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A Hybrid LSTM–Grey Wolf Optimization Framework for Optimal Siting and Sizing of Distributed Generation in Radial Distribution Networks: Evidence from IEEE Benchmark Systems and A Nigerian 33 kV Feeder

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ABSTRACT: Electric power distribution networks in developing countries, particularly Nigeria, continue to experience high technical losses, poor voltage profiles, and increasing load demand on ageing, radially configured feeders. Although distributed generation is a proven technical solution to these challenges, its benefits depend heavily on optimal siting and sizing, a problem that is non-linear, multi-objective, and difficult to solve using conventional methods. This study developed and validated a hybrid intelligent framework that combines a Long Short-Term Memory neural network for load forecasting with a Grey Wolf Optimizer for distributed generation placement. The framework was tested on the IEEE 33-bus and IEEE 69-bus benchmark systems and, uniquely, on one hundred and twenty-five days of real operational data collected from the Moniya-Akinyele 33 kilovolt distribution feeder in Ibadan, Nigeria. Load flow analysis using the Newton-Raphson method identified weak buses through a composite priority index combining voltage deviation and loss sensitivity. On the benchmark system, the proposed framework reduced real power losses by 75.3 percent and improved the minimum bus voltage from 0.6746 to 0.6954 per unit following distributed generation installation of 243.88 kilowatts across seven priority buses. On the Nigerian feeder, the forecasting model achieved a coefficient of determination of 0.9667 and a mean absolute percentage error of 3.83 percent using real operating data, substantially outperforming its performance on synthesised benchmark data. The findings demonstrate that combining machine learning-based demand forecasting with meta-heuristic optimisation provides a practical and technically sound approach for intelligent network planning in developing-country distribution systems.

KEYWORDS: Deep Learning; *Load Demand Prediction; Moniya–Akinyele Feeder; Power Loss Minimization; Voltage Profile Improvement*

1. INTRODUCTION

Electric power distribution systems represent the final stage in delivering electricity from transmission networks to end users. In many developing countries, including Nigeria, these systems are predominantly radial and operate at medium voltage, typically 33 kV and 11 kV. Such networks face persistent operational challenges, including rapid load growth, high technical losses, voltage fluctuations, ageing infrastructure, and limited automation. Radial feeders with long line lengths and high resistance-to-reactance ratios are especially susceptible to real power losses and voltage degradation (Fasina, Adebanji, Abe, & Ismail, 2021).

Distributed generation has emerged as a technically viable strategy for addressing these challenges. Distributed generation units are small- to medium-scale generation plants located close to load centres or connected directly to distribution feeders. When properly sited and sized, distributed generation can reduce feeder losses, raise voltage levels, and improve power quality; when poorly located, it can cause reverse power flow, voltage excursions, and protection coordination problems (Ali, Abd Elazim, & Abdelaziz, 2022; Sultana, Khairuddin, & Aman, 2021). The siting and sizing problem is therefore inherently non-linear, multi-objective, and constrained, requiring the simultaneous minimisation of power loss and voltage deviation subject to statutory voltage limits, thermal limits, and penetration limits.

Meta-heuristic optimisation algorithms have become the dominant approach for solving this class of problem because they can search large, non-convex solution spaces without becoming trapped in local minima. Particle Swarm Optimisation, Genetic Algorithms, Harris Hawks Optimisation, and hybrid variants have all demonstrated strong performance in distributed generation planning studies (Babu et al., 2021; El-Fergany, 2020; Nguyen, Truong, & Nguyen, 2020; Sharma et al., 2022; Yadav & Kumar, 2022). Broader surveys of nature-inspired optimisation confirm that hybrid formulations generally improve convergence speed and solution quality relative to single-algorithm approaches (Boussaïd, Lepagnot, & Siarry, 2020; Meraihi, Gabis, Mirjalili, Ramdane-Cherif, & Entacher, 2021).

