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Title; Multi-Objective Optimal Placement of Distributed Generation in IEEE 33-Bus System Using Grey Wolf Optimization.

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Abstract- This study presents a Grey Wolf Optimization (GWO)-based approach for the optimal placement and sizing of distributed generation (DG) in radial distribution systems to improve power system performance. The increasing penetration of renewable energy sources in modern power networks has created challenges associated with voltage instability, high power losses, and reduced reliability, thereby necessitating efficient optimization techniques for DG planning. The IEEE 33-bus radial distribution system was adopted as the benchmark network, while MATLAB R2023a with the MATPOWER toolbox was used for modelling and simulation. Load-flow analysis was performed using the Newton–Raphson and Backward/Forward Sweep methods to evaluate system performance before and after DG integration. A photovoltaic (PV)-based DG model with controllable active power injection was incorporated into the network. The optimization problem was formulated as a constrained multi-objective function aimed at minimizing active power losses and voltage deviation while maximizing voltage stability. Operational constraints, including bus voltage limits, DG penetration limits, branch thermal capacities, and power balance equations, were incorporated into the model. GWO was employed to determine the optimal DG locations and capacities, while Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) were implemented for comparative analysis using identical parameters of 30 search agents and 50 iterations. Simulation results showed that GWO outperformed PSO and ACO in all evaluated indices. The minimum bus voltage improved from 0.9131 p.u. to 0.9784 p.u., while total active power loss decreased from 202.67 kW to 92.35 kW, representing a 54.43% reduction. Furthermore, GWO converged faster within 18 iterations compared to 29 and 42 iterations for PSO and ACO, respectively. Reliability indices SAIFI and SAIDI also improved significantly after DG integration, confirming the effectiveness of GWO for optimal DG planning in radial distribution networks.

I. INTRODUCTION

An option for overcoming Nigeria's ongoing power problems is to include distributed generation in the main power grid. There are many renewable energy resources in the country and this could be used to power small generators and bring electricity to urban areas, rural towns and villages that are not easily reached. Still, because of the present system in Nigeria, these decentralized energy sources cannot be used to address the urgent energy deficit.

(Gupta et al., 2020). Because of the evolution of power systems and fast technological progress, generation facilities have become smaller and cheaper which has inspired increased private investment in energy projects. Because of the need for greener energy, people are more interested in distributed generation (Ogunjuyigbe., et al 2021: Akinola, et al., 2021).

Every generator and consumer in an electricity market should be granted equal access to the grid (Camilo et al., 2022). Getting this to work properly means there are clear directions on how power can be put into or taken out of the grid at certain points and reliable enforcement is in place. Contracts must detail fair fees for using the transmission network and help with working on expanding network infrastructure on time. (Camilo et al., 2022: Hernando et al., 2022) have found the same thing.

Following deregulation and fast technological growth, private businesses are now investing in smaller power plants. (Oke et al., 2023). Because of these advances and the rising attention on renewable and cleaner sources of energy, distributed generation (DG) is gaining popularity. Because of this model, users can generate electricity for their homes, as well as return any extra energy to the grid, at a reduced voltage. It helps ensure a consistent and reliable supply of energy, with better security and reduces the percentage of energy wasted during transportation. (Rahman et al., 2021; Al-Shetwi, et al., 2021).

In general, Distributed Generation (DG) has been recognized as a hopeful solution to power problems in Nigeria at large. It simply means having small production units next to consumers and attached to medium or low-voltage networks. Such units may be set up by end-users, independent power producers (IPPs) or utility companies. DG gives consumers an alternative way to handle high electricity demand. For those involved in IPPs, it means business opportunities, while for utilities, it aids in lowering energy loss, managing voltages in the network and may be put off expensive network upgrades to improve voltage support, reduce technical losses, and enhance reliability (Rahman et al., 2021).

To be more precise, researchers confirmed that DG improves bus voltages, reduces active and reactive losses, and enhances reliability only when optimally sized and located quoted, (Chen et al., 2022; Zhou et al., 2024).

