International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 07 July 2025, pp: 192-201 www.ijaem.net ISSN: 2395-5252

Improved Deployment of Distributed Generation for Loss Minimization in Power Distribution Networks Using Genetic Algorithm Optimization

Dr. Ikenna Mbamalu
Department of Electrical and Electronics Engineering, Enugu State University of Science and Technology

Date of Submission: 01-07-2025 Date of Acceptance: 10-07-2025

ABSTRACT
The paper establishes a method of optimization of voltage profiles and power minimization in the 11kV Emene Injection substation distribution network which belongs to Enugu Electricity Distribution Company (EEDC). The system to be studied is 30 bus radial feeder whose model is created with empirical load flow data recorded at the substation. A first Newton-Raphson type of load flow analysis showed that certain buses (especially buses 9, 11, 12 and 13) experienced a violation of voltage, making reactive power compensation on the system mandatory, as well as system reinforcement. In order to mitigate such problems, a Genetic Algorithm (GA) was used to size and to determine optimal locations of the Distributed Generation (DG) units in the network. The objective of the GA-based optimization was a reduction in the losses; therefore, this scheme concentrated on the power factor and the voltage deviation profit as its fitness measure. The MATLAB/Simulink was utilized to simulate the optimized DG schemes. It was found that there were significant improvements in the voltage profiles at buses which were earlier faulty and the voltages were reduced to within the acceptable range of 0.95-1.05 p.u. These reasons include the reduced power losses, improved voltage stability and the system performance due to integration of DG. The novelty of work approves the power of evolutionary methods in smart optimization of a power distribution network and provides applicable information on the enhancement of power quality in the same kind of power systems which are under development.

Keywords: Distributed Generation, Loss Minimization, Voltage Stability, Load Flow, Genetic Algorithm, Optimization, Power Distribution.

I. INTRODUCTION

Power distribution networks in developing countries are prone to technical and non-technical losses due to poor voltage regulation, network overloading, and insufficient planning (Mohammed et al., 2020). One of the major solutions gaining traction is the integration of Distributed Generation (DG) units at strategic points within the network. DG can provide local voltage support, reduce line losses, and enhance system reliability (Ajenikoko et al.,2017). The electric power system consists of units for the generation of electricity, devices that make use of the electricity, and a power grid that connects them. The power grid is the network that enables the transport of electrical energy from the production to the consumption, while maintaining an acceptable reliability and voltage profile for all customers (Cavus, 2025).

The design of traditional power system was for unidirectional energy flow from a small number of generators to scattered areas of demand through long transmission and distribution networks (Qiu et al., 2023). Such generators are at large power plants, mainly thermoelectric (fossil fuel-fired and nuclear) and hydro, which are placed remotely from consumption centres. Electricity is generated to be consumed at the same time. This is due to the fact that it cannot be stored efficiently in large amounts. Power system operators must balance power generation and demand constantly without violating the active and reactive power constraints (Usanova and Bharadwaj, 2024; Anthony and Arunachalam, 2025).

As distribution systems were designed for radial operation the presence of generation units at

International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 07 July 2025, pp: 192-201 www.ijaem.net ISSN: 2395-5252

distribution level was not considered in the design (Pragati et al., 2023). This in itself does not mean that distributed generation will cause problems but it does lead to a serious fear among many power system operators that the reliability and quality of the supply can no longer be guaranteed. This change in structure demands the coordination of the operation of a large number of systems and the electricity networks (Ricardo, 2006). Several potential problems have been reported in literature, with voltage control being widely considered the most serious one (Bollen, 2008), often leading to blackouts and ultimately system collapse. A major blackout occurs when a large area, or a complete area of a power system, collapses. The main cause of a major blackout is a succession of cascading failures that trip a transmission line or some generation units.

These failures or faults are called contingencies (Javed et al., 2021). A partial blackout may start with a severe contingency which can cause a large variation in power flow and bus bar voltage which, in turn, can cause the outage of generation units or transmission lines (Nilsson, 2023; Li et al., 2023; Chen and Li, 2024; Liu et al., 2022). This certainly causes an imbalance in the demand for and generation of power (Franki et al., 2023). This process can be the beginning of a major blackout when it spreads uncontrollably throughout the power system. For economic reasons, most power systems operate at the minimum level required for security. This increases the likelihood of a conversion from a local to a major blackout occurring. All of these factors make it necessary to have a generic security scheme to help in protecting and maximizing the efficiency of the distribution system by reducing power losses and improving the operation of the equipment responsible for voltage and reactive power control.

