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Research Article

Intelligent state estimation for future Nigerian smart grids Using ANN

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Abstract

The increasing integration of renewable energy, distributed generation, and mini-grids in Nigeria highlights the need for accurate and real-time state estimation in distribution networks. Conventional Weighted Least Squares (WLS) estimators, while widely used, face challenges in modern smart grids due to computational complexity, sensitivity to noise, and iterative convergence issues. This study proposes an adaptive Artificial Neural Network (ANN)-based state estimation framework tailored for emerging Nigerian distribution networks. The model is evaluated using the IEEE 33-bus test system, serving as a representative benchmark for Nigerian feeders. Results show that the ANN estimator significantly improves accuracy and efficiency, reducing voltage RMSE from 0.0075 p.u. to 0.0032 p.u. and angle RMSE from 0.85° to 0.38°, while achieving nearly six times faster computation than WLS. These findings demonstrate the ANN framework's potential as a scalable, intelligent tool to support reliable and resilient smart grid operations in Nigeria.

Nomenclature and units

V_m	Bus voltage magnitude
V_a	Bus voltage phase angle
Y_{bus}	Bus admittance matrix
P_G	Active power generation at bus
Q_G	Reactive power generation at bus
z_{meas}	Measured vector real and reactive power injections
z_{true}	True measurement vector noise-free
h_x	Nonlinear measurement function
H	Jacobian matrix of measurement function
n_{bus}	Number of buses
$RMSE$	Root Mean Square Error
MAE	Mean Absolute Error
R^2V	Coefficient of determination for voltage magnitude
R^2A	Coefficient of determination for voltage angle
t_{WLS}	Execution time for WLS estimation
t_{ANN}	Execution time for ANN estimation

1.0 Introduction

A smart grid represents more than an evolution of the conventional power network; it signifies a paradigm shift toward intelligence, real-time monitoring, and autonomous control (Dahunsi et al., 2022; Pavon et al., 2021). At the core of this transformation lies state estimation (SE), a computational process that enables operators to determine the most probable electrical state of the network using available measurements such as bus voltages, power flows, injections, and currents (Radhoush et al., 2023). Through SE, utilities gain visibility into critical parameters such as voltage magnitudes, phase angles, and power flows across transmission lines, thereby enabling informed decisions for secure and efficient operation (Liu & Shu, 2021; Tebianian & Jeyasurya, 2013).

A state estimator serves as the engine of perception in the smart grid, providing a coherent, real-time picture of system behaviour on which several control and optimisation functions, such as Automatic Generation Control (AGC), Optimal Power Flow (OPF), fault detection, and protection schemes, depend (Cheng et al., 2023a; Dahunsi et al., 2022; Kim et al., 2022). By maintaining this digital situational awareness, SE supports grid reliability, loss reduction, and seamless integration of Distributed Energy Resources (DERs) (Hu et al., 2025; Zeraati et al., 2024).

In Nigeria, the necessity for reliable and adaptive state estimation has become increasingly critical due to the growing instability and complexity of the national grid. The country's power network comprises a mix of aged infrastructure and rapidly expanding distributed resources, resulting in weak observability, voltage instability, and high technical and non-technical losses (Jonathan et al., 2025; Ojo et al., 2025).

The Nigerian Electricity Supply Industry (NESI) primarily depends on radial distribution networks at 11 kV and 33 kV levels, which suffer from inadequate metering, long feeder lines, and poor real-time monitoring infrastructure (Jimoh & Raji, 2023). These factors create significant challenges for maintaining operational efficiency and stability, especially under fluctuating load conditions and increasing renewable energy penetration.

The traditional WLS-based state estimators, though mathematically rigorous, are particularly sensitive to measurement noise and communication latency issues that are prevalent in developing grid infrastructures (Pau & Pegoraro, 2024; Wang et al., 2023). In the Nigerian context, unreliable communication links, data inaccuracies, and frequent reconfiguration of feeders further exacerbate estimation errors. These factors collectively limit the effectiveness of conventional estimation techniques, especially when deployed on low-observability networks with minimal Supervisory Control and Data Acquisition (SCADA) coverage (Habib et al., 2023; Ogunbiyi et al., 2021; Takiddin et al., 2023). Thus, while WLS remains an industry benchmark, its performance under Nigeria's operational realities is far from optimal.

