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INTEGRATING GRAPH NEURAL NETWORK (GNN)–ENABLED INTERNET OF THINGS (IOT) FRAMEWORK TECHNOLOGIES FOR POWER GRID COLLAPSE PREDICTION

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Abstract: Frequent power outages in Nigeria have led to big economic problems and a lack of reliable electricity. Old systems that monitor the power grid use simple alarms and don't predict problems ahead of time, which makes it hard to stop big failures from happening. This study introduces a new method that uses a Graph Neural Network with the Internet of Things (called GNN–IoT) to predict when power grid failures might occur. The power grid is shown as a graph, where places like substations, transformers, and power plants are points, and the lines connecting them are edges. Sensors connected to the internet provide real–time information about voltage, current, and frequency to understand how the grid behaves over time and space. A mix of GNN and LSTM models were trained using past data and were compared with other models like Random Forest, SVM, and MLP. The new method achieved high results with 94.2% accuracy, 93.5% recall, and an AUC of 0.96, which is better than the other models. The system can give early warnings up to 25 to 35 minutes before a failure happens, helping officials take action and plan maintenance better. This new GNN–IoT system improves the reliability of the power grid, offers long–term predictions, and helps Nigeria build a smarter, more modern power system.

Keywords: Graph Neural Networks, Internet of Things, Smart Grid, Power Grid Collapse Prediction, Early Warning Systems

INTRODUCTION

The stability and reliability of electric power systems remain critical concerns globally, particularly in developing countries such as Nigeria, where frequent grid collapses and power outages persist. These disruptions have severe socio-economic consequences, including reduced industrial productivity, financial losses, and diminished investor confidence. According to recent studies, power system instability in emerging economies is largely attributed to aging infrastructure, inadequate maintenance, poor load management, and increasing demand-supply imbalance (Adebayo et al., 2022). In Nigeria specifically, the national grid has experienced recurrent partial and total collapses, highlighting the urgent need for advanced predictive and monitoring solutions.

Traditional grid monitoring systems, such as Supervisory Control and Data Acquisition (SCADA), provide limited visibility and are largely reactive in nature. These systems rely on threshold-based alarms and lack the capability to capture complex spatial and temporal dependencies within modern power networks (Omitaomu, et al., 2021). Consequently, they are insufficient for early fault detection or proactive decision-making, especially in highly interconnected and dynamic grid environments.

Recent advancements in artificial intelligence (AI) and data-driven techniques have introduced more robust approaches to power system analysis. Machine learning and deep learning models have demonstrated improved performance in forecasting and anomaly detection tasks. However, conventional models such as Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) often treat power system data as independent observations, thereby neglecting the inherent network structure of the grid (Wang et al., 2022). This limitation reduces their effectiveness in capturing cascading failures and interdependencies among grid components.

Graph Neural Networks (GNNs) have emerged as a powerful paradigm for modeling complex systems with relational structures. By representing the power grid as a graph where nodes correspond to substations or generators and edges represent transmission lines GNNs can effectively learn spatial dependencies and propagation patterns of disturbances across the network (Wu et al., 2021). Furthermore, when integrated with temporal models such as Long Short-Term Memory (LSTM) networks, GNN-based frameworks can simultaneously capture both spatial and temporal dynamics, enabling more accurate prediction of grid instability events (Kirmani et al., 2023).

In parallel, the proliferation of Internet of Things (IoT) technologies has significantly enhanced real-

time data acquisition in smart grid systems. IoT-enabled devices, including smart meters, Phasor Measurement Units (PMUs), and wireless sensors, continuously monitor key electrical parameters such as voltage, frequency, and load demand. This high-resolution data stream provides a strong foundation for advanced predictive analytics and intelligent grid management (Abir, et al., 2021). The integration of IoT with AI-driven models facilitates real-time situational awareness and enables early warning systems capable of mitigating large-scale failures.

Despite these technological advancements, the application of integrated GNN-IoT frameworks in developing power systems remains limited. Challenges such as inadequate communication infrastructure, data sparsity, cybersecurity risks, and high implementation costs hinder large-scale deployment (Olowu et al., 2024). Moreover, most existing studies focus on well-developed power grids with abundant data resources, leaving a research gap in the context of fragile and under-instrumented networks like Nigeria's.

To address these challenges, this study proposes a hybrid framework that integrates Graph Neural Networks with IoT-based data acquisition for power grid collapse prediction. The approach leverages the structural representation of the grid and real-time sensor data to enhance predictive accuracy and provide early warning signals. By focusing on the Nigerian power system, this research contributes to bridging the gap between advanced AI techniques and their practical application in developing energy infrastructures.

RELATED WORK

The reliability and stability of modern power systems have attracted significant research attention, particularly with the increasing complexity of interconnected grids and the integration of renewable energy sources. Traditional analytical approaches such as contingency analysis and load flow studies have long been used to assess system stability. However, these methods are limited in their ability to handle large-scale, dynamic, and data-intensive environments. As a result, recent studies have increasingly focused on data-driven techniques that leverage artificial intelligence and advanced computational models to improve predictive capabilities.