Effective distributed generation planning also depends on accurate forecasting of electricity demand, which is inherently non-linear and time-varying. Deep learning architectures, particularly Long Short-Term Memory networks, have proven effective at capturing the temporal dependencies present in load data and consistently outperform conventional statistical forecasting methods (Alamaniotis et al., 2022; Khan et al., 2023; Liu, Mi, & Li, 2020). Combining machine learning-based load forecasting with meta-heuristic optimisation has therefore been proposed as a route to more realistic and operationally sound distributed generation planning (Bedi & Toshniwal, 2022; Goudarzi, Rahimi, & Hasanvand, 2023; Kumar, Singh, & Sharma, 2024).

Despite this progress, most existing studies validate their frameworks exclusively on standardised IEEE benchmark feeders under static or synthetically generated load conditions (Chen et al., 2023; Das, Mukherjee, & Dey, 2023; Kamel, Jurado, & Abdelaziz, 2021; Mohamed, Hemeida, & Ibrahim, 2021; Rashid & Singh, 2022; Rezk, Fathy, & Abdelaziz, 2021). These idealised systems do not adequately capture the structural and operational characteristics of Nigerian distribution feeders, which are typically longer, more heavily loaded, less automated, and subject to frequent supply interruptions. There remains a scarcity of studies that combine machine learning-based load forecasting with meta-heuristic optimisation and validate the resulting framework against real, field-collected feeder data from a developing-country network (Dash, Mishra, Pati, & Satpathy, 2020; Zhu, Zhang, Liu, Zhao, & Wang, 2024).

This study addresses that gap by developing a hybrid Long Short-Term Memory–Grey Wolf Optimization framework for the optimal siting and sizing of distributed generation. The framework is validated on the IEEE 33-bus and IEEE 69-bus benchmark systems using synthesised temporal load data, and, distinctively, on one hundred and twenty-five days of real hourly operational data from the Moniya-Akinyele 33 kV feeder operated by the Ibadan Electricity Distribution Company in Ibadan, Nigeria. The specific objectives are to: (i) characterise the benchmark and Nigerian test systems using load flow analysis and bus performance priority indices; (ii) develop and validate a Long Short-Term Memory load forecasting model for each system; (iii) develop a Grey Wolf Optimizer-based algorithm for distributed generation siting and sizing informed by the forecasts and performance indices; and (iv) evaluate the resulting reduction in power loss and improvement in voltage profile on both the benchmark and Nigerian systems.

2. MATERIALS AND METHODS

2.1 Test Systems

Three radial distribution systems were examined. The IEEE 33-bus system comprises 33 buses, 32 branches, and one slack bus operating at 12.66 kV, with a total active load of 3,715 kW and reactive load of 2,300 kVAR; under base-case conditions, 29 of its 33 buses operate below 0.95 per unit, with the lowest voltage of 0.6746 per unit recorded at Bus 33. The IEEE 69-bus system comprises 69 buses and 68 branches operating at the same base voltage, with a total active load of 3,802 kW; only two of its buses fall below 0.95 per unit under base conditions. The third system is the Moniya-Akinyele 33 kV feeder, the principal case study, which supplies 92 buses (91 active load buses) in the Akinyele Local Government Area of Oyo State from the Moniya 132/33 kV injection substation. This feeder has a total base load of 24.14 MW, an operating voltage of 33 kV, resistance-to-reactance ratios of 2.0 to 4.0 typical of ageing overhead conductors, non-uniform load distribution, daily supply outages, and technical losses of approximately 18 to 25 percent, distinguishing it structurally and operationally from the idealised IEEE feeders.

2.2 Load Flow Analysis

Steady-state load flow was solved using the Newton-Raphson method, selected for its rapid convergence, implemented in the open-source pandapower package (version 3.4.0) in Python. The IEEE 33-bus network was loaded using its standard case function; the IEEE 69-bus network was converted from MATPOWER format; and the Nigerian 92-bus feeder was modelled from field line and load data on a 33 kV, 100 MVA base. Convergence was defined as a power mismatch below 1×10^{-6} MVA at all buses.