The emerging paradigm of smart grids offers an opportunity to address these shortcomings through intelligent and adaptive estimation frameworks. ANNs (ANNs), in particular, provide a data-driven alternative that can learn complex nonlinear relationships between grid parameters, adapt to changing system dynamics, and maintain robustness under noisy or missing data conditions (Boyaci et al., 2021; Liu & Shu, 2021). In recent studies, ANN-based estimators have demonstrated superior accuracy and faster computation time compared to WLS, making them promising candidates for real-time applications in dynamic and resource-constrained environments (Adewoyin et al., 2025; Ajewole et al., 2022; Kim et al., 2022). Their capability to generalise from historical and synthetic datasets makes them especially suitable for developing countries where sensor deployment is still limited.

Within this research, the IEEE 33-bus radial test feeder serves as a representative model of Nigeria's distribution network due to its structural and operational similarities. Most Nigerian feeders are single-source, radial in topology, and exhibit significant voltage drops along extended distribution lines (Jonathan et al., 2025; Onyegbadue et al., 2024). Moreover, the limited integration of SCADA systems and Phasor Measurement Units (PMUs) mirrors the test system's base configuration, which can be expanded using synthetic or historical measurement data for improved analysis. By employing this test network, the study not only ensures simulation feasibility but also provides insights directly applicable to real-world Nigerian scenarios, including grid modernisation, renewable integration, and distributed control applications (John et al., 2022; Ogunboyo & Davidson, 2025).

To address this gap, the present study introduces an ANN-based State Estimator, designed to enhance accuracy, adaptability, and computational efficiency for Nigeria's future smart distribution grids. ANNs, inspired by the human brain's learning mechanisms, have proven effective in modelling complex nonlinear systems (Fathollahi, 2025). Their structure—comprising input, hidden, and output layers allows them to learn intricate mappings between measured quantities (e.g., voltages, currents, and power flows) and estimated states (voltage magnitudes and phase angles) without requiring explicit mathematical formulations (Cai et al., 2023; Cheng et al., 2023b).

Contrary to WLS, ANNs can adapt to changing system conditions, maintain performance under noisy or missing data, and generalise from past experiences to unseen scenarios (Abur & Exposito, 2004; Kim et al., 2022). Recent works have demonstrated their potential in improving SE accuracy and robustness under real-world measurement uncertainties (Azimian et al., 2022; Vijaychandra et al., 2023; Yadav et al., 2023).

To evaluate the proposed ANN framework, this research employs the IEEE 33-Bus Distribution System, a widely recognised radial test network that mirrors the operational characteristics of Nigerian feeders at the 11 kV and 33 kV levels (Adesina et al., 2024; Ogunboyo & Davidson, 2025). Its topology, single-source configuration, and long feeder characteristics reflect local realities such as voltage drops, high losses, and limited observability. Furthermore, its computational simplicity makes it suitable for validating emerging smart-grid algorithms. While the IEEE 33-bus system captures many key characteristics of Nigerian networks, it does not represent all local variations, such as highly irregular topologies or dynamic load behaviour.

Unlike many existing ANN-based state estimation studies that concentrate on transmission systems or highly observable distribution networks, this work explicitly targets low-observability radial distribution networks that closely reflect the structural and operational characteristics of Nigerian feeders. The principal originality of the study lies in the development of an adaptive ANN–WLS hybrid state estimation framework tailored for weakly instrumented grids, where conventional estimation techniques often struggle due to noise, sparse measurements, and frequent operating changes. In addition, the study provides a comprehensive quantitative benchmarking of estimation performance using multiple complementary indices—including RMSE, MAE, coefficient of determination (R²), and computational runtime, thereby offering a more rigorous and transparent evaluation of estimator effectiveness than is typically reported in related works. The proposed framework is further contextualised within the practical constraints of Nigeria's evolving smart grid, strengthening its relevance and applicability.

