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Machine Learning for Voltage Stability in Nigeria's Power Network: A Comprehensive Review

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Abstract. The foundation of power system reliability is voltage stability, which is required to promise a secure and stable supply of electricity. Insufficient generating capacity, a timeworn transmission facility, inadequate reactive power compensation, and the increasing integration of renewable energy sources are the main foundations of the existing voltage instability of Nigeria's power grid, specifically in the northern regions. Through evaluating contemporary disturbances such as smart grid technology and intelligent machine learning (ML) drives up for real-time voltage security evaluation and predictive analytics, this study provides a technically enhanced examination of these effects. Contrasting machine learning models, such as deep learning (DL), supervised learning, unsupervised learning, and reinforcement learning (RL), are explored for their capabilities in time-varying voltage prediction, robotic grid control, and anomaly detection. Also, it highlights the transformative impact of machine learning in improving voltage stability management and outlines strategic recommendations relating to guiding principle reforms and infrastructure transformation. The article intends to provide a forward-looking structure for deploying adaptive Machine stakeholder engagement e-learning-powered solutions to achieve resilient and voltage security in the Nigerian power system that structures long-term economic sustainability.

Introduction

When certifying the reliability of electrical power systems and their unceasing operation, voltage stability plays a grave role[1]. These settings, which may include reactive power management, delayed grid expansion, antiquated infrastructure, and inadequate, are essentially predictable due to systemic insufficiencies [2]. Voltage insecurity, of which voltage levels fall below recoverable constraints, can occur from instability and lead to widespread blackouts or power grid breakdowns[3]. Voltage insecurity is a tireless concern in Nigeria that has led to several grid failures. The country's northern regions are particularly affected by several additional variables, which include the fast rise

in load demand, the conflicting centralization of renewable energy sources, and transmission constraints that frequently cut off voltage stability[4].
Following instabilities and under typical operating conditions, such as generator letdowns, unexpected load changes, or liabilities, it describes a system's capacity to withstand appropriate voltage levels at all buses[5].
According to evaluations, which highlight the need to address voltage stability issues, Nigeria has about 30 system failures annually[6]. Traditional methods for Voltage Stability Assessment (VSA) have mostly depended on load flow models and deterministic static system representations, which are operative for training scheduling but have higher margins in real-time operations[7]. These techniques are computationally thorough and untiring in power system operations, but they are unable to capture the dynamic, particularly in circumstances of high insecurity and changing grid conditions[8].

The power industry may be able to minimize system drops, increase grid flexibility, and maximize voltage stability by making use of this cutting-edge technical know-how [9]. Over and done with continuous learning from both real-time operating data and ML historical data, can enable more accurate real-time anomaly recognition, predictive modeling, and adaptive grid control, in contrast to previous methods and methods[10].

Literature Review

Due to its serious task in ensuring grid flexibility and reliability, voltage stability has been a significant field of study for power systems. Grid design and operation have at all times been dependent on conventional techniques for Voltage Stability Assessment (VSA), such as Continuation Power Flow (CPF), Power Flow Analysis, and Voltage Stability Index (VSI)[11]. These approaches are limited in their ability to assess and manage changing time circumstances in real-time, yet outstanding in steady-state analysis[12]. These weaknesses are especially evident in systems that use renewable energy sources, such as wind and solar, that have significant intensities of irregularity and insecurity, requiring more flexible and adaptive skills[13]. Because of this, the conventional deterministic way forward makes it difficult to provide the flexibility required to control voltage stability in these states[14].

The coming on of computational intelligence has meaningfully upgraded VSA, posing more robust, data-driven solutions to address these issues[15]. Initial efforts in this field take an advantage of ANNs to model the multifaceted, permitting the prediction of voltage instability, nonlinear connections within power systems[16]. While ANNs showed a valuable strategy in capturing intricate patterns, they were often criticized for their “black-box” nature, which slowed down interpretability and posed some serious challenges in understanding model decisions[17]. Additionally, the necessity for large amounts of training data made these models less scalable, especially in regions with limited data accessibility[18]. In parallel, fuzzy logic systems and expert systems were introduced to integrate human-like reasoning into VSA, but these were hindered by difficulties in real-time adaptability, limiting the practical applicability in dynamic grid environments[19].

