APWEN Journal of Engineering, Science and Technology
ISSN: 2714-2396, Volume 9 Issue 1

OPTIMAL PLACEMENT OF DISTRIBUTED GENERATION AND SIZING FOR REAL POWER LOSS MINIMIZATION AND VOLTAGE PROFILE IMPROVEMENT OF AMADI-AMA DISTRIBUTION NETWORK VIA ARTIFICIAL BEE COLONY

Uwho, K. O. [1], and Amadi, H. N. [2*]

[1] Department of Electrical and Electronics Engineering, Rivers State University, PMB 5080 Port-Harcourt, Nigeria
[2] Department of Electrical and Electronics Engineering, Rivers State University, PMB 5080 Port-Harcourt, Nigeria

Corresponding email: kingsley.uwho@ust.edu.ng

Received: 14 May 2026 **Accepted**: Date 30 May 2026 **Published**: 16 June 2026

Abstract. Several studies have been conducted on the rightful location of distributed generation (DG) in a distribution network in order to reduce power loss which is a factor for voltage drops and poor power quality but none has been done in Amadi-Ama 11kV energy network. This research seeks to evaluate the impact of Artificial Bee Colony (ABC) in improving the power quality of the distribution network using DG (photovoltaic plant) by reducing the real power loss and increasing the voltage profile of the system. The study utilizes Forward Backward Sweep (FBS) load flow technique to ascertain the state of the network before and after the integration of DG. FBS is utilized due to the high R/X (resistance/inductance) ratio in a distribution line, its weakly meshed configuration and large number of nodes. The losses in the system are determined by calculating the current in the branches via compensation method and Kirchhoff's current law. In the forward sweep, voltage drops are determined with power flow update while in the backward sweep, the currents are computed from the branches in the last layer and ending at the branches joined to the root node. Summing downstream currents on a branch gives the branch current used to compute voltage drops. The network total real loss equals sum of per branch losses across all branches. Sensitivity based candidate ranking is employed to reduce the search space of the metaheuristic algorithm for DG integration, contributing to the overall efficiency, high score indicates expected benefit from DG. Linear regression model is used to analyze the relationship between the length of line (number of lines/buses) and power losses/voltage profile before and after the inclusion of photovoltaic plant in the system. Artificial Bee Colony (ABC) maps solution fitness to selection probability for onlookers while employed bees update the solution by exploring neighborhood, this governs ABC's search for DG sizes and location. ABC installed a DG size of 150 kW at bus 6 and records a voltage deviation of 0.7850 V with a corresponding total active power loss of 245.76 kW as against 374kW, which is a 39% active power loss reduction. This shows that the optimizer fulfilled the primary objective of this research (active power loss reduction) and maintaining the regulatory voltage limit of 0.95-1.05 p.u. Based on these performance metrics, it is found that ABC demonstrates effective power loss minimization and significant voltage enhancement, making it a practical and efficient solution for DG integration in Amadi-Ama distribution systems. The simulation analysis was carried out on MATLAB/Simulink Software 2021.

Keywords: Artificial bee colony, distributed generation, forward backward sweep load flow, linear regression model, photovoltaic plant, sensitivity-based candidate Ranking

1. Introduction

The rise in demand for electricity and the urgency for sustainable energy sources have led to the addition of distributed generation in distribution systems closer to the consumers of energy instead of building new power stations with its associated transmission and distribution lines thereby, reducing cost. The placement of DG (distributed generation) units at the right position is crucial in order to lower power loss and improve voltage magnitude and thus, enhance the reliability of the system. A dependable, eco and nature friendly operation in power generation has been at the heart of Engineers and stake holders in the energy sector. To this end, renewable energy based distribution network is the answer to enhance power system reliability and reduce the negative impact of environmental thermal generators. Power distribution line is a vital link between the utility and the end users of energy and so, it is the chief means in the entire energy delivery processes. Because of this known fact, when planning the power system network, one must be careful in reducing the level of damage at the distribution level so as to usher in better energy quality to the users. [1] addressed the energy crises in the Faculty of Engineering, Rivers State University by installing a 500kW PV plant linked to the grid that was able to produce 1,114,502kWh/year with 20% loss to meet the energy demand of the Faculty and sell the extra energy to the grid. This form of distributed generation boost the reliability of the energy sector. [2] analyzed the losses and hence, the performance of PV plant connected to the grid and discovered that 3,811.050kWh/year was lost due to modular quality, 24,705kWh/year was lost to module's incompatibility, 10,941kWh/year was wasted due to wiring (Ohm loss) and 26,294kWh/year was lost as sum of inverter losses. The researchers also noted that 9044.009 tons of carbon was saved from being sent to the atmosphere.
Traditionally, power systems (PSs) are modelled to handle energy flow in one way however, due to some economic a natural factor such as high cost of fuel and greenhouse gas radiations, renewable energy linked dispersed generation (RDGs) are utilized as another way to fossil fuels. Despite the various economic and technical advantages gotten from RDGs, if they are poorly designed or installed in the distribution system, the system will be open to instability challenges which will mar the quality of energy supply like increased losses, injection of harmonic currents and poor voltage magnitude. Power loss can either be technical or non-technical. Technical loss is the one that happens on its own and is part and parcel of the system. Its operations arise from resistance and current flow mainly in the distribution cables (feeders), transformer windings and transformer core [3]. Copper or variable losses are dependent on load current and takes place in couctors (cables) and transformers. Current loss relies on theresistance and the current in the circuit. Old and non-functional distribution systems, small connections, improper gaskets and coils are among the factors causing great resistance in the lines and in transformers thus, creating technical power losses. Technical losses in distribution network accounts for about 22.5% of the losses and depend largely on the network functions and operating modalities [4]. Fixed and variable losses make up technical losses. Fixed loss is not related to load but mainly happens in distribution transformers such as hysteresis and eddy current losses while variable loss concerns the load and occurs commonly in transformers, lines; and cable conductors. Technical losses are easier to calculate and control as long as the power system in particular has known quantities of load [5].
A two-step optimization method to examine the aftermath of including a storage backup (BESS) into a distribution line which has renewable energy means has been studied by [6]. Their number one approach was to find the optimal size and placement of the photovoltaic (PV) arrays that result in low power losses, cost and voltage distortions considering the bus under focus and secondly, performed a second optimization task to ascertain the optimal size and where to locate the BESS

that could bring about more reduction of the desired objectives. Genetic Algorithm was used in their analysis considering a 13-bus system. A combination of analytical and heuristic search method has been proposed by [7]. The approach was geared towards searching for the right position to place several distributed generation types in a distribution system in order to lower the energy loses. The weight (size) of the DGs are examined at a given bus using the analytical technique while the particle swarm optimization was used in determining the location of placement of the DG. The objective function was minimized under operating constraints. An algorithm for the optimal placement of wind based DGs (WDG) in distribution networks has been presented by [8] to minimize the energy losses and nodal voltage deviations (from 1 p.u.). Time variations of dynamic nodal demands, nodal voltage magnitudes, and wind speed in the WDG placement process were all taken into cognizance in the algorithm. By this means, an exact dynamic model of the active and reactive powers injected by WDG to the system was employed in which the flow between the WDG and the distribution network are analyzed. To handle the power losses challenges in the distribution system, [9] applied Ant Colony and also Genetic optimization techniques to size and place distributed generation in distribution system. They emphasized that distributed generation (DG) can take care of the increasing load demand. The DG is used to enhance power generation systems and improve distribution networks' efficiency. The active power loss was reduced from 36.65MW to 28.56MW, a 22% reduction with installation of a single DG using Ant Colony (ACO). [10] worked on optimal siting and sizing of DG in a 43-bus IEEE distribution system. Power losses alongside voltage deviation, looking at objective function that calculates present percentage losses in 11kV Dike feeder. Buses with poor voltage profile without DG installation were noticed during the load flow analysis using ETAP 12.6 and determined optimal sizing and siting of DGs where losses can be mitigated and power quality improved using Genetic Algorithm technique resident in MATLAB 2015. An efficient methodology for placing DG optimally in radial distribution system has been presented by [11]. Fuzzy composition criterion was used in fixing the DG at the right position. Backward-Forward sweep method was used to solve the load flow analysis. The numerical example confirms the validity of the proposed method. [12] combine the strength of particle swarm optimization and that of evolutionary programming to accurately size and place DG in the distribution network. The model was examined and validated on IEEE-69 bus radial system with multiple units of DG. [13] proposed hybrid ABC-CS optimization algorithm which blends the behavior of the artificial bee colony (ABC) and Cuckoo search (CS) algorithms to install multi DGs optimally by considering power loss, penalty function (PE) and voltage profile (VP) as objective functions.