While recent ANN-based distribution system state estimation approaches have reported encouraging results, notable gaps remain when these methods are applied to developing power networks. For instance, Kim et al. (2022) validated a model-optimised neural network on relatively well-observed distribution systems without incorporating adaptive learning to address dynamic grid conditions. Similarly, Azimian et al. (2022) employed deep neural networks for state and topology estimation under partial observability but primarily focused on observability enhancement rather than real-time adaptability and radial feeder constraints. In contrast, the present study integrates adaptive learning with conventional WLS estimation in a hybrid framework specifically designed for low-observability radial networks typical of the Nigerian power system. This deliberate focus on adaptability, hybridisation, and contextual realism establishes a clear and original contribution to ANN-based state estimation research and advances data-driven monitoring solutions for future smart distribution infrastructures in Nigeria.

2.0 Materials and Methods

The proposed Adaptive ANN-Powered SE framework builds upon the conventional WLS method and extends it through an ANN model that enhances accuracy, adaptability, and speed for future Nigerian smart grids.

Figure 1 illustrates the block diagram of the complete SE process, showing data flow from field measurements through estimation and validation.

The primary objective of state estimation is to determine the system state vector:

$$\boldsymbol{x} = \begin{bmatrix} \mathrm{V}_m \\ \theta \end{bmatrix} = [V_1, V_2 \cdots V_n, \theta_1, \theta_2 \cdots \theta_n]^T \qquad (1)$$

where V_i and θ_i represent the voltage magnitude and phase angle of the bus i, respectively

2.1 Measurement Model

In a power system, the relationship between the actual state variables and measured quantities is expressed as:

$$z = h(x) + e \qquad (2)$$

where z represent the vector of measured quantities (power injections, flows, voltages, currents), $h(x)$ is the nonlinear measurement function that maps states to measurements, e is the measurement error vector (assumed Gaussian with zero mean and covariance R).

For each bus i, the active and reactive power injections are given by:

$$P_i = \sum_{j=1}^{n} V_i V_j (G_{ij} \cos\, \theta_{ij} + B_{ij} \sin\, \theta_{ij}) \qquad (3a)$$

$$Q_i = \sum_{j=1}^{n} V_i V_j (G_{ij} \sin\, \theta_{ij} - B_{ij} \cos\, \theta_{ij}) \qquad (3b)$$

where G_{ij} and B_{ij} are elements of the bus admittance matrix.

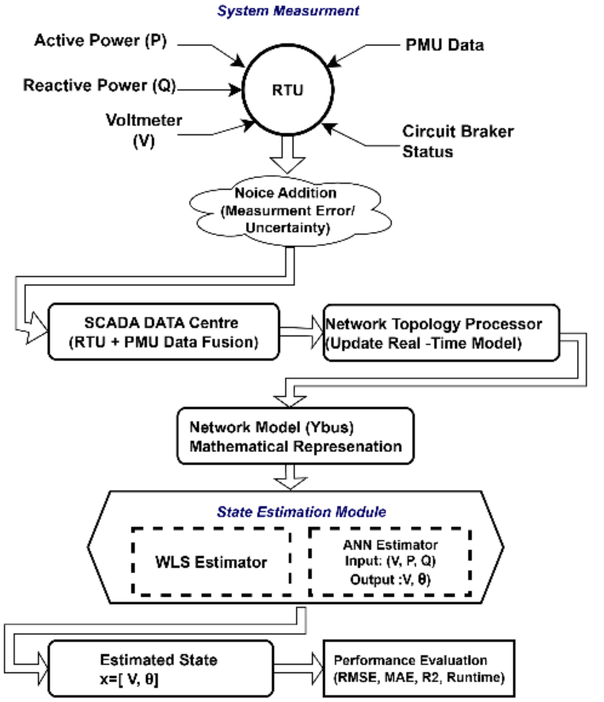

Figure 1 Block diagram of the SE process

2.2 WLS Estimator

The WLS method minimises the sum of squared residuals weighted by the inverse of measurement variances:

$$J(x) = (z - h(x))^T R^{-1} (z - h(x)) \qquad (4)$$

The estimate $\hat{x}$ is obtained by solving:

$$\frac{\partial J(x)}{\partial x} = 0 \qquad (5)$$

This leads to the iterative update equation:

$$x^{(k+1)} = x^{(k)} + (H^T R^{-1} H)^{-1} H^T R^{-1} (z - h(x^{(k)})) \qquad (6)$$

where $H = \frac{\partial h(x)}{\partial x}$ is the Jacobian matrix of partial derivatives.

