used to ML models. These output classifiers, ranging from support vector machines to ensemble approaches, are highly accurate in diagnosing mechanical and electrical defects [10]. It is also a crucial part of predictive maintenance, such data-driven load monitoring in distribution transformers. ML algorithms have been used to track energy usage trends, identify irregular consumption patterns, and assess the likelihood of an overload. These facilitates automatic maintenance planning and energy balancing, particularly during high demand periods. Load monitoring combined with prediction defect detection creates a comprehensive maintenance plan for energy utilities [11]. Cloud-based analytics and ML models coupled into predictive maintenance systems allow digital industrial platforms to monitor the grid's performance. These systems additionally frequently include dashboards for near-real-time monitoring and automatic reporting to assist operators in managing emergent concerns. Cloud integration scalability improves predictive analytics over regionally distributed energy grid assets, allowing for better fault localization and recovery times [12]. Furthermore, it is critical to examine data in real time when monitoring grid components. Sensors generate continuous motion data, which is

then analyzed using clustering, classification, and regression techniques. While these models initially incorporate the prediction of the RUL of specific components, then develop an optimal time schedule for maintenance tasks. Moving forward, as sensor technology becomes more affordable and scalable, real-time predictive analytics will become a standard part of smart grids [13]. Intelligent sensors and predictive maintenance tools used in smart manufacturing environments aim to improve production efficiency. Deep learning-based systems use algorithms such as CNNs and RNNs to extract information from complex datasets. However, the same methodologies can be used to predict smart grid problems by altering voltage, current, and temperature patterns from energy assets [14]. In addition, powerful AI approaches are being used to detect early warning signals of asset failure in oil and gas pipelines by analyzing raw sensor data. These use a combination of sensor data fusion, ML classification, and decision-making algorithms to send maintenance alerts at the appropriate moment. These safety-critical sectors demonstrate the efficiency of combining AI, IoT, and predictive analytics, confirming their relevance in the smart grid domain, where dependability and responsiveness are equally vital [15].

### III. PROPOSED SYSTEM

Existing smart grid infrastructure largely relies on conventional maintenance strategies, primarily reactive or time-based preventive maintenance. Reactive maintenance responds only after failures occur, leading to costly downtime, inefficiencies in resource utilization, and potential disruptions in power delivery. While preventive maintenance provides scheduled inspections and repairs, it often overlooks real-time operational conditions, leading either to excessive maintenance thus wasting resources or insufficient interventions, which leave hidden issues undetected. Most grid monitoring systems are either done by hand or only partly automated, which causes delays in finding problems, wrong assessments, and inefficiencies because these lack real-time data analysis and predictions based on the condition of the equipment. These issues create new challenges for traditional methods, which greatly affect power delivery systems by not being able to predict and address future problems or declines in equipment health. Unlike such typical systems, the study provides a novel predictive

maintenance architecture designed specifically for smart grid infrastructure that makes use of IoT and ML technologies. The key difference from the existing system is that it combines online sensor data collection, sophisticated raw data processing, and a decision-making mechanism for predicting equipment breakdowns in real time. In contrast, the proposed approach employs a vast network of IoT sensors strategically placed across the grid infrastructure, including transformers, circuit breakers, power lines, substations, and more. The sensors continuously capture vital operating data such as voltage, current, temperature, vibration, humidity, and other important equipment health indicators. The proposed system is built around cutting-edge machine learning algorithms for processing and predictive analytics in real-time data. These techniques use supervised learning models like RF, which are trained on historical data. The first step is to preprocess the raw datasets and real-time data gathered from IoT sensors using techniques such as data cleansing, normalization, and dimensionality reduction to improve their quality and the efficiency of the input dataset. The IoT-Enabled Predictive Maintenance Workflow for Smart Grids is illustrated in fig.1.

