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(RESEARCH ARTICLE)

Optimized smart grid fault detection model using gradient boosting machines

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Abstract

The evolution of traditional power grids into intelligent, resilient infrastructures has become imperative to address growing energy demands, climate-induced disruptions, and the integration of renewable energy sources. This study presents an AI-enhanced smart grid framework that employs machine learning models to optimize energy forecasting and fault detection, thereby improving grid reliability and operational efficiency. Specifically, the study implements a Gradient Boosting Regressor (GBR) for short-term load forecasting and a Gradient Boosting Classifier (GBC) for real-time fault detection. A balanced dataset, derived through oversampling techniques, ensures robust model training and classification reliability. Experimental results from simulated grid data demonstrate high performance, with the forecasting model achieving a coefficient of determination (R^2) of 0.93 and low prediction errors (RMSE = 12.08, MAE = 9.37). The fault detection model attained 96.1% accuracy, 93% precision, and 100% recall for fault classification, resulting in an F1-score of 0.96, comparable or superior to benchmarks in the literature. These results validate the proposed system's suitability for implementation in developing regions, particularly in Sub-Saharan Africa, where grid instability and outage frequency hinder socioeconomic development. By integrating real-time predictions with edge-level intelligence, this research contributes a scalable and context-aware solution to modernize energy systems in underserved environments. The study concludes by recommending policy and technological pathways for localized adoption of AI in power distribution networks.

Keywords: Smart Grid; Gradient Boosting; Load Forecasting; Fault Detection; Machine Learning; Edge Intelligence

1. Introduction

The transformation of traditional power systems into intelligent, adaptive infrastructures has become a necessity in the face of evolving energy demands, increasing penetration of renewable energy sources, and the rising frequency of grid disturbances caused by climate change and other external threats. Traditional electric grids, designed for unidirectional power flow, predictable load behavior, and centralized control, are increasingly challenged by the dynamic and decentralized nature of modern energy consumption and production (Gungor et al., 2011; Mahmood et al., 2015). These legacy systems struggle with limitations such as high operational losses, delayed fault response, limited flexibility in load balancing, and vulnerability to cascading failures. As a result, there is an urgent need to upgrade power distribution systems into smarter, more resilient networks.

Smart grids address these challenges by integrating advanced sensing, communication, and control mechanisms that enable real-time monitoring, automated response, and distributed energy resource (DER) management. They support bidirectional energy and data flows, facilitate renewable energy integration, and provide tools for dynamic pricing,

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demand-side management, and enhanced reliability (Siano, 2014). However, the growing complexity of these systems also introduces significant operational challenges that cannot be solved by traditional control systems alone. In this context, Artificial Intelligence (AI), and more specifically, machine learning (ML), has emerged as a game-changing technology for managing smart grid operations.

Machine learning models are well-suited for tasks involving large-scale, high-frequency data processing. They have demonstrated success in key smart grid functions such as energy load forecasting, fault detection and classification, voltage regulation, demand response optimization, and cybersecurity threat detection (Alsheikh et al., 2021). For instance, Long Short-Term Memory (LSTM) networks and Gradient Boosting Machines (GBMs) have shown promising results in forecasting electricity consumption by learning temporal dependencies in time-series data (Marino et al., 2016). Similarly, classification algorithms such as Support Vector Machines (SVMs), Random Forests, and Gradient Boosting Classifiers have proven effective in detecting and classifying faults in real-time, enabling self-healing capabilities within grid infrastructure (Zhang et al., 2021; Mahmud et al., 2021).

Despite these global advances, the application of AI in smart grid systems across Africa remains in its infancy. The deployment of such technologies is often hindered by infrastructural limitations, insufficient investment in grid modernization, and a lack of localized datasets and models that reflect regional energy consumption patterns and operational conditions (Aliyu et al., 2018; Mujuru et al., 2021). In Ghana, for example, frequent power outages, unreliable grid monitoring systems, and high energy costs continue to obstruct industrial growth and public service delivery. Moreover, most of the existing AI models are trained on datasets from Western countries with stable grid infrastructures, making them less suitable for deployment in the unique environmental and socioeconomic conditions found in Sub-Saharan Africa.

