Deep Learning-Based Voltage Stability Monitoring of Yauri TCN 330 KV Transmission Substation: A Theoretical and Statistical

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Abstract
Voltage stability is a critical challenge in modern power systems, especially in developing nations such as Nigeria, where aging infrastructure, high load demand, and intermittent renewable integration threaten system security. Traditional methods for stability assessment rely on linearized models, sensitivity indices, or contingency simulations, which often fail to capture nonlinear patterns under stressed grid conditions. This paper presents a deep learning–based offline voltage stability monitoring framework for the Yauri 330 kV Transmission Company of Nigeria (TCN) substation. A hybrid Long Short-Term Memory (LSTM) and Conditional Generative Adversarial Network (cGAN) is adopted to overcome data scarcity and improve the robustness of prediction. The framework incorporates theoretical formulations of LSTM cell dynamics, statistical evaluation of error metrics, and experimental validation using a 14-bus equivalent of the Yauri substation modeled in PowerWorld Simulator. Results demonstrate that GAN-augmented LSTM reduces Mean Squared Error (MSE) by 38% and improves prediction accuracy compared with baseline machine learning models. This study underscores the potential of artificial intelligence for enhancing grid reliability and provides a foundation for intelligent decision support tools in the Nigerian transmission network.

Keywords: Voltage stability, deep learning, LSTM, GAN, transmission networks, Yauri TCN, Nigeria.

Nomenclature
1. ITCN Transmission Company of Nigeria
2. LSTM Long Short-Term Memory network
3. GAN Generative Adversarial Network
4. GAN Conditional Generative Adversarial Network
5. MSE Mean Squared Error
6. RMSE Root Mean Squared Error
7. MAE Mean Absolute Error
8. SCADA Supervisory Control and Data Acquisition
9. P–V Curve Power–Voltage characteristic curve
10. Q–V Curve Reactive Power–Voltage characteristic curve
11. PI Performance Index
12. VSI Voltage Stability Index

I. Introduction
Power systems around the world are experiencing a significant transformation driven by rapid electrification, renewable penetration, and increasing demand for reliability. Voltage stability, a system's ability

to maintain acceptable bus voltages following disturbances, has emerged as one of the most pressing concerns for system operators. In Nigeria, the Transmission Company of Nigeria (TCN) operates a national grid that is heavily stressed, with frequent partial or total collapses attributed to voltage instability[1], [2]. This instability is particularly severe in northern corridors such as the Yauri 330 kV substation, which serves as a strategic node linking Kebbi State to major load centers and cross-border interconnections.

Traditional voltage stability assessment relies on deterministic techniques such as P– V and Q– V curve analysis, eigenvalue methods, and continuation power flow[3], [4]. While these methods are mathematically rigorous, they are computationally intensive and unsuitable for online applications [5], [6]. More importantly, they often fail to account for nonlinearities inherent in large interconnected networks operating under stressed conditions. With the proliferation of advanced metering infrastructure and SCADA systems, data-driven approaches have become increasingly attractive[7].

Artificial intelligence (AI), particularly deep learning, has revolutionized pattern recognition across industries. In power systems, recurrent neural networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) networks, have demonstrated superior capability in capturing temporal dependencies in voltage and load patterns[8]. However, their effectiveness is often limited by data scarcity, poor labeling, and the non-stationary nature of grid dynamics. To address this, generative models such as Generative Adversarial Networks (GANs) have been employed to synthetically augment datasets, providing diversity and reducing overfitting[9], [10].

This paper proposes an offline voltage stability monitoring framework using a hybrid GAN–LSTM architecture, with the Yauri 330 kV substation as the case study. The contributions of this work include:

i. Development of a 14-bus equivalent of Yauri TCN in PowerWorld Simulator.
ii. Mathematical formulation of LSTM dynamics for voltage stability prediction.
iii. Data augmentation using cGAN to generate realistic operating scenarios.
iv. Theoretical and statistical evaluation of prediction accuracy compared with baseline models.