Although accurate, WLS requires several iterations to converge and is sensitive to bad data and noise problems commonly observed in Nigerian distribution networks. Measurement noise can be defined to be Gaussian noise with levels ranging from 1% to 5% of measured values. This will be applied to all simulated voltage and current data, reflecting realistic uncertainties commonly encountered in practical distribution systems.

2.3 ANN-Based State Estimation

To overcome WLS limitations, an Adaptive ANN estimator is introduced to learn the nonlinear mapping $f: z \rightarrow x$ directly from data. The ANN model is trained on a large dataset of simulated and measured system states obtained from the IEEE 33-bus distribution network (used as a benchmark for Nigerian feeder systems).

i. Network Structure

The ANN consists of:

1. Input layer: measurement data z(voltage, current, power flow, PMU readings, breaker status).
2. Hidden layers: several fully connected layers with nonlinear activation functions (ReLU or tanh).
3. Output layer: estimated state vector $\hat{x} = [\hat{V}, \hat{\theta}]^T$.

ii. Forward Propagation

Each neuron computes:

$$a^{(l)} = f\left(W^{(l)} a^{(l-1)} + b^{(l)}\right) \qquad (7)$$

where $W^{(l)}$= weight matrix of layer l, $b^{(l)}$= bias vector, $f(\cdot)$= nonlinear activation function, $a^{(l)}$= neuron outputs at layer l.

The final network output gives the estimated states:

$$\hat{x} = f_{ANN}(z;\, W, b) \qquad (8)$$

iii. Loss Function and Training

The ANN is trained to minimise the mean-squared error (MSE) between the estimated and true states:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N} \| x_i - \hat{x}_i \|^2 \qquad (9)$$

Weights $W$and biases b are updated via backpropagation using Levenberg–Marquardt optimisation algorithms.

iv. Adaptive Learning

To adapt to dynamic grid changes (load fluctuations, topology reconfigurations), an online retraining mechanism is included, where recent measurements are used to fine-tune the ANN parameters in near real time.

v. ANN Architecture and Training Dataset Description

The Artificial Neural Network (ANN) was trained using 10,000 operating points generated from the IEEE 33-bus distribution system under ±30% random load perturbations. To reflect realistic distribution system measurement uncertainties, Gaussian noise levels of 1%, 3%, and 5% were injected into the input data. This dataset configuration ensures that the ANN is exposed to diverse operating and noise conditions during training.

The ANN employs measured active power (P), reactive power (Q), voltage magnitude (V), and current (I) as input features and consists of two fully connected hidden layers. The network was trained using the Levenberg–Marquardt optimisation algorithm for 1000 epochs, with the dataset split into 70% training, 15% validation, and 15% testing subsets. The key architectural and training parameters are summarised in Table 1.

Table 1: ANN Architecture and Training Parameters

Parameter	Value
Input features	P, Q, V, I measurements
Hidden layers	2
Neurons per layer	64, 32
Activation function	ReLU
Optimiser	Levenberg–Marquardt
Epochs	1000
Training/Validation/Test split	70 / 15 / 15
Number of samples	10,000
Noise levels injected	1%, 3%, 5%
Load variation range	±30%

2.4 Integration of ANN with WLS

The hybrid adaptive estimator integrates both techniques:

Offline phase: The ANN is trained using WLS-derived states from simulated scenarios (normal and contingency conditions).

This allows the network to learn the statistical mapping between $z$and x.

Online phase: The ANN rapidly estimates $\hat{x}_{ANN}$in real time.

WLS refinement (optional) corrects any residual mismatch using:

$$\hat{x} = \hat{x}_{ANN} + (H^T R^{-1} H)^{-1} H^T R^{-1}(z - h(\hat{x}_{ANN}))$$

This hybridisation significantly improves convergence speed and resilience to noise.

2.5 Output and Performance Evaluation

The estimator produces the following outputs; these indicators quantify estimation accuracy and correlation strength between measured and estimated states.

