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Optimal Placement of Distributed Generation Units in Power Distribution Networks Using Particle Swarm Optimization

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ABSTRACT

Power losses and voltage drops in distribution networks are critical issues in power system operation, reducing efficiency, reliability, and overall quality of the power supply to customers. Additionally, the rising electricity demand, deregulation of energy markets, and congestion in transmission networks have further contributed to the declining performance of the grid. To address these challenges, integrating distributed generation units (DGUs) into electric distribution systems has gained significant attention. Furthermore, the integration of DGUs into conventional fossil fuel-based power plants is becoming necessary to reduce greenhouse gas emissions. However, proper placement and sizing of DGUs are crucial for achieving optimal benefits. Inappropriate placement and sizing can lead to increased losses and degraded system performance, whereas optimal placement can enhance voltage stability and minimize power losses, thereby improving overall system performance. This study presents a particle swarm optimization (PSO) technique for determining the optimal placement and sizing of DGUs in power distribution networks. The proposed PSO approach considers voltage and power constraints to ensure operational requirements are met. The methodology is validated using IEEE 33-bus system simulations under three different scenarios: a network without DGUs, a network with one DGU, and a network with two DGUs. Simulation results demonstrate that optimal DGU placement significantly reduces power losses, minimizes voltage drops, and enhances system performance compared to a network without DGUs.

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INTRODUCTION

The complexity of power systems makes their operation challenging, particularly due to the high demand for electrical supply and load density. Load demand, which varies based on the energy requirements of different consumer groups, is a major source of uncertainty in power system planning (Abdul Kadir et al., 2013). In such environments, voltage degradation is a common issue, especially as the distance from the substation increases, which leads to a decrease in the voltage profile along the distribution network (Dsnmrao & Kumar, 2018). As electricity demand grows, the necessity of transporting power through extensive transmission and distribution networks has also increased (Acharya et al., 2006). Most traditional electricity generation methods rely on finite energy sources, which are unsustainable and non-renewable, further emphasizing the need for Distributed Generation Units (DGUs) and their technologies.

The concept of the smart grid, which integrates distributed generation (DG) systems, is now central to modern power distribution networks. DG can come from a variety of sources, including fossil fuels like internal combustion engines, turbines, fuel cells, photovoltaic systems, wind turbines, small hydro plants, and biomass (Moradi & Abedini, 2012). The flexibility and modular nature of DGUs make them advantageous in competitive power markets. Research has shown several benefits of distributed systems, such as reduced pollutant emissions (Brown & Chapman, 2021). alleviation of transmission and distribution congestion (Huang, 2025), reduced peak demand losses, minimized energy losses, improved frequency stability (Yu et al., 2025), enhanced power factor and system stability, increased distribution capacity, and overall reduction in power losses and improvement of voltage profiles (Hemdan & Kurrat, 2011). The implementation of DGUs all benefits from reduced lead time and minimal investment risk (Makolo et al., 2018).

To address the optimization challenge of determining the optimal placement and sizing of DGUs, various techniques have been proposed, ranging from traditional methods to stochastic search algorithms. For instance, conventional methods such as power voltage sensitivity constants precise loss formulas (Selim et al., 2020) load concentration factor-based methods have been applied. However, these traditional methods have limitations, especially in solving nonlinear optimization problems, which are common in DG allocation (Nadjemi et al., 2017). Traditional optimization approaches often struggle with finding the global optimum, leading to challenges in DG placement.

Advancements in stochastic search algorithms have provided effective solutions to these problems. These population-based methods address many of the shortcomings of traditional approaches. Algorithms such as the Artificial Immune System (AIS) (M. Suwi & J. Justo, 2024), Adaptive Quantum-Inspired Evolutionary Algorithm (AQiEA), Genetic Algorithms (GA), Firefly Algorithm, Chaotic Stochastic Fractal Search Algorithm (Babu & Swarnasri, 2020), and Particle Swarm Optimization (PSO) (Kansal et al., 2016) have been successfully used to tackle DG placement challenges. With proper sizing and placement, DGs can significantly improve system performance by reducing losses, although poor placement may result in increased costs and power losses(Ali et al., 2017).

DG allocation is considered a complex combinatorial optimization problem, and various optimization strategies have been proposed to address it. Evolutionary algorithms such as Multi-Objective Evolutionary Algorithm with Tables (MEAT) (Huy et al., 2023), Ant Lion Optimization Algorithm (ALOA) (Camacho et al., 2014), and other nature-inspired algorithms have demonstrated effectiveness in solving DG placement and sizing problems. Furthermore, different DG types with distinct operational characteristics have been studied. For example, Type I DGs inject active power at unity power factor, Type II DGs inject reactive power, Type III DGs inject both active and reactive power, while Type IV DGs consume reactive power and inject active power (Razavi et al., 2019).

This paper proposes using Particle Swarm Optimization (PSO) for determining the optimal placement and sizing of DGUs in power distribution systems. The proposed method takes into account voltage and power operating constraints. Simulation studies were conducted on a 33-bus system under various scenarios: without DGUs, with one DGU, with two DGUs, and with three DGUs. Results show that the presence of DGUs significantly reduces power losses, mitigates voltage drops, and enhances overall system performance. The PSO approach successfully identifies the ideal locations and sizes for three DGUs, aiming to minimize power loss, reduce voltage deviation, and improve voltage profiles in the distribution network.