[14] utilized Genetic Algorithm (GA) for optimal location and sizing of multiple dispersed generation (DG) for loss minimization. The study was examined on a 33-bus radial distribution system to optimally allocate different numbers of DGs for the minimization of total active power losses and voltage deviation at power constraints of 0–2 MW and 0–3 MW respectively. A PQ model of DG and Direct Load Flow (DLF) technique that uses Bus Incidence to Branch current (BIBC) and Branch Current to Bus Voltage (BCBV) matrices was used. The result obtained a minimum base case voltage level of 0.9898 p.u at bus 18 with variations of voltage improvements at other buses after single and multiple DG allocations in the system.

Power loss is a crucial checker used to evaluate the performance of distributions networks. [15] utilized Particle Swarm Optimization (PSO) joint with Newton Raphson power flow method to optimize the location alongside the size of a renewable energy source. The main aim was to reduce power losses and keep the voltage profile within acceptable limit. [16] worked on metaheuristic rider optimization algorithm (ROA) for searching the optimal size and location of renewable energy sources (RES) inclusive of wind turbine (WT), photovoltaic (PV), and biomass-based Distributed Generation (DG) units in distribution systems (DS). The focal point of the study is to lower the sum of energy losses. Energy loss sensitivity factor (PLSF) was applied with the ROA to examine the suitable candidate buses and accelerate the solution process. [17] established a technique for optimum scheduling and operating of DG to lessen power loss, revamp voltage profile and overall network reliability by using Artificial intelligence method called particle swarm optimization (PSO) utilized for finding the best site and size of DG to lessen power loss and boost the voltage profile. They employed IEEE 33 distribution system to display applicability of the PSO. The results of the PSO were compared with the results gotten by other methods (GA, HSA, BA & CSA) embarked by researchers.

[18] presented a technique based on Particle Swarm Optimization (PSO) to identify the switching operation plan for feeder reconfiguration and optimum size value of DG simultaneously. The key purpose was to diminish the real and reactive power losses and improve the bus voltage profile in the system while satisfying all the distribution constraints. PSO algorithm was utilized to find out the minimum formation and their impact on the network real power losses and voltage profiles. The results are obtained through MATLAB coding and was found satisfactory.
[19] proposed a hybrid intelligent meta-heuristic Particle Swarm Optimization and Crow Search Algorithm (PSO-CSA) for optimal DG sitting and sizing in a radial distribution line. The algorithm was tested on standard bench mark IEEE 33-bus system and the power loss was found reducing from 202.418kW to 111.1928kW when DG type-1 was installed. This work was evaluated with constant loading condition. The optimum placement of type-I and type-III DG units are identified by determining the power loss reduction as objective function with single and two distributed generation consideration also with different penetration levels and was found satisfactory. [20] presented the application of firefly algorithm (FA) for optimally location of the most suitable place for distributed generation (DG) in IEEE 33-bus radial distribution network. This strategy aimed at minimizing losses together with improving the voltage profile in distribution network. The losses in real power and voltages at each bus are obtained using load flow analysis which was performed on an IEEE 33-bus radial distribution network using forward sweep method. The proposed method comprises of simulation of the test system with DG as well as in the absence of DG in the system [21]. [22] presented a novel Improved Artificial Bee Colony Algorithm (IABC) aimed to robustly detect the optimal site and size of DG units for minimization of total power losses without violating the equality and inequality constraints. The proposed algorithm was simulated in MATLAB environment, and the effectiveness of the algorithm validated on the IEEE 34 bus and IEEE 69 bus radial distribution systems. The performance of the proposed technique has been validated by comparing the results obtained from other algorithms. Comparison shows that the proposed technique was more efficient in terms of simulation results of power loss and convergence than the other reported algorithms, suggesting that the solution obtained is a global optimum.

In ABC algorithm, the position of a food source is a possible solution to the optimization problem and the quality and quantity of the nectar signifies the quality (fitness) of the solution. The number of the employed bee is the same as the quantity of food sources (solutions) [23]. ABC algorithm can be in four stages knowing that each employed bee is associated to only one food source. Power losses in an electrical distribution system lead to a lot of negative impacts on the system, resulting to financial losses for the utilities and consumers due to wasted energy which reduced revenue and increased costs. Losses decrease the overall efficiency of the distribution network thus, increasing energy consumption leading to strain on the grid. Excessive losses can cause equipment overheating, reducing the lifespan and increased the cost of repairs or replacements. The loss in power in distribution system causes voltage drops and thus affect the power quality. This work aims to minimizing the real power loss in the system and improve the voltage magnitude.

2. Materials and Method

2.1 *Materials*

The materials used for the simulation and analysis are stated below, Table 2.1 and 2.2 show the load and line data:

i. The single line diagram of the existing Amadi-Ama 11kV distribution network (Amadi-Ama feeder) which consists of nineteen (19) buses
ii. Load Data consisting of 19 buses and 19 transformers
iii. Line Data consisting of resistance and reactance
iv. 1 X 15MVA Rainbow injection substation Transformer
v. Fifteen (15) 500kVA distribution transformers
vi. Three (3) 100kVA distribution transformers
vii. One (1) 50kVA distribution transformer
viii. MATLAB/Simulink 2021 model
ix. DG (Photovoltaic plant)

Table 2.1: Amadi-Ama Distribution Load Data (Source: Port-Harcourt Electricity Distribution Company)

Bus No	Bus ID	Rated KVA	Rated kV	Rated Current	Load Current	% TF Loading	KVA Load	KW load	PF
1	Chf. Sam Mgbor 1	500	11	695.60	374.00	53.77	268.85	228.52	0.85
2	Chf. Sam Mgbor 2	500	11	695.60	326.33	46.91	234.55	199.37	0.85
3	Along Sophike Hospital Rd.	500	11	695.60	278.83	40.08	200.40	170.34	0.85
4	Bethel	500	11	695.60	237.33	34.12	170.60	145.01	0.85
5	Church Rd.	500	11	695.60	376.00	54.05	270.25	229.71	0.85
6	Post Office	500	11	695.60	301.00	43.27	216.35	183.89	0.85
7	Amadi Street	500	11	695.60	295.67	42.51	212.55	180.67	0.85
8	Last Born	500	11	695.60	306.33	44.04	220.20	187.17	0.85
9	First Road	500	11	695.60	462.00	66.42	332.10	282.29	0.85
10	MTN	100	11	139.12	129.33	92.96	92.96	79.02	0.85
11	Amadi New Layout	500	11	695.60	259.67	37.33	186.65	158.65	0.85
12	Airtel	100	11	139.12	155.00	111.41	111.41	94.70	0.85
13	Olumba (Amadi New Layout)	500	11	695.60	387.33	55.68	278.40	236.64	0.85
14	NLNG Rd.	500	11	695.60	387.67	55.73	278.65	236.85	0.85
15	Market	500	11	695.60	263.33	37.86	189.30	160.91	0.85
16	Linfox Oil	50	11	695.60	103.67	149.03	74.52	63.34	0.85
17	Amadi	500	11	695.60	259.67	37.33	186.65	158.65	0.85
18	Doreana Hotel	100	11	139.12	201.67	144.96	144.96	123.22	0.85
19	Amadi Town Hall	500	11	695.60	313.00	45.00	225.00	191.25	0.85

Table 2.2: Amadi-Ama Distribution Line Data (Source: Port-Harcourt Electricity Distribution Company)

From	To	Length_km	Resistance_Ohm	Reactance_Ohm
1	2	0.369482862	0.23757748	0.030667078
2	3	0.331709948	0.213289497	0.027531926
3	4	0.395022205	0.253999278	0.032786843
4	5	0.303444608	0.195114883	0.025185902
5	6	0.343874436	0.221111262	0.028541578
6	7	0.338155846	0.217434209	0.028066935
7	8	0.376551679	0.242122729	0.031253789
8	9	0.37951999	0.244031354	0.031500159
9	10	0.31868726	0.204915908	0.026451043
10	11	0.34897644	0.224391851	0.028965044
11	12	0.34455862	0.221551193	0.028598365
12	13	0.364631301	0.234457927	0.030264398
13	14	0.370936483	0.238512159	0.030787728
14	15	0.375468668	0.241426354	0.031163899
15	16	0.327602508	0.210648412	0.027191008
16	17	0.367970268	0.236604882	0.030541532
17	18	0.3655098	0.235022802	0.030337313
18	19	0.316261174	0.203355935	0.026249677

2.2 *Methods*

The Amadi-Ama 11kV distribution network was modeled using MATLAB/Simulink Software 2021 as in Fig. 2.1. Load Flow was conducted using the Forward Backward Sweep (FBS) technique to check the initial condition of the system (power loss and voltage profile). Sensitivity based candidate bus ranking was deployed to reduce the search space for heuristic optimizer (ABC). Following the energy balance equation, Artificial Bee Colony algorithm is employed to optimally size the DG and identify the appropriate bus for the installation of the photovoltaic plant (DG). The load flow is repeated after the installation of the DG into the network. Linear registration model was used to analyze the relationship between the length of line/number of buses and the power losses/voltage profile.