This paper evaluates the impact of DG on voltage stability and loss minimization in a 30-bus distribution network. The focus is on applying a Genetic Algorithm (GA) to optimize DG placement and sizing, thereby demonstrating the potential for improved energy efficiency and system stability.

II. METHODOLOGY

The methodology used in this study is the investigation of Emene Injection substation of Enugu Electricity Distribution Company (EEDC) distribution network covering Enugu zone only. Located in Enugu State of Nigeria, the test system is a three-wire delta feeder operating at a nominal voltage of 11 kV. The system loads consist of a mix of constant PQ, constant current and constant impedance. The system corresponds to a suburban Medium Voltage distribution network. In this radial distribution network, the substation is equipped with an on load tap changer and shunt capacitors banks whose power can be discretely controlled. The transformer has a rated voltage ratio of 33/11 kV and a rated average power of 15 MVA. The capacitor banks at the substation have a rated power of 1000 kvar with steps of 200 kvar. The total feeder load is about 45 KVA at a power factor of 0.875. Being balanced, all the system loads are constant PQ. The parameters from the Emene injection substation in Enugu (EEDC Distribution Network) is shown in Table 1

Table 1: Load Data from Injection Substation Emene

MARCH 2016	TR1 7.5MVA	TR2 7.5MVA	EMENE 2	EMENE 3
ENERGY(MW)	3.50mw	4.7mw	3.50mw	4.7mw
CURRENT(AMP)	231	310.2	231	310.2
VOLTAGE(v)	11.9	11.09	11.9	11.09
ENERGY(MW)	0.4mw	1.7mw	0.4mw	1.7mw
CURRENT(AMP)	26.4	112.2	26.4	112.2
VOLTAGE(V)	12.0	11.08	12.0	11.08
August 2016	TR1 7.5 MVA	TR2 7.5 MVA	EMENE 2	EMENE 3
ENERGY(MW)	3.50mw	4.7mw	3.50mw	4.7mw
CURRENT(AMP)	231	310.2	231	310.2
VOLTAGE	11.9	11.09	11.9	11.09
ENERGY(MW)	0.4mw	1.7mw	0.4mw	1.7mw
CURRENT(AMP)	26.4	112.2	26.4	112.2
VOLTAGE(V)	12.0	11.08	12.0	11.08
NOV 2016	TR1 7.5 MVA	TR2 7.5 MVA	EMENE 2	EMENE 3
ENERGY(MW)	4.20MW	6.85MW	4.20MW	6.85MW
CURRENT(AMP)	277.2	452.1	277.2	452.1

International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 07 July 2025, pp: 192-201 www.ijaem.net ISSN: 2395-5252

ENERGY(MW)	0.5MW	2.69MW	0.5MW	2.69MW
CURRENT	33	177.54	33	177.54
VOLTAGE(V)	11.1	10.9	11.1	10.9

This study is limiting to 30 buses. The collected data for these 30 buses are as stated below

Table 2 Empirical Load Flow Data for 33/11KV Collected from EEDC.

BUS NO	BUS CODE	VOLTAGE p.u	ANGLE DEGREE	LOAD (MW)	GENERATION (MW)
1	1	1.06	0.0	0.0	0.0
2	2	1.043	0.0	21.70	40
3	0	1.0	0.0	2.4	0
4	0	1.06	0.0	7.6	0
5	2	1.01	0.0	9.4	0
6	0	1.0	0.0	0.0	0
7	0	1.0	0.0	22.8	0
8	2	1.01	0.0	30.0	0
9	0	1.0	0.0	0.0	0
10	0	1.0	0.0	5.8	0
11	2	1.082	0.0	0.0	0
12	0	1.0	0.0	11.2	0
13	2	1.071	0.0	0	0
14	0	1	0.0	6.2	0
15	0	1	0.0	6.8	0
16	0	1	0.0	3.5	0
17	0	1	0.0	9.0	0
18	0	1	0	3.2	0
19	0	1	0	9.5	0
20	0	1	0	2.2	0
21	0	1	0	17.5	0
22	0	1	0	0	0
23	0	1	0	3.2	0
24	0	1	0	8.7	0
25	0	1	0	0	0
26	0	1	0	3.5	0
27	0	1	0	0	0
28	0	1	0	0	0
29	0	1	0	2.4	0
30	0	1	0	10.6	0

2.1 Load Flow Analysis

Initial load flow analysis was conducted using the Newton-Raphson method. The network consists of 30 buses, with all power supplied from a central substation. No shunt compensation or DG units were present in the base case. Voltage magnitudes were monitored to identify buses operating outside acceptable limits (typically ±5% of nominal voltage).