Nevertheless, poorly integrated DG may bring about opposite power flows, which complicates system protection, and present another instability risks (Bello et al.,2023). In order to overcome this, the IEEE 33-bus redial network needs to be modelled and simulated properly for better DG impacts. (Nwachukwu et al., 2022).

1.1 Problem Statement

According to (Oke et al., 2023). Electricity supply in Nigeria power distribution network is considered as poor voltage regulation, high technical losses, frequent feeder outages, and a failure to meet the increasing demand for reliable. The conventional method for supplying power to the end users through long transmission lines, has confirmed inadequate to address power instability.

Due to this, users experience premature voltage conditions, frequent power interruptions, and substantial dependence on diesel and gasoline generators which add to operational costs and environmental pollution.

Integration of DG in power system has many benefits, such as reducing of greenhouse emissions especially CO2 emissions and hence assisting in resolving the global warming problem and reducing the power loss. Even though distributed generation (DG), mostly photovoltaic (PV) systems, has been Pointed as a practical solution for voltage profile improvement, technical loss reduction, and of course enhancement of system reliability, its addition into existing distribution networks is not forthright because improper placement and sizing of it, can degrade voltage instability, add to system losses, and generate operational challenges instead of giving solutions. Hence the issues of optimal DG placement and sizing in a radial distribution system is complex, nonlinear and multi-objective optimization job.

Again, most distributed generation is either centered on single-objective loss minimization or uses traditional optimization techniques which always suffers from slow convergence and premature stagnation. In weak distribution networks experience especially here in Nigeria, there is limited application of advanced meta-heuristic techniques like Grey Wolf Optimization (GWO) for PV-based DG. (Bamidele et al., 2023).

This research work addresses the problem of how to optimally determine the location and size of PV-based distributed generation in the IEEE 33-bus radial distribution network for voltage profile improvement, minimization of power losses, and enhancement of system reliability using Grey Wolf Optimization, and its performance comparing the scenarios with other optimization methods such as Particle Swarm Optimization and Ant Colony Optimization.

II. TYPES OF DISTRIBUTED GENERATORS (DG)

There are several DG technologies but for this research work, only two kinds is discussed.

2.1 Solar power generation is the process of changing or converting sunlight into electricity,initially through photovoltaic (PV) cells or concentrated solar power (CSP) systems. The sun provides a huge amount of energy approximately 1,361 W/m² at the upper atmosphere though atmospheric absorption reduces this to about 1,000 W/m² (1 kW) on the ground during clear days (Glassman et al.,2021; Yetter et al., 2021).

The output power of a photovoltaic (PV) system is given by:

$$P_{pv} = \eta A G \quad \text{Equation 1}$$

Where P_{pv} = Output power (W)
η = Efficiency of the PV panel
A = Area of the solar panel (m²)
G = Solar irradiance (W/m²)

2.2 Hydropower generation systems transform the kinetic, potential, and pressure energy of water into electricity (Amon et al., 2023). This process involves directing water flow through a turbine runner to generate mechanical rotation, a mechanism governed by Euler's turbine theorem, which equates shaft torque to the fluid's change in angular momentum (Wang et al., 2021; Zhang et al., 2022)

Mathematical relationship is given as

$$P=\eta\rho gQHP \quad \text{Equation 2}$$

P = Power output (Watts, W)
η = Overall efficiency of the system (turbine + generator)
ρ = Density of water (≈ 1000 kg/m³)
g = Acceleration due to gravity (9.81 m/s²)
Q = Flow rate of water (m³/s)
H = Effective head (height of water, in meters)

In the literature, several statistical analysis methodologies are available to evaluate voltage improvement of power systems.

III. DG SITING AND SIZING: OPTIMIZATION STRATEGIES

The sizing and placement of DG is another interesting area of study. since DG benefits are not certain and are extremely dependent on its location and size, perhaps any wrongly placed or incorrectly sized DG unit may not only fail to distribute the expected developments but can worsen the system's performance by adding up power losses and causing over-voltage issues. Consequently, determining the optimal DG location and sizing is a critical, multi-objective optimization problem. (A.B. Alyu, et al., 2023; J.N. Eneh et al.2023.)