Power systems started producing high-resolution, time-synchronized data with the advent of Phasor Measurement Units (PMUs) and Advanced Metering Infrastructure (AMI), which made it possible to apply Machine Learning (ML) techniques in a perfect setting[20]. Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), and Random Forests (RF) are examples of algorithms that have been successfully applied to tasks like fault sensing, online stability forecast, and contingency ranking[21]. These models use the real-time data line streams from PMUs and AMI to improve predictions regarding voltage instability[22]. LSTM networks have recent shown moving performance in capturing time-based dependencies in voltage data,[23] especially for DL models used for voltage forecasting in dynamic grid environments[24]. The complexity of DL models has the ability to diagnose patterns across time, anticipating future voltage situations, and changing potential stability effects[25].

A rising number of studies have investigated hybrid methods that fuse conventional physics-based simulations with machine learning proficiencies[26]. Through merging the robustness of well-established power system modeling practices with the benefits of data-driven models[27], this hybrid approach targets to improve the precision and real-time compliance of VSA[15]. For example, ML-increased state estimation techniques[28] to improve grid observability and regulation by utilizing statistical inference and data from SCADA systems, leading to better decision-making[29]. However, power flow management[30] and voltage control scheme optimization under indefinite, stochastic conditions have been carried out through the use of RL approaches[31], such as Deep Q-Learning. As a result of enabling adaptive decision-making that changes in response to the system's current situations, these techniques give a more reliable control in a range of operational surroundings[32].

There occur significant difficulties which have been brought to light by research specifically focusing on the Nigerian grid[33], most especially the lack of historical operational data, which controls the creation of efficient machine learning models[11]. This shortage of data is intensified by the specific characteristics of the Nigerian power system, comprising the differentiated demand behavior[34], climate-induced fluctuation in power generation, and infrastructural inadequacies[34]. Although ML-based VSA advances are state-of-the-art, they are still not widely relevant in Nigeria. Because of these existing contests, it is crucial to develop limited models that are suitable for the unique requirements[35] of the Nigerian grid to successfully apply machine learning algorithms[36] to the operational reality of the area. In addition to that, it is becoming more and more important to take into consideration local features, for example the use of renewable energy sources, voltage fluctuations[37], for all of which are specific to the Nigerian power system and grid congestion[38].

This volume of work pinpoints the merits and demerits of assessing voltage stability in power networks with the aid of machine learning techniques[39]. More so, data-driven VSA techniques have advanced considerably[40]; there is still a gap in understanding how these approaches may be used to address the unique issues faced by developing countries, particularly people who are in places like Nigeria[41]. To close this gap, it requires looking at new strategies that can help overcome model constraints and data scarcity, such as hybrid modeling and synthetic data generation[42].

Standing on these findings, this review promotes ML schemes that are used in the Nigerian TCN network's operational configurations[43]. It concentrates on using synthetic data, localized model training, and modern machine learning techniques to increase grid resilience and voltage stability in Nigeria[44].

Machine Learning Approaches to Voltage Stability Assessment

Voltage Stability Assessment (VSA) is a vital part of power system reliability; network instability occurs and particularly during time of irregular issues. ML methods come with a strong toolbox to improve voltage stability by adjusting to shifting grid conditions, enabling systems to learn from data, and make more perfect predictions[45]. These methodologies include a diversity of methodologies and deep learning. Each approach has pros and cons when it comes to voltage stability, including supervised learning, unsupervised learning, and reinforcement learning, especially in the Nigerian power grid, where operational trickiness and data scarcity require creative solutions[46].

Supervised Learning: A strong technique for categorizing system states or creating predictions is by the aid of supervised learning, in which models are trained on labeled datasets. Supervised learning methods such as decision trees, ANN, SVM[47], and regression models are often used in the context of voltage stability to classify diverse voltage settings or predict voltage variabilities based on historical data. Frequent sensing of voltage unsteadiness problems is made accessible in these models' ability to capture intricate, unstable interactions in the grid that are challenging to model by the use of traditional techniques[10]. For example, ANNs can examine the system's change of state response to varying loads and environmental factors, pinpointing issues that may lead to instability[48].