2.2 Genetic Algorithm Optimization

A Genetic Algorithm was employed to identify optimal DG locations and capacities. The fitness function was designed to minimize total real power loss and maintain bus voltages within the standard operating range. Constraints included:

- Voltage magnitude limits: 0.95–1.05 p.u.
- DG size and number limits.
- Thermal limits on distribution branches.
- Short-circuit ratio bounds.

Genetic algorithm is an evolutionary approach which utilizes fitness computation strategy to determine losses on the power system network by measuring variation in the voltage level. The variation in the power flow is monitored considering power factor which relates active and

International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 07 July 2025, pp: 192-201 www.ijaem.net ISSN: 2395-5252

reactive power to determine when the there is loss on the line and then initiate the DG as the control model to address the problem through active or reactive power compensation. The fitness model was presented in the Equation 1;

$$Ft = \frac{x_i}{\sum_{k=1}^{n} \text{fitness } (x_k)} \quad (1)$$

Where x_i is the least power factor values which is 0.9000. x_k is the number of busses below the ideal power factor values, n is the total number of busses on the power network. The fitness determines the initial state of the power system network through computation of the power factor on the bus, and then update until it does not satisfy the fitness threshold when then implied losses on the network. Figure 1 presents the system flow chart.

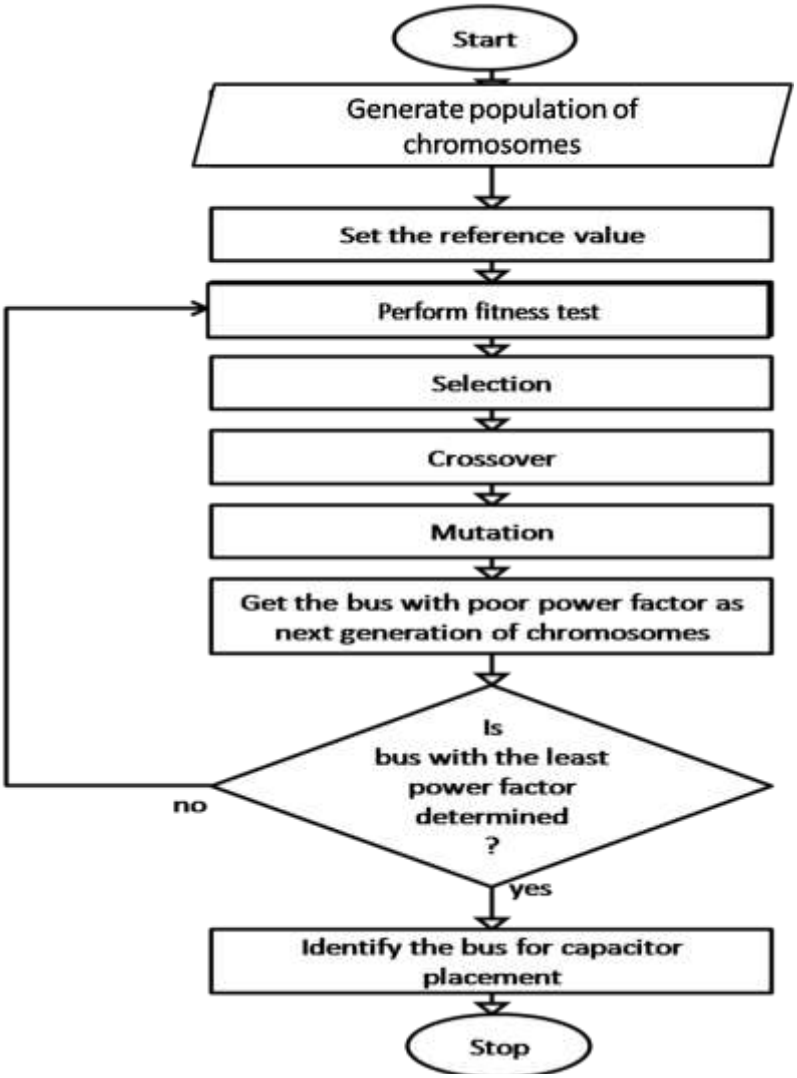

Figure 1: The Genetic algorithm for the Load flow optimization

The Figure 1 presented the genetic algorithm developed for the load flow optimization. The algorithm identified the busses interconnected on the feeder and then used the fitness model to determine the busses with poor power factor which was identified as the next generation of chromosomes (i.e number of busses which have poor power factor), then the fitness is used to compute the next busses with the poor power factors and the process continued iteratively until the busses with the poorest power factor is identified an then process returns. The optimization process was executed using MATLAB, and the resulting DG model was reintegrated into the load flow simulation for analysis.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 07 July 2025, pp: 192-201 www.ijaem.net ISSN: 2395-5252