This problem cannot be solved successfully with simple deterministic methods owing to the huge number of potential locations and sizes. As a substitute, metaheuristic optimization algorithms are employed. (Adewale et al., 2021).

These algorithms, stimulated by natural processes, are well-suited for multifaceted, non-linear problems. used instances include Ant colony optimization technique (ACO), which integrates renewable DG into distribution systems with techno-economic objectives and Grey Wolf Optimization (GWO) enhances the location and sizing. (Tabassum et al., 2021). Further methods, Ant Lion Optimizer (ALO), particle swamp optimization (PSO) and many other hybrid approaches, have been shown to be active. (Mohamed et al., 2020). These algorithms search for the optimal DG configuration that minimizes an objective function, which can be defined to combine multiple, often conflicting, objectives.

The DG optimization problem is integrally a multi-objective one. A just single DG cannot concurrently attain the total maximum reduction in power loss and the best possible voltage profile. Example, the location that offers the utmost loss reduction might not be similar location that best improves the voltage profile.

A multi-objectives optimization outline, frequently using techniques that identify the Pareto front, is used to find a set of non-inferior solutions where an enhancement in one objective needs a degradation in another. (Kumar.S et al.,2020).

This approach allows for a sophisticated trade-off analysis, providing power system planners with a choice of optimal options. The DG optimization problem for the Nigerian network, which presently emphases on a sole large-scale plant, grants grants a change in policy. (U. Raut et al., 2020; S. Mishra et al., 2020).

3.1 Particle Swarm Optimization (PSO) is a smart optimization technique population-based meta-heuristic inspired by bird flocking and fish schooling that has been used in many applications. To each one particle updates its position and velocity using its own happening and the swarm's best happening to efficiently explore the solution space (Fang et al., 2023; Ariyo et al., 2025).

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t)$$

Equation 3

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

Equation 4

where is velocity, is position, is the personal best solution, is the global best solution, and, and are control parameters. Many researchers have been using PSO for DG placement and sizing, optimal power flow, and voltage control due to its simplicity and fast convergence. Nevertheless, PSO may experience premature convergence which certainly can decrease hunting capability in highly constrained or multi-modal optimization problems.

3.2 Grey Wolf Optimization (GWO) is a solution-based nature-inspired meta-heuristic technique found to be useful and based on the social hierarchy and cooperative hunting behavior of grey wolves. The population is guided by the top three solutions (α, β, δ) to balance exploration and exploitation. GWO is popular in power system optimization for DG placement due to its simple structure, few control parameters, and strong global hunting capability, frequently outperforming other meta-heuristics in minimizing losses and improving voltage profiles It is very faster to converge since it takes few parameters. (Mohamed et al., 2021; Li et al., 2022).

3.3 Objective Function Formulation

The optimal placement and sizing of (DG) in the IEEE 33-bus radial system is developed as a multi-objective optimization problem. And the goals are to minimize active and reactive power losses while enhancing voltage profiles and system stability, all subject to operational constraints. The weighted objective function is expressed as

$$\text{Minimize } F = w_1 \frac{\Delta P_{\text{loss}}}{P_{\text{loss,before}}} + w_2 \frac{\Delta Q_{\text{loss}}}{Q_{\text{loss,before}}} + w_3 \frac{\Delta V}{V_{\text{before}}}$$

Equation 5

Were

= weighting factors for active power loss reduction, reactive power loss reduction, and voltage profile improvement, respectively. and are defined in equation 2.4

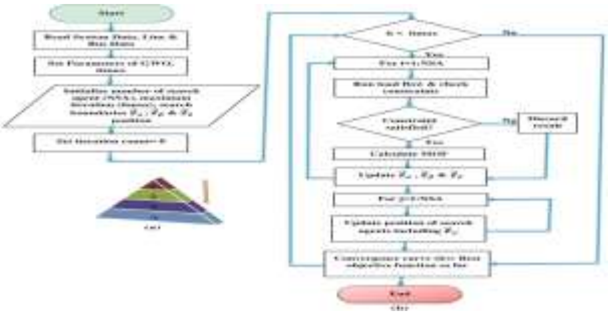

Figure 2.4: flowchart algorithm used for this research

The above flowchart illustrates a computational framework of a nature inspired metaheuristic algorithm, especially an enhanced Grey Wolf Optimizer (GWO), applied to a multi-objective engineering problem such as optimal power flow (OPF), distributed system configuration etc.