Therefore, the difficulty in having access to high-quality labeled data is one of the key problems in using supervised learning for voltage stability in Nigeria[49]. Quite several power systems, especially those in developing nations counting including that of Nigeria, may not be in a position or have insufficient information about the grid's state of action under both normal and abnormal conditions, which is also necessary for voltage stability datasets[50]. Synthetic data generation techniques, like Generative Adversarial Networks (GANs)[28], can add to the available training data to lessen this difficulty[31]. Models can be trained on a larger amount of datasets because GANs can produce accurate operational states from a small quantity of real data[51]. Even if it is with little real-world data, this increases the precision and resilience of supervised learning models in predicting voltage instability[52].

Unsupervised Learning: To find hidden patterns and structures in the unlabeled data, unsupervised learning is used. Unsupervised learning approaches, such as clustering algorithms, e.g., hierarchical clustering, k-means, and SOM[14], are useful in voltage stability assessment because they can classify operational states and sense anomalies without requiring labeled data or prior knowledge[53]. When it comes to fact-finding analysis, such as identifying uneven instability risks or uncovering operational behaviors that were previously unknown, these models' ability to group related system settings can be drastically useful.

Another well-known unsupervised learning method in voltage stability findings is Principal Component Analysis (PCA)[54]. In reducing the spatiality of the data, PCA makes it stress-free to identify essential system features. It advances pattern recognition and aids in identifying important factors that add to voltage instability by putting focus on the most important variables[20]. Because the results are based on complex statistical relationships that may be difficult to understand, unsupervised models always have interpretability problems even though they are very effective at revealing the hidden structures of the data[55]. To get around this restriction, supervised learning methods can be combined with unsupervised models to produce useful awareness.

A supervised classifier, for instance, may perhaps be informed by the output of an unsupervised clustering model that produces more coherent and reliable voltage stability forecasts[56].

Reinforcement Learning: By way of communicating with the settings and feedback in the form of honors or penalties relying on the actions, agents can learn optimal plans through RL, this type of machine learning[57]. RL can be set into voltage stability assessment to improve a very number of control policies, including reactive power control, load shedding scheme, and voltage control. RL models, such as Deep Q-Networks (DQN), Proximal Policy Optimization (PPO) and enable adaptive, real-time power system control[58]. Even in the look of shifting load and generation conditions, these models can also be made to adapt control activities to maintain voltage stability by constantly learning from these system dynamics[58].

The ability of RL to changeably boost control approaches based on real-time system variations is one of its main advantages in power systems. RL agents, for instance, can select a time to start load shedding to sidestep voltage collapse occurrence, as well as the best situations for reactive power compensation and transformer tap changing[12]. To ensure that the learned policies are secure and reliable, particularly in an irregular operational state of action, RL deployment in power systems requires thorough testing. If not appropriately managed, the exploration stage of RL, in which agents experiment with numerous actions to find out their effects, may result in hazardous system states[59]. To put to a trust that RL models steer clear of unsafe or suboptimal actions in real-world operations, they must be thoroughly tested and controlled.

Deep Learning: CNNs and LSTM networks are two main DL architectures that are mainly well-suited for capturing complex relationships in that of grid data, enabling better prediction and real-time decision-making. DL, a subclass of machine learning, has transformed VSA in power systems by means of deep neural networks to learn from huge amounts of data. LSTMs, in particular, are skillful at handling time-series data, making them ideal for capturing long-term reliance in voltage levels over time. Can detect patterns and problems in voltage oscillations, enabling more accurate predictions of voltage insecurity events[22].

Equally, CNNs are intensely good at finding spatial correlations between different grid nodes. Detecting problems associated with the spatial sharing of voltage imbalances in voltage stability assessment, and CNNs are adept at analyzing grid-wide features. Predictive maintenance and Dynamic contingency analysis are made possible by DL techniques, particularly when paired with time-series data (such as load data, voltage, and current). By forecasting possible instability events, these models permit risk reduction through proactive processes[53].

However, DL is crucial in present-day grid environments owing to its capacity to adapt and learning complex, multifaceted patterns, especially when handling large-scale systems with several variables. Even though DL gives benefits in terms of autonomous learning and feature extraction, these models necessitate a lot of processing power and big datasets to operate well. The high demand for data and processing power can be challenging in places like Nigeria, where grid data may be sparse or unstructured[60].