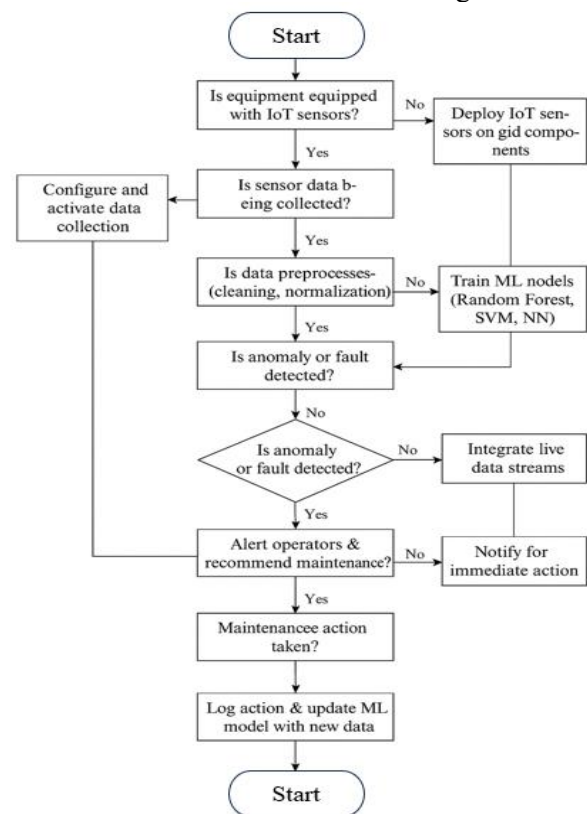


Fig.1. IoT-Enabled Predictive Maintenance Workflow for Smart Grids.

The processed data is then sent into ML algorithms, which discover anomalies, analyze conditions, and diagnose defects at an early stage. Collectively, the technique provides predictive, rather than reactive, insights into the health of essential components within these systems, resulting in better operational performance. Installing the proposed predictive maintenance system is the next step. The steps are as follows. In Phase One, IoT sensors are carefully installed across the grid's important components to provide complete data-collecting coverage. After sensors are placed, an IoT gateway collects sensor data and securely transmits it to a centralized cloud-based analytics platform, where it can be processed and analyzed in real time. The next stage is to train ML models using historical data to define baseline equipment behavior and performance thresholds. After training, these models will keep analyzing the incoming sensor data forever, spotting when things go wrong, detecting signs of possible failures, and predicting how long parts will last. The technique is accompanied by a simple real-time visualization dashboard that provides operators with actionable information as well as fast notifications and recommendations on when to schedule maintenance. Implementing an IoT-based predictive maintenance solution has numerous advantages. The method dramatically increases grid dependability by informing maintenance before breakdowns occur, avoiding costly interruptions caused by unanticipated downtime. The method greatly enhances the accuracy and speed of finding problems, enabling maintenance to be done based on the actual condition of the equipment instead of on a set schedule. These improvements reduce operational costs, distribute resources more effectively, and extend the lifespan of the drivetrain by enabling necessary actions to be taken before a major failure occurs. On top of that, powerful data analytics and machine learning improve decision-making quality, ensuring that the grid is maintained in a much smarter and more dynamic manner. As a result, the proposed system improves the overall infrastructure's performance and resilience while also significantly lowering operational risks, making it easier to meet the needs of modern smart grids.

#### *System Architecture Design:*

The predictive maintenance system architecture consists of multiple layers, including levels for analytics, data, communication, sensing, and visualizations. The sensing layer is made up of a large number of existing IoT-enabled sensors put on

various smart grid assets (such as power lines, transformers, and circuit breakers) that monitor operating parameters (voltage, current, temperature, vibration, and humidity) in real time. These sensors deliver data to an IoT gateway (or edge computing unit), which configures and filters it at the first level. This is followed by the authentic and secure transmission of data to the central cloud-based analytics platform via MQTT/HTTP. The architecture is tiered, allowing for low-latency communication within levels as well as modularization between layers. The second layer is the visualization layer, which provides real-time dashboards and alarms, while the cloud layer receives bulk data and does model inference. Its continuous observation, simplicity of integration in a real-world system, and scalable deployment in a broad grid network make it appropriate for dynamic and diverse smart grid systems.

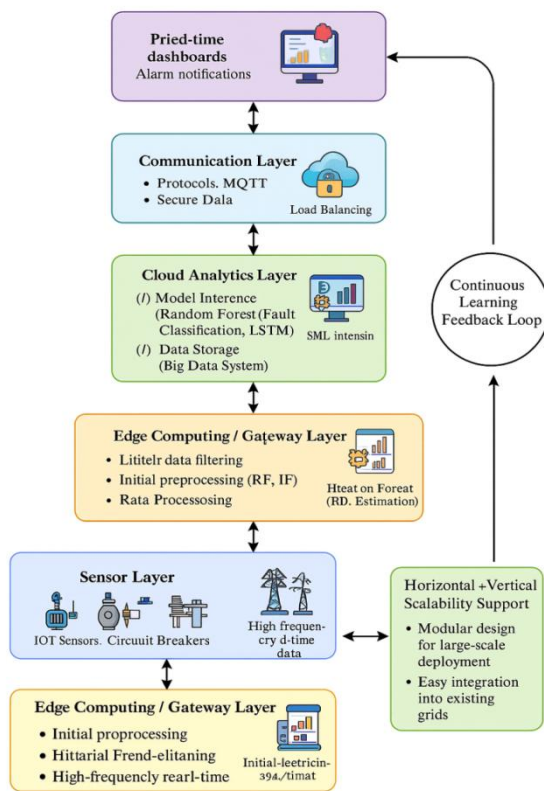
#### *Data Acquisition and Preprocessing:*