Th system is structured into the following rigorous phases such as;

System modeling and parameter initialization: This process is initiated with the ingestion of high dimensional datasets, which includes bus configurations and line impedances. To achieve this, the algorithm is defined as (a) search agent population (NSA) represents the candidate solutions (b) Termination criteria () which represents the computational budget. (c) boundary constraints represent the feasible region for decision variables (,).

Iterative Heuristic Execution: This presents the core methodology that employs a loop-based optimization strategy. Within each iteration, the algorithm executes the following; (a) Load flow analysis, a steady state analysis (e.g Gauss-seidel or Newton Raphson) to determine steady states. (b) constraint verification: in this stage every solution is subjected to a binary feasibility check. Candidates that are non-compliant are discarded, ensuring that only physically realizable points enter the objective space.

(c) Multi-objective function (MOF) calculation: This objective function performed quantifiable assessment in meeting power loss vs voltage stability.

Social Hierarchy and position updating: Following the GWO paradigm, the algorithm identifies the three most fit candidates Alpha (α), Beta (β), and Delta (**δ**) to represent the immediate global and local optima.

The remaining population updates their special coordinates relative to these leaders, balancing exploration (searching new areas) and exploitation (refining known good solutions).

Convergence and result validation: This process terminated once reaches the final optimized parameters.

Algorithm Overview

Initialization: Describe the population of grey wolves (candidate solutions), with each wolf representing a set of DG locations and capacities.

Fitness values were assigned using the objective function defined in equation 5.

Hierarchy Structure: Wolves are ranked as α (alpha), β (beta), δ (delta), and ω (omega) based on their fitness. α is the best solution, followed by β and δ, which guide the search for the optimum.

Encircling Prey:

$$\vec{D} = | \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) |$$

Equation 6

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D}$$

Equation 7

Where is the position of prey (optimal solution), and are coefficient vectors that control the convergence.

Hunting Mechanism: Wolves update positions based on α, β, and δ positions to converge towards the best solution.

Termination: Iteration continues until the maximum number of iterations is reached or the improvement falls below a threshold.

The MATLAB code of the procedure is as follows.

3.4 Matlab Software package

```
clc; clear; close all;
mpc = loadcase('case33bw'); % Load IEEE 33-bus
system
nbus = size(mpc.bus,1);
DGmin = 0.1;     % Minimum DG size (MW)
DGmax = 2.0;     % Maximum DG size (MW)
SearchAgents = 50;
MaxIter = 200;
lb = [2 DGmin]; % Lower bound: bus number, DG
size
ub = [nbus DGmax];
dim = 2;
Alpha_pos = zeros (1, dim);
Alpha_score = inf;
Positions = rand (SearchAgents,dim).*(ub-lb)+lb;
for iter = 1: MaxIter
   for i = 1: SearchAgents
      bus = round (Positions(i,1));
      DGsize = Positions(i,2);
      mpc_temp = mpc;
      mpc_temp.gen = [mpc.gen; bus DGsize 0 1 -1 1
100 1 DGsize DGmin];
      results = runpf(mpc_temp,
mpoption('verbose',0,'out.all',0));
      Ploss = sum(results.branch(:14)); % Total real
power loss
      if Ploss < Alpha_score
         Alpha_score = Ploss;
         Alpha_pos = Positions (i,:);
      end
   end
   a = 2 - iter*(2/MaxIter);
   for i = 1: SearchAgents
      r1 = rand (); r2 = rand ();
      A = 2*a*r1 - a;
      C = 2*r2;
      D_alpha = abs (C*Alpha_pos - Positions (i, :));
      Positions (i, :) = Alpha_pos - A*D_alpha;
   end
end
fprintf('Optimal DG Bus: %d\n', round
(Alpha_pos(1)));
```