2.2.1 Problem Formulation

I. Branch Current from Nodal Injections (Backward sweep core)

In radial distribution FBS, branch currents are computed from downstream nodal power injections and known voltages. Using complex power S_k at node k and node voltage V_k, the current injection is $I_k = \bar{S_k}/\bar{V_k}$. Summing downstream currents on a branch gives the branch current used to compute voltage drops in the forward sweep as in equation 1 [13].

$$I_{ik} = \sum_{k\in\mathcal{D}(i)} \frac{\bar{S_k}}{\bar{V_k}} \tag{1}$$

Parameters:
$\mathcal{D}(i)$: set of nodes downstream of branch i.
I_{ik}: complex current in branch ik.
$S_k = P_k + jQ_k$: complex power injection at node k (load positive, injection negative if DG injects).
V_k: complex voltage at node k. Over line denotes complex conjugate.

II. Branch Voltage Drop (Forward sweep)

In the forward sweep, the sending-end voltage equals receiving-end voltage plus drop across branch impedance. With branch series impedance $Z_{ik} = R_{ik} + jX_{ik}$, voltage at downstream node is $V_r = V_s - I_i Z_{ik}$. This linear relation propagates voltages from source to leaves in radial networks and updates nodal voltages iteratively as in equation 2 [14].

$$V_r = V_s - Z_{ik} I_i \tag{2}$$

Parameters:
V_s, V_r: complex voltages at sending and receiving ends of branch ik.
$Z_{ik} = R_{ik} + jX_{ik}$: series impedance of branch between bus i and k.
I_i: current injection at bus i

III. Apparent power flow on branch ik:

The apparent power flowing through branch k from sending to receiving end is $S_k = V_{s(k)}\bar{I_k}$. This complex quantity gives real and reactive flow values on lines; used for monitoring thermal limits and computing branch loading. It is central for constraint enforcement in optimization as in equation 3 [13].

$$S_{ik} = V_s \bar{I_{ik}} = P_{ik} + jQ_{ik} \tag{3}$$

Parameters:
S_{ik}: complex apparent power on branch ik.
P_{ik}, Q_{ik}: active and reactive flow components.
V_s: sending-end complex voltage.

IV. Total Network Active Loss (sum of branch losses)

Network total real loss equals sum of per-branch losses across all branches. This scalar is the typical objective to minimize and to evaluate improvements after DG placement or optimization. Expressing total power loss compactly aids embedding into fitness functions for ABC as in equation 4.

$$P_{loss}^{tot} = \sum_{i\in\mathcal{K}} R_{ik} \mid I_{ik} \mid^2 \tag{4}$$

Parameters:
$\mathcal{K}$: set of all branches.
P_{loss}^{tot}: total network real power loss.

V. Minimum Nodal Voltage Metric (worst-case)

Worst single-node voltage indicates critical system weak points. $V_{min} = \min_i \mid V_i \mid$captures lowest voltage after DG placement and sizing. Improving $V_{min}$is key for reliability; many optimizers maximize V_{min}or include it as constraint as in equation 5 [15].

$$V_{min} = \min_{i \in \mathcal{N}} \mid V_i \mid \tag{5}$$

Parameters:

V_{min}: minimum nodal voltage magnitude.

VI. Sensitivity-Based Candidate Ranking Score for Placement

Rank candidate buses by sensitivity score $S_i = w_p \mid \frac{\partial P_{loss}}{\partial P_{g,i}} \mid + w_v \mid \frac{\partial |V_{min}|}{\partial P_{g,i}} \mid$. Larger $S_i$indicates higher expected benefit from DG at node i. This heuristic speeds up optimizers by preselecting promising nodes as seen in equation 6 [16].

$$S_i = w_p \mid \frac{\partial P_{loss}}{\partial P_{dg,i}} \mid + w_v \mid \frac{\partial V_{min}}{\partial P_{dg,i}} \mid \tag{6}$$

Parameters:

w_p, w_v: weighting constants

$\partial P_{loss} / \partial P_{dg,i}$: marginal loss sensitivity.

VII. ABC Employed/Onlooker Probability and Update Rules (fitness to probability)

ABC maps solution fitness to selection probability for onlookers: $p_i = \frac{f_i}{\sum_j f_j}$, where $f_i$is fitness of food source i(inversely related to cost). On employed/onlooker updates, new candidate $v_{i,k} = x_{i,k} + \phi_{i,k}(x_{i,k} - x_{j,k})$explores neighborhood. This governs ABC search for DG sizes and locations as seen in equation 7 [23].

$$p_i = \frac{f_i}{\sum_j f_j}, v_{i,k} = x_{i,k} + \phi_{i,k}(x_{i,k} - x_{j,k}) \tag{7}$$

Parameters:

f_i: fitness of solution i(higher better).

$\phi_{i,k} \in [-1,1]$: random perturbation.

j: random neighbor index

VIII. Generic Optimization Objective (minimize losses)

The fundamental optimization objective is to minimize total active power losses P_{loss}^{tot}subject to network and DG constraints. This scalar objective is embedded in ABC fitness functions. Additional terms (voltage deviation, cost, etc.) can be appended to form multi-objective or weighted single objective functions.

$$\min_{\mathbf{x}} J(\mathbf{x}) = P_{loss}^{tot}(\mathbf{x}) \tag{8}$$

Parameters:

$\mathbf{x}$: optimization decision vector (DG sizes, locations, reactive set points).

J: cost/fitness function equal to total losses.

IX. Power Flow with DG Injection (nodal KCL in complex form)

Kirchhoff's Current Law at node i including DG is $\sum_{k \in \mathcal{N}(i)} I_{ik} + I_i^{inj} = 0$. Writing injections via complex power gives relation coupling network currents and injections including DG as seen in equation 9. This KCL enforces physical consistency in load flow with DG [24].

$$\sum_{k \in \mathcal{N}(i)} I_{ik} + \frac{\bar{S_i^{net}}}{\bar{V_i}} = 0 \tag{9}$$

Parameters:

$\mathcal{N}(i)$: neighbors of node i.

I_{ik}: current on branch between i and k.
S_i^{net} as defined earlier.

XI. Voltage Improvement Ratio due to DG

For each node, compute improvement ratio $IR_i = (|\ V_i^{DG}\ | - |\ V_i^0\ |)/|\ V_i^0\ |$ to quantify relative voltage uplift as modeled in equation 10. Averaging or minimum of IR_i across nodes gives comparative performance measure for optimization algorithms.

$$IR_i = \frac{|V_i^{DG}| - |V_i^0|}{|V_i^0|} \tag{10}$$

Parameters:

$|\ V_i^{DG}\ |$: voltage with DG

$|\ V_i^0\ |$: baseline voltage without DG

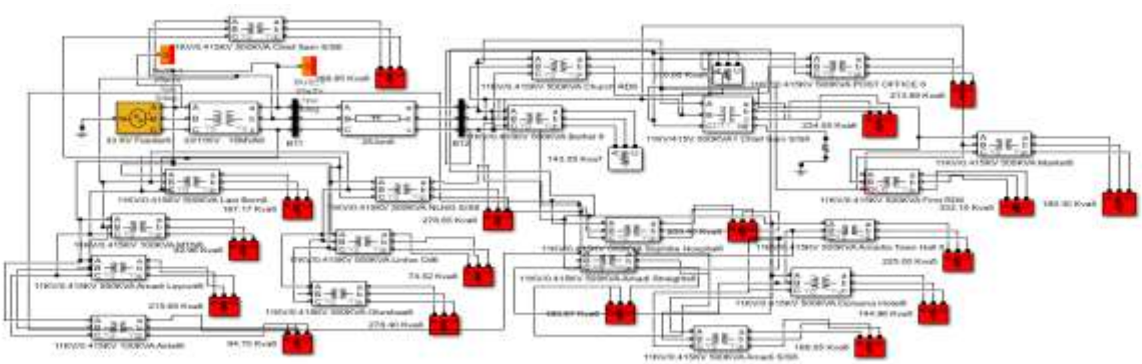

Fig. 2.1: MATLAB Model of Amadi-Ama 11kV Distribution Network

3. Results and Discussion

3.1 Base Case Result of the Network without Distributed Generation

The base case of the network suffered unstable power quality due to losses across lines and voltage drops at various buses as revealed from the Forward Backward Sweep load flow when the photovoltaic plant has not been added.