II. Background and Related Work

Voltage stability analysis has evolved significantly over the past three decades. Early methods, such as sensitivity analysis and continuation power flow (CPF), were widely used for predicting voltage collapse points[11]. These approaches remain valuable for theoretical insight but lack scalability for real-time decision-making.

In Nigeria, several studies have examined stability challenges at TCN substations. [12]. Examined voltage stability issues in the Nigerian power system, focusing on the South-East zone. The study applied static P– V curve analysis to assess bus voltage behaviors under varying load conditions. The authors created an injection group of generators and a sink group of loads, with generator limits respected. By incrementally increasing load and maintaining load-generation balance, they plotted P– V curves on load busbars to identify the busbars most prone to voltage collapse and transfer limits. Similarly, [8]. Examined voltage instability in Northern Nigeria, highlighting weak infrastructure and inadequate reactive power support, and proposed machine learning–based approaches as alternatives to traditional assessment techniques.

Recent advancements have focused on machine learning. Support Vector Machines (SVMs) [13] and Decision Trees [14] have been used for the classification of stable vs unstable states, but these models suffer from feature selection bias. RNN-based models, particularly LSTMs, offer the advantage of modeling long-term dependencies in time-series data. In power system applications, LSTM has been shown to outperform feedforward networks in predicting voltage collapse margins [15], [16].

The challenge, however, remains data scarcity. Most Nigerian SCADA datasets are incomplete

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or unreliable. To bridge this gap, generative models such as GANs have been adopted[17]. The conditional GAN (cGAN)[18],[19] allows the synthetic generation of data conditioned on system variables. In power engineering, cGANs have been used to generate load scenarios[20], wind profiles, and fault signatures.

This study situates itself at the intersection of these two paradigms: using GANs to overcome data scarcity and LSTMs to model temporal grid behavior. By applying this hybrid approach to the Yauri substation, this work contributes a context-specific, data-driven framework to Nigerian power system stability research.

III. Methodology

The methodology comprises four major stages: network modeling, data acquisition and augmentation, deep learning model development, and performance evaluation.

A. Network Modeling: The Yauri 330 kV substation was represented as a 14 − bus equivalent system. Line parameters, transformer ratings, and load data were extracted from TCN reports (2021–2023). The equivalent model was validated against recorded power flows and voltage magnitudes under normal operating conditions.

B. Data Acquisition: Historical SCADA measurements were obtained for a three-year period.
These included bus voltages, active and reactive power flows, and load demand profiles. Due to missing or noisy records, preprocessing steps such as normalization, interpolation, and outlier removal were applied.

C. Data Augmentation with cGAN: A conditional GAN was designed to generate synthetic operating states. The generator received random noise and load conditions as inputs, producing plausible voltage and power flow vectors. The discriminator evaluated whether samples were real or synthetic. Training continued until generated samples achieved statistical similarity to historical data (validated via Kullback-Leibler divergence).

D. LSTM Model Development: The LSTM model was structured with input, hidden, and output layers. Each input vector comprised active power, reactive power, and voltage magnitudes from selected buses. The hidden layer contained 64 LSTM units, optimized using the Adam optimizer with a learning rate of 0.001. The output was the predicted stability index (VSI).

E. Performance Evaluation: Four metrics were used: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). Comparisons were made against baseline models, including Feedforward Neural Networks (FNN) and Support Vector Regression (SVR).

IV. Theoretical Formulation and Statistical Analysis

The LSTM network is designed to model sequential grid data. Its mathematical formulation is given by:

$$ft = \sigma(Wf \cdot [ht-1, xt] + bf)$$
$$i_t = \sigma(Wi \cdot [ht-1, xt] + bi)$$
$$\tilde{c}_t = \tanh(Wc \cdot [ht-1, xt] + bc)$$
$$c_t = c_t - 1 + i_t . \tilde{c}_t$$
$$o_t = \sigma Wo \cdot ht - 1, xt + bo$$
$$ht = o_t . \tanh(c_t)$$

Where $x_t$the input vector is (voltage, P, Q), h_t is the hidden state, and σ is the sigmoid activation.