III. RESULTS AND DISCUSSION

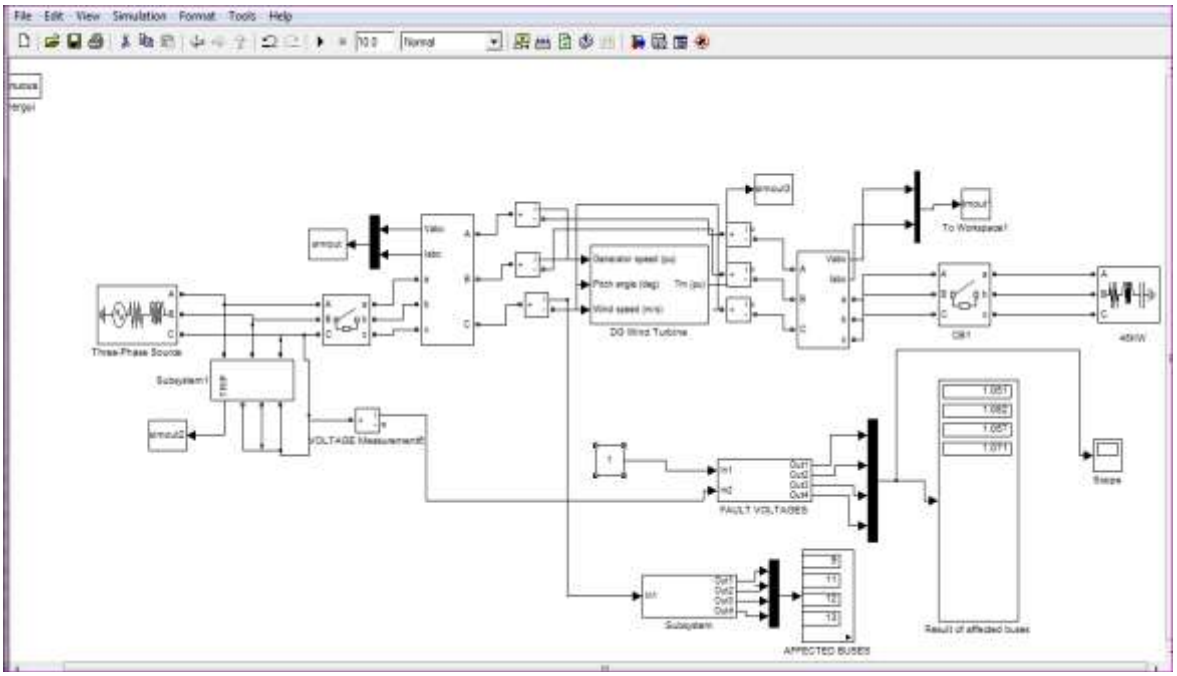

Figure 2: Designed Simulink Model for the DG to be used based on the Result of the above Study

Figure 2 shows designed Simulink model for the DG to be used based on the result of the above study. The result obtained are faulty buses that have voltage profile of 1.051p.u,1.082 p.u, 1.057 p.u. and 1.071 p.u. To design a Simulink model for deployment of distributed generation in distribution system for loss minimization using optimized genetic algorithm.