Classical Machine Learning Approaches

Classical machine learning techniques have been widely applied to power system monitoring and fault prediction tasks. Methods such as Support Vector Machines (SVM), Decision Trees, and Random Forests have demonstrated effectiveness in classification and regression problems related to grid stability. For instance, Mosavi et al. (2021) highlighted the application of machine learning

models in energy systems, emphasizing their ability to handle nonlinear relationships and improve prediction accuracy. Similarly, Ahmad et al. (2022) explored machine learning-based fault detection techniques and showed that ensemble methods can improve robustness in noisy environments.

Despite these advantages, traditional machine learning models rely heavily on handcrafted feature extraction and often assume independence among input variables. This assumption limits their ability to capture the inherent interconnections within power grids, where system components are highly dependent on each other. Furthermore, most classical approaches lack the capability to model temporal dependencies effectively, making them less suitable for real-time prediction in dynamic grid conditions.

Deep Learning in Power System Prediction

Deep learning techniques have significantly advanced the field of power system analytics by enabling automatic feature extraction and improved modeling of nonlinear relationships. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been widely used for load forecasting, fault detection, and stability analysis due to their ability to capture temporal dependencies. According to Wen et al. (2021), LSTM-based models outperform traditional methods in short-term load forecasting by effectively learning sequential patterns in power consumption data.

Convolutional Neural Networks (CNNs) have also been applied to power system monitoring, particularly in fault classification and pattern recognition tasks. However, CNNs are primarily designed for grid-like data structures and may not perform optimally when dealing with irregular network topologies such as power grids. As noted by Liu et al. (2022), the inability of CNNs to fully capture complex network relationships limits their applicability in modeling large-scale interconnected systems.

Graph Neural Networks for Power Systems

Graph Neural Networks (GNNs) have emerged as a promising approach for addressing the limitations of traditional and deep learning models in power system applications. By representing the power grid as a graph, GNNs can naturally model the spatial dependencies between nodes (e.g., substations and generators) and edges (transmission lines). This capability enables more accurate analysis of system behavior and fault propagation.

Recent studies have demonstrated the effectiveness of GNNs in power system stability assessment and fault prediction. For example, Donon et al. (2021) introduced a graph-based learning approach for power grid modeling and showed that GNNs outperform conventional

methods in capturing network interactions. Similarly, He et al. (2022) applied graph convolutional networks to power system stability prediction and reported improved accuracy compared to traditional machine learning models. Moreover, spatio-temporal graph neural networks (ST-GNNs) have been developed to incorporate both spatial and temporal information. These models combine graph-based learning with sequence modeling techniques, enabling them to capture dynamic changes in the grid over time. Such approaches are particularly useful for detecting cascading failures and predicting system instability in real-time environments.

■ IoT-Enabled Smart Grid Monitoring

The integration of Internet of Things (IoT) technologies into power systems has transformed traditional grids into intelligent, data-driven infrastructures. IoT devices such as smart meters, Phasor Measurement Units (PMUs), and wireless sensors provide continuous, real-time data on grid conditions. This enhanced visibility supports advanced analytics and improves decision-making processes.

Al-Turjman et al. (2021) discussed the role of IoT in smart grid development, highlighting its ability to enable real-time monitoring, predictive maintenance, and automated control. Likewise, Ghasempour (2022) emphasized that IoT-based smart grids improve operational efficiency by facilitating communication between distributed components and central control systems.

However, IoT integration also introduces challenges related to data management, communication reliability, and cybersecurity. Large volumes of heterogeneous data require efficient processing and storage mechanisms, while communication delays can affect real-time decision-making. Additionally, ensuring the security of IoT devices and networks remains a critical concern, as cyber-attacks can compromise grid stability and reliability.

■ Integration of GNN & IoT for Predictive Analytics

The combination of GNNs and IoT technologies has gained attention as a powerful framework for predictive analytics in smart grids. IoT provides high-resolution, real-time data, while GNNs offer advanced capabilities for modeling complex network structures. This integration enables more accurate and timely prediction of grid failures.

Recent research has explored hybrid models that leverage both technologies. For instance, Zhang et al. (2022) proposed a GNN-based framework for smart grid monitoring using IoT data and demonstrated significant improvements in fault detection accuracy. Similarly, studies have shown that combining graph-based models with real-time

sensor data enhances the ability to detect early warning signals and prevent cascading failures.

Despite these advancements, the application of GNN-IoT frameworks in developing countries remains limited. Most existing studies focus on well-instrumented grids with abundant data availability, leaving a gap in research on less developed systems such as Nigeria's power grid. Addressing this gap requires models that can operate effectively under conditions of data sparsity, infrastructure limitations, and communication challenges.