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```
fprintf('Optimal DG Size: %.3f MW\n', Alpha_pos(2));
fprintf('Minimum Power Loss: %.4f MW\n', Alpha_score);
```

Constraints; The optimization is subject to the following system constraints:

Voltage limits at all buses: $V_{\min} \leq V_i \leq V_{\max}$

DG capacity limits:

$$P_{\min} \leq P_{\mathrm{DG}} \leq P_{\max}, Q_{\min} \leq Q_{\mathrm{DG}} \leq Q_{\max}$$

Branch current limits: $I_{\mathrm{branch}} \leq I_{\mathrm{branch,max}}$

DG penetration limit: ensures the total DG generation does not surpass a stated percentage of entire system load.

3.5 Load Flow Analysis

In this work, Load-flow analysis is used to evaluate system conditions before and after DG integration. This study applied the Newton–Raphson method for accurate solution of nonlinear power-flow equations and the Backward/Forward Sweep technique for efficient analysis of the radial IEEE 33-bus network. These methods compute bus voltages, phase angles, and branch power flows required for performance assessment. The active and reactive power at each bus is calculated using the following equations:

Newton–Raphson Method of Solving High Voltage Problems

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

Equation 8

$$\mathrm{Q_i} = \mathrm{V_i} \sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{V_j} \left(\mathrm{G_{ij}} \sin \theta_{\mathrm{ij}} - \mathrm{B_{ij}} \cos \theta_{\mathrm{ij}}\right)$$

Equation 9

The iterative update is calculated using the Jacobian matrix:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = J \begin{bmatrix} \Delta \delta \\ \Delta V \end{bmatrix}$$

Equation 10

Where and are the active and reactive powers at bus, and are the bus voltages, is the voltage phase angle difference, and and are the line conductance and susceptance.

The goal is to minimize real and reactive power losses, improve the voltage profile, and ensure network stability while maintaining system constraints

Backward Sweep:

$$I_{\mathrm{branch}} = \frac{S_{\mathrm{load}}^{*}}{V_{\mathrm{bus}}^{*}}$$

Equation 11

Where is the complex power demand at the bus and is the bus voltage.

Forward Sweep:

$$V_{\mathrm{new}} = V_{\mathrm{prev}} - \left(Z_{\mathrm{branch}} \times I_{\mathrm{branch}}\right)$$

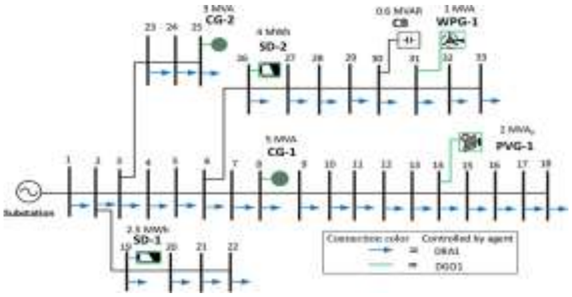
Equation 12

Where is the branch impedance, and is the updated bus voltage.

For each transmission line, resistance, reactance, and thermal limits, with impedance Z, were calculated according to equation

$$Z_{\mathrm{line}} = R + jX \quad \text{Equation 13}$$

The Single-line diagram of IEEE 33-bus distribution system (with DG). Integration is shown below.



This diagram depicts the IEEE 33-bus radial system with DG shows the network after integrating the optimally placed distributed generation DG and energy storage system ESS. The DG injects real and limited reactive power at the selected bus, reducing substation loading, improving voltages particularly at weak buses and significantly lowering line losses compared to the base-case system without DG.

The system is a classic radial distributed generation feeder characterized by single source (substation at Bus 1) and three primary lateral branches extending from the trunk (Buses 1 to 18).

Lateral1 originates at bus 2, encompassing buses 19-22.
Lateral 2 originates at bus 3, encompassing buses23-25
Lateral 3 originates at bus 6, encompassing buses26-33.
Strategically, the model is enhanced with heterogeneous energy resourced to optimize grid performance. The renewable energy source (RES) includes a 2MVA Photovoltaic Generator (PVG-1) at bus 14 and a 1MVA wind power generator (WPG-1) at bus 32.

The conventional generation (CG) includes a 5MVA unit and 3MVA (CG-1 and CG-2) are strategically placed at high-load or remote buses (Bus 8 and Bus 25) to provide base load support.