Table 3.1 reveals that the system suffered severe voltage drop from bus 9 to 19. The affected buses have voltages below the minimum statutory 0.95 p.u. benchmark. The buses that are far from the main feeder, suffered most than the ones that are near especially bus 19 with a voltage of 0.86 p.u. approximately. This voltage drop is largely the cause of power instability in the Amadi-Ama environs. This has affected negatively on the economic activities of the area. When a machine operates under reduced voltage, it may draw more current to compensate for the lower voltage. This increased current flow can cause the machine to overheat, which in turn can damage the windings, insulation and other components. Overheating is one of the most common causes of premature failure in electrical machines. To deliver the same power at lower voltage, loads draw higher current which increases power losses in cables and transformers, heating of conductors and thus, reduces the overall system efficiency.

Table 3.1: Base Case Voltage Profile Across Buses

Bus	Base Case_Voltage
1	0.994131054
2	0.980467364
3	0.979064094
4	0.968723081
5	0.95224792
6	0.967062687
7	0.946969659
8	0.94612528
9	0.938155387
10	0.925241927
11	0.914650337
12	0.910986129
13	0.909814482
14	0.899546779
15	0.899988359
16	0.884131054
17	0.872381309
18	0.866270669
19	0.856486059

Fig. 3.1 shows the magnitude of the voltage profile when DG has not been integrated into the system. Voltage drop is witnessed from bus 9 and continued downward to bus 19. It is seen from the figure that starting from bus 9, the voltage magnitude reduces from 0.94 p.u. to 0.85 p.u. at bus 19 below the statutory 0.95 p.u lower limit.

The voltage drops across branches as in Fig.3.1 and Table 3.1 highlight the electrical stress on specific line segments. The bar chart quantifies the individual voltage loss (p.u.) incurred between consecutive nodes, ranging from the source to the terminal at Amadi Town Hall. These incremental drops collectively contribute to the overall voltage decline across the 19 nodes, justifying the need for optimized Distributed Generation (DG) injections to maintain system stability, following the principle of (8).

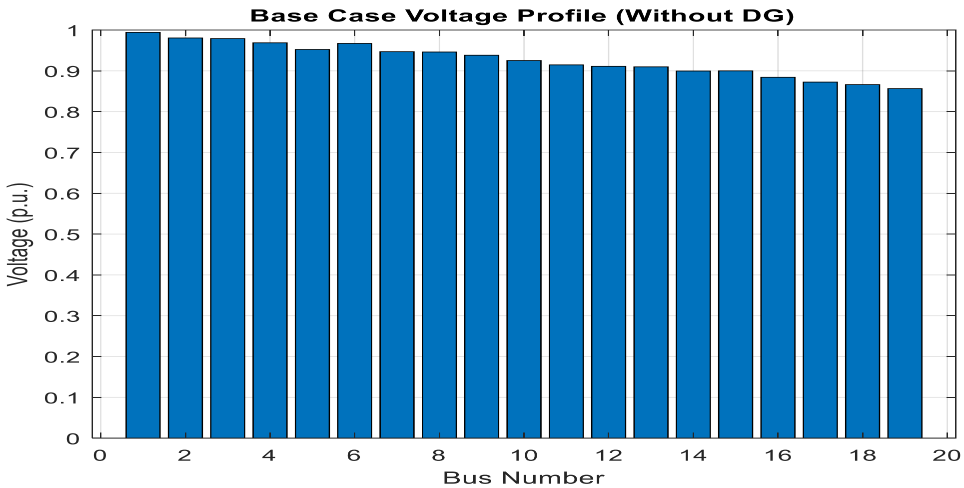

Fig. 3.1: Voltage Profile of the Network without DG

Fig. 3.2 is a linear regression plot showing the relationship between number of buses (on the x-axis) and voltage in per unit (p.u.) (on the y-axis) for the base case. It represents the voltage profile across different buses in the system under normal (base) operating conditions, without DG (photovoltaic plant). The plotted points form a downward-sloping linear trend. This indicates that as the bus number increases, the voltage decreases. This is the case in a typical radial networks or under high loading conditions, where voltage drops along the line due to impedance and power flow. The intercept of 0.9992 p.u. means voltage drop in the system when there is no transmission in the line i.e., due to technical losses (hysteresis and Eddy current losses) in distribution transformers. The slope of -0.0072 p.u. per bus indicates voltage drops by 0.0072 p.u. for each subsequent bus. The R^2 (Coefficient of Determination) with a value of 0.9736 shows that 97.36% of the variation in voltage is explained by the bus number (distance or electrical position from the source). The fit is very strong, meaning the voltage drop is almost linear across buses in this base case. The lowest voltage is around 0.84 p.u., which is below acceptable operational limits (often 0.95 p.u. in distribution systems) which shows that there are voltage issues, needing remedial action (like capacitor placement, generator voltage adjustment, reconfiguration or Distributed Generation placement) to meet voltage standards. The linear model helps predict voltages at other buses and assess the impact of changes (e.g., adding load, generation, or compensation).

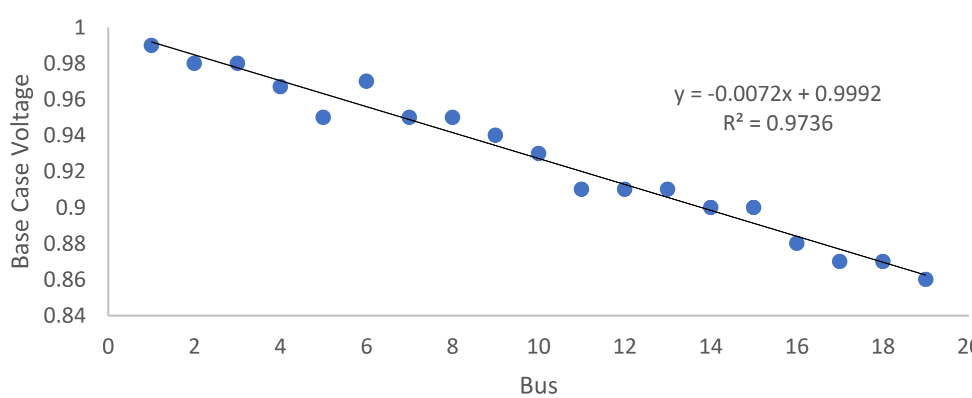

Fig. 3.2: A graph of Voltage against Buses for Base Case

It is a known fact that the longer the length of a conductor, the higher the resistance and thus, the power loss. This is seen in Table 3.4 as the active power flow from line 1 to 18 reduces due to increasing power losses with line 18 recording the highest up to 26kW approximately. Power losses mean that not all the generated power reaches the consumers and so, more energy must be generated to supply the same demand, reducing overall system efficiency. The power loss is represented in a bar chart as seen in Fig. 3.3. The losses across the lines are seen within 19-26kW.