The sensor data is periodically monitored, and the encoded data is transferred to the cloud for preprocessing. Outliers are handled using Z-score filtering, missing values are interpolated, and a normalizer, Min-Max Scaling, is used to standardize disparate feature values. The temporal data is organized into structured sequences for time-series modeling. It uses a sliding window-based approach to partition data into temporal zones and identify trends depending on current behaviors. It also utilizes methods to extract valuable information from the data, subsequently incorporating it into an ML model to address these challenges. The process could include techniques like Principal Component Analysis (PCA) for dimension reduction, Fast Fourier Transform (FFT) for analyzing frequencies, and determining statistical variables like mean and standard deviation, among others. The next stage is to remove noise and duplicate data from the dataset and accurately depict the condition of grid assets for health trends, allowing predictive models to execute and learn more effectively.

#### *Fault Classification Using Random Forest:*

The RF method is used for fault classification because of its excellent accuracy, anti-overfitting performance, and ability to handle noisy and high-dimensional data. The preprocessed feature dataset is used to train the RF model, which allows each decision tree in the forest to vote on the class of input samples. The proposed system is trained using historical data (fault categories include overload,

overheat, and insulation failure). Given the sensor measurements, the model learns to distinguish between these patterns and correctly assigns a new test sample to one of the occurrence fault categories. RF ensemble nature allows for higher generalization and dependability across a range of operational situations. It also provides feature importance scores, which allow one to identify crucial parameters that lead to certain errors. In the deployment step, the previously trained classifier is used to identify real-time anomalies and classify them into fault types, allowing for maintenance based on fault type and severity. IoT-Integrated Multi-Layer Predictive Maintenance Architecture for Smart Grids is shown in fig.2.



Predictive Maintenance System  
 Fig.2. IoT-Integrated Multi-Layer Predictive Maintenance Architecture for Smart Grids.

**Anomaly Detection Using Isolation Forest:**  
 It employs the Isolation Forest method to discover anomalies in their early stages. Isolation Forest is unsupervised when compared to supervised models and performs better with data points that deviate from regular behavior. It builds trees in which anomalies can be isolated with fewer splits by randomly picking features and split values. It generates a model using past typical operating data

to determine what constitutes "healthy" behavior. Fresh sensor data is assessed during runtime, and examples with high anomaly scores are reviewed. It helps us to discover anomalous equipment degradation or malfunctions early, even if these do not correspond to previously identified defect types. Isolation Forest was chosen because it provides robustness against the high complexity of the sensor dataset, as well as speed and scalability, which are required for real-time edge-based anomaly detection in smart grids. Furthermore, its lightweight design makes it suitable for use in IoT gateways to provide speedy localized responses.

**RUL Estimation Using LSTM:**

It uses LSTM networks, a form of RNN ideal for time-series forecasting, to estimate the RUL of grid components. The LSTM approach is more suited for sensor data since it learns long-term dependencies and temporal patterns. The model is then trained on sequences of past sensor data annotated with the actual failure timestamp. In fact, it dynamically connects changes in key indicator patterns with corresponding time-to-failure. At inference time, an actual sequence is entered into the model, and the model output predicts when the component will fail. The estimation allows electricity providers to plan maintenance efforts more accurately and avoid unexpected failures. The architecture of LSTM includes memory cells and gating mechanisms to effectively preserve relevant patterns over long-time lags, resulting in precise and trustworthy estimates of equipment life in the field.

**Model Training and Validation:**

All ML models, including RF, Isolation Forest, and LSTM, are trained using a historical dataset split (usually 70% training, 30% testing). To adjust hyperparameters such as the number of estimators and tree depth in the RF instance, grid search is utilized. The ratio of anomalies is specified by tuning the contamination rate for Isolation Forest. The LSTM model is trained with the Adam optimizer and uses backpropagation through time (BPTT) along with the mean squared error (MSE) to measure errors. Dropout regularization and early halting were employed to avoid overfitting. Evaluate the robustness and generalization of the model using K-fold cross-validation. As assessment measures, it takes into account RMSE for RUL prediction, AUC for anomaly detection, and accuracy and F1-score for classification. The phase of validation prior to deploying a model to production requires making

sure it is operating reliably under various circumstances. For real-time inference, the proposed system serializes each trained model and makes them accessible on both the cloud and edge.