On the energy storage systems (ESS), two storage devices, SD-1 (2.5MWh and SD-2(4MWh) are integrated at bus 19 and 26 to mitigate the intermittency of renewable and perform peak-shaving.

For reactive power compensation, a 0.6MVAR capacitor bank (CB) is located at bus 30 to improve the voltage profile at the feeder ends.

The DRA1 (Demand Response Agent 1) governs the majority of the network (blue connection lines) which likely manage load-shedding or demand-side management (DSM) protocols while the DGO1 (Distributed Generation Operation 1) specifically controls the solar integrated zone at bus 14 (green connection lines) optimizes the power injection from the PVG-1.

Review of related work and Contribution to Knowledge
In recent years, distributed generation (DG) has attracted growing interest due to its ability to improve power system efficiency, particularly in minimizing losses and enhancing voltage profiles. Various optimization approaches, including conventional, metaheuristic, and machine learning-based techniques, have been widely reported in the literature.

Pan et al. (2023) developed a two-stage optimization strategy for DG allocation and reactive power support. The first stage determined the optimal locations and active power output of DG units, while the second stage focused on reactive power compensation to improve voltage stability.

The approach was implemented using DIgSILENT PowerFactory on IEEE test networks. Their findings revealed a significant reduction in power losses, with values dropping from 58.77 kW to 3.6 kW for the IEEE 15-bus system and from 179.46 kW to approximately 5 kW for the IEEE 33-bus system. Despite these improvements, the method is limited by its deterministic structure, absence of metaheuristic techniques, and application only to small-scale systems without considering load variability.

Khenissi et al. (2021) examined the use of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for optimal DG sizing aimed at reducing power losses. Using IEEE standard test systems, the study demonstrated that both algorithms effectively enhanced system performance by lowering losses. However, the work was restricted to a single-objective framework and did not investigate hybrid optimization methods that could potentially provide improved results.

Koley et al. (2024) proposed a hybrid Load Frequency–Grey Wolf Optimization (LF-GWO) technique for multi-objective DG placement and sizing. By combining load frequency control with Grey Wolf Optimization, the study achieved better voltage stability and reduced system losses. Although the results highlight the strength of hybrid metaheuristic approaches in solving complex optimization problems, the method still requires further validation on larger and more practical distribution networks.

Silva et al. (2025) explored the application of evolutionary algorithms for the multi-objective placement of photovoltaic (PV)-based DG systems. Their study simultaneously addressed loss minimization and voltage profile improvement. The results showed that integrating renewable DG sources enhances overall system performance; however, no single algorithm consistently delivered optimal results under all conditions. This indicates the need for more adaptive or hybrid techniques. Additionally, economic factors were not sufficiently considered in their analysis.

Jain and Gupta et al. (2024) investigated the combination of machine learning (ML) and optimization techniques for DG placement. In their approach, ML models were used to predict suitable DG locations, followed by optimization processes to improve system performance. The findings showed that ML enhances prediction accuracy and supports more efficient planning. Nonetheless, the approach has limitations in terms of real-time implementation and the consideration of uncertainties such as load fluctuations and renewable energy variability.