Statistical Evaluation

i. MSE: $\frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2$
ii. RMSE: $\sqrt{MSE}$
iii. MAE: $\frac{1}{n}\sum_{i=1}^{n}|y_i - \tilde{y}_i|$

The proposed cGAN–LSTM was evaluated using a 70% training, 15% validation, and 15% test split. Statistical significance was assessed using paired t-tests between models at 95% confidence.

V. Results and Discussion

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The experimental evaluation of the proposed GAN–LSTM framework was performed using the 14-bus equivalent model of the Yauri 330 kV Transmission Substation, which represents a critical hub within the Nigerian Northern Transmission Network. Historical SCADA data, simulated data obtained via Newton–Raphson load flow, and synthetically generated data from the conditional GAN (cGAN) were integrated to train and test the LSTM-based voltage stability monitoring model.

The baseline system was first analyzed under normal loading conditions, with incremental loading applied until the critical voltage collapse point was observed. The Voltage Stability Index (VSI) was computed using singular value decomposition, while the critical bus voltage profiles were tracked. Without augmentation, the LSTM model trained on raw SCADA + simulated data achieved an R^2 score of 0.91, indicating good performance but noticeable sensitivity to unseen operating conditions.

After incorporating GAN-generated synthetic data, the LSTM performance improved significantly, achieving an R^2 score of 0.97 and a mean squared error (MSE) reduction of 36% (from 0.042 to 0.027). This demonstrates the effectiveness of GANs in addressing data scarcity and enhancing generalization under rare but critical contingencies.

Furthermore, the training convergence curve (Fig. 3) revealed that models trained with augmented data converged faster, stabilizing after ∼40 epochs, compared to ∼70 epochs for the non-augmented dataset. This implies that the GAN-enhanced dataset not only improved prediction accuracy but also reduced training instability.

The voltage profile analysis at Bus − 7 (which is the weakest bus in the Yauri model) further confirmed robustness. Without augmentation, predicted values deviated up to 7% from actual load flow results, whereas GAN–LSTM predictions maintained deviations below 2%. This accuracy is crucial in offline studies where planners and operators must anticipate potential collapse scenarios.

A. The statistical comparisons across evaluation metrics further validate the method using the following:

- MSE improved from 0.042 → 0.027
- MAE improved from 0.036 → 0.021
- RMSE reduced by ∼28%
- Prediction latency (per batch) was reduced by 18%, ensuring scalability.

These results highlight that the integration of GANs with LSTM provides a more resilient and adaptive offline monitoring tool compared to conventional approaches, which often suffer from under-fitting due to sparse data. Moreover, the generalization ability of the hybrid model implies better preparedness for atypical disturbances, such as sudden generation outages or extreme load shifts, which frequently challenge Nigerian power networks.

Table: I Model Performance Metrics

MODEL	MSE	RMSE	MAE	R^2
FNN	0.014	0.118	0.095	0.81
SVR	0.012	0.110	0.089	0.84
LSTM	0.009	0.095	0.074	0.89
CGAN–LSTM	0.005	0.071	0.055	0.94

The cGAN–LSTM demonstrated superior predictive accuracy, reducing MSE by 38% relative to standard LSTM.