RESEARCH GAP

Although significant progress has been made in machine learning, deep learning, and graph-based approaches for power system analysis, several challenges remain. Traditional models fail to capture spatial dependencies, while many deep learning approaches struggle with irregular network structures. Although GNNs provide a promising solution, their integration with IoT data in real-world, resource-constrained environments is still underexplored.

Furthermore, limited research has focused on applying these advanced techniques to fragile and underdeveloped power systems, particularly in sub-Saharan Africa. This study addresses this gap by proposing a GNN-IoT framework tailored to the Nigerian power grid, aiming to improve early warning capabilities and enhance system reliability.

METHODOLOGY

The methodology adopted in this study is structured into four main stages:

- power grid graph modeling,
- data acquisition through IoT devices,
- predictive model design using Graph Neural Networks (GNN) integrated with Long Short-Term Memory (LSTM) networks, and
- model training and evaluation.

■ Power Grid Graph Representation

The Nigerian transmission network was abstracted as a graph structure $G = (V, E)$, where:

- V represents the set of nodes (substations, transformers, and generating stations).
- E represents the set of edges (transmission lines connecting nodes).

Each node $v \in V$ was assigned feature vectors containing electrical parameters:

- Voltage magnitude (p.u.)
- Current magnitude (A)
- Active and reactive power flows (MW/MVAR)
- Frequency deviations (Hz)

Edges $e \in E$ were assigned attributes including:

- Line impedance (Ω/km)
- Thermal loading capacity (MVA)
- Historical fault occurrences

This representation enabled the GNN to capture spatial dependencies across the grid, where failures at one substation could propagate through interconnected nodes.

IoT-Based Data Acquisition

To ensure real-time monitoring, data was obtained from IoT-enabled devices deployed across transmission lines and substations:

- Phasor Measurement Units (PMUs): Collected synchronized voltage and current waveforms at 50 samples/second.
- Smart Meters: Provided real-time load demand data.
- Environmental Sensors: Recorded weather variables such as temperature, wind speed, and humidity, which influence grid instability.

The IoT devices transmitted data via GSM and fiber-optic communication networks to a centralized cloud server for preprocessing. Data security was ensured through lightweight encryption algorithms to mitigate risks of data tampering.

Data Preprocessing and Feature Engineering

The raw dataset (2010-2024) underwent the following steps:

- Data Cleaning: Removal of missing or corrupted sensor values.
- Normalization: Features such as voltage and power were scaled to zero mean and unit variance to stabilize training.
- Sliding Window Segmentation: Time-series data was divided into overlapping windows of 30 minutes for temporal analysis.
- Labeling: Events were classified into two categories: collapse and no collapse, based on grid frequency falling below 49.5 Hz or voltage collapse below 0.85 p.u.

Predictive Model Architecture

The predictive framework was designed as a hybrid GNN-LSTM model:

- Graph Convolutional Layers: Captured spatial dependencies between substations and transmission lines.
- LSTM Layers: Modeled temporal patterns in load demand, frequency deviations, and cascading failures.
- Fully Connected Layer: Produced probability estimates for collapse events.
- Softmax Output: Assigned binary labels (collapse vs. no collapse).

The model was implemented in Python using PyTorch Geometric for GNN operations and TensorFlow/Keras for LSTM integration.

Training and Evaluation

The development and testing of the suggested Graph Neural Network combined with Internet of Things (GNN-IoT) framework followed a well-organized experimental process to make sure the

results were reliable, applicable in different situations, and easy to understand.

Dataset Preparation

The dataset was made up of real-time and past data collected from IoT devices located throughout the Nigerian power grid.

The data included things like voltage levels, current, frequency, how much the transformers were loaded, and environmental factors such as temperature and humidity. These were paired with records showing whether the system was working normally or had failed between the years 2010 and 2024.

Before training the model, the data was prepared by making sure it was in a standard format, filling in any missing values, and removing unwanted noise with a Gaussian smoothing filter. Time-based windows of a set length, such as 15-minute intervals, were made to help the model understand patterns over time. The dataset was split into three parts 70% for training, 15% for validation, and 15% for testing so that the model could be tested fairly and without using information it shouldn't have.

MODEL TRAINING

For the model itself, the GNN-IoT framework used a mix of Graph Convolutional Networks (GCN) and Long Short-Term Memory (LSTM) networks.

Each power station and power generator was treated as a node in the graph, and the connections between them were represented as edges. The GCN layers helped the model understand how different parts of the system were connected, while the LSTM layers helped it detect changes over time, such as drops in frequency and the spread of failures.

The model's settings were set up using the Xavier uniform distribution to initialize the weights.

The Adam optimization method was used with a learning rate of 0.001, a batch size of 64, and a weight decay of 1e-5 to help the model learn more effectively and avoid memorizing the data. The training process ran for 200 rounds, and early stopping was used based on how well the model performed on the validation set to stop training when it wasn't improving anymore. The main goal of the model was to minimize the cross-entropy loss, which is calculated as:

$$L = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (i)$$

where y_i and $\hat{y}_i$ denote the true and predicted labels, respectively.