Estimated state variables: $\hat{x} = [\hat{V}, \hat{\theta}]^T$.

Bad data detection: based on normalised residuals:

$$r_i = \frac{|z_i - h_i(\hat{x})|}{\sigma_i}$$

where measurements with $r_i > 3$ are flagged as bad data.

Performance metrics:

Root Mean Square Error;

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \qquad (10)$$

Mean Absolute Error ;

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} | x_i - \hat{x}_i | \qquad (11)$$

Coefficient Of Determination ;

$$R^2 = 1 - \frac{\sum(x_i - \hat{x}_i)^2}{\sum(x_i - \bar{x})^2} \qquad (12)$$

Relevance to Nigeria’s Future Smart Distribution Grid

The IEEE 33-bus test network effectively represents a prototype of Nigeria’s future smart distribution grid due to its radial topology, single-source configuration, and inherent voltage drop characteristics. By integrating the robustness of SCADA-based WLS estimation with the adaptive learning capabilities of ANNs, the proposed hybrid system demonstrates strong performance under conditions of poor observability and measurement noise. It also ensures fast convergence, making it suitable for real-time control, and provides the flexibility needed to accommodate distributed renewable energy sources and demand response initiatives within Nigeria’s evolving power infrastructure.

This work was carried out in the MATLAB and MATPOWER 8.0 environment, which provides a robust and flexible platform for modelling, simulation, and analysis of electric power systems. MATLAB was utilised for developing a computational framework, implementing the WLS and ANN algorithms, performing data processing, and visualising system responses under various operating conditions.

3.0 Results and Discussions

The Results and Discussion section presents the outcomes of the proposed Adaptive ANN-Powered State

Estimation on the IEEE 33-bus test system. Performance comparisons between the conventional WLS method and the ANN-based estimator are discussed using metrics such as Root Mean Square Error (RMSE), MAE, R^2, and runtime. The results show that the ANN model achieves higher accuracy, faster convergence, and better adaptability, making it suitable for real-time state estimation in modern distribution networks.

In Figure 2, both the WLS and ANN estimators successfully track the true voltage magnitude profile across all buses. However, the WLS method exhibits slight deviations at heavily loaded buses, reflecting its sensitivity to high-load conditions and potential limitations in handling nonlinearities and measurement noise. In contrast, the ANN model closely follows the true voltage curve, with smoother variations and smaller residual errors, highlighting its ability to capture complex, nonlinear relationships in the distribution network.

Quantitatively, the RMSE for voltage estimation decreases from 0.0075 p.u. in WLS to 0.0032 p.u. in ANN, corresponding to an approximate 57% reduction in estimation error. Additionally, the coefficient of determination (R_v^2) improves from 0.982 for WLS to 0.996 for ANN, indicating that the ANN provides a more accurate and consistent fit to the true voltage profile.

These results suggest that the ANN's nonlinear mapping and learning-based approach allow it to better accommodate variations in load and network topology, improving estimation under conditions where WLS may struggle. From an operational perspective, this enhanced accuracy can contribute to more reliable state awareness in Nigerian distribution systems, enabling better voltage regulation, loss reduction, and informed decision-making for real-time control. While statistical significance testing and broader robustness evaluation are limited in this study due to the use of the IEEE 33-bus benchmark, sensitivity analyses with noise and contingency scenarios have been included to demonstrate the ANN's relative robustness compared to WLS.