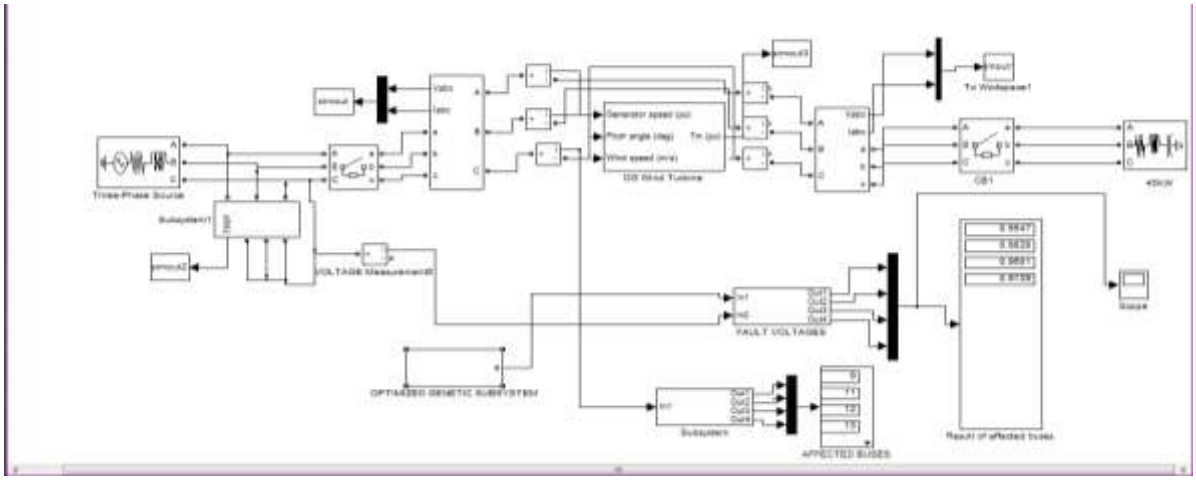

Figure 3: Designed Simulink Model for Deployment of Distributed Generation in Distribution System for loss Minimization using Optimized Genetic Algorithm

Figure 3 shows designed Simulink model for deployment of distributed generation in distribution system for loss minimization using optimized genetic algorithm

3.1 Faulty Bus Voltage Analysis (Without DG)

Initial simulation revealed that Buses 9, 11, 12, and 13 consistently operated outside voltage tolerances, with significant voltage dips and spikes. This behaviour results in poor power quality and system instability.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 07 July 2025, pp: 192-201 www.ijaem.net ISSN: 2395-5252

Table 1: Voltage Profiles of Faulty Buses (Without DG)

FAULTY VOLTAGE (P.U) AT BUS 9	FAULTY VOLTAGE (P.U) AT BUS 11	FAULTY VOLTAGE (P.U) AT BUS 12	FAULTY VOLTAGE (P.U) AT BUS 13	TIME(S)
0	0	0	0	0
1.4	1.5	1.52	1.54	1
0.8	0.9	0.92	0.94	2
1.2	1.22	1.24	1.26	3
1.051	1.082	1.057	1.071	4
1.051	1.082	1.057	1.071	5
1.051	1.082	1.057	1.071	6
1.051	1.082	1.057	1.071	7
1.051	1.082	1.057	1.071	8
1.051	1.082	1.057	1.071	9
1.051	1.082	1.057	1.071	10

These fluctuations contribute to increased technical losses, transformer overloading, and customer complaints.

3.2 Corrected Voltage Analysis (With DG Integration)

After optimizing and integrating DG into the network, voltage magnitudes at the same buses improved substantially. Fluctuations were significantly dampened.

Table 2: Corrected Voltage Profiles After DG Deployment

CORRECTED VOLTAGE IN Bus 9	CORRECTED VOLTAGE IN Bus 11	CORRECTED VOLTAGE IN Bus 12	CORRECTED VOLTAGE IN Bus 13	TIME (S)
0	0	0	0	0
1.3	1.4	1.6	1.8	1
0.7	0.8	0.9	0.93	2
1	1.1	1.2	1.23	3
0.9555	0.9836	0.9609	0.9736	4
0.9555	0.9836	0.9609	0.9736	5
0.9555	0.9836	0.9609	0.9736	6
0.9555	0.9836	0.9609	0.9736	7
0.9555	0.9836	0.9609	0.9736	8
0.9555	0.9836	0.9609	0.9736	9
0.9555	0.9836	0.9609	0.9736	10

The power system showed enhanced stability and sustained voltage regulation throughout the simulation period. The graphical representation of these results are presented from Figure 4-7.

3.3 DG Impact Visualization

A comparative plot of Bus 9 voltage before and after DG deployment (Figure 3) highlights the stabilizing effect of DG. The pre-DG curve (red) displays erratic behaviour, while the post-DG curve (blue) indicates a stable voltage trajectory. Figures 3-7 presents a graphical

International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 07 July 2025, pp: 192-201 www.ijaem.net ISSN: 2395-5252

representation of the system behaviour before and after the DG deployment to the system.