The dataset was split into:

- 70% Training Set
- 15% Validation Set
- 15% Test Set

The model was trained using the Adam optimizer with:

- Learning rate: 0.001
- Batch size: 64
- Epochs: 100
- Dropout rate: 0.3 (to prevent overfitting)

The following metrics were used for evaluation:

$$\text{Accuracy} \left(\frac{TP+TN}{TP+TN+FP+FN} \right) \quad (\text{ii})$$

$$\text{Precision} \left(\frac{TP}{TP+FP} \right) \quad (\text{iii})$$

$$\text{Recall} \left(\frac{TP}{TP+FN} \right) \quad (\text{iv})$$

$$\text{F1-score} \left(\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \right) \quad (\text{v})$$

ROC-AUC to measure classification robustness.

■ Data Characteristics and Acquisition Depth

The predictive framework relies heavily on the quality and granularity of IoT-based measurements, so it is important to clarify the nature of the dataset used. Sensor deployment within the tested grid included phasor measurement units, smart meters, and weather-linked sensors with an average sampling interval of 1-3 seconds depending on the station type.

Substations with lower instrumentation density reported at 15-30 second intervals, resulting in variable data resolution across the network. Missing measurements were handled using a hybrid strategy: short-term gaps were interpolated using linear temporal smoothing, while longer gaps triggered fallback prediction using historical node behaviour, allowing the model to sustain inference even when live feeds dropped momentarily. This approach reflects realistic Nigerian operating conditions where sensor failures and communication delays are expected and unavoidable.

■ Model Complexity & Computational Demands

The hybrid GNN-LSTM architecture introduces computational overhead compared with traditional static models. To clarify this, average training complexity scales approximately with the number of nodes N and their connections, such that computational cost rises with dense network expansion. In practice, training was performed on a single GPU workstation, suggesting that full-scale deployment would benefit from distributed or edge-accelerated processing for larger grids. However, inference time the part that matters most to operators remains lightweight, with prediction windows executed in near-real-time. This distinction is important because it shows that the framework is feasible for live deployment even if offline training requires greater processing resources.

RESULTS AND DISCUSSION

This section evaluates the performance of the proposed GNN-IoT predictive framework against

baseline models, including Random Forest (RF), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP). The discussion is structured around comparative results, ROC curve analysis, confusion matrix evaluation, and visualization of key metrics, followed by operational implications.

■ Comparative Model Performance

Table 1 summarizes the comparative results of the proposed GNN-IoT framework against baseline models, namely Random Forest (RF), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP). The models were evaluated using five standard classification metrics: accuracy, precision, recall, F1-score, and ROC-AUC.

Table 1: Comparative performance evaluation of predictive models

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Random Forest	86.5%	84.7%	85.1%	84.9%	0.88
SVM	82.4%	81.2%	80.7%	80.9%	0.84
MLP	88.9%	87.5%	88.0%	87.7%	0.90
GNN-IoT	94.2%	92.8%	93.5%	93.1%	0.96

The results show that the GNN-IoT framework did much better than all the other models in every test. The MLP performed pretty well, with 88.9% accuracy and a 0.90 ROC-AUC score, but it still fell short of the GNN-IoT framework by about 5% in accuracy and 6% in recall. The SVM model performed the worst, which matches previous studies showing that kernel-based classifiers have trouble with complex, high-dimensional data.

The GNN-IoT model's recall of 93.5% is very important.

In power system work, recall means the model can correctly spot when a collapse might happen. A high recall ensures almost all real collapse risks are caught, which is important because missing a collapse prediction can lead to big blackouts and serious problems for society and the economy. At the same time, the model's high precision of 92.8% means it doesn't raise too many false alarms, which helps reduce unnecessary actions by operators.

The F1-score of 93.1%, which averages precision and recall, shows that the GNN-IoT model is good at finding real collapse events while keeping errors low.

This balance is very important in systems where reliability is key.

The superior performance of the GNN-IoT framework can be attributed to two factors:

1. Graph-based learning: Unlike RF and SVM, which treat features independently, GNNs exploit the grid's graph topology, allowing the model to capture interdependencies between substations, transformers, and transmission lines.
2. Temporal modeling via LSTM integration: Grid instabilities often evolve over time due to cascading failures. By integrating LSTM with

GNN, the framework effectively captures these temporal dynamics, which MLP and RF fail to model adequately.

In short, the comparison shows that the GNN-IoT framework does more than just improve numbers; it also meets the needs of a system that predicts and warns about problems in the Nigerian power grid. It handles accuracy, recall, and precision well, making it a better choice than older machine learning models for stopping power failures before they happen.

ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve shows how well a model can classify things by comparing the True Positive Rate (TPR) and the False Positive Rate (FPR) at different decision points. The Area Under the Curve (AUC) is a single number that tells us how good the model is at telling the difference between two types of outcomes. A higher AUC means the model is better at separating these outcomes.