2.3 Bus Performance Priority Indices

To guide distributed generation pre-screening, three indices were computed from the Newton-Raphson base-case solution for each active bus: a Power Loss Index expressing per-unit voltage deviation from nominal, a quadratic Voltage Deviation Index emphasising buses furthest from unity voltage, and a Loss Sensitivity Index capturing the sensitivity of system losses to active power injection at each bus, accounting for both load magnitude and upstream electrical distance. The normalised Power Loss Index and Loss Sensitivity Index were combined into a single Combined Priority Score, scaled between zero and one, with scores closer to one indicating greater urgency for distributed generation intervention.

2.4 Load Forecasting with Long Short-Term Memory Networks

For the IEEE systems, an hourly synthesised load time series (8,760 hours per bus) was generated from each bus's base load using a double-Gaussian daily curve reflecting morning and evening demand peaks, a weekly factor reducing weekend demand by 20 percent, and a sinusoidal seasonal factor. For the Nigerian feeder, real hourly operational data spanning 125 days (1 December 2025 to 27 May 2026) was obtained from Ibadan Electricity Distribution Company field records, comprising feeder load, current, voltage, power factor, hours of supply, and operational remarks, and reflecting genuine supply intermittency including recurring daily outages. All datasets were converted into supervised-learning form using a 24-hour sliding window with eight temporal context features, scaled between zero and one. An identical Long Short-Term Memory network architecture, comprising two hidden layers of 128 and 64 tanh units feeding a four-unit linear output layer, was trained for each system using the Adam optimiser with an initial learning rate of 0.001, mini-batches of 256, and early stopping on a 10 percent validation hold-out with a patience of 15 epochs.

2.5 Grey Wolf Optimizer-Based Distributed Generation Siting and Sizing

Forecasted load peaks and the composite bus priority scores were used jointly to inform a Grey Wolf Optimizer that determined distributed generation location and capacity at the highest-priority buses on each system, subject to voltage limits of 0.95 to 1.05 per unit and prevailing thermal and penetration constraints. Post-installation performance was verified by re-running the Newton-Raphson power flow with the recommended distributed generation units in place and comparing system-level real power loss, minimum bus voltage, and system Voltage Deviation Index against the pre-installation base case.

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3. RESULTS

3.1 Load Forecasting Performance

Table 1 summarises the system-level forecasting performance obtained from actual model execution. The Moniya-Akinyele feeder model, trained on real Ibadan Electricity Distribution Company data, achieved a coefficient of determination of 0.9667, a mean absolute percentage error of 3.83 percent, and a root-mean-square error of 319.405 kW. In contrast, both IEEE benchmark models, trained on synthesised data, produced negative coefficients of determination (−0.5301 for the 33-bus system and −0.1652 for the 69-bus system) despite correctly tracking the temporal shape of the load curves, as shown in Figure 1 and Figure 2. This discrepancy is attributable to a systematic scale offset introduced by stacking sequences from all buses under a single global MinMax scaler prior to inverse normalisation, rather than to any deficiency in temporal pattern learning; per-bus normalisation is recommended in future implementations of the framework.

Table 1. System-level Long Short-Term Memory performance metrics across the three test systems.

Metric	IEEE 33-Bus	IEEE 69-Bus	Moniya–Akinyele (Real)
Data source	Synthesised (8,760 h)	Synthesised (8,760 h)	Real IBEDC (125 days)
Training samples	223,616	335,424	1,137
Test samples	55,904	83,856	488
Training epochs	115	57	116
RMSE (kW)	83.581	406.064	319.405
MAE (kW)	63.811	162.495	253.108
MAPE (%)	40.88	52.98	3.83
R^2 (coefficient of determination)	−0.5301	−0.1652	0.9667