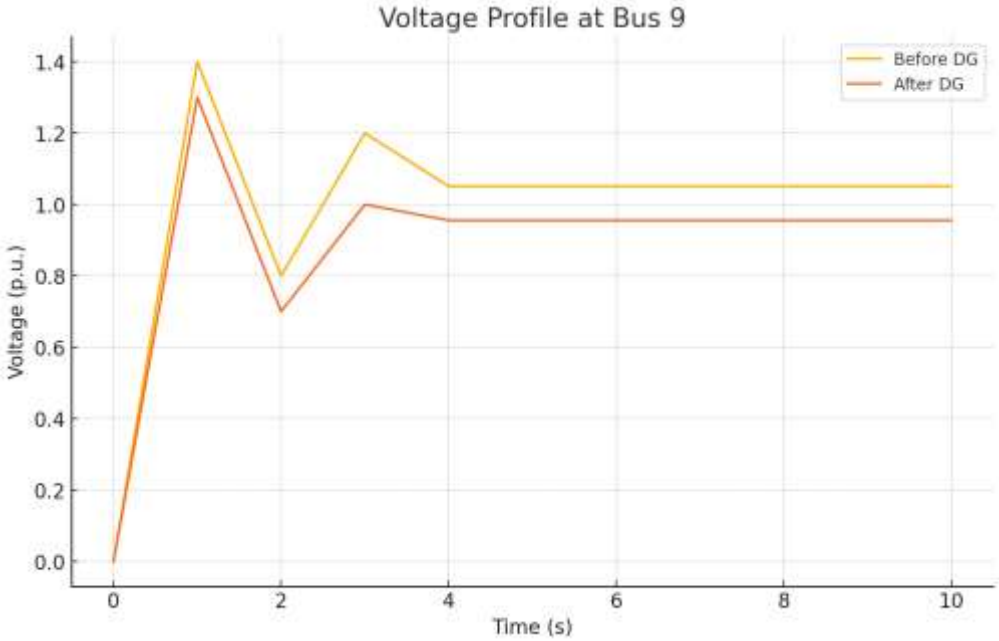

Figure 4: Bus 9 Voltage Profile

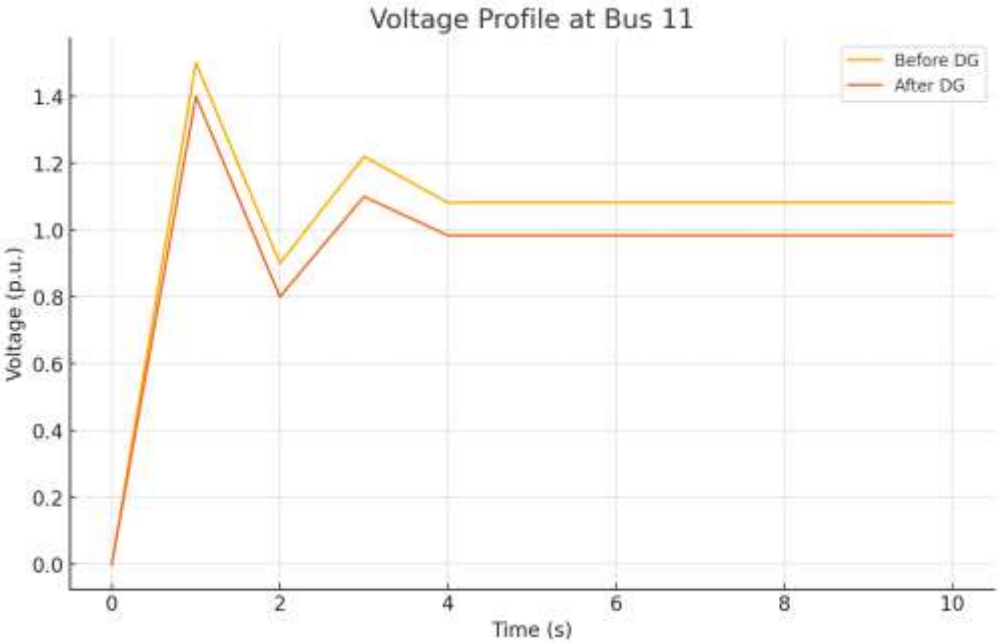

Figure 5: Bus 11 Voltage Profile

International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 07 July 2025, pp: 192-201 www.ijaem.net ISSN: 2395-5252