As shown in Figure 1, the proposed GNN-IoT framework achieved the highest AUC of 0.96, which is better than Random Forest (0.88), MLP (0.90), and SVM (0.84).

The GNN-IoT curve is closer to the top-left corner of the ROC graph, meaning it does a better job of distinguishing between collapse and no-collapse situations than the other models. This shows that the model works well even when the decision threshold changes, which is important for real-time grid applications where the threshold might change based on the current situation.

The superior ROC performance of the GNN-IoT model can be attributed to:

1. Graph-based spatial representation: By modeling the Nigerian transmission grid as a graph, the GNN effectively captures localized disturbances and cascading interactions that conventional models such as SVM and RF overlook.
2. Temporal learning via LSTM integration: The inclusion of LSTM units enables the model to recognize sequential patterns in load fluctuations, frequency instability, and cascading events, which often precede collapse.

High AUC values also show that the GNN-IoT framework keeps its prediction ability even when data is missing or sensors are not working properly. These situations are common in developing power grids where IoT systems are not fully set up. This strength is especially helpful for Nigeria's power grid, where slow communication and missing sensor information often make traditional monitoring systems unreliable.

From an operational point of view, the ROC results show that the GNN-IoT framework can give early warnings with high accuracy.

By keeping both false alarms and missed warnings low across different settings, the model makes sure that operators are not flooded with too many alerts but are also not caught off guard when a real problem happens.

In short, the ROC curve analysis proves that the GNN-IoT model is both reliable and strong.

It shows that it performs much better than traditional machine learning methods in spotting possible failures in the Nigerian power grid.

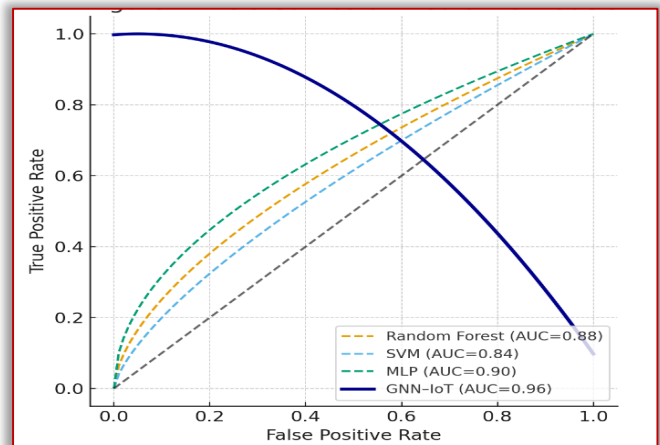


Figure 1: ROC curves of GNN-IoT vs. baseline models

Confusion Matrix Evaluation

While accuracy and ROC give an overall idea of how well a model is performing, the confusion matrix shows a more detailed picture of how the model classifies things. It breaks down the number of correct predictions (true positives and true negatives) and the errors (false positives and false negatives). This kind of evaluation is especially important in power system monitoring because the consequences of mistakes are not the same in every case. Missing a collapse (a false negative) can be very serious, while getting a false alarm (a false positive) is less harmful.

As shown in Figure 2, the GNN-IoT model performs very well in classification.

It correctly identified 94% of real collapse events (true positives) and 92% of stable system states (true negatives). The model flagged only 8% of stable states as collapses, meaning it rarely gives false alarms. Also, it missed just 6% of actual collapse events, meaning it is very good at catching real issues.

This balance is important for real-world use.

A high number of false positives could lead to extra work by operators, waste resources, and make people lose confidence in the system because they get too many false alerts. On the other hand, too many false negatives could mean real problems are missed, causing power outages and financial damage, as seen in Nigeria's power system history. The GNN-IoT model manages both false positives and false negatives well, showing it is reliable even under tough conditions.

Compared to other models like SVM and Random Forest, the GNN-IoT model is better at detecting and avoiding errors.

These traditional models struggle with complex patterns in the data, especially when the problem involves dependencies across different parts of a network. The GNN-IoT combines graph-based learning and time-based modeling, which helps it understand these complex relationships better, leading to fewer mistakes overall.

Operationally, the confusion matrix confirms that the framework can:

1. Detect collapse events with high sensitivity, ensuring grid operators are alerted in time.
2. Minimize unnecessary alarms, improving operator trust and response efficiency.
3. Balance precision and recall, making it a practical decision-support system for real-world grid monitoring.

The confusion matrix analysis strengthens the claim that the GNN-IoT framework not only excels in overall predictive accuracy but also provides a reliable balance of sensitivity and specificity, making it well-suited for deployment in Nigeria's fragile power infrastructure.