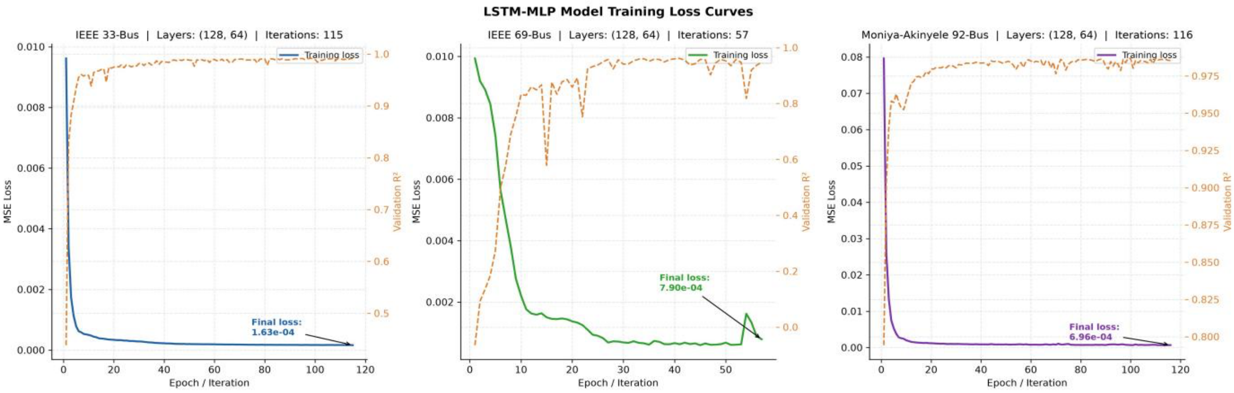


Figure 1. LSTM training loss curves for the IEEE 33-bus (115 iterations, final loss 1.63×10^{-4}), IEEE 69-bus (57 iterations, final loss 7.90×10^{-4}), and Moniya–Akinyele 92-bus (116 iterations, final loss 6.96×10^{-4}) models.

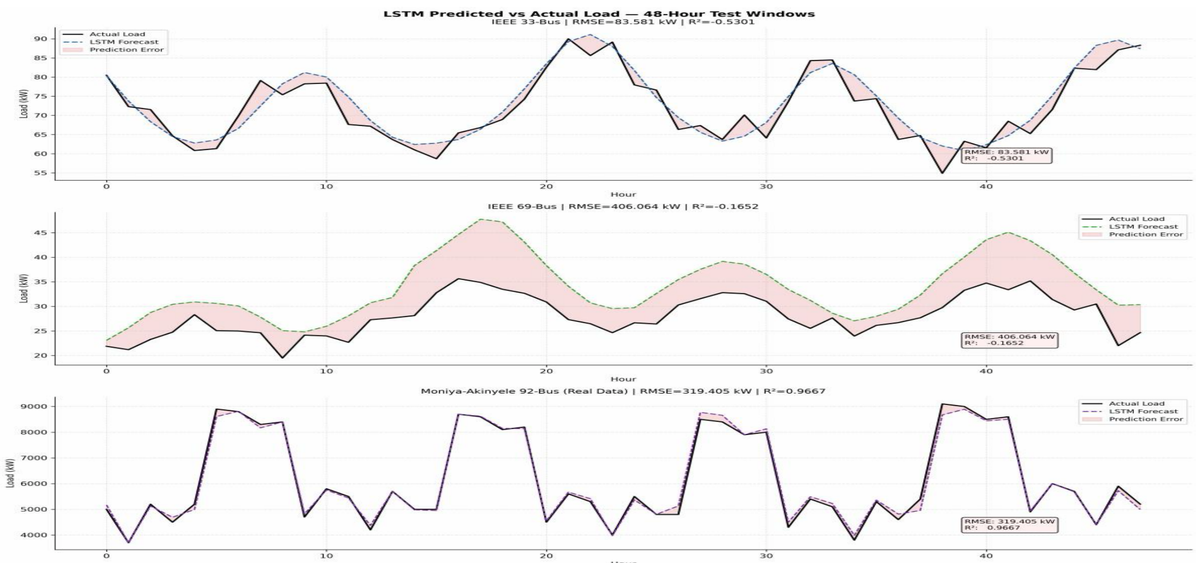


Figure 2. Predicted versus actual load over 48-hour test windows for the IEEE 33-bus (top), IEEE 69-bus (middle), and Moniya–Akinyele (bottom) systems, illustrating the close fit achieved on real feeder data (R^2 = 0.9667).