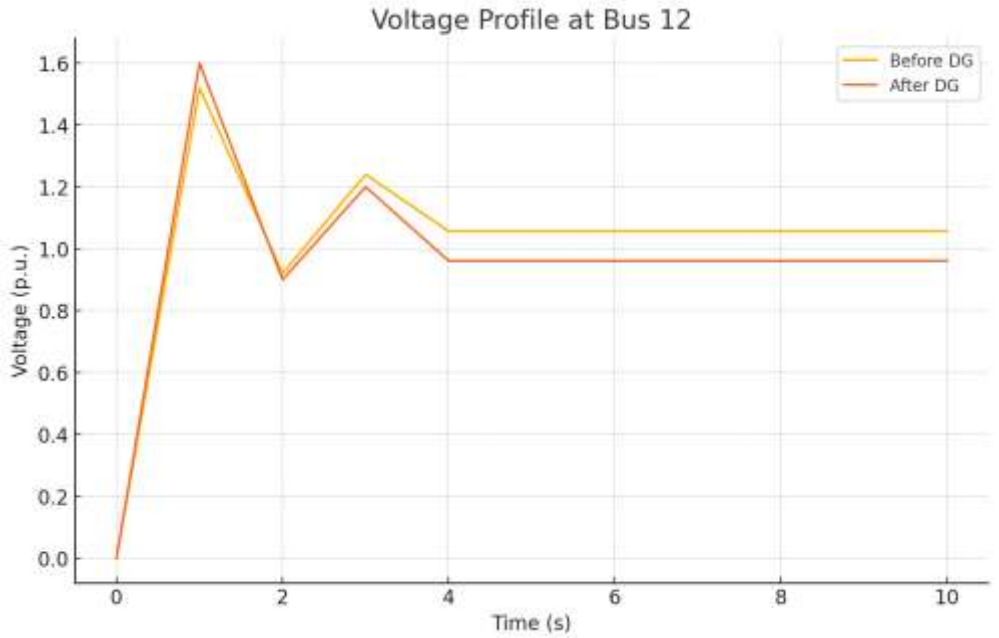

Figure 6: Bus 12 Voltage Profile

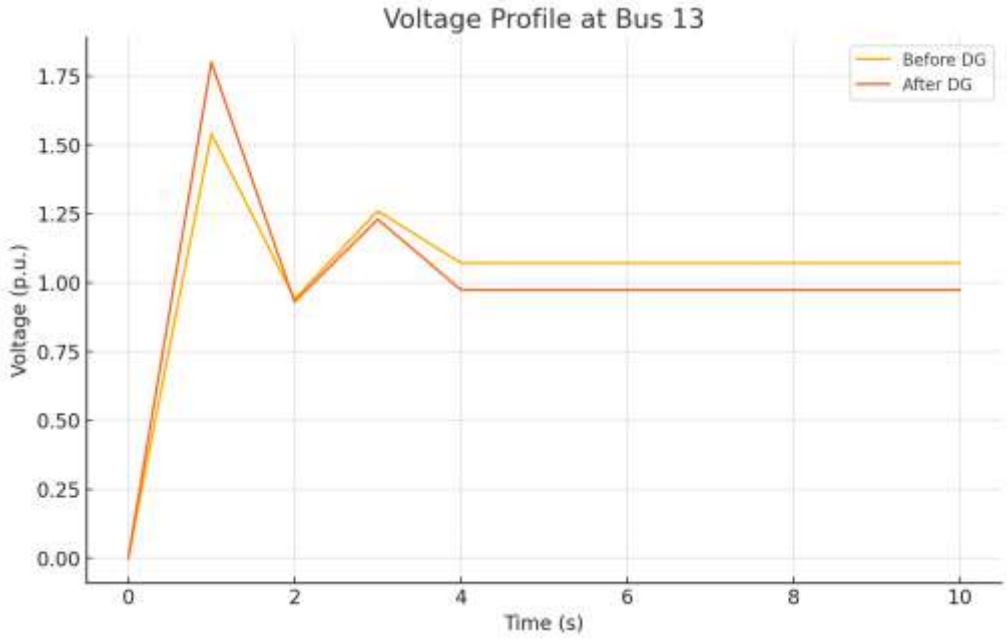

Figure 7: Bus 13 Voltage Profile

From the plots in the voltage profile results above, it can clearly be seen how the DG dampens the large swings and brings the steady-state voltage into the acceptable 0.95 – 1.05 p.u. band for Buses 9, 11, 12, and 13.

IV. CONCLUSION

The paper has conducted a research on the optimization of the Emene Injection Substation distribution network of the Enugu Electricity Distribution Company (EEDC) under the use of a solution to minimise losses within its distribution network by utilising a Genetic Algorithm (GA) solution. The Newton-Raphson load flow analysis preliminarily was carried out to determine the voltage fluctuations and susceptible load buses in the 30-bus 11kV distribution system. The findings revealed that bus 9, 11, 12 and and 13 were always