#### *Deployment and Real-Time Monitoring:*

The trained models are then integrated into a real-time monitoring system as the final phase. Sensor data streams are ingested by IoT gateways, which process them based on edge/cloud latency needs. RF classifiers and Isolation Forest models are deployed using lightweight Python-based inference servers, and RUL prediction using LSTMs is carried out in batches to control the GPU load of lengthy inference procedures. A monitoring dashboard that shows the current state of several components in terms of estimated RUL, anomaly scores, and fault kinds. Alerts are set off and automated reports are created to schedule maintenance tasks when the threshold values are exceeded. Grid operators receive notifications seamlessly as a result of connection with current SCADA systems. Because new data that can be labeled is periodically utilized to retrain models, causing the models to gradually adapt to the grid, the real-time loop enables these models to continue learning. It provides production deployment on actual smart grid systems, minimal SLAs, and both horizontal and vertical scalability.

```

BEGIN
  FOR each grid device IN smart_grid_devices DO
    Read voltage, current, temperature, vibration,
    humidity
    Send data to IoT Gateway
  END FOR
  FOR each data_point IN incoming_sensor_data DO
    Handle missing values (e.g., interpolate or
    discard)
    Remove outliers using Z-score filtering
    Normalize features using Min-Max Scaling
    Extract features (mean, std, FFT, etc.)
  END FOR
  anomaly_score =
  IsolationForest.predict(preprocessed_data)
  IF anomaly_score > threshold THEN
    Flag data_point as anomalous
    Alert maintenance team
  END IF
  fault_type =
  RandomForestClassifier.predict(preprocessed_data)
  Log fault_type and affected device
  time_series_input = CreateSequence(window_size,
  preprocessed_data)

```

```

RUL_estimate =
LSTM_Model.predict(time_series_input)
Log RUL_estimate
Update dashboard with:
  - Anomaly status
  - Fault classification
  - RUL estimate
IF RUL_estimate < warning_threshold THEN
  Schedule preventive maintenance
END IF
IF new failure data available THEN
  Label data
  Retrain Random Forest, Isolation Forest, and
  LSTM models
  Update deployed models
END IF
END

```

The IoT and ML are integrated into the predictive maintenance pseudocode flow. The technique uses the grid devices sensor, Satan, pre-processes pudding for analysis, uses Isolation Forest to find anomalous conventions, uses RF to categorize errors, and proposes RUL using LSTM. RUL the components of the technique detail. The dashboard displays the results, and it continuously modifies the models as it receives fresh failure data.

In summary, using ML and the IoT to do predictive maintenance on smart grid infrastructure offers a powerful way to monitor equipment in real time and facilitate early issue diagnosis. A key component of the path toward more intelligent, resilient energy networks, the technology increases equipment life, reduces maintenance costs, and improves grid dependability through the use of automated diagnostics and advanced analytics.

## IV. RESULTS AND DISCUSSION

The section on results and analysis compares the performance of the proposed fault detection system with the existing systems in use. The analysis incorporates several important metrics, such as mean time to repair, component-wise fault, and detection accuracy. The comparative results demonstrate the proposed system advantages, quick response times, and dependability for predictive fault management and smart grid maintenance.

*Table 1 Comparison of Fault Detection Accuracy*

Maintenance Strategy	Accuracy (%)	Precision (%)	Recall (%)
Y. K. Teoh et al.[8]	45.2	40.5	39.8
S. Elkateb et al. [9]	68.7	65.4	62.1
Proposed System	92.6	90.8	91.2

Table I compares the performance of all maintenance procedures in terms of fault detection. The existing system [8] and [9] showed relatively low accuracy rates of 45.2% and 69.7%, and the unreliability in fault detection was backed up by the matching precision and recall values. However, the proposed system greatly outperforms the existing systems with an accuracy of 92.6% and precision and recall of 90.8% and 91.2%, respectively. Overall, it shows how useful the proposed system is for efficiently identifying and diagnosing issues, which will also improve the analytical tool's sustainability and productivity in smart grid maintenance. Visual graph for Comparison of Fault Detection Accuracy is shown in fig.3.