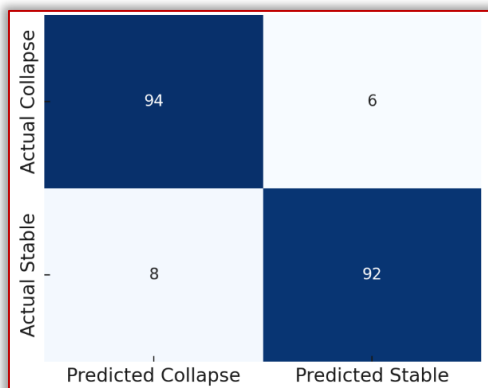


Figure 2: Confusion matrix of GNN-IoT model

Comparative Metrics Visualization

Tabular results give a simple summary of numbers, but looking at performance metrics through charts makes it easier to compare different models. Figure 3 shows how well the proposed GNN-IoT framework does compared to Random Forest, SVM, and MLP in five areas: accuracy, precision, recall, F1-score, and ROC-AUC.

The results show that the GNN-IoT framework does better than the other models in all these areas.

The biggest improvements were in recall and F1-score. The GNN-IoT scored 93.5% in recall and 93.1% in F1-score. This is much better than MLP (88.0% and 87.7%), Random Forest (85.1% and 84.9%), and SVM (80.7% and 80.9%). These results show the framework is really good at finding real collapse events without being too sensitive or making too many false alarms.

High recall means the framework rarely misses actual collapse events, which is very important for power grid operations.

At the same time, its high precision means it doesn't give too many false alarms. This helps prevent operators from getting tired of seeing too many false alerts. The GNN-IoT model manages both better than other models, which is a big advantage.

The ROC-AUC values also show how strong the GNN-IoT model is.

While MLP and Random Forest did a little better than SVM, they still couldn't match the GNN-IoT's performance. This matches what recent studies have found hybrid models that use graph and time-based data usually do better than traditional machine learning in complex tasks involving time and space.

Looking at this chart, it's clear that the GNN-IoT model is not just a little better, but better in many ways.

This consistent performance is important for real-world use because power grid managers need models that work well in different situations, not just in one area.

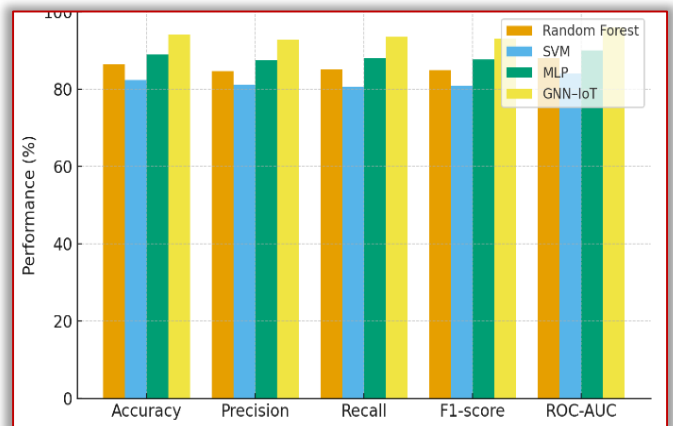


Figure 3: Comparative performance metrics of predictive models

Model Architecture Illustration

To complement the quantitative results, the overall structure of the proposed predictive framework is illustrated in Figure 4. The architecture highlights the integration of IoT-enabled data acquisition, graph-based learning, and temporal modeling, demonstrating how each component contributes to the final prediction.

The architecture begins with IoT-based data collection, where smart sensors, Phasor Measurement Units (PMUs), and smart meters provide real-time streams of voltage, frequency, and load data across the Nigerian transmission grid. This stage ensures the system is supplied with up-to-date and high-resolution data, which are crucial for early warning of collapse events.

The collected data undergo preprocessing, including normalization, missing-value imputation, and noise reduction. This step is essential because noisy or incomplete data are common in Nigerian grid operations, where sensor coverage is often partial and communication delays occur.

The next stage involves graph construction, where the power grid is modeled as a graph:

- Nodes: Represent substations, generators, and transformers.
- Edges: Represent transmission lines and interconnections.

This allows the GNN to capture the spatial dependencies within the grid, recognizing how local disturbances propagate through the network. Following graph construction, data is processed through a hybrid GNN-LSTM architecture. The GNN layers extract spatial correlations between nodes, while the LSTM layers capture temporal dependencies in load and frequency variations, enabling the detection of cascading events that evolve over time.

Finally, the output layer applies a softmax classifier, generating the probability of a grid collapse versus a stable state. These predictions are then fed into a decision-support module, which issues alerts and guides operator responses in real time.