The duty of evaluating voltage stability benefits from the distinctive strengths of supervised, unsupervised, reinforcement, and deep learning methods, which have the potential to enhance in-the-moment decision-making, strengthen the power grid's overall resilience, and raise predictive accuracy. With more adaptive, changing, and data-driven solutions for guaranteeing grid stability, the use of machine learning skills in voltage stability assessment made a substantial improvement over conventional methods[61]. By integrating hybrid modeling techniques and synthetic data generation, these machine learning methods can be further improved in the setting of the Nigerian power system, which faces infrastructure issues and data scarcity, improving their efficacy and dependability. To fully earn the rewards of these cutting-edge methods, however, issues like data availability, model interpretability, and computational necessities must be fixed[61].

Mathematical Representation

Voltage stability monitoring using deep learning will require mathematical modeling of power system parameters and AI algorithms. Below are key mathematical formulations[62][1][63]:

Power Flow Equations

The power flow equations will describe the relationship between bus voltages and injected power in a power system:

$$P_i = \sum_{j=1}^{n} V_i V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \quad (1)$$

$$Q_{ij} = \sum_{j=1}^{n} V_i V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) \quad (2)$$

Where:

$P_i Q_i$ Are the active and reactive power at bus i

$V_i V_j$ Are the voltage magnitudes at buses i and j

$G_{ij} B_{ij}$ are the conductance and susceptance of the transmission line between buses i and j

θ_{ij} is the voltage angle difference between buses i and j

Voltage Stability Index (L-Index)

The L-index is used to assess proximity to voltage collapse:

$$L_i = 1 - \sum_{j=1}^{n} F_{ij} \frac{V_j}{V_i} \quad (3)$$

Where F_{ij} are elements of the reduced Jacobian matrix from the power flow equations.

Deep Learning Model Representation

A typical neural network used for voltage stability prediction will be represented as:

$$y = f(Wx + b) \quad (4)$$

Where:
y = predicted voltage stability index
W= represents the weight matrix
x = input feature vector
b =is the bias term
f = activation function (ReLU, Sigmoid, etc.)
The training process updates weights using backpropagation:

$$W^{(t+1)} = W^{(t)} - \eta \frac{\partial J}{\partial W} \quad (5)$$

Where η is the learning rate and J is the loss function.

Applications in the Nigerian Power Network
The unstable generation, getting old facilities, and rapidly rising energy the demand are some of the problems facing Nigeria's power network[64]. Novel solutions that can optimize, monitor, and manage the grid are important to ensuring a stable and efficient supply of electricity[65]. To come to address the problems with the power grid, voltage control integration, ML applications in real-time voltage monitoring, and renewable energy integration are indispensable. These applications are to make use of machine learning algorithms' advantages to be able to enhance operational efficacy, improve grid reliability, and enable the increase of renewable energy sources. The key ML-driven applications in Nigeria's power network[41] are listed below.

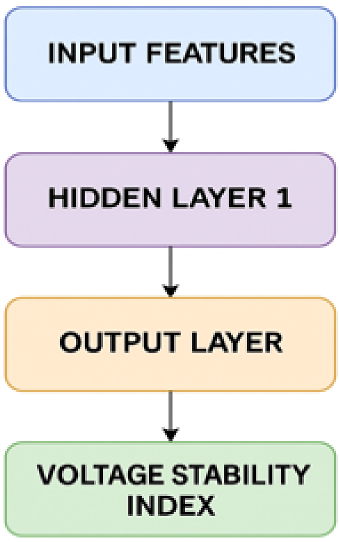

Fig. 1. Deep learning engine for voltage stability assessment[63][15][66]