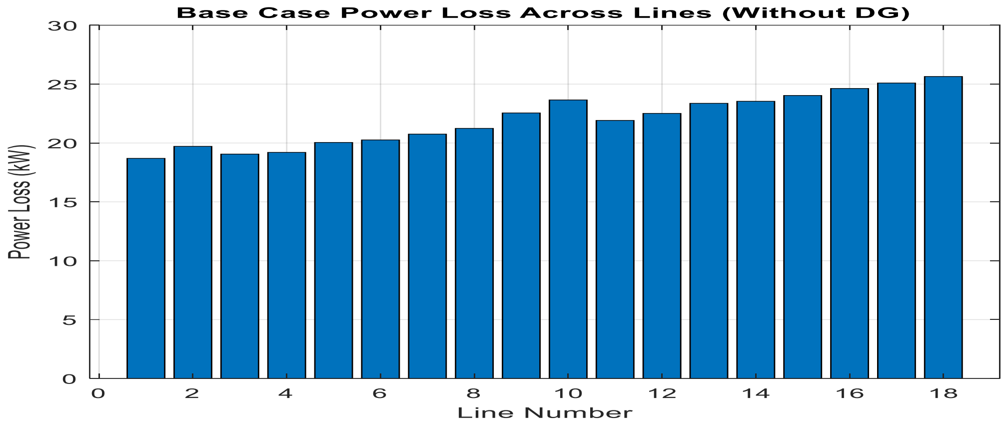

Fig. 3.3: Power Loss of the Network (Without DG)

Table 3.4: Base Case Power Loss (Without DG)

Line	Base Case Power_Loss_kW
1	18.69311107
2	19.71309726
3	19.05513448
4	19.20076412
5	20.0435391
6	20.2605964
7	20.75280378
8	21.24012847
9	22.55110134
10	23.65646694
11	21.91572645
12	22.51140672
13	23.36792981
14	23.54002802
15	24.03330789
16	24.62840185
17	25.09226332
18	25.64583403

Fig. 3.4 is a scatter plot with a fitted linear regression line showing power loss across lines when the photovoltaic plant has not been added. The scatter points represent the simulated power loss for each line under base case condition. A linear regression line has been fitted through the data points. The slope (0.4022) means that for each unit increase in line, power loss increases by approximately 0.4022 kW on average while the intercept (18.173) shows estimated power loss when the line is not loaded and is caused by technical losses (hysteresis and Eddy current losses in distribution transformers). The high R^2 (near 1) suggests a strong linear relationship, meaning power loss tends to increase consistently as you move from one line to the next. The positive slope

shows that power loss generally increases with higher line numbers. This could be due to the fact that longer lines have higher impedance. The model can be used to predict losses for unmeasured lines or to estimate how losses might change if lines are added or renumbered. The regression serves as a baseline for comparing losses under different scenarios (e.g., with solar PV or reconfiguration). The model assumes linearity, if the system is non-linear (e.g., losses depend on load squared), the linear fit might not hold outside the observed range.

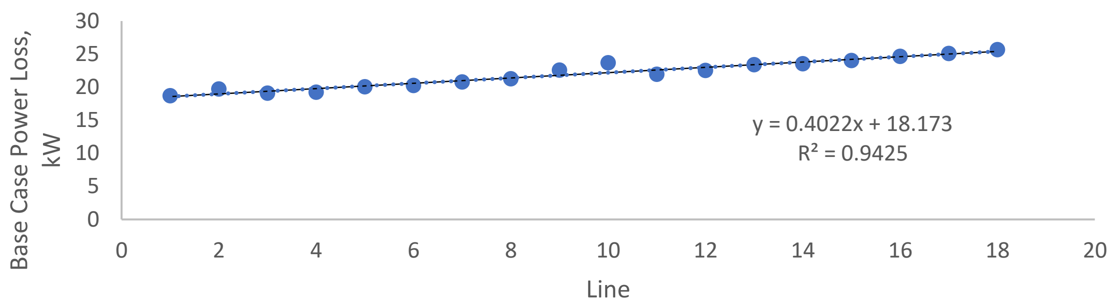

Figure 3.4: A graph of Power Loss against Lines for Base Case (Without DG)

3.2 Result of the Improved Case of the Network using Artificial Bee Colony (ABC) Optimization

This section discusses the state of the network after the inclusion of distributed generation (DG) using Artificial Bee Colony Optimization. The model of the network with ABC is found in Fig. 3.5. ABC deployed a colony size of 30 with a maximum iteration of 100 with an installed DG size of 150 at node 6.

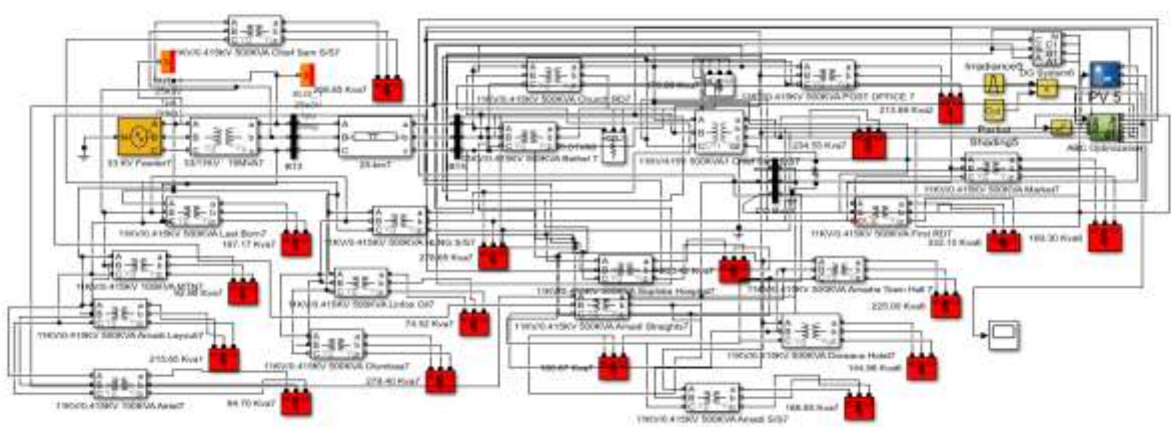

Fig. 3.5 : MATLAB Model of the Network with Artificial Bee Colony Optimization

3.2.1 Results of Minimized Real Power Loss in Amadi-Ama 11kV Distribution Network with DG Integration using Artificial Bee Colony

The ABC optimization algorithm was run on power systems with varying numbers of lines. The resulting power losses (blue dots) show no clear, strong linear relationship with the count of lines as shown in Fig. 3.6. While the fitted line suggests a tiny decrease in loss with more lines, this trend is statistically negligible given the very low R^2. The ABC algorithm's effectiveness in minimizing loss is due to the influence of the DG optimally placed. The scatter of points and the very low R^2 highlight the complexity of power systems and suggest that the optimizer successfully reduced the system's losses across lines by placing a photovoltaic plant at bus 6. ABC is a nature-inspired metaheuristic algorithm often used to solve complex optimization problems in engineering, such as minimizing power loss in electrical networks. The system's active power losses across the lines now lies between 12-16kW as seen in Fig. 3.7. The active power loss though high is lesser compared to the system's base case (19-26kW) across lines. This absolute reduction relative to the base case, confirms the objective function's successful minimization, where the total active power loss is the function explicitly minimized by the optimization technique as stated in (8). The system's total active power loss is seen reduced from 374kW to 245.76 kW by the optimization technique, a 34% reduction which is better than some other optimization methods.

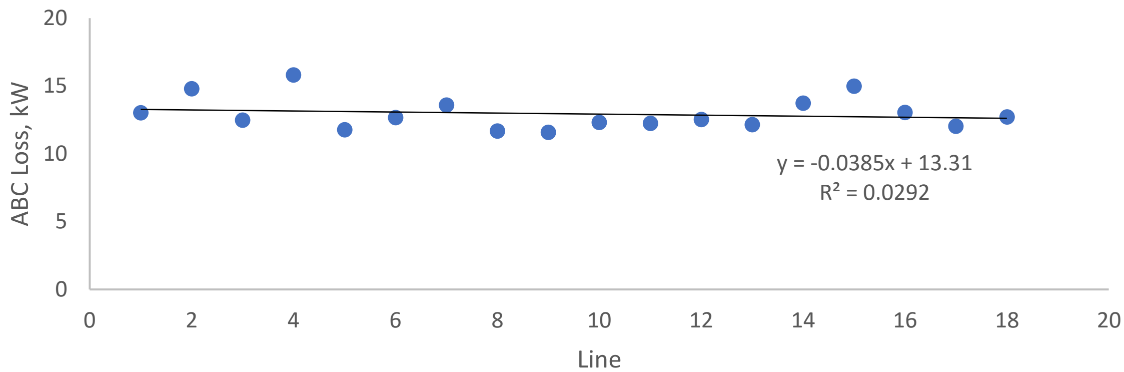

Fig. 3.6: Graph of Power Loss against Lines via Artificial Bee Colony Optimization