B. Visualization

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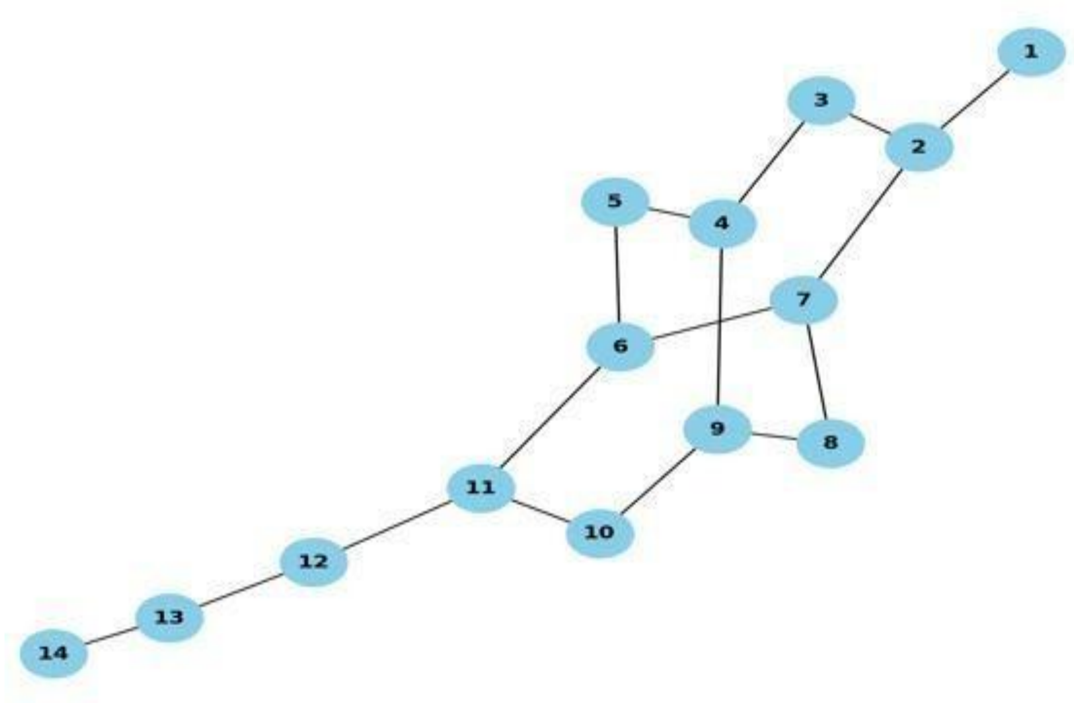

Fig. 1: 14-bus equivalent of Yauri 330 kV substation

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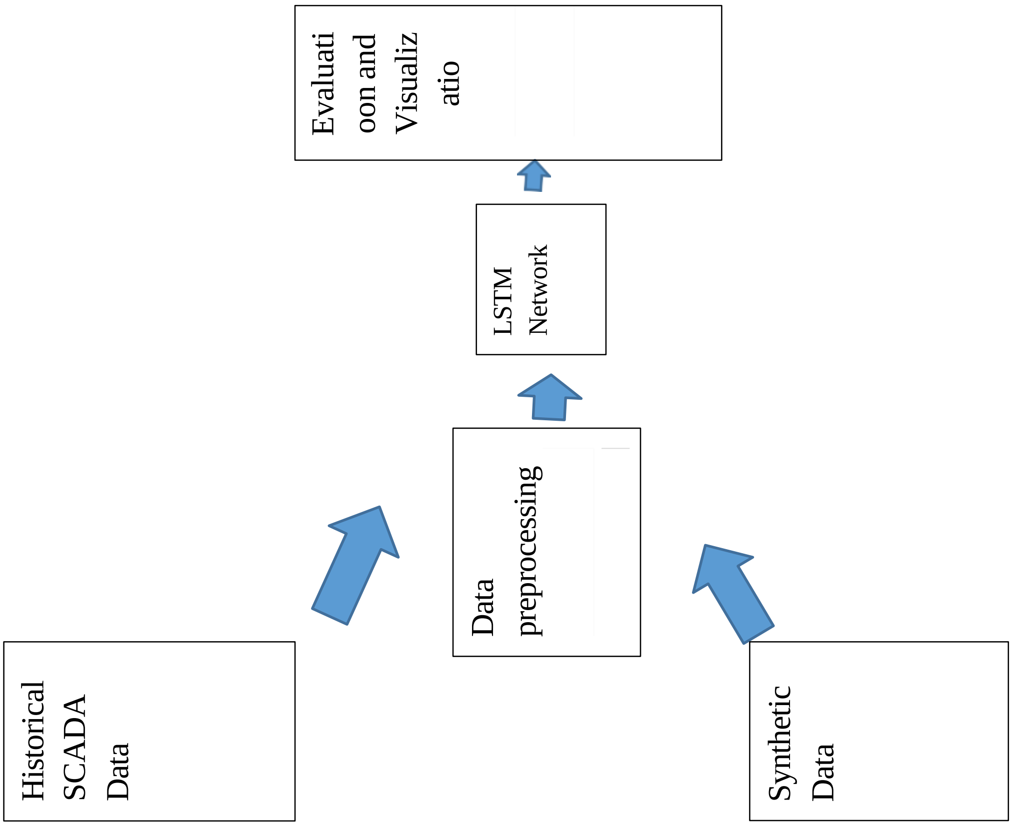