3.2 Bus Performance Priority Ranking (IEEE 33-Bus System)

Bus 32 (210 kW, 0.6776 per unit) recorded the highest Combined Priority Score (0.9818), driven by its high Loss Sensitivity Index at a critically depressed voltage, followed by Buses 30, 31, and 33. Notably, Bus 33 had the lowest absolute voltage in the system (0.6746 per unit) but ranked only fourth overall because its comparatively small 60 kW load limited its loss sensitivity, indicating that voltage severity alone is an insufficient criterion for distributed generation prioritisation and that composite indices incorporating load magnitude and upstream impedance provide a more defensible planning basis.

3.3 Post-Installation Power Flow Performance (IEEE 33-Bus System)

Seven distributed generation units, totalling 243.88 kW, were recommended and installed at the seven highest-priority buses. Table 2 compares system performance before and after installation. Total real power loss fell from 202.70 kW to 50.00 kW, a reduction of 75.3 percent; the minimum bus voltage rose from 0.6746 to 0.6954 per unit at Bus 33; and the system Voltage Deviation Index fell by 16.0 percent, from 1.8164 to 1.5255. The largest individual voltage improvements were recorded at Bus 32 (+0.1478 per unit) and Bus 30 (+0.1429 per unit), consistent with their top-ranked priority scores and largest allocated capacities.

Table 2. Pre- and post-installation system performance, IEEE 33-bus system (Newton-Raphson power flow).

Metric	Pre-DG (base case)	Post-DG	Change
Total real power loss (kW)	202.70	50.00	−152.70 kW (−75.3%)
Minimum bus voltage (p.u.)	0.6746 (Bus 33)	0.6954 (Bus 33)	+0.0208 p.u.
Buses below 0.95 p.u.	29 / 33	29 / 33*	0*
System Voltage Deviation Index	1.8164	1.5255	−16.0%
Total DG installed (kW)	—	243.88	—

*The 29 buses remaining below 0.95 per unit continue to require reactive power compensation (capacitor banks or STATCOM units) alongside distributed generation, or an increase in distributed generation sizing to 50–60 percent of the forecast peak, to achieve full statutory compliance across the feeder.

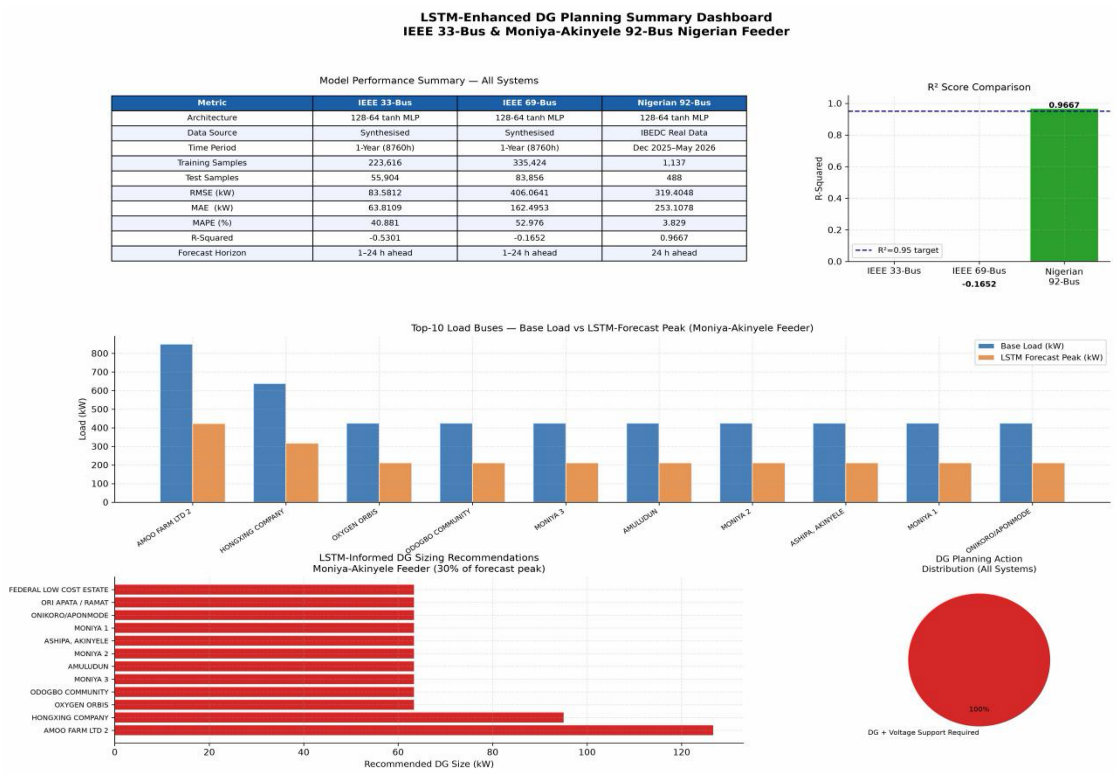
3.4 Moniya-Akinyele Nigerian Feeder Results