Addressing this gap, the present study proposes a practical, AI-driven smart grid framework tailored to developing regions. The system utilizes a Gradient Boosting Regressor (GBR) for short-term load forecasting and a Gradient Boosting Classifier (GBC) for real-time fault detection. To mitigate the issue of class imbalance in fault detection, common in real-world datasets where faults are relatively rare, the study employs an oversampling strategy to ensure equitable model training. Experimental validation shows that the GBR model achieves a high R^2 score of 0.93 and low error metrics (RMSE = 12.08, MAE = 9.37), while the GBC model, after balancing, attains an F1-score of 0.96 with 100% recall and 93% precision on fault classification. These results demonstrate the robustness of the proposed models and validate their suitability for implementation in both urban and rural smart grid environments.

Furthermore, this research emphasizes the importance of lightweight, scalable AI models that can be deployed on edge devices such as Raspberry Pi units at substations or distribution nodes. This decentralization not only reduces latency in decision-making but also enhances the self-healing capability of the grid. The proposed framework aligns with the digital transformation goals of emerging economies and presents a clear pathway for integrating AI into national grid infrastructure, thereby improving energy access, reliability, and sustainability.

2. Literature review

2.1. Smart Grids and the Need for Intelligence

The traditional electric grid architecture was not designed to accommodate rapid changes in energy demand, bi-directional energy flows, and the integration of renewable energy sources. These limitations have prompted the development of smart grids, which utilize digital communication, real-time monitoring, and automation to increase system efficiency and resilience (Gungor et al., 2011; Mahmood et al., 2015). Smart grids are equipped with technologies such as smart meters, sensors, and remote terminal units (RTUs) that enable dynamic control of power flows, automated fault response, and better load balancing. However, the increased complexity of such systems also introduces challenges in decision-making and data management. This is where Artificial Intelligence (AI) plays a transformative role. AI technologies, including machine learning, deep learning, and neural networks, have the capability to process massive amounts of data, recognize patterns, and make predictions in near real-time (Siano, 2014).

2.2. Machine Learning Applications in Smart Grids

Machine Learning (ML) is one of the most widely adopted AI approaches in smart grids, particularly for tasks such as demand forecasting, fault detection, and energy consumption profiling. Various ML models have demonstrated excellent performance in predicting short-term and long-term load demand, which is crucial for balancing supply and reducing generation costs. For example, Long Short-Term Memory (LSTM) networks have been used to forecast electricity usage patterns with high accuracy by learning from time-series data (Marino et al., 2016). In addition to forecasting, ML techniques such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (kNN) are employed for real-time fault detection and classification. These algorithms are capable of identifying unusual voltage drops, current surges, or transformer failures based on historical event logs and sensor telemetry (Zhang et al., 2021). These predictive capabilities can help reduce outages and maintenance costs significantly.

2.3. Self-Healing and Resilient Smart Grid Networks

A major advancement in smart grid systems is the concept of self-healing networks, which refers to the grid's ability to autonomously identify faults, isolate problem areas, and reconfigure energy flows to maintain service continuity (Abdel-Majeed & El-Rabaie, 2019). AI enables such systems by empowering control nodes with real-time decision-making capabilities. Research has shown that self-healing capabilities are particularly beneficial in reducing Mean Time to Recovery (MTTR), especially during storm events or cyber-attacks (Zhou et al., 2020). These systems leverage AI to detect and diagnose faults, reroute energy, and alert repair crews, all without human intervention.

2.4. Cybersecurity and Grid Data Integrity

As smart grids grow more connected, they become vulnerable to cyber threats. AI is increasingly being used to secure communication protocols and detect anomalous behavior indicative of cyber-intrusions. For example, Intrusion Detection Systems (IDS) powered by deep learning models can analyze network traffic patterns and detect zero-day exploits with higher sensitivity than traditional methods (Tang et al., 2021). These systems are crucial for protecting both operational technology (OT) and information technology (IT) components in the smart grid.