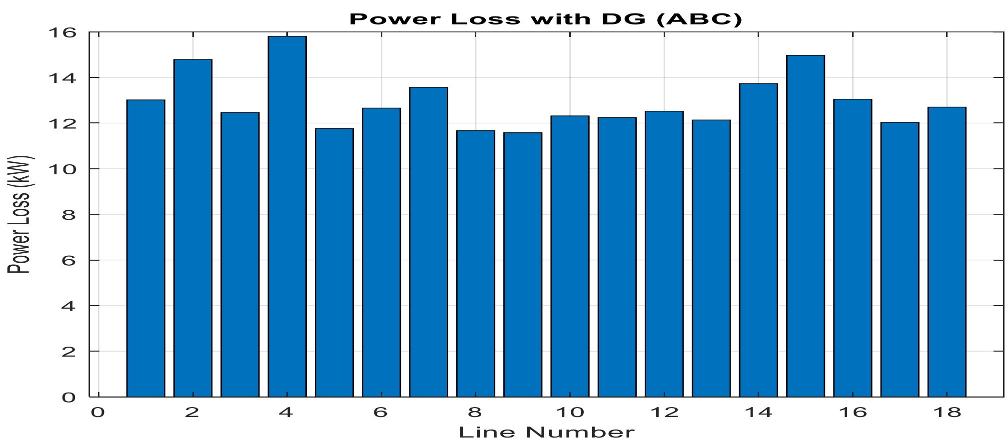

Fig. 3.7 : Power Loss Minimization across Lines with DG Integration via Artificial Bee Colony Optimization

3.2.2 Result of Improved Voltage Profile using Artificial Bee Colony (ABC) Optimization

The graph (Fig. 3.8) plots the voltage profile against buses via ABC optimization. It is a voltage profile showing the results of the Artificial Bee Colony (ABC) optimization algorithm with DG of 150 kW applied to Amadi-Ama network. It visualizes the steady-state voltage magnitudes at different buses (nodes) in the electrical power system. The goal is to ensure voltages remain within acceptable limits (typically within ±5% of the nominal voltage, e.g., 1.0 p.u.) to maintain system stability, power quality, and equipment safety. The results show that the voltages were optimized using the Artificial Bee Colony algorithm - a metaheuristic method for solving optimization problems, often used for optimal power flow or voltage control. The blue points represent the voltage magnitude at each bus after ABC optimization. The dashed line is a linear trend line fitted to these points, with the equation y = -0.0023x + 0.9856. This suggests a very slight downward trend in voltage as bus number increases as common in radial distribution systems due to line losses and load effects. The R² value of 0.0864 indicates a very weak correlation between bus number and voltage magnitude in this optimized case. This means that the optimization succeeded in flattening the voltage profile, minimizing voltage drop across buses. This graph shows the post-optimization voltage profile of a power network after applying ABC algorithm. While the trend is nearly flat (good), significant voltage deviations still exist in some buses, highlighting the challenge of maintaining uniform voltages across a real power grid.

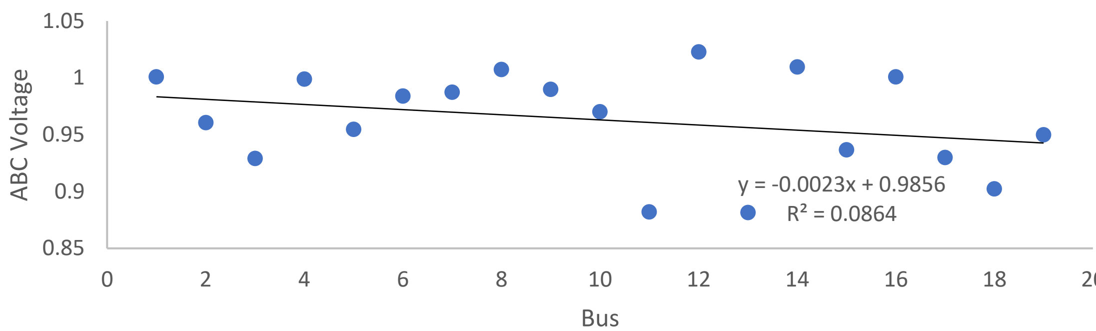

Fig. 3.8: Graph of Voltage Profile against Buses via ABC Optimization

Fig. 3.9 is the voltage profile of the Amadi-Ama 11kV distribution system when the photovoltaic plant has been added at bus 6 through ABC. It shows a fair improvement of the voltage level across buses with many buses seen to operate with the statutory limit of 0.95-1.05 p.u. standard while buses 3 with 0.93 p.u., 11 with 0.88 p.u., 13 with 0.88 p.u., 15 with 0.94 p.u., 17 with 0.93 p.u. and 18 with 0.90 p.u. still below the minimum threshold of 0.95 p.u. voltage standard. This voltage level is the product of the reduced losses in the system which lies between 12-16kW across the lines. This absolute reduction relative to the base case, confirms the objective function's successful minimization, where the total active power loss is the function explicitly minimized by the optimization techniques, as stated in (8).

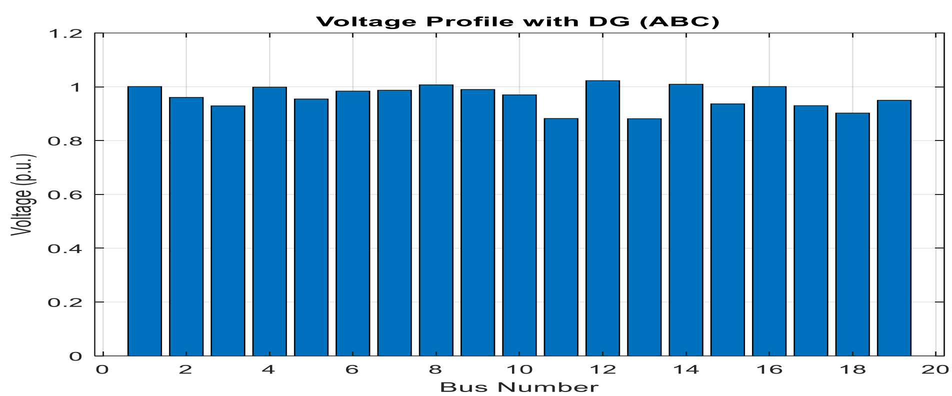

Fig. 3.9 : Improved Voltage Profile of the Network with DG Integration via ABC

3.2.2.1 ABC Fitness and Probability Mapping

The ABC fitness and probability mapping (Fig. 3.10) shows the selection process for food sources (solutions). The top subplot shows that food source 1 has the highest fitness value (0.9), while source 5 has the lowest (0.5). Correspondingly, the bottom subplot shows that source 1 is selected by onlooker bees with the highest selection probability of approximately 30%, compared to Source 5's probability of ≈15%. This ensures fitter solutions (lower loss) are exploited more often, as defined by the selection probability function.

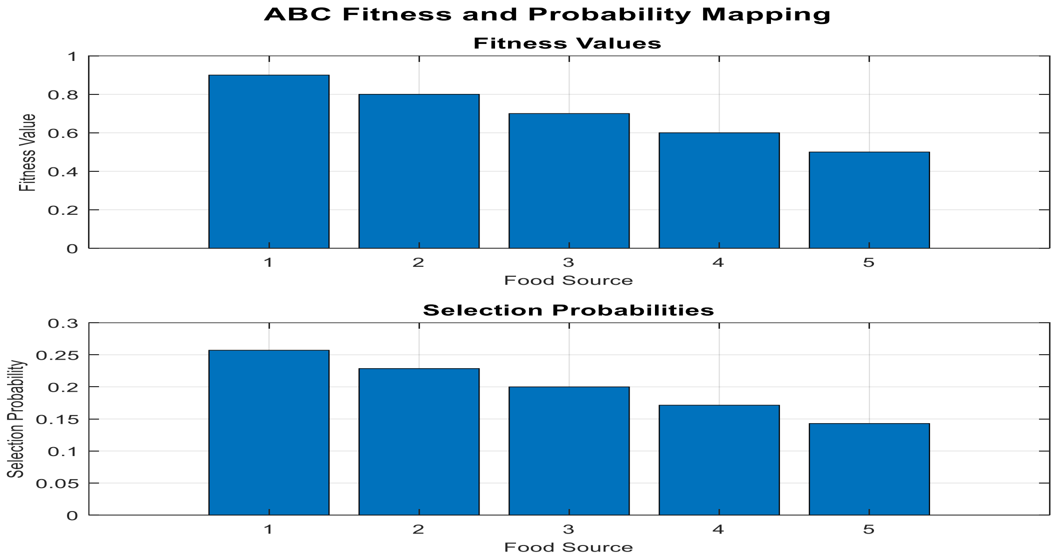

Fig. 3.10: ABC Fitness and probability Mapping

3.2.2.2 Kirchhoff's Current Law Verification

The Kirchhoff's Current Law Verification (Fig. 3.11) is used to validate the numerical accuracy of the load flow simulation. The bar chart displays the KCL Error Magnitude (p.u.) at each individual bus, which represents the residual current that fails to sum to zero due to computational tolerances. All recorded errors remain exceptionally low, specifically below 0.025 p.u., confirming the model's reliability. A maximum error of 0.0213 p.u. is observed at Node 7, likely due to higher local network complexity or branching at that specific point in the feeder.