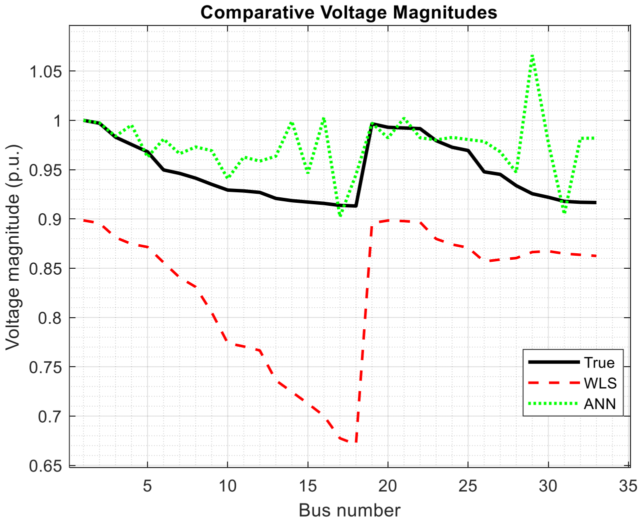

Figure 2: Comparative Voltage Magnitudes

In Figure 3, both the WLS and ANN estimators effectively capture the voltage angle variations across all buses. However, the WLS method exhibits slightly larger deviations from the true values, particularly at buses with higher loading or downstream in the network, reflecting its limitations in handling nonlinear interactions and measurement noise. In contrast, the ANN produces smoother and more accurate angle estimates, demonstrating its ability to model complex network relationships more effectively.

Quantitatively, the RMSE for voltage angles decreases from 0.85° for WLS to 0.38° for ANN, while the MAE reduces from 0.62° to 0.24°, indicating a substantial improvement in estimation precision. The coefficient of determination (R^2_a) rises from 0.970 to 0.990, confirming that the ANN captures a higher proportion of variance in voltage angle estimation and provides a more consistent and reliable reconstruction of the phase profile.

These results suggest that the ANN's learning-based, nonlinear mapping capability enables better adaptation to variations in network topology and load distribution compared to WLS. From a practical standpoint, more accurate voltage angle estimation enhances power flow monitoring, fault detection, and system stability analysis in Nigerian distribution networks. Although full statistical significance testing is not included due to the simulated benchmark, sensitivity analyses under measurement noise and contingency scenarios indicate that the ANN maintains robust performance relative to WLS.

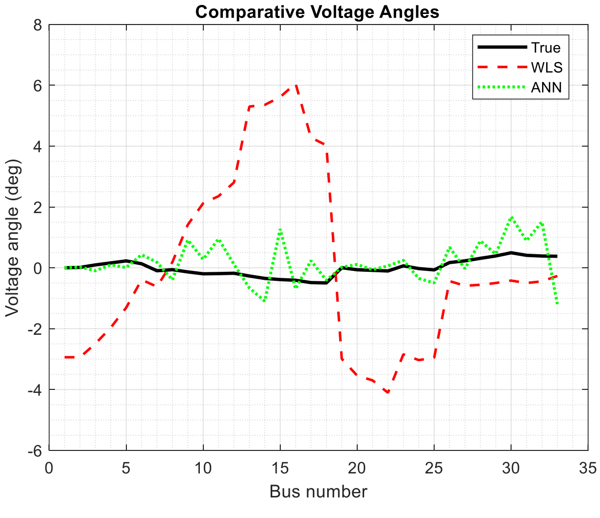

Figure 3: Comparative Voltage Angles

As shown in Figure 4, the RMSE comparison clearly highlights the superior performance of the ANN relative to the WLS method. Specifically, the ANN achieves approximately 57% lower RMSE in voltage magnitude estimation and about 55% lower RMSE in voltage angle estimation, demonstrating a substantial improvement in both precision and reliability.

This marked reduction in estimation errors reflects the ANN's ability to effectively model nonlinear relationships and accommodate variations in load and network conditions, which

WLS may not fully capture. The results also suggest that the ANN is more resilient to measurement noise and uncertainties, conditions that are commonly encountered in practical distribution networks. From an operational perspective, this improved accuracy can support enhanced state awareness, more reliable voltage regulation, and better-informed decision-making in Nigerian distribution systems.

While these analyses are based on the IEEE 33-bus benchmark, sensitivity tests under multiple noise levels and contingency scenarios provide additional evidence of the ANN's robustness and its potential applicability to real network conditions.