operating within the range of maximum and minimum voltage thus threatening the quality of power as well as system reliability. Genetic Algorithm was effectively utilized to bring out best places and capacity of the Distributed Generation (DG) units. It was envisaged that the fitness function formulated on the basis of movement in power factors would go through an iterative process of selecting buses to be compensated, thus, keeping the voltage within the normal operating level of 0.95-1.05 p.u. The DG configurations that were optimal were executed in MATLAB/Simulink and the load flow analysis that followed formed evidence to the considerable changes of the voltage levels of the sacrificial buses that were faulty previously. The corrected current power profiles showed that according to the integration of DG, the bus voltages resolved the stabilization, less technical losses, and overall system reliability. The results indicate that the application of the evolutionary algorithm like GA can be effective in the optimization of the working of a distribution system using very little computational complexity. Thus, geographic placement of DG units at the locations of insufficient performance of power distribution networks can be the stable solution to the problem of voltage regulation, loss minimization, and quality improvement of services provided by the power industry of Nigeria or other countries.

Acknowledgments

The author wishes to thank the Enugu Electricity Distribution Company for access to technical data and simulation environments, and acknowledges the support of colleagues in the Business Intelligence Unit.

REFERENCES

[1]. Ajenikoko, G. A., Olabode, O. E., & Olayanju, O. W. (2017). Distributed generation (DG) integration on utilities distribution system: A survey. International Journal of Advanced Engineering and Technology, 1(4), 1–10. https://www.newengineeringjournal.com

[2]. Anthony, K., & Arunachalam, V. (2025). Voltage stability monitoring and improvement in renewable energy dominated deregulated power system: A review. Advances in Electrical Engineering, Electronics and Energy, 11, 100893. https://doi.org/10.1016/j.prime.2024.100893

[3]. Bollen, M. Y. (2008). Integration of distributed generation in the power system – A power quality approach. IEEE.

[4]. Cavus, M. (2025). Advancing power systems with renewable energy and intelligent technologies: A comprehensive review on grid transformation and integration. Electronics, 14(6), 1159. https://doi.org/10.3390/electronics14061159

[5]. Franki, V., Majnarić, D., & Višković, A. (2023). A comprehensive review of Artificial Intelligence (AI) companies in the power sector. Energies, 16, 1077. https://doi.org/10.3390/en16031077

[6]. Javed, U., Mughees, N., Jawad, M., Azeem, O., & Abbas, G. (2021). A systematic review of key challenges in hybrid HVAC–HVDC grids. Energies, 14, 5451. https://doi.org/10.3390/en14175451

[7]. Li, Y., Bu, F., Li, Y., & Long, C. (2023). Optimal scheduling of island integrated energy systems considering multi-uncertainties and hydrothermal simultaneous transmission: A deep reinforcement learning approach. Applied Energy, 333, 120540. https://doi.org/10.1016/j.apenergy.2022.120540

[8]. Liu, Z., Sun, Y., Xing, C., Liu, J., He, Y., Zhou, Y., & Zhang, G. (2022). Artificial intelligence powered large-scale renewable integrations in multi-energy systems for carbon neutrality transition: Challenges and future perspectives. Energy AI, 45, 109–125. https://doi.org/10.1016/j.egyai.2022.100195

[9]. Nilsson, S. (2023). Feasibility study of HVDC grids. In High voltage DC transmission systems: HVDC (pp. 1–33). Springer. https://scholar.google.com/scholar_lookup?title=Feasibility+Study+of+HVDC+Grids&author=Nilsson,+S.&publication_year=2023&pages=1%E2%80%9333

[10]. Oluwasuji, O. I., Malik, O., Zhang, J., & Ramchurn, S. D. (2020). Solving the fair electric load shedding problem in developing countries. Autonomous Agents and Multi-Agent Systems, 34(1), 12.

[11]. Pragati, A., Mishra, M., Rout, P. K., Gadanayak, D. A., & Hasan, S. (2023). A comprehensive survey of HVDC protection system: Fault analysis, methodology, issues, challenges, and future perspective. Energies, 16, 4413. https://doi.org/10.3390/en16114413

[12]. Qiu, D., Wang, Y., Zhang, T., Sun, M., & Strbac, G. (2023). Hierarchical multi-agent reinforcement learning for repair crews dispatch control towards multi-energy microgrid resilience. Applied Energy, 336, 120826. https://doi.org/10.1016/j.apenergy.2023.120826

[13]. Ricardo, D. (2006). Distributed generation with high penetration of renewable energy sources: Final public report.

[14]. Usanova, K. I., & Bharadwaj, V. Y. (2024). Reinforcement learning-based energy storage management in smart grids. MATEC Web of Conferences, 392, 01171. https://doi.org/10.1051/matecconf/202439201171