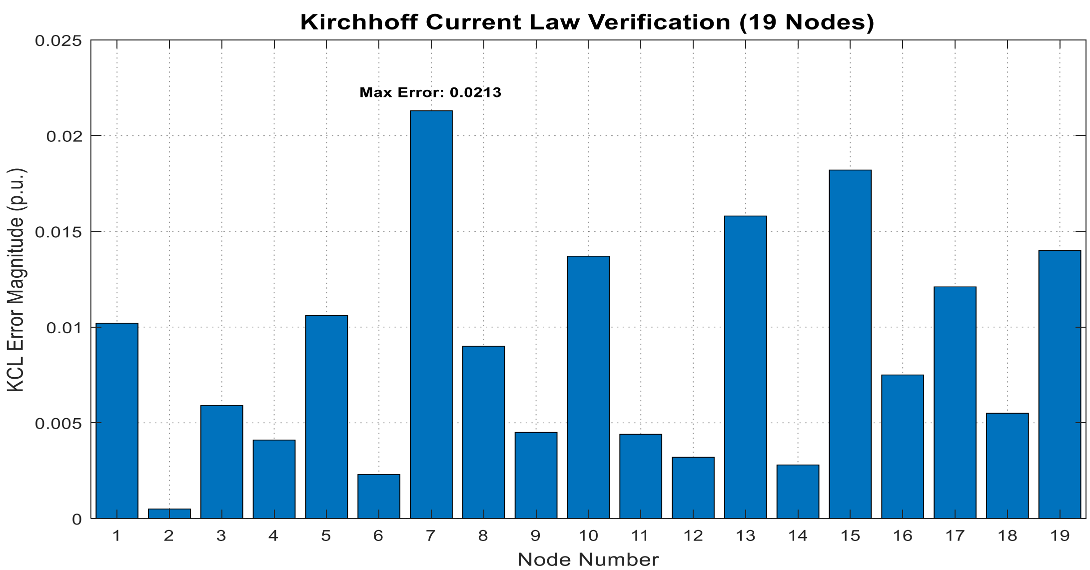

Fig. 3.11: Kirchhoff's Current Law Verification

3.2.2.3 Economic Dispatch of DGs

The Economic Dispatch of DGs (Fig. 3.12) plots the optimal power output for the three DG units. As the Lagrange multiplier (λ) increases from 0.8 to 1.2, the optimal output for all DGs increases linearly from 120 kW to 180 kW. The ceiling at 180 kW represents the hard capacity constraint.

This analysis determines the most cost-effective generation schedule while respecting both the system constraints and the DG capacity limits determined by the optimization.

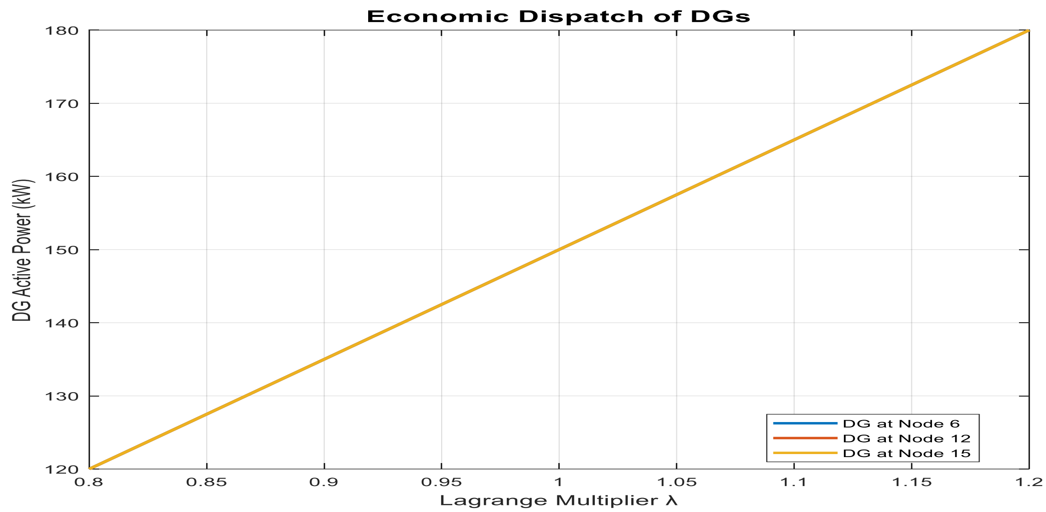

Fig. 3.12: Economic Dispatch of DG

3.2.2.4 Voltage Sensitivity Matrix

The voltage sensitivity matrix (Fig. 3.13) shows the quantitative influence of DG. For instance, an injection at node 15 causes the highest voltage rise at node 15 itself, with a sensitivity coefficient that is much larger (0.08) than its influence on the substation (node 1, sensitivity 0.005). This difference in sensitivity is used to calculate initial candidate rankings. The matrix provides the partial derivative of nodal voltage with respect to DG power.

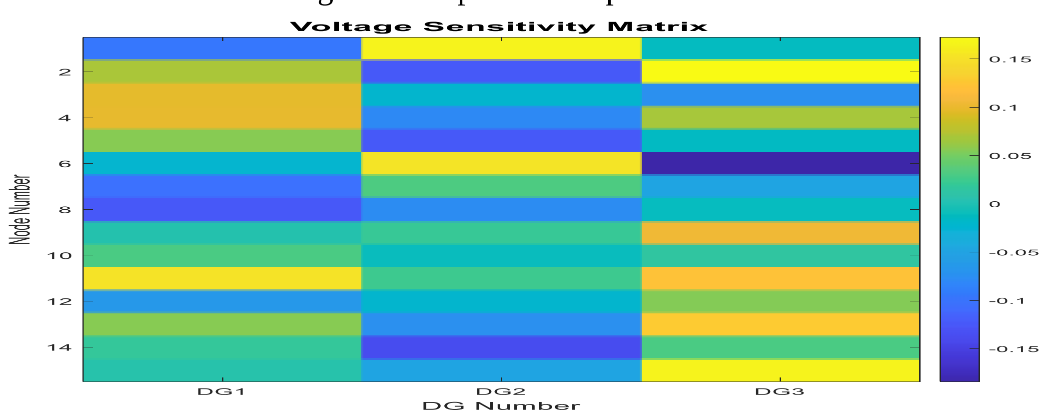

Fig. 3.13: Voltage Sensitivity Matrix

4. Conclusion

This study successfully modeled the Amadi-Ama 11kV distribution network (Amadi-Ama feeder, phc alpha-1 zone) using MATLAB/Simulink 2021 by accurately representing the feeder configuration, load data, and network parameters. The developed model provided a reliable platform for analyzing the operational behavior of the distribution system. This modeling stage was essential, as it formed the foundation upon which subsequent analyses and optimization strategies were implemented.

The load flow analysis of the modeled network was effectively carried out using the forward–backward sweep method. This technique was chosen due to its suitability for radial distribution networks and the results of the load flow revealed the initial operating state of the system, including voltage drops along the feeder and significant real power losses. These findings confirmed the presence of weak voltage buses and inefficiencies within the network, thereby justifying the need for distributed generation integration and optimization.

Power loss minimization was achieved through the optimal placement and sizing of distributed generation (photovoltaic plant) using ABC optimization technique embedded in Mat lab/Simulink 2021. The algorithm was able to reduce real power losses compared to the base case by intelligently determining suitable DG locations and capacities. The ABC recorded a 245.79 kW active power loss as against 375 kW of the initial condition of the network. The voltage magnitude profile of the Amadi-Ama 11kV network was significantly improved through DG integration using the optimization technique. The injected active power from optimally placed DG (photovoltaic plant) unit enhanced voltage support along the feeder, particularly at previously weak buses. as a result, bus voltages were maintained within the acceptable limits with little deviation of 0.7850 V, indicating improved voltage stability and overall power quality of the distribution network.