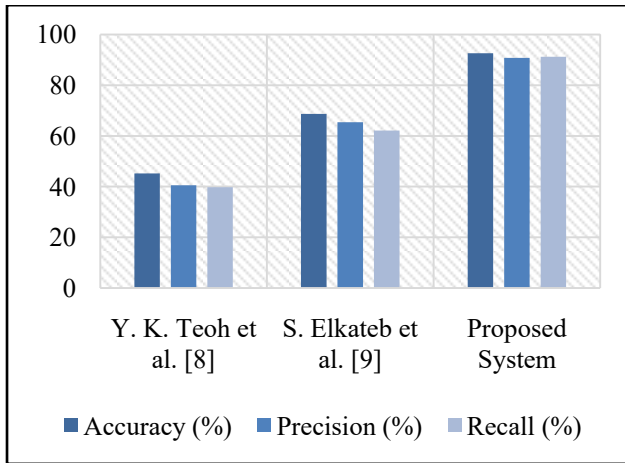


Fig.3. Visual graph for Comparison of Fault Detection Accuracy.

*Table 2 Fault Detection Accuracy (%)*

System	Transformer Faults	Circuit Breaker Faults	Overall Accuracy
Y. K. Teoh et al.[8]	62.3	58.9	60.6
S. Elkateb et al. [9]	74.5	70.1	72.3
Proposed System	91.7	88.4	90.0

Table II compares the accuracy of fault detection for both transformer and circuit breaker problems

between the proposed system and the existing system [8] and [9]. The existing system provides moderate results for performance, with overall detection rates of 60.6% and 72.3%, respectively. With an accuracy of 90.0% overall, 91.7% for transformer problems, and 88.4% for circuit breaker faults, the proposed system performed better than theirs. The significant enhancement highlights the potential of the proposed system as a substitute for predictive maintenance to prevent inaccurate fault categorization in smart grid components.

*Table 3 Average Downtime per Failure (in Hours)*

System	Transformer Downtime	CB Downtime	Total Downtime
Y. K. Teoh et al.[8]	8.2	6.7	7.5
S. Elkateb et al. [9]	5.3	4.9	5.1
Proposed System	2.1	1.8	1.9

Table III compares the average downtime per failure (hours) for the systems' CBs (circuit breakers) and transformers. Average downtimes for DTU's existing system [8] and [9] are 5.1 and 7.5 hours, respectively. In particular, the CB downtime is 6.7 and 4.9 hours, while the transformer downtime is 8.2 and 5.3 hours. The proposed system, in contrast, records increased efficiency while transformers and CBs go down for 2.1 and 1.8 hours, respectively, resulting in an average total downtime of 1.9 hours, demonstrating its quick fault resolution capability.

The proposed predictive maintenance architecture, which combines IoT sensors and ML analytics, has great potential for asset management and smart grid problem identification. It transforms the focus from reactive or scheduled interventions to on-demand, real-time condition monitoring and maintenance, rather than just scheduling or reacting when something fails. ML models will reliably identify the type of defect, detect anomalies at an early stage, and forecast the component's lifetime, allowing for more prompt and informed decision-making. It improves grid dependability and lowers the danger of unexpected equipment malfunctions. Substations, transformers, circuit breakers, and other critical infrastructure components can effectively utilize the system. In contrast, it can assist utilities in prioritizing maintenance, automating diagnostics, and, eventually, extending asset life. In addition, its interaction with alarm systems and dashboards

ensures that grid operators obtain actionable insights on time. The technique has many advantages, including accurate maintenance, reduced downtime, greater resource usage, and fewer operational expenses. The ability to grow does not come without a cost, as large networks can be expensive unless these have a flexible and modular architecture that allows for mass adoption. It also enables the system to respond to changing grid circumstances as a result of learning from both historical and streaming data. The technique prevents predictive and data-driven intelligence from totally dominating smart grid maintenance.

## V. CONCLUSION

In conclusion, IoT and ML-based predictive maintenance solutions provide a game-changing technique for strengthening the smart grid infrastructure, making it more resilient, efficient, and dependable. The proposed system of continuous surveillance, instant troubleshooting, and data-driven decisions significantly improves fault management, reducing downtime, optimizing resource use, and providing uninterrupted service while overcoming critical limitations of traditional asset maintenance. However, a few more system limitations limit its encouraging outcomes. For smaller utilities, the expense and complexity of setting up extensive IoT sensor networks can be a barrier. Second, the accuracy of sales estimates depends on the available historical information, which may not always be comprehensive. Third, it requires a lot of processing power to carry out continuous model adaptation and real-time model retraining, and in contexts with restricted resources, it may experience latency issues. Working on transfer learning to adapt knowledge from similar or different tasks to boost respective model performance under such data-scarce scenarios, integrating cybersecurity approaches to protect sensor data and communication from tampering or intrusion, and integrating edge AI to reduce dependency (cloud usage) and latency are all examples of future work. These enhancements will help enable autonomous and intelligent operations for grid maintenance by strengthening the system's robustness, scalability, and adaptability to a range of smart grid environments.

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