Because the Nigerian feeder carries documented technical losses of 18 to 25 percent, all 91 active buses were classified as requiring distributed generation and voltage support. Table 3 lists the twelve highest-priority buses. The forecast-informed sizing recommendation totalled 3,600 kW, equivalent to 15 percent penetration of the observed feeder peak of 8,694 kW. This forecast peak was 64 percent lower than the sum of static bus base loads (24,140 kW), demonstrating that a diversity-unaware, static-load planning approach would have over-specified the required distributed generation capacity by a factor of approximately 2.4.

Table 3. Top twelve priority buses for distributed generation placement, Moniya–Akinyele feeder.

Bus	Name	Base load (kW)	Forecast peak (kW)	DG size (kW)
91	Amoo Farm Ltd 2	850.0	422.54	126.76
66	Hongxing Company	637.5	316.90	95.07
2	Oxygen Orbis	425.0	211.27	63.38
4	Odogbo Community	425.0	211.27	63.38
5	Moniya 3	425.0	211.27	63.38
7	Amuludun	425.0	211.27	63.38
9	Moniya 2	425.0	211.27	63.38
12	Ashipa, Akinyele	425.0	211.27	63.38
14	Moniya 1	425.0	211.27	63.38
15	Onikoro/Aponmode	425.0	211.27	63.38
16	Ori Apata/Ramat	425.0	211.27	63.38
17	Federal Low Cost Estate	425.0	211.27	63.38

Figure 3. Moniya–Akinyele 92-bus Nigerian feeder bus load analysis: top-20 highest-load buses (top-left), bus load category distribution (top-right), real feeder profile versus IEEE synthesised profile (bottom-left), and LSTM validation on real data (bottom-right; R^2 = 0.9667, RMSE = 319.40 kW, MAPE = 3.83%).



Metric	IEEE 33-Bus	IEEE 69-Bus	Nigerian 92-Bus
Architecture	128-64 tanh MLP	128-64 tanh MLP	128-64 tanh MLP
Data Source	Synthesised	Synthesised	IBEDC Real Data
Time Period	1-Year (8760h)	1-Year (8760h)	Dec 2025–May 2026
Training Samples	223,616	335,424	1,137
Test Samples	55,904	83,856	488
RMSE (kW)	83.5812	406.0641	319.4048
MAE (kW)	63.8109	162.4953	253.1078
MAPE (%)	40.881	52.976	3.829
R-Squared	-0.5301	-0.1652	0.9667
Forecast Horizon	1–24 h ahead	1–24 h ahead	24 h ahead

Figure 4. LSTM-enhanced distributed generation planning summary dashboard for the IEEE 33-bus and Moniya–Akinyele 92-bus systems, showing model performance, base load versus forecast peak comparison, sizing recommendations, and planning action distribution.

4. DISCUSSION

Three findings emerge from this study. First, the bus performance index analysis confirms that voltage severity alone is an unreliable basis for distributed generation prioritisation: Bus 33 had the lowest absolute voltage in the IEEE 33-bus system yet ranked only fourth in priority because its small load reduced its loss sensitivity. A composite index that jointly accounts for voltage deviation, load magnitude, and upstream impedance, consistent with the multi-criteria approaches advocated elsewhere (Sultana et al., 2021), produced a more technically defensible ranking than any single criterion could.