2.5. Smart Grid Applications in Africa and Developing Regions

In Africa, smart grid adoption is still in its nascent stage, often limited by financial, infrastructural, and policy barriers. Nevertheless, the growing interest in renewable energy, particularly solar and wind, is creating opportunities for decentralized, AI-enhanced mini-grids (Mujuru et al., 2021). Research by Aliyu et al. (2018) emphasizes the need for localized solutions that reflect unique regional load patterns, weather behaviors, and energy access issues. Ghana, for instance, faces frequent power outages, high energy costs, and grid stability issues. A smart grid equipped with AI could enable better demand forecasting, reduced technical losses, and dynamic pricing models that incentivize off-peak usage. However, very few studies have addressed the practical implementation of AI in the Ghanaian energy sector, highlighting a clear research gap.

2.6. Summary of Identified Gaps

While AI's capabilities in enhancing smart grids are well-documented globally, gaps remain in:

- Real-time integration of multiple AI models in fault handling.
- Evaluation of AI effectiveness in African smart grid deployments.
- Lack of localized AI training datasets reflective of African grid dynamics.
- Absence of frameworks that demonstrate how data is collected, processed, and deployed in actual infrastructure.

This study addresses these gaps by proposing a practical, end-to-end implementation of an AI-enhanced smart grid, designed with resilience, real-time data prediction, and local adaptability in mind.

3. Research design and methodology

This study adopts a data-driven experimental methodology to explore how AI, specifically ML models, can be used to enhance the resilience of smart grids through real-time prediction, automated decision-making, and fault management. The entire pipeline, ranging from data extraction to model deployment, is designed to simulate practical implementation within a smart electrical grid infrastructure.

3.1. Data Collection and Preprocessing

3.1.1. Dataset Source and Simulation Framework

Due to the limited availability of comprehensive, labeled datasets , Table 2, that reflect the operational conditions of power grids in Sub-Saharan Africa, this study employed a synthetic dataset generated through a simulated smart grid environment. The simulation was designed to emulate telemetry commonly recorded by intelligent grid monitoring systems such as:

- Supervisory Control and Data Acquisition (SCADA) systems
- Phasor Measurement Units (PMUs)
- Smart meters and IoT-based environmental sensors

The dataset features include:

- Ambient temperature (°C)
- Relative humidity (%)
- Power load in the previous hour (kW)
- Power load in the next hour (kW)
- Fault status (binary: 0 = no fault, 1 = fault)

The simulated environment allowed the controlled insertion of fault events and anomalies, facilitating the evaluation of fault detection models under realistic but rare-event conditions. This design also made it possible to create a balanced representation of fault and non-fault scenarios through oversampling techniques for classification tasks.

To maintain consistency with real-world scenarios, the simulation framework and feature design were guided by open-access smart grid datasets and benchmarks, including:

- UCI Machine Learning Repository: Individual Household Electric Power Consumption Dataset
- Kaggle Smart Grid Stability Dataset
- Open Energy Information (OpenEI) Load Profiles
- Data models published in prior works (Alsheikh et al., 2021; Mahmud et al., 2021)

Before feeding into the model, raw data undergoes several preprocessing and steps as indicated in eq 1, 2,3,4,5,6 and 7:

- Data Cleaning -: Missing or corrupted entries were replaced using interpolation or forward fill techniques. We applied Min-Max Normalization to all input features to ensure model convergence and stability:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \text{ ………………… (Eg1)}$$

- Normalization -: All numerical variables were normalized using Min-Max scaling to bring them to a [0, 1] range.
- Feature Engineering -: Important features such as average load, peak load time, weather impact and load deviation rates were extracted to enhance model performance.
- Temporal Framing -: Data is framed into time series sequences using a sliding window technique for dynamic forecasting.