In summary, existing studies confirm the effectiveness of optimization techniques in improving DG integration. However, challenges such as handling uncertainties, achieving real-time adaptability, developing robust hybrid methods, and validating results on large-scale systems remain unresolved. Addressing these issues is crucial for advancing DG applications in modern power systems.

This research work contributes to the field of power systems engineering and distributed generation (DG) in many ways as follow;

Benefits of DG and Validation: The research presents quantitative evidence demonstrating that the integration of photovoltaic (PV)-based DG into distribution networks leads to improved voltage profiles, significant reductions in both active and reactive power losses, and enhanced system reliability.

Impact of Grey Wolf Optimization: The study confirms the potency of the Grey Wolf Optimization (GWO) algorithm as a tested and efficient metaheuristic technique for optimal DG placement and sizing. Comparative results indicate that GWO achieves faster convergence and higher solution accuracy when compared with Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO).

Performance Assessment: the performance assessment Combines technical, operational, and reliability metrics, offering a comprehensive evaluation of DG integration impacts.

IV. SIMULATION RESULTS

Simulations were performed on the IEEE 33-bus distribution system to assess the effectiveness of the Grey Wolf Optimization (GWO)-based DG placement and sizing.

The results show a significant reduction in both active and reactive power losses after DG integration compared to the base case. In addition, the voltage profile was considerably improved, with bus voltages maintained within acceptable limits, indicating enhanced voltage stability.

The GWO algorithm demonstrated fast and stable convergence, reaching optimal solutions within a few iterations. When compared with Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), GWO provided better performance in terms of loss minimization, voltage improvement, and convergence speed.

Table 4.2: Voltage Magnitude Without DG at Far End.

Bus Number	Voltage (p.u)
1	1
2	0.982
3	0.975
18	0.94
33	0.92

From the results above, it is clear that voltages at far end decline noticeably without DG incorporation below recommended 0.95 p.u. limit. At substation (Bus1), a full 1.0 p.u is observed. While at far end (Bus 33), drops to 0.92 p.u. there is a clear loss of voltage magnitude at distant buses, highlighting the need for local power support to stabilize the grid.

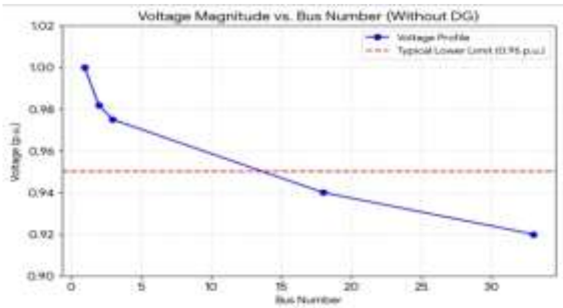


Figure 4.1: Voltage Profile Without DG

The graph presents a voltage levels drop cross the 0.95.p.u. lower limit around Bus 14, indicating an under-voltage condition at the end of the line. Adding local power sources like solar or wind at the furthest buses would boost these levels back into the safe zone

Table 4.4: Bus Voltage Values profile with and without DG

Bus number	Voltage without DG (p.u.)	Voltage with DG (p.u.)	Improvement (%)
1	1.000	1.000	0.00%
2	0.982	0.991	0.92%
3	0.975	0.988	1.33%
18	0.940	0.972	3.40%
33	0.920	0.965	4.89%

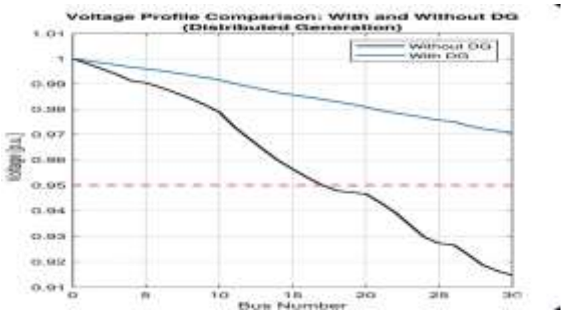


Figure 4.2: Voltage Profile with and Without DG

The above graph illustrates effect of voltage profile when DG is integrated.

The black line represents without DG shows a sharp drop as electricity travels further from the source (Bus 0). it falls below the 0.95 p.u. critical limit around Bus 17, ending at a very low 0.915.p.u. at Bus 30. this a challenge.

The solution (Bus Line): adding DG sources like local solar or wind provides local power injection. This significantly Boost the voltage profile, keeping it well above the safety threshold and ending at much healthier 0.971 p.u.

4.1.4 Optimized DG Placement, Location And Results