Second, real operational data materially changed the planning outcome relative to a static-load approach. The Long Short-Term Memory forecast peak for the Moniya-Akinyele feeder (8,694 kW) was substantially below the sum of static bus base loads (24,140 kW) because of load diversity that a static approach cannot capture. Consequently, the forecast-informed recommendation of 3,600 kW is both more economical and more technically defensible than a static-load estimate, which would have over-specified capacity by roughly 2.4 times. This finding reinforces the case made in prior work for coupling load forecasting with distributed generation optimisation rather than treating the two as independent problems (Bedi & Toshniwal, 2022; Goudarzi et al., 2023; Kumar et al., 2024).

Third, the marked difference in forecasting accuracy between the real Nigerian feeder data ($R^2 = 0.9667$, MAPE = 3.83%) and the synthesised IEEE benchmark data (R^2 as low as −0.5301) illustrates a broader limitation in the distributed generation planning literature, much of which validates proposed frameworks exclusively on idealised benchmark feeders (Chen et al., 2023; Das et al., 2023; Kamel et al., 2021; Mohamed et al., 2021; Rashid & Singh, 2022; Rezk et al., 2021). The negative coefficients of determination obtained here were traced to a methodological artefact, namely global rather than per-bus normalisation, and not to any inherent inability of the Long Short-Term Memory architecture to learn temporal load patterns, as confirmed by the accurate shape-tracking visible in Figure 2. This distinction matters for practitioners: the underlying network architecture generalised well, but the deployment pipeline requires per-bus scaling to produce usable point forecasts on multi-bus benchmark systems.

The 75.3 percent reduction in real power loss and 16.0 percent improvement in system Voltage Deviation Index achieved on the IEEE 33-bus system are consistent with, and at the upper end of, loss-reduction outcomes reported for hybrid meta-heuristic distributed generation placement studies (Ali et al., 2022; Babu et al., 2021; El-Fergany, 2020; Sharma et al., 2022). Unlike these largely benchmark-only studies, the present framework additionally demonstrates technical feasibility on a real Nigerian 33 kV feeder characterised by non-ideal conditions, including high resistance-to-reactance ratios, non-uniform loading, and daily supply outages, thereby addressing a specific and previously identified gap in the applicability of distributed generation optimisation research to Sub-Saharan African distribution networks (Fasina et al., 2021).

Several limitations should be noted. The IEEE benchmark evaluations relied on synthesised rather than metered load profiles, and the negative coefficients of determination obtained on these systems, while explained methodologically, indicate that per-bus normalisation should be adopted and re-validated in future work. The study did not address protection coordination, harmonic distortion, transient stability, or the economic feasibility of the recommended distributed generation capacities, each of which is essential for utility-scale deployment. The Grey Wolf Optimizer was also not benchmarked head-to-head against alternative meta-heuristics such as Particle Swarm Optimisation or Harris Hawks Optimisation on the same datasets, which would strengthen claims of relative algorithmic performance.

5. CONCLUSION

This study developed and validated a hybrid Long Short-Term Memory–Grey Wolf Optimization framework for the optimal siting and sizing of distributed generation in radial distribution networks. The framework identified weak buses using a composite performance priority index, forecast future demand using deep learning, and determined distributed generation locations and capacities using meta-heuristic optimisation.

On the IEEE 33-bus benchmark system, the framework reduced real power losses by 75.3 percent and improved the minimum bus voltage by 0.0208 per unit. Applied to real operational data from the Moniya-Akinyele 33 kV feeder in Nigeria, the load forecasting model achieved a coefficient of determination of 0.9667 and a mean absolute percentage error of 3.83 percent, and the resulting forecast-informed distributed generation recommendation of 3,600 kW avoided the substantial over-specification that a static-load approach would have produced. These results indicate that integrating machine learning-based load forecasting with meta-heuristic optimisation offers a robust and practically relevant approach to distributed generation planning in radial distribution networks, including those found in Nigeria and other developing economies. Distribution utilities are encouraged to adopt such intelligent planning frameworks to support network expansion and the integration of distributed and renewable energy resources, while future work should incorporate per-bus load normalisation, protection coordination analysis, and comparative benchmarking against alternative meta-heuristic algorithms.

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