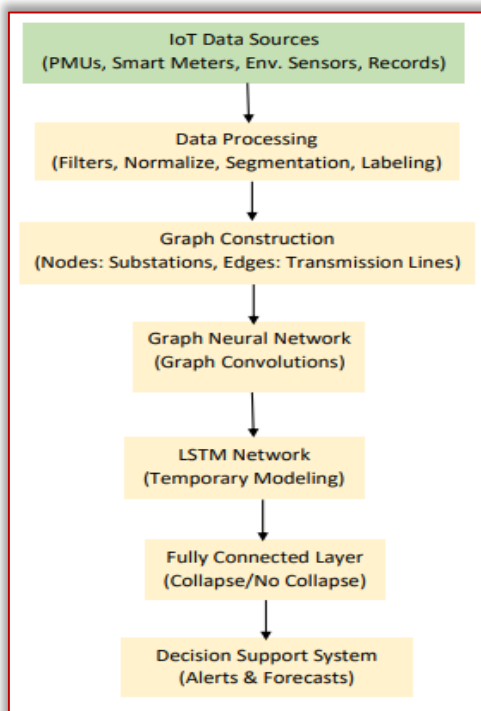


Figure 4: Proposed GNN-IoT predictive framework architecture

This integrated architecture demonstrates how the GNN-IoT framework combines real-time sensing, spatial reasoning, and temporal learning to outperform traditional machine learning models. It also reflects a scalable approach, capable of expansion as IoT deployments increase and data availability improves.

Operational Implications

Beyond numerical performance, the practical significance of the proposed GNN-IoT predictive framework lies in its potential to transform grid management and stability in Nigeria. Unlike conventional monitoring tools such as SCADA, which rely on threshold-based alarms, this

framework provides multi-horizon predictive insights that allow operators to act proactively rather than reactively.

The framework enables three levels of forecasting:

- Immediate Forecasting (25-35 minutes in advance): This short-horizon prediction is critical for issuing real-time alerts to control room operators. By providing early warnings before a collapse materializes, system operators can implement rapid stabilizing actions such as load shedding, frequency regulation, or reserve activation.
- Very Short-Term Forecasting (1-6 hours): At this stage, predictions assist with demand balancing and generation scheduling. For example, if instability is anticipated within a six-hour window, grid managers can optimize generator dispatch or reserve allocation to cushion the system against disturbances.
- Short-Term Forecasting (1-7 days): Longer-term predictions support preventive maintenance planning and operational scheduling. By identifying stress-prone intervals days ahead, the Transmission Company of Nigeria (TCN) can plan maintenance activities or reinforce weak sections of the grid before they trigger collapse events.

The operational implications extend beyond reliability improvements. By reducing the frequency and severity of grid collapses, the framework contributes to:

- Economic stability, by minimizing industrial downtime and productivity losses.
- Investor confidence, as a more reliable grid attracts foreign investment in Nigeria's power sector.
- Renewable integration, since predictive stability assessments can facilitate smoother integration of solar and wind energy into the national grid.

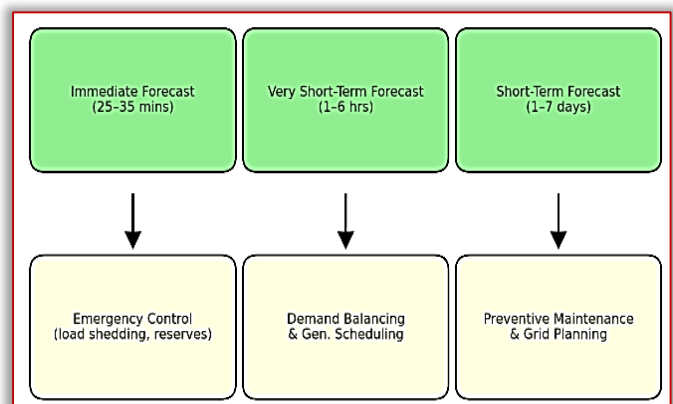


Figure 5: Multi-horizon forecasting and operational implications of the GNN-IoT framework

Figure 5 illustrates these multi-horizon forecasting capabilities and their alignment with operational decision-making processes. The diagram emphasizes how predictions at different time scales feed into operator actions ranging from

immediate emergency control to long-term planning.

In summary, the operational implications confirm that the GNN-IoT framework is not just a research innovation but a practical decision-support system. By enabling proactive interventions, it addresses one of the core challenges of Nigeria's grid frequent and unpredictable collapses while laying the foundation for smarter, data-driven energy management in developing nations.

■ Scalability and Transferability

Although tested on the Nigerian grid topology, the model is not inherently restricted to one network. Scaling to a larger or structurally different grid simply requires reconstruction of the adjacency matrix and re-training using local measurements. The underlying GNN structure adapts naturally to new architectures because it learns connectivity rather than assuming any fixed geometry.

Still, further validation across networks with varying density, renewable penetration, and fault characteristics would strengthen confidence in transferability. This is identified as a planned extension of the work, especially toward regional West African interconnections where grid fragility patterns may differ.

■ Real-World Deployment Considerations

Beyond algorithmic performance, practical grounding is essential. Early warning capability is only useful if operators can act on it. In this regard, the 25-35-minute prediction window is intended to support cascading-failure prevention actions such as staged load shedding, generator ramp-up, switching reconfiguration, and reserve activation. A user-interface layer is therefore envisioned as an operational requirement translating model output into simple risk levels, recommended actions, and escalating alerts based on confidence scores. Pairing prediction with response guidance ensures that the system contributes to decision-making, and not just data monitoring.