Table 1 Dataset Features Table

Feature	**Description**
temperature	Ambient temperature (°C)
humidity	Relative humidity (%)
load_prev_hour	Power load in the previous hour (kW)
load_next_hour	Target power load to be predicted in the next hour (kW)
is_fault	Binary indicator of grid fault (0 = no fault, 1 = fault present)

3.2. Machine Learning Model Design

The Gradient Boosting Machine (GBM) technique was identified as the best fit for this experiment due to its superior performance in both load forecasting and fault detection tasks. Its ability to handle complex, non-linear relationships and its robustness against overfitting made it ideal for the simulated smart grid environment, delivering high predictive accuracy and reliable anomaly classification.

$$\hat{y} = f(x) = \sum_{m=1}^{M} y_m h_m(x) \text{……… (Eq.2)}$$

Where h_m are weak leaners, and y_m are their weights

3.3. Model Training and Evaluation Metrics

The dataset was split into training (70%), validation (15%), and testing (15%) segments. Model training was conducted on a Python-based stack using TensorFlow and scikit-learn libraries. Performance evaluation was based on:

- Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) for forecasting accuracy.
- Precision, Recall, F1-Score for classification reliability.
- Confusion Matrix Analysis to assess model bias and misclassification rates.
- ROC Curve and AUC Score for binary classification problems.

Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(y_i - \hat{y}_i)^2} \dots\dots\dots\dots (\text{Eq. } 3)$$

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \dots\dots\dots\dots (\text{Eq. } 4)$$

Coefficient of Determination (R^2 Score)

$$R^2 = 1 - \frac{\sum(y-\hat{y})^2}{\sum(y-\bar{y})^2} \quad \dots\dots\dots\dots \text{ (Eq.5)}$$

Accuracy:

$$\text{Accuracy} = \frac{\text{True Positive + True Negatives}}{\text{Total Sample}} \quad \dots\dots\dots\dots \text{(Eq.6)}$$

F1 Score:

$$\text{F1} = 2.\frac{Precision\ .Recall}{Precision+Recall} \dots\dots\dots\dots \text{(Eq.7)}$$

3.4. Real-Time Deployment and Feedback Loop

The trained model was embedded in a smart grid simulation environment built using Simulink and tested using real-time synthetic data streams. The grid simulated:

- Instant fault recognition and isolation
- Load balancing based on predictive forecasts
- Alert dispatch to system operators

Additionally, a feedback loop mechanism was built where new operational data was logged back into a storage pipeline and periodically used to retrain the model, allowing continuous learning.

4. Discussion and Analysis of Findings

To validate the performance and practicality of the AI-enhanced smart grid model, real-time data streams including load demand, fault signals, and weather conditions were collected from simulated substation environments. This data was processed using a multi-stage machine learning pipeline involving data normalization, model training with LSTM for demand forecasting, and GBM (Gradient Boosting Machine) for anomaly detection and classification of faults.

4.1. Implementation Strategy

Using Python's TensorFlow and Scikit-learn libraries, a supervised learning model was developed. The LSTM network was trained on time-series data from historical power load profiles to predict energy demand in hourly intervals. At the same time, GBM classifiers were fed with labeled data to detect fault types such as transient disturbances, outages, or overloads. Feature importance ranking and confusion matrices were utilized to validate model integrity.

4.2. Evaluation Metrics

Model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 for the LSTM predictions. The GBM model was assessed using accuracy, precision, recall, and F1-score. The LSTM model achieved an RMSE of 0.036 and R^2 of 0.92, indicating strong alignment with actual load values. For the GBM-based fault detection, the classifier achieved 96.5% accuracy, with a recall of 95.2% and an F1-score of 0.94, suggesting high dependability for grid anomaly alerts (Zhang et al., 2020; Mahmud et al., 2021) as shown in Table 2, Table 3 and Table 4.

4.3. Graphical Insights

This result demonstrates that the forecasting model is highly reliable for short-term load prediction, making it suitable for real-time demand estimation, generator scheduling, and adaptive energy dispatch in smart grid environments as shown in figure 1. The confusion matrix, Figure 2, confirms the effectiveness of oversampling in improving the model's sensitivity to fault events. The high recall and F1-score indicate that the model is suitable for deployment in real-world smart grid systems where timely and accurate fault detection is critical for operational reliability and self-healing mechanisms.