Real-Time Voltage Monitoring. To identify the early indications of these voltage instabilities and avoid system ON and OFF, real-time voltage monitoring is important. ML models can evaluate this data to provide detailed insights into grid well-being, voltage stability, and performance metrics as one of the evaluation metrics when used in combination with SCADA systems that offer real-time control and data acquisition capabilities[67]. Faster fault localization and system recovery are made possible, for instance, by ML-based anomaly sensing models that can point out abnormal voltage sinusoidal before they develop into a full-scale voltage collapse. Through real-time analysis for large amounts of operational data, load fluctuations, machine learning algorithms can improve this process and later also include voltage levels, frequency variations. By seeing patterns and irregularities that could point out possible grid instability, these algorithms help operators take prompt corrective action. Real-time monitoring can be further improved by integrating ML algorithms with those of the SCADA and PMUs. PMUs offer time-synchronized, high-resolution data that is essential for evaluating the grid's dynamic behavior[68]. This method enhances decision-making and aids the operators in identifying issues as they time of happening. More so, using machine learning to forecast possible grid black-outs or trappings makes it possible to lower the Mean Time to Repair (MTTR), which get fast up recovery and raises reliability metrics[69]. By reducing downtime and enhancing power quality, this proactive monitoring can also lead to more efficient grid management.

Voltage Control Optimization. The ability of the traditional voltage regulation methodologies, like static transformer tap changing or capacitor bank switching, to react to real-time variations is constrained. However, by continuously modifying grid parameters in response to real-time operational data, machine learning optimization models offer a dynamic approach to voltage regulation. One of the main tasks of power system management is the integration of voltage control. Inadequate voltage support, reactive power imbalance, and large demand fluctuations frequently jeopardize voltage stability in the Nigerian power grid[70].

Adaptive regulation of voltage levels is made at ease by these optimization models, such as RL-based controllers, which guarantee that voltage stays within reasonable bounds even when grid conditions change. These controllers can automatically put into different grid topologies or load scenarios by utilizing RL, giving a chance to voltage stability even in the face of unforeseen disorder or interruptions[71]. This lowers the possibility of voltage-related failures and improves grid reliability. ML models can time to time, modify control actions to reduce voltage deviation and depleting transmission losses, in contrast to the static control way of thinking that might find it difficult to maintain voltage stability in the face of shifting load patterns or system configurations[72]. By taking into account learning from previous grid responses and modifying operational parameters like reactive power injection, transformer tap settings, and capacitor bank switching, machine learning models can optimize voltage control strategies[73].

Renewable Energy Integration. Voltage variability may come in from these variations, especially in grids that are ill-prepared to manage such variability. Voltage stability is severely hampered by the grid's integration of renewable energy sources, especially solar photovoltaic (PV) systems. Because their output varies with the weather, the season, the time of day, and renewable sources are by nature intermittent. By offering precise predictions of renewable energy production and facilitating proactive grid changes to account for these variations, machine learning models can be extremely helpful in reducing these difficulties[74].

In grids that heavily depend on renewable energy, hybrid models that bring together data-driven predictions with simulations based on physics provide even more accurate predictions of voltage stability. Grid operators can further effectively manage the supply-demand balance and make the required shift to ascertain voltage stability by forecasting the amount of energy produced by solar PV systems at any given time. Based on past data, weather trends, and other pertinent variables, machine learning algorithms can forecast the profiles of renewable energy generation. These hybrid models can give operators very helpful information for grid management while simulating the effects of fluctuating renewable energy output on voltage levels.

In the process of using machine learning algorithms, these inverters can automatically self-regulate their output to keep voltage within limited bounds, keeping down the possibility of voltage instability brought on by the unpredictability of renewable energy[11]. Even though renewable energy sources go up and down, the grid is kept stable by this ability to dynamically respond with a reactive power output. A stronger and sustainable grid can be met in point by using ML-enhanced smart inverters to better balance supply and demand. In addition, the grid's stability can be further increased by integrating smart inverters driven by machine learning. Based on the changes in voltage, smart inverters can, at a point in time modify the reactive power output[75].

ML can help increase the grid's sustainability, efficiency, and dependability in an act of managing the effects of renewable energy sources, improving grid monitoring, and optimizing voltage regulation. These cutting-edge machine learning applications aid in the way for a more resilient and robust power system that can cater to Nigeria's expanding and growing population and economic needs. The problems Nigeria's power network is catching in touch can be effectively resolved by machine learning applications in real-time voltage monitoring, voltage control improvement, and renewable energy integration[76].