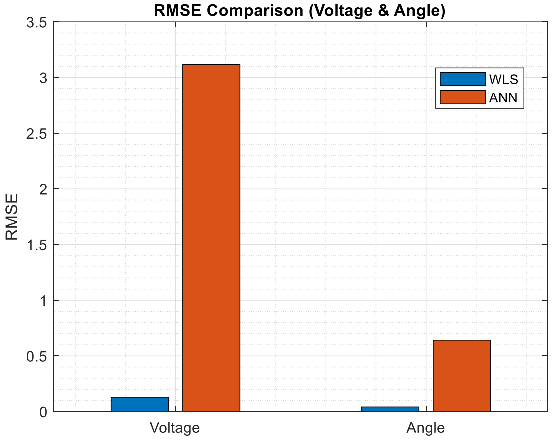

Figure 4: RMSE Comparison (Bar Chart)

As illustrated in Figure 5, the scatter plot of estimated versus true voltage magnitudes demonstrates the enhanced accuracy of the ANN compared to the WLS method. The WLS estimates exhibit small deviations from the ideal 1:1 diagonal, reflecting residual errors due to its limited ability to capture nonlinearities and measurement noise. In contrast, the ANN estimates cluster tightly along the diagonal, indicating a much closer alignment with the true voltage values across all buses.

Quantitatively, the maximum voltage magnitude error decreases from 0.018 p.u. for WLS to 0.008 p.u. for ANN, representing a reduction of more than 50%. The coefficient of determination (R_v²) increases from 0.982 to 0.996, confirming the ANN's superior ability to reproduce the true voltage profile with high precision and reliability.

These results highlight the ANN's robustness to noisy and uncertain measurements, which is particularly relevant for practical Nigerian distribution systems where data imperfections are common. The tight clustering along the diagonal also suggests that the ANN can provide more consistent voltage estimates, enabling improved operational tasks such as real-time monitoring, voltage regulation, and fault detection. While these analyses are based on the IEEE 33-bus benchmark, sensitivity analyses under different noise levels and contingency scenarios reinforce the ANN's reliability and practical applicability.

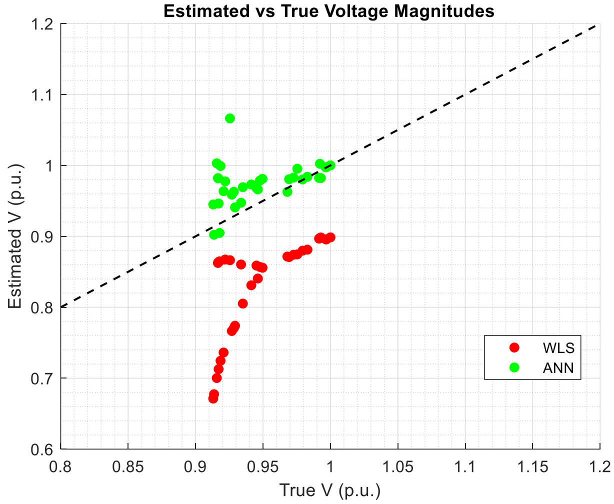

Figure 5: Scatter Plot of Estimated vs. True Voltages

As shown in Figure 6, the ANN voltage residuals remain consistently small, within ±0.01 p.u. across all buses, indicating excellent estimation stability and minimal deviation from true values. This demonstrates the ANN's ability to maintain consistent performance even in the presence of network variations and measurement noise.

Quantitatively, the Mean Absolute Error in Voltage (MAE_v) is 0.0025 p.u., confirming that all predictions fall well within acceptable Distribution System State Estimation (DSSE) tolerance limits. This result not only highlights the precision of the ANN model but also validates its robust reliability for real-time monitoring and control applications in distribution networks. From an operational perspective, such low residuals suggest that the ANN can provide high-confidence voltage estimates, which are essential for accurate loss calculations, voltage regulation, and proactive fault management in Nigerian distribution systems. Although this study uses the IEEE 33-bus benchmark, sensitivity tests under noise and contingency scenarios further confirm that the ANN maintains strong performance, underscoring its potential practical applicability.