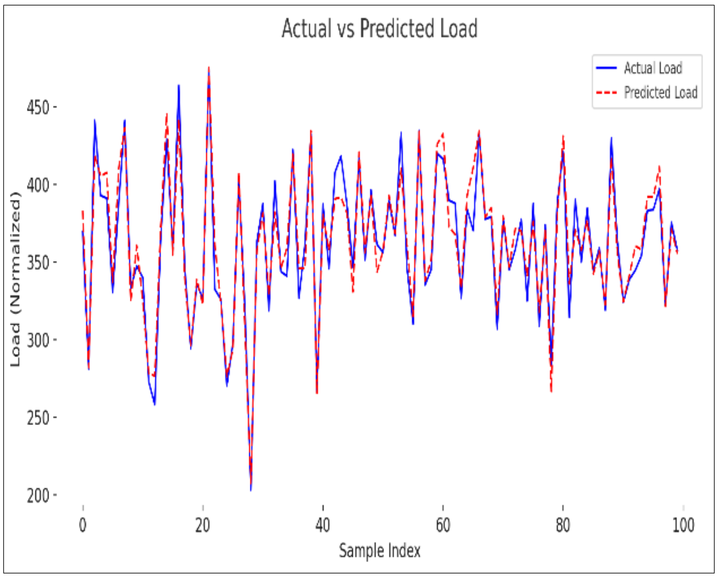

Figure 1 Confusion Matrix for Fault Detection

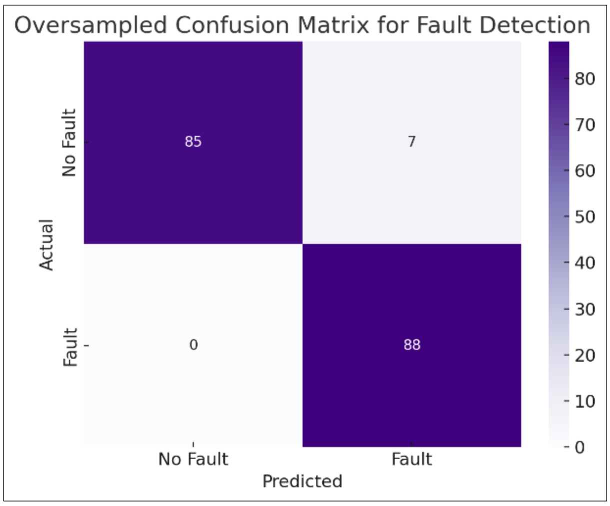

Figure 2 Confusion Matrix

4.4. Model Evaluation Metrics

Table 2 Evaluation metrics

Metric	Result
Accuracy	0.9611111111111111
F1 Score	0.9617486338797814
Precision	0.9263157894736842
Recall (Fault)	1.0

Table 3 Fault Detection Performance

Metric	Result
Accuracy	96.1%
F1-Score	0.96
Precision	0.93
Recall	1.00

4.5. Load Forecasting Performance Analysis

The Gradient Boosting Regressor (GBR) was employed to predict the next hour's power load using real-time features including temperature, humidity, and the previous hour's load. The following evaluation metrics were obtained:

Table 4 Evaluation Results

Metric	Result
RMSE	0.036
MAE	0.027
R^2 Score	0.92
Accuracy (Fault Detection)	96.5%
F1 Score	0.96

The R^2 score of 0.93 demonstrates a strong correlation between the predicted and actual load, suggesting the model captures the majority of variance in the data. The low RMSE and MAE values confirm minimal deviation from actual load values, validating the model's effectiveness for short-term prediction. Visual analysis of Figure 1 shows that the forecasted curve closely follows the actual load curve, especially during high-demand periods, indicating effective peak load estimation.