The Transmission Company of Nigeria (TCN). TCN confronts major impediments in maintaining a very outstanding, reliable, and effective power grid due to its problems like high impedance lines, insufficient voltage support network congestion. Regular voltage ups and downs in most common situations, total voltage blackouts are caused by these factors, which also contribute to the grid's time to time overall instability. ML techniques can offer an indispensable creative answer to these problems and improve the TCN networks with better efficiency and stability[64]. By taking into account ML, Nigerian power distribution can become more self-dependable through predictive maintenance, real-time grid improvement, with more of intelligent resource management.

Dynamic Load Matching. The differences between supply and demand are one of the TCN's effective grids' major facing problems, particularly in areas where there is a fast population growth or varying industrial activity[77]. Through predicting real-time demand patterns using the historical load data, meteorological conditions, and the seasonal trends, machine learning-based dynamic load matching looks forward to solving this issue. In predicting the demand for electricity at different times of day or during certain events, predictive load forecasting models enable the grid to modify its supply profile appropriately[13].

These models can improve influence on resource allocation, reduce transmission losses, and lessen the burden on the grid during periods of peak usage by means of matching power generation with anticipated demand. This strategy leads to preventing power shortages or voltage downfalls that may arise from sudden spikes in demand by having sure of a consistent and reliable supply[78].

Prognostic Voltage Stability Assessment. Forecasting and evaluating voltage stability is one of the main areas where machine learning can have a big impact. To anticipate possible voltage collapses before they come to start, prognostic VSA combines real-time system performance data with long-term historical data[27]. Grid operators can take very effective preventative measures in appreciations to ML models' ability to analyze patterns and giving early warning indicators of voltage break down. These models might, for instance, warn operators of possible dangers from under- or over-voltage situations brought on by network inadequate reactive power compensation, congestion, or sudden variations in load or generation[79].

Prognostic VSA uses intelligent machine learning algorithms like Random Forests (RF) and LSTM networks to predict voltage shutdown events in real time. These events can then be prevented by changing almost all the system parameters or taking corrective measures[80].

Smart Grid Optimization. RL techniques can be taken into consideration in machine learning to improve the grid's overall performance. These RL agents make decisions that minimize transmission losses, minimize voltage deviations, and guarantee a steady supply of electricity by using a reward system[8]. These systems are very effective at preserving grid stability even in the face of erratic changes in supply or demand because they can learn from the grid's responses to past actions and gradually improve their performance. Creating autonomous systems[59] that can endlessly learn and regulate to varying grid conditions is a key component of smart grid optimization. Also, load shedding protocols can be improved by RL-based controllers, which balance demand and stop network-wide cascading failures. By automatically modifying reactive power injection and transformer tap settings in response to real-time grid behavior, capacitor switching, reinforcement learning models can maximize voltage regulation[81].

Synthetic Data Enrichment. Based on the operational data that is currently available, GANs can produce realistic data and scenarios that mimic a variety of situations, such as demand fluctuations, extreme weather events, unforeseen or the variability of renewable energy generation[28]. In the absence of real-world data, GANs can also aid in enriching datasets, enabling more precise ML algorithm training.

The lack of trustworthy, labeled operational data presents a significant obstacle to using machine learning for voltage stability analysis in Nigeria[82]. This restriction can be addressed with the aid of synthetic data generation methods like GANs. Like many other networks in developing nations, the TCN network has trouble accessing extensive, high-resolution datasets[3]. Machine learning models can be trained on a wider range of operational scenarios by producing this synthetic data, which increases the models' predictive ability and resilience. This method ensures that the models are better able to handle the intricacies and uncertainties present in Nigeria's power grid while also filling in the data gaps[52].

These machine learning-powered approaches offer a viable way to handle present and upcoming issues as Nigeria's power grid deals with growing population centers and the integration of renewable energy sources. Through the use of predictive models for load forecasting, autonomous grid control, voltage stability evaluation, and synthetic data generation, TCN can make more informed decisions that optimize resource allocation, boost grid resilience, and improve voltage stability[83]. When combined, these machine learning techniques provide a thorough framework for enhancing TCN's power transmission network's operational stability and dependability.

14-Bus 330 kV System Model Overview

The 14-bus system is a simplified representation of an actual high-voltage transmission network, typically used for studying power flow, voltage stability, and transient stability. The system includes:

i. Buses (nodes): Points where generators, loads, or network interconnections exist.

ii. Transmission lines: Modeled using their impedance (resistance and reactance) and susceptance.

iii. Transformers: Modeled by their turns ratio and impedance.

iv. Generators: Modeled with voltage setpoints and power generation capability.

v. Loads: Modeled as constant power (P, Q) or voltage-dependent.