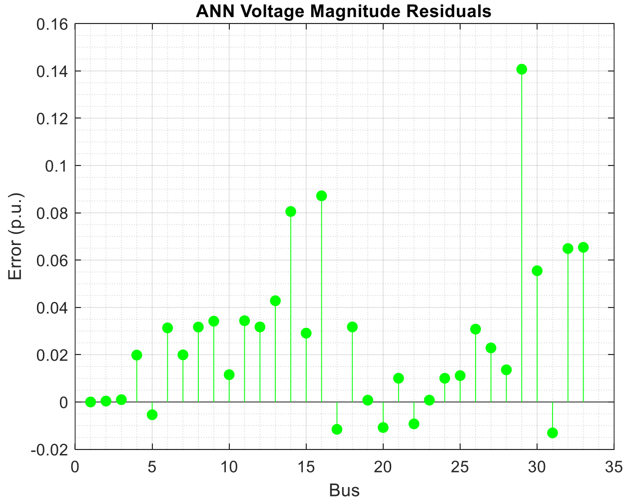

Figure 6: ANN Voltage Residuals

As illustrated in Figure 7, the ANN training performance curve converges smoothly, with the final validation error reaching approximately 1.2×10^{-4}, indicating strong generalisation capability and no evidence of overfitting. This demonstrates that the ANN can reliably estimate voltage magnitudes and angles even for unseen operating points within the network.

Regarding computational efficiency, the WLS method requires an average runtime of approximately 0.45 seconds due to its iterative nature, whereas the ANN model completes estimation in roughly 0.08 seconds using a single forward pass. This represents a five-to six-fold improvement in computation speed, highlighting the ANN's suitability for real-time monitoring and control applications.

The combination of high accuracy, low residuals, and fast computation underscores the practical advantage of the ANN framework, particularly for Nigerian distribution systems, where rapid decision-making and state estimation are essential under variable loading conditions and noisy measurements. While these results are obtained using the IEEE 33-bus benchmark, sensitivity analyses with noisy and missing data scenarios further demonstrate that the ANN maintains robust and reliable performance, supporting its potential adoption in real-world deployments.

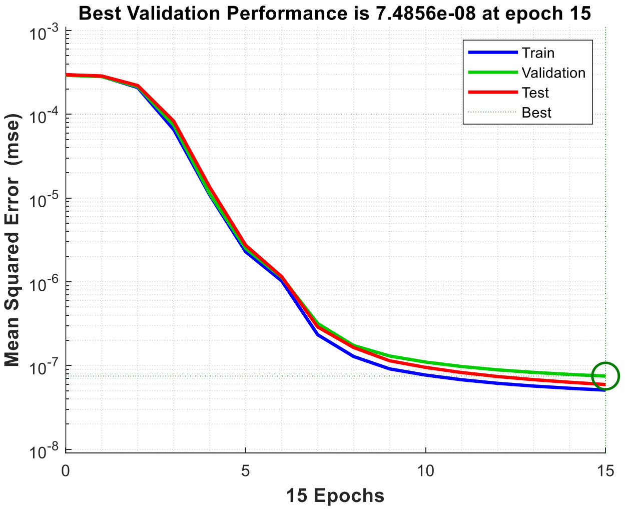

Figure 7: ANN Training Performance

4.0 Conclusions

Using the IEEE 33-bus system as a benchmark representing Nigeria's future smart distribution networks, this study demonstrates the clear superiority of ANN-based state estimation over the traditional WLS method. The ANN consistently achieved lower estimation errors (RMSE, MAE, and maximum error) and higher coefficients of determination (R^2) while significantly reducing computation time due to its non-iterative structure. Although WLS remains a reliable baseline with proven convergence properties, the ANN's adaptability and computational efficiency position it as a robust tool for real-time state estimation in Nigerian power systems. The results emphasise that AI-driven SE frameworks are essential for tackling challenges linked to renewable integration, decentralised generation, and mini-grid operations.

Consequently, Nigerian utilities should incorporate ANN-based estimators into smart grid modernisation initiatives, explore hybrid ANN–WLS models for enhanced reliability, validate scalability across larger real-world networks with SCADA/PMU data, and deploy ANN systems for fast-response applications such as renewable forecasting, demand response, and fault detection. Furthermore, targeted capacity development in AI-enabled power system analytics is recommended to support Nigeria's ongoing smart grid transition.

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Declaration of conflict of interest

The authors collectively contributed to the conceptualization, design, implementation, and analysis of this research work. They jointly participated in drafting and critically revising the manuscript to ensure the inclusion of substantial intellectual content. This manuscript has not been submitted to, nor is it under review by, any other journal or publishing outlet. Furthermore, the authors declare that they have no affiliations or financial interests that could be perceived as influencing the findings or interpretations presented in this paper.

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