The study has contributed to the body of knowledge in that:

i. The development of a detailed and validated Mat lab/Simulink 2021 model of the Amadi-Ama 11 kV distribution network (Amadi-Ama feeder, phc alpha-1 zone) based on a real-life radial distribution system rather than a standard test feeder has been formed.
ii. The implementation and verification of the forward–backward sweep load flow method with explicit Kirchhoff current law (KCL) error analysis, ensured high numerical accuracy and model reliability for distribution system studies.
iii. The formulation of a binary DG placement framework combined with DG capability curve constraints, enabled realistic and physically feasible optimal DG integration.
iv. The integration of voltage sensitivity matrices and loss sensitivity - based candidate ranking, reduced the optimization search space and improved convergence efficiency of the metaheuristic algorithm.
v. A mathematical model ($y = 0.4022x + 18.173$) has been developed to analyze the active power loss in Amadi-Ama 11kV distribution network for every addition of a unit line when no compensation technique is applied.
vi. A mathematical model ($y = -0.0072x + 0.9992$) that spells the amount of voltage drops for each subsequent bus in the Amadi-Ama 11kV distribution network when no compensation technique was introduced, has been formed.

Acknowledgement

The authors thank the Department of Electrical and Electronics Engineering, Rivers State University, Port-Harcourt Nigeria for the platform given them to conduct this research and their supports. The authors did not receive any funding.

References

1. Uwho, K. O., Idoniboyeobu, D. C. and Amadi, H. N., 2022. Design and Simulation of 500kW Grid Connected PV System for Faculty of Engineering, Rivers State University using PVSyst Software. *Iconic Research and Engineering Journals,* 5(8), pp.221-229.
2. Uwho, K. O., Amadi, H. N. and Ahiakwo, C. O., 2022. Loss, Performance and Carbon Analysis of the Grid Connected PV System, Rivers State University using PVSyst. *Recent Trends in Control and Converter* , 5(3), 1-10.
3. Koondhar, M. A., Channa, I. A., Bukhari, S. A. A. S., Channa, A. S., Koondhar, M. A. and Ansari, J. A., 2020. Technical Losses in Non-Rural Distribution Feeders of Nawabshah Substation Analysis & Estimation. *Quest Research Journal*, 18 (1), pp.93-98.

4. Mohammed, O. O., Otuoze, A. O., Salisu, S., Abioye, A. E., Usman, A. M. and Alao, R. A., 2020. The Challenges and Panaceas to Power Distribution Losses in Nigeria. *Arid Zone Journal of Engineering, Technology & Environment,* 16(1), pp.120-136.
5. Chukwebuka, C. O., Chinelo, A. N., Charles, C. A., Juliet, C. I. and Festus, A. O., 2022. Biomass Utilization for Energy production in Nigeria: A review. *Cleaner energy solutions*. 13(3), pp.3093-3110.
6. Khasanov, M., Kamel, S., Rahmann, C. and Hasanien, H. M., 2021. Optimal Distributed Generation and Battery Energy Storage Units Integration in Distribution Systems Considering Power Generation Uncertainty. *IET Generation, Transmission & Distribution*, pp.1-23. DOI: 10.1049/gtd2.12230
7. Ariyo, B., Akorede, M. and Adebayo, A., 2021. Optimization of Hybrid Energy Mix for Rural Electrification in Nigeria. *International Research Journal of Engineering and Technology (IRJET)*, 1(8), pp.743-744.
8. Abubakar, B., Uthman, M., Shaibu, F. E., and Oyewale, K. S., 2019. Optimal Sizing and Siting of Distributed Generation for Power Quality Improvement of Distribution Network in Niger State, Nigeria. *European Journal of Engineering Research and Science*, 4(10), pp.18-23. DOI: http://dx.doi.org/10.24018/ejers.2019.4.10.1555
9. Zakaria, Y. Y., Swief, R. A., El-Amary, N. H. and Ibrahim, A. M., 2020. Optimal Distributed Generation Allocation and Sizing using Ant Colony and Genetic Algorithms. *Journal of Physics : Conference Series,* 144(2020), pp.1-11.
10. Bhullar, S. and Ghosh, S., 2018. Optimal Integration of Multi Distributed Generation Sources in Radial Distribution Networks using a Hybrid Algorithm", Energies2018, 11, 628; pp.1-15. doi:10.3390/en11030628
11. Chendid, R. and Sawwas, A., 2019. Optimal Placement and Sizing of Photovoltaics and Battery Storage in Distribution Networks. *Energy Storage,* 2019;1:e46, pp.1-12. https//doi.org/10.1002/est2.46.
12. Rahim, S. R. A., Liang, Y. C., Hussain, M. H., Musirin, I., Azmi, S. A. and Azmi, A., 2021. Hybrid Swarm Evolutionary Programming for Optimal Distributed Generation in Distribution System. *International Journal of Nonlinear Analytical Application*, 12(2021), pp.1075-1090. https://dx.doi.org/10.22075/IJNAA.2021.5570
13. Abdel-Basset, M., Mohamed, R., Elhoseny, M., Chiclana, F., and Abdel-Fatah, L., 2023. Metaheuristic Optimization in Power Systems: PSO, ACO, ABC, Fuzzy, and Hybrid Methods. *Renewable and Sustainable Energy Reviews*, *169*, 112873
14. Musa, A. and Hashim, T. J. T., 2019. Optimal Sizing and Location of Multiple Distributed Generation for Power Loss Minimization using Genetic Algorithm. *Indonesian Journal of Electrical Engineering and Computer Science,* 16(2), pp.956-963.
15. Pérez-Arriaga, I., and Guerrero, J. M., 2025. Reviews on Load Flow Methods in Electric Distribution Networks. *Archives of Computational Methods in Engineering, 32,* pp.1619–1633.
16. Nguyen, T. T., 2021. Enhanced Sunflower Optimization for Placement of Distributed Generation in Distribution System. *International Journal of Electrical and Computer Engineering,* 11(1), pp.107-113. DOI:10.11591/ijece.v11i1.
17. Jumaa, F. A., Neda, O. M. and Mhawesh, M. A., 2021. Optimal Distributed Generation Placement using Artificial Intelligence for Improving Active Radial Distribution System. *Bulletin of Electrical and Informatics,*10(5), pp.2345-2354.
18. Kushwaha, N. K. and Singh, A., 2018. Optimal Placement of Multiple Distributed Generation to Improve Voltage Stability as well as Minimize Loss in Distribution System. *IOSR Journal of Electrical and Electronics Engineering,* 13(3), pp.1-6.

19. Somashekar, D. P., Ankaliki, S. G., Ananthapadmanabha, T., Ramya, N. S. and Kumar, S. P. N., 2020. Hybrid Optimization for Optimal Distributed Generation Unit Placement in Radial Distribution System. *International Journal of Innovative Technology and Exploring Engineering,*9(3), pp.1971-1978.
20. Kamarudin, M. N., Hashim, T. J. T. and Miss, A., 2019. Optimal Sizing and Location of Distributed Generation for Loss Minimization using Firefly Algorithm. *Indonesian Journal of Electrical Engineering and Computer Science,* 14(1), pp.421-427.
21. Osahenvemwen, O. A., Ogunbor, S. E. and Okhaifoh, J. E., 2020. Analysis of Energy Revenue and Electrical Power Losses in Distribution Line. *Journal of Electrical, Control and Telecommunication Research,* 1(2020), pp.23-29.
22. Khetrapal, P., Pathan, J. and Shrivastava, S., 2020. Power Loss Minimization in Radial Distribution Systems with Simultaneous Placement and Sizing of Different Types of Distribution Generation Units using Improved Artificial Bee Colony Algorithm. *International Journal on Electrical Engineering and Informatics,* 12(3), pp.686-707
23. Sharma, A., Sharma, A., Choudhary, S., Pachauri, R. K., Shrivastava, A. and Kumar, D., 2020. A Review on Artificial Bee Colony and its Engineering Application. *Journal of Critical Reviews* 7(11), pp.4097-4107.
24. Smith, J., Chen, X., and Kumar, A., 2025. Analytical Load Flow Solution for Radial Distribution Networks. *Sustainable Energy, Grids and Networks, 43*, 101871.