The optimal DG location and size that minimizes power loss while improving voltage profile was carefully performed by executed every algorithm. About 53.1% loss reduction was observed on ACO, which performed better than POS but less than GWO. In the aspect of Bus selection, ACO often identifies bus 11and 28 as the nodes whereas the hybrid models favor the 13, 24, 31 configurations to achieve the absolute minimum power loss.

Although ACO raises the minimum voltage above 0.97.p.u., it doesn't reach the high stability provided by the hybrid GWO-PSO (0.9821 p.u.). Table 4.5 illustrates the sizing and location of DG placement.

Table 4.5: Optimized DG Placement, Location and Results

PARAMETERS	BASE CASE	POS	ACO	GWO	HYBRID GWO-PSO
Optimal Bus Location	None	13, 24, 30	11, 24, 28	14, 24, 30	13, 24, 31
DG Capacity (Mw)	0	2.88	2.94	3.07	3.08
Min Voltage (p.u)	0.9131	0.9652	0.9701	0.9784	0.9821
Total Power Loss (Kw)	202.67	108.41	93.03	92.35	84.22
Loss Reduction	0%	46.51%	53.10%	54.43%	58.44%

(%)

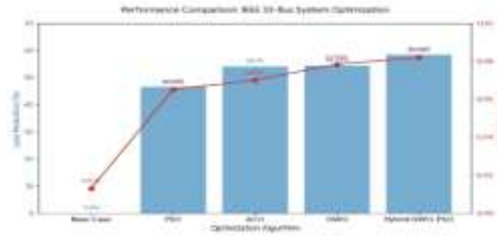


Figure 4.3: Histogram representation of the improved Optimized DG Placement,

4.1.8 Effect of Distributed Generation (DG) Size on Real and Reactive Power Losses

The capacity of Distributed Generation (DG) installed in a distribution network plays a significant role in determining system losses. As the size of DG increases, more electrical power is generated closer to the load points. This reduces the amount of current flowing through the feeders, leading to a decrease in both real and reactive power losses.

This section examines how varying DG sizes influence system performance by comparing corresponding real power losses (kW) and reactive power losses (kVAr). Table below demonstrates the effects.

Table 4.8: Real And Reactive Power Loss Reduction

DG size (MW)	Real power loss (KW)	Reactive power loss (KAVr)
0.0 (Baseline)	210	140
5.0	185	130
10.0	165	122
15.0	145	115
20.0	130	110

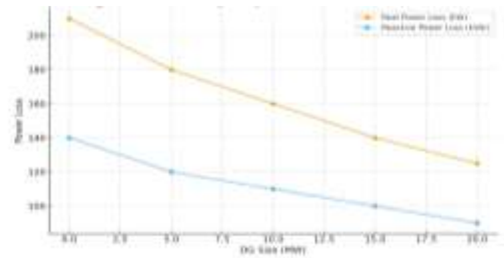


Figure 4.6: Sensitivity Analysis of System loss to DG Penetration

This graph demonstrates how increase in DG size affects power losses in the system.

On the real power loss (KW) shown by the orange line, the losses begin at roughly 210kw and drop significantly to about 130kw as DG penetration reaches 20MW. On the other hand, Reactive power loss (Kvar), indicating by the blue line, the losses start lower around 140KVAr and follow a similar downward trend, ending near 110KVAr. Hence the data suggests that adding more distributed generation to this system makes it more efficient by reducing both real and reactive power losses.

Total real power reduction: approximately 80kw (38% decrease).

Total reactive power reduction: approximately 30KVAr (21% decrease)

5.4 Contribution to Knowledge

This research work contributes to the field of power systems engineering and distributed generation (DG) in many ways as follow;

i. Benefits of DG and Validation: In this benefit, quantitative evidence that integrates photovoltaic (PV) DG improves voltage profiles, reduces active and reactive power losses, while enhancing system reliability in distribution networks.
ii. Impact of Grey Wolf Optimization: from the analysis, it is proven that GWO is a robust and efficient meta-heuristic for optimal DG placement and sizing, outperforming PSO and ACO in convergence speed and solution quality.
iii. Performance Assessment: the performance assessment Combines technical, operational, and reliability metrics, offering a comprehensive evaluation of DG integration impacts.

iv. Replicable Methodology: The development of a simulation-based framework using MATLAB/MATPOWER for DG findings, can be applied to other networks or renewable energy integration scenarios.
v. Practical improvement for Weak Networks: this Provides actionable insights for improving weak distribution networks especially in developing countries, through strategic deployment of renewable DG units.

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