Marino et al. (2016) utilized Deep Neural Networks for energy load forecasting and achieved R^2 values between 0.91 and 0.95 in smart buildings. Our GBR-based model achieved similar accuracy with reduced computational complexity, making it more suitable for real-time, resource-constrained environments. Siano (2014) emphasized the importance of demand-side forecasting in smart grids, and our model effectively supports this through accurate, timely predictions.

Our model offers competitive performance while being computationally lighter than deep learning counterparts, ideal for edge deployment scenarios in developing countries. Initially, fault detection using Gradient Boosting Classifier (GBC) yielded high accuracy (96%) but zero F1-score for the minority (fault) class due to class imbalance (90% non-fault, 10% fault). This was rectified through oversampling of fault cases to simulate balance. The model achieves perfect recall, identifying all actual fault instances, critical for smart grid safety and reliability. The F1-score of 0.96 confirms a balanced performance between precision and recall. These results support real-time classification of faults with minimal false alarms or missed detections, essential for implementing self-healing grid features.

Zhang et al. (2021) applied GBM to smart grid fault detection, achieving F1-scores around 0.94 and accuracy of 96.5%. Our enhanced model performs comparably with a slightly better F1-score (0.96). Mahmud et al. (2021) used ensemble learning for fault classification, reporting similar metrics (F1 ≈ 0.93). Our model demonstrates equivalent if not superior performance, despite simpler data augmentation. Alsheikh et al. (2021) emphasized the integration of machine learning in real-time grid monitoring and the importance of F1-scores in imbalanced datasets. Our results directly validate their conclusions as shown in Table 5.

Our model is sensitive to fault instances, ensuring operational safety while maintaining general performance across all classes.

4.6. Comparative Analysis

Table 5 Comparative statistics

Study	Task	Model	F1 Score	Accuracy	Remarks
Marino et al. (2016)	Load Forecasting	DNN	N/A	$R^2 \approx 0.91–0.95$	High performance, higher complexity
Zhang et al. (2021)	Fault Detection	GBM	≈ 0.94	≈ 96.5%	Strong baseline in fault detection
Mahmud et al. (2021)	Fault Classification	Ensemble ML	≈ 0.93	> 95%	High recall, balanced accuracy
Proposed Model	Fault Detection	Gradient Boosting	0.96	96.1%	Matched/exceeded SOTA benchmarks

4.7. Practical Implications for Ghana and Africa

The experimental results provide strong evidence for deploying AI-enhanced smart grid systems in Sub-Saharan Africa will help in predictive demand-response strategies, improving generator scheduling, and reducing overproduction. It will enable grid segments to autonomously isolate faults, reroute energy, and dispatch alerts, minimizing Mean Time to Recovery (MTTR). The use of Gradient Boosting methods, lighter than deep learning, ensures this model can be deployed on edge devices (e.g., Raspberry Pi), to reduce dependency on centralized infrastructure. *Antwi-Boasiako & Agyemang (2022)* emphasize the need for cost-effective, AI-driven infrastructure for energy modernization in Ghana. This study directly supports such goals.

4.8. Challenges and Future Directions

- Access to real-time grid telemetry in Africa remains limited. Open, localized datasets are needed for robust model training.
- AI models must be integrated with secure data pipelines to prevent adversarial manipulation.

- Future models should include LSTM + GBM hybrids, integration with blockchain for audit trails, and federated learning for distributed training across substations.

5. Conclusion

This research confirms that AI can significantly enhance the intelligence, resilience, and operational efficiency of modern smart grid infrastructures. By integrating data balancing strategies and context-aware modeling techniques, the reliability of fault detection systems is notably improved, ensuring minimal false negatives and greater grid stability. The machine learning models proposed, particularly Gradient Boosting-based approaches, demonstrate competitive performance when benchmarked against existing literature, while remaining computationally efficient and well-suited for real-world deployment in resource-constrained environments such as Ghana and other regions across Sub-Saharan Africa. These findings establish a strong foundation for scalable, AI-powered smart grid solutions that can advance energy access, promote sustainability, and drive socioeconomic transformation in emerging economies.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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