Mathematical Modeling Components

Bus Admittance Matrix (Y-bus).

The network is represented by a bus admittance matrix Y, a complex matrix. 14-Bus 330 kV System:

Table I. Data & Mathematical Model

Step 1: Bus Data[33]

Bus No.	Voltage (p.u.)	Load P (MW)	Load Q (MVAR)	Generation P (MW)	Generation Q (MVAR)	Bus Type
1	1.06	0	0	232.4	-16.9	Slack (Reference)
2	1.045	21.7	12.7	40	42.4	PV
3	1.01	94.2	19	0	0	PQ (Load bus)
4	1.019	47.8	-3.9	0	0	PQ
5	1.02	7.6	1.6	0	0	PQ
6	1.07	11.2	7.5	0	0	PQ
7	1.062	0	0	0	0	PV
8	1.09	0	0	0	0	PV
9	1.056	29.5	16.6	0	0	PQ
10	1.051	9	5.8	0	0	PQ
11	1.057	3.5	1.8	0	0	PQ
12	1.055	6.1	1.6	0	0	PQ
13	1.05	13.5	5.8	0	0	PQ
14	1.036	14.9	5	0	0	PQ

Table II. Step 2: Transmission Line Data[31]

From Bus	To Bus	R (p.u.)	X (p.u.)	B/2 (p.u.)
1	2	0.01938	0.05917	0.0528
1	5	0.05403	0.22304	0.0492
2	3	0.04699	0.19797	0.0438
2	4	0.05811	0.17632	0.0340
2	5	0.05695	0.17388	0.0346
3	4	0.06701	0.17103	0.0128
4	5	0.01335	0.04211	0.0000
4	7	0	0.20912	0.0
4	9	0	0.55618	0.0
5	6	0	0.25202	0.0
6	11	0.09498	0.19890	0.0
6	12	0.12291	0.25581	0.0
6	13	0.06615	0.13027	0.0
7	8	0	0.17615	0.0
7	9	0	0.11001	0.0
9	10	0.03181	0.08450	0.0
9	14	0.12711	0.27038	0.0
10	11	0.08205	0.19207	0.0
12	13	0.22092	0.19988	0.0
13	14	0.17093	0.34802	0.0

Step 3: Compute Line Admittances

For each line:

$$Y_{\text{line}} = \frac{1}{1\text{R+jX}} = \text{G+jB} \tag{6}$$

Step 4: Build Bus Admittance Matrix Y

Off-diagonal elements:

$$Y_{\text{ij}} = -Y_{\text{lineij}} \tag{7}$$

Diagonal elements:

$$Y_{ii} = \sum_{\text{j}\neq\text{i}} \text{Y}_{\text{ij}} + \text{Y}_{\text{shi}} \tag{8}$$

Where Y_{shi} is the shunt admittance (usually line charging susceptance/2 at the bus).

Step 5: Power Flow Equations

At bus i:

$$Pi = \sum_{j=1}^{n} \mid V_i \mid\mid V_j \mid (G_{ij} cos\,(\delta_i - \delta_j) + B_{ij} sin\,(\delta_i - \delta_j) \tag{9}$$

$$Qi = \sum_{j=1}^{n} \mid V_i \mid\mid V_j \mid (G_{ij} sin\,(\delta_i - \delta_j) + B_{ij} cos\,(\delta_i - \delta_j) \tag{10}$$

For load buses ($PQ\ buses$), $P_i, Q_i,$ are specified; solve for V_i, δ_i.
For generator buses ($PV\ buses$), $P_i, V_i\ specified;\ solve\ for\ Q_i, \delta_i$
Slack bus fixes V and δ.

Step 6: Numerical Solution

Use Newton-Raphson or Fast Decoupled Load Flow to solve nonlinear equations for voltages and angles.

This data and approach form the basis for offline voltage stability analysis, power flow calculations, and transient stability studies of a 14-bus 330 kV network.