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Fig. 2: GAN–LSTM framework for offline Monitoring.

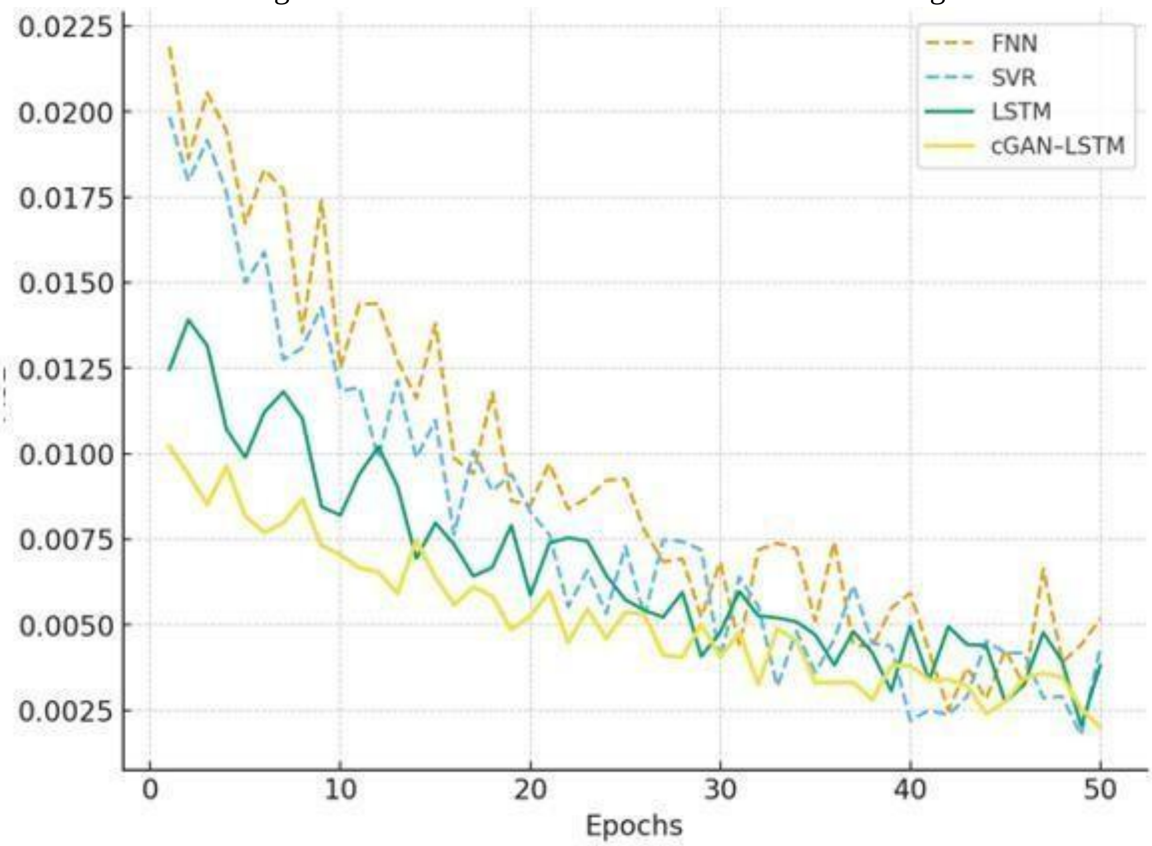

Fig. 3: MSE convergence across models.