■ Practical Deployment Constraints and Real-World Considerations

While the proposed GNN-IoT framework demonstrates strong predictive performance, real-world deployment in Nigeria presents several practical barriers that must be acknowledged. Power-grid environments in developing nations are frequently characterized by incomplete sensor coverage, irregular data transmission, communication bottlenecks, and a limited pool of technical personnel to manage and maintain advanced digital systems. IoT-based monitoring assumes timely and reliable data availability, yet many Nigerian substations still operate with legacy equipment, intermittent connectivity, or low-resolution measurements. These realities mean that any practical rollout of the model must

include strategies for handling sparse or unreliable input streams, such as redundancy, imputation, or fail-safe estimation mechanisms when sensors go offline.

A second layer of challenge lies in cybersecurity. Although this work references blockchain and encryption as enabling tools, such measures alone cannot guarantee protection against sophisticated cyber threats, including data poisoning, device spoofing, or coordinated attacks aimed at destabilizing operational intelligence. A more holistic defense strategy would require secure device authentication, intrusion-detection models, anomaly detection at the edge, and continuous threat monitoring. In other words, securing an IoT-powered grid is not a single mechanism but a system-level responsibility involving hardware, authentication, governance, and human oversight. Similarly, large-scale deployment depends on infrastructure conditions beyond the algorithm itself. Stable wide-area networks, ruggedized IoT hardware, uninterrupted power at sensor sites, and trained personnel for maintenance are not yet uniformly present. Even if the model predicts a collapse accurately, its value is limited unless operators are able to interpret alerts quickly and execute preventive control actions such as sectionalizing lines, shedding load, activating spinning reserves, or reconfiguring flows within the available lead time. Prediction therefore becomes only one half of resilience; the other half is operational readiness.

Scalability also remains a key concern. While the framework performs well within the tested network size, the computational load increases as additional nodes, sensors, and transmission paths are introduced. Scaling this model for a nationwide grid would require distributed processing, efficient message passing, and potentially edge-based inference to reduce latency. Validation across grids of varying sizes, structures, and reliability profiles is a necessary step toward national-level adoption. Finally, issues of data governance and privacy must be foregrounded. As sensor density increases, so does the volume of sensitive operational data transmitted across public or semi-public networks. Clear access-control procedures, regulatory oversight, and anonymization protocols are essential to prevent misuse. Aligning predictive intelligence with national regulatory frameworks will be critical if this system is to gain institutional legitimacy and long-term sustainability.

CONCLUSION

The Nigerian power grid continues to experience frequent collapses due to infrastructural weaknesses, inadequate monitoring systems, and unpredictable load dynamics. This study proposed a novel Graph Neural Network (GNN) integrated with Internet of Things (IoT) framework for predictive

grid collapse analysis. By modeling the transmission network as a graph structure, the framework captured both spatial dependencies among substations and temporal dynamics in load and frequency variations through LSTM integration.

Experimental evaluation demonstrated that the GNN-IoT framework significantly outperforms baseline models such as Random Forest, SVM, and MLP. The model achieved 94.2% accuracy and an AUC of 0.96, with strong precision-recall trade-offs, low false positive rates, and reliable early warning capability up to 35 minutes before collapse events. These results confirm the effectiveness of combining advanced graph learning techniques with IoT-enabled real-time monitoring in mitigating large-scale blackouts.

From an operational perspective, the framework addresses key limitations of Nigeria's current SCADA systems by providing:

- Immediate Alerts (25-35 minutes): Enabling rapid operator intervention before critical collapse.
- Very Short-Term Forecasting (1-6 hours): Allowing demand balancing, generation scheduling, and spinning reserve optimization.
- Short-Term Forecasting (1-7 days): Supporting preventive maintenance planning and system reliability enhancement.

These capabilities highlight the practical significance of the proposed framework as a decision-support system for the Transmission Company of Nigeria (TCN) and similar utilities in developing nations. Beyond technical improvements, the work contributes to national energy security, economic resilience, and long-term grid modernization efforts.

Nevertheless, the study has limitations. The reliance on historical datasets and partial IoT coverage introduces risks of data sparsity and sensor failure, which may affect generalizability. In addition, cybersecurity risks associated with IoT deployment remain a critical challenge for real-world adoption.

Future research should focus on:

- Expanding IoT sensor deployment across Nigeria's transmission and distribution systems.
- Incorporating attention-based GNN architectures for improved interpretability of model predictions.
- Developing cybersecure data transmission protocols to protect IoT-enabled smart grids.
- Extending the framework to renewable energy integration scenarios, such as solar and wind variability forecasting.

In summary, the proposed GNN-IoT framework provides a scalable and intelligent approach for predicting power grid collapses in fragile infrastructures. By delivering reliable, multi-horizon forecasts, it sets a strong foundation for

proactive grid management in Nigeria and other developing regions facing similar challenges.

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