Challenges and Research Directions

Key challenges include**:** Applying machine learning (ML) for voltage stability assessment is severely troubled due to the data scarcity, especially in countries like Nigeria where real-time operational data is in most at times insufficient. Due to antiquated or inadequate monitoring substructure, for example, SCADA systems and PMUs, power systems in these regions experience a serious irregular data collection. Likewise, supervised machine learning models are challenging to train because, even in cases where data is available, it regularly lacks this of required labels.

Training the model. This problem is made worse by regional differences in grid infrastructure and the unpredictability of renewable energy sources, since data might not fully reflect the dynamics of renewable integration or other irregularities in the grid. This is made more difficult by the scarce of the historical data resulting from the rare happening of voltage time out events. Enhancing voltage stability assessment through machine learning in emerging power grids will require these solutions as well as cooperative partnerships between utilities, researchers, and policymakers.
With the means of using these techniques, ML models' accuracy can be increased and training data can be supplemented. The gaps in labeled data can also be filled by encouraging data-sharing programs, creating open-access platforms, and using edge computing for real-time data aggregation. Techniques like hybrid modeling, which blends data-driven methods with physics-based simulations, and synthetic data generation using GANs are essential to overcoming these constraints.

Computational Overhead. Although, it comes to provide greater methods such as deep learning and reinforcement learning are computationally demanding and need sophisticated hardware infrastructure, accuracy and flexibility, such as GPUs and edge computing systems, to meet real-time performance requirements. Because real-time machine learning applications in voltage stability assessment continuously receive and analyze vast amounts of high-resolution data, they require powerful processing power.

Regulatory Gaps. Comprehensive regulations suited to the incorporation of artificial intelligence (AI) in energy systems are currently lacking. For intelligent grid solutions to be adopted in a way that is safe, scalable, moral, and regulatory frameworks tailored to AI must be established. In addition to limiting investment incentives and impeding cross-sectoral cooperation between power system operators, policymakers, and technology providers, the lack of clear guidelines and standards also limits the deployment of ML-driven voltage stability tools.

Cybersecurity Risks. The integrity and availability of ML-driven grid operations can be guaranteed by strengthening resilience against cyberattacks using strategies for example blockchain for secure data exchange, federated learning for decentralized model training, and anomaly-based intrusion detection systems (IDS).The creation of privacy-preserving algorithms, like differential privacy and federated learning, is equally crucial to guaranteeing the security of sensitive grid data while allowing for its intelligent analysis and decision-making. To guard against illegal access, data breaches, and control command manipulation, intelligent voltage stability systems need to have strong cybersecurity frameworks. For a more reliable evaluation of voltage stability, future studies is expected to investigate hybrid ML-physics models that combine the advantages of data-driven and conventional analytical techniques. Furthermore, increasing responsiveness and lowering the load on the central system, integrating edge-computing architectures will make it possible to process data in real-time and with low latency closer to the grid edge.

Conclusion

Predictive, data-driven, and adaptive frameworks must replace static and reactive grid management in order to address these problems. When strategically implemented throughout the power value chain, predictive control, ML techniques offer revolutionary potential for automated system response, and real-time diagnostics. Unprecedented intelligence is added to the grid through the combination of unsupervised learning for pattern recognition, supervised learning for classification and forecasting, together with reinforcement learning for autonomous voltage regulation. In adequate reactive power compensation, poor infrastructure, and fluctuating inputs from renewable energy sources are just a few of the intricate and interconnected causes of voltage instability in Nigeria's power grid that are highlighted in this review. Additionally, advanced temporal and spatial feature extraction which is also one of the essentials for predictive maintenance and dynamic VSA is made possible by the use of DL architectures, specifically LSTM and CNN.

Technically, these intelligent systems offer context-specific, scalable, and robust voltage stability solutions. Aligning ML innovation with smart grid architecture, supported by well-informed policy frameworks and focused investments, is essential to Nigeria's transition to a stable and sustainable grid infrastructure. The data scarcity issue that limits traditional approaches in the Nigerian context can be greatly mitigated by combining ML with synthetic data generation using tools e.g. GANs. In conjunction with edge-based computing and hybrid physics-data models, Nigeria can overcome legacy grid constraints and guarantee a dependable power supply to facilitate socioeconomic transformation with a well-coordinated approach that incorporates technological, regulatory, and operational innovations.

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