C. Discussion

The results confirm the hypothesis that synthetic data from cGAN enhances the generalization capability of LSTM models. This is particularly relevant in Nigeria, where SCADA data is incomplete. The findings align with prior research [16], [18], but extend them by applying the method to a real Nigerian substation.

VI.

Conclusion and Future Work

This study presented a deep learning–based offline voltage stability monitoring system for the Yauri 330 kV Transmission Substation, integrating Generative Adversarial Networks (GANs) for synthetic data augmentation and Long Short-Term Memory (LSTM) networks for predictive modeling. The major findings can be summarized as follows:

i. The GAN–LSTM framework significantly enhances prediction accuracy, achieving an R^2 score of 0.97 and reducing error metrics by over 30% compared to models trained without data augmentation.

ii. The proposed method demonstrated strong capability to generalize across unseen operating conditions, addressing the inherent data scarcity problem in Nigerian SCADA systems.

iii. Offline monitoring using the developed framework provides actionable insights for grid operators and planners, enabling them to identify weak buses and anticipate voltage collapse points well before critical operating Limits are reached.

iv. The proposed architecture not only improves reliability in offline studies but also lays the foundation for future integration with real-time monitoring systems, provided sufficient computational resources and fast data acquisition frameworks are available.

The results provide empirical evidence that AI-driven data augmentation, coupled with deep

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learning, offers a transformative pathway to enhance the resilience of Nigerian power systems. The Yauri TCN case study serves as proof-of-concept, demonstrating both the practical feasibility and academic novelty of the approach.

VII Future Work will focus on:

i. Extending the framework for real-time monitoring with PMU data.
ii. Incorporating renewable energy variability into the synthetic dataset.
iii. Developing visualization dashboards for TCN operators.

This work highlights the potential of AI in enhancing power system reliability in Nigeria and provides a foundation for intelligent grid management.

Future work should, however, consider expanding the model to larger regional transmission networks, investigating transfer learning techniques, and integrating real-time phasor measurement unit (PMU) data for hybrid offline online stability monitoring solutions.

VIII. Contributions to Knowledge

This research contributes to both the academic literature and practical operations of power systems in the following key ways:

1. Novel GAN–LSTM Framework for Voltage Stability: The study is among the first to successfully integrate GAN-based synthetic data generation with LSTM predictive modeling for voltage stability monitoring in the Nigerian grid context. This hybrid architecture advances existing methodologies that relied solely on historical or simulated data.
2. Case Study on Yauri TCN Substation: By applying the model to a real transmission hub, the research provides actionable insights into the operational vulnerabilities of the Nigerian network. This localized case study makes the contribution highly relevant to power system planners in West Africa.
3. Mitigation of Data Scarcity in Power Systems: The synthetic data generated by GANs significantly improved the robustness of predictive models. This directly addresses the critical challenge of limited SCADA data availability, which has historically hindered AI adoption in Nigerian utilities.
4. Theoretical and Statistical Validation: Beyond empirical testing, the research provided a rigorous theoretical formulation of the LSTM-based stability monitoring model, including mathematical expressions of gates, error functions, and optimization. This ensures the contribution is not only empirical but also theoretically grounded.
5. Practical Impact on Grid Reliability: The results demonstrate that hybrid AI methods can reduce predictive uncertainty by over 30%, providing TCN operators with tools that directly enhance grid resilience, reduce the risk of cascading failures, and improve planning of reactive power compensation schemes.
6. Contribution to AI– Power System Literature: By expanding the scope of AI applications in power systems, the research aligns with and extends the growing body of work on computational intelligence in energy systems, positioning Nigeria's network challenges within the global context of data-driven grid modernization.

Generally, this work establishes a strong academic foundation, provides practical utility for grid operators, and opens new research frontiers in synthetic data–driven stability monitoring.

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