PROBLEM FORMULATION

The primary objective in determining the placement and sizing of DGUs is to minimize voltage deviation and reduce active power loss. However, practical challenges may arise, such as technical and geographical constraints. An alternative approach is to identify the optimal locations for DGUs and determine the minimum required size to achieve a specific power loss target. Power losses in distribution systems have always been a critical issue due to the efficiency of energy use and the costs of electricity (Aly et al., 2017).
Optimization problems typically involve an objective function, which needs to be optimized subject to various constraints. The goal of constrained optimization is to find feasible solutions that improve the objective value. A typical constrained optimization problem can be formulated as:

Objective Function:
Find x to minimize f(x),
Minimize

$$F(X) = f_1(X) + f_2(X) + f_3(X) \quad (1)$$

Where:

- $f_1(X)$ = Active power loss (Objective 1),
- $f_2(X)$ = Reactive power loss (Objective 2),
- $f_3(X)$ = Voltage deviation (Objective 3).

Objective Function for DGUs Placement

The goal is to enhance the voltage profile and minimize both active and reactive power losses in the distribution system while adhering to various constraints.

Active Power Loss Minimization:
Total **real power loss** in a radial distribution system is given by:

$$P_{Loss} = \sum_{i=1}^{N} I_i^2 R_i \quad (2)$$

where: I_i is the current flowing in branch I; R_i is the resistance of branch I; N is the total number of branches.

Reactive Power Loss Minimization:
The total reactive power loss is given by:

$$Q_{Loss} = \sum_{i=1}^{N} I_i^2 X_i \quad (3)$$

X_i is the reactance of branch i.

Voltage Deviation:(V_{dev}):
To improve the voltage profile, the voltage deviation (VD) is calculated as follows:

1. **Voltage Deviation** (V_{dev}):

$$V_{dev} = \sum_{i=1}^{N} |V_i - V_{ref}| \quad (4)$$

where:

- V_i is the voltage at bus i,
- V_{ref} is the reference voltage at the slack bus (typically 1.0 pu).

Multi-Objective Function Formulation

To assess the performance of the system for DG sizing and placement, the Multi-Objective Function (MOF) is given by:

$$Min\,F = w_1\sum P_{loss} + w_2\sum Q_{loss} + w_3\sum|V_{deviation}| \quad (5)$$

where: ω_1 , ω_2 and ω_3 are the weights assigned to the respective factors, and the sum of the weights equals 1.

Operational Constraints

The objective function must satisfy operational constraints, classified into equality and inequality constraints. The optimization problem is subject to the following physical and operational constraints:

A. Power Balance Constraints: (Ashton et al., 2013)

Active Power Balance:

$$P_{gen} - P_{load} = P_{loss} \quad (6)$$

where: P_{gen} is the total active power generated by the DGUs, P_{load} is the total active power demand from the network, P_{loss} is the active power loss in the network.

Reactive Power Balance:

$$Q_{gen} - Q_{load} = Q_{loss} \quad (7)$$

where: Q_{gen} is the total reactive power generated by the DGUs, Q_{load} is the total reactive power demand from the network, Q_{loss} is the reactive power loss in the network.

B. Voltage Limits:

Voltage at each bus must remain within acceptable limits:

$$V_{\min\leq} \leq V_i \leq V_{\max} \quad (8)$$

where:

$V_{\min}$ and $V_{\max}$ are the lower and upper bounds for voltage at bus I; V_i is the voltage at bus iii.

C. Generation Capacity Constraints:

The DG capacity at each bus must be within the feasible generation limits:

$$P_{DGU\,\min} \leq P_{DGUi} \leq P_{DGU\,\max} \quad (9)$$

where: P_{DGUi} is the active power generated by the DG at bus i, $P_{DGU\,\min}$ and $P_{DGU\,\min}$ are the minimum and maximum generation limits for the DG.

Similarly for reactive power:

$$Q_{DG_{\min}} \leq Q_{DG_i} \leq Q_{DG_{\max}} \quad (10)$$

D. Load Demand Constraints:

The total load demand at each bus must be met:

$$P_{load_i} + P_{DG_i} = P_i^{gen} \quad (11)$$

Objective Function Parameters

To evaluate the performance of the distribution system, two key indices are used: the Real Power Loss Reduction Index (PLR) and the Reactive Power Loss Reduction Index (QLR). A weight is assigned to each index to determine the optimal results. (Mohamed & Kowsalya, 2014). The Real Power Loss Reduction Index (PLR) is calculated as follows:

$$PLR = \frac{P_{Loss,Base} - P_{Loss\,with\,DG}}{P_{Loss,Base}} \quad (12)$$

where: $P_{Loss,Base}$ is the total active base power loss in the system without DGUs $P_{Loss\,with\,DG}$ is the total real power loss with DGUs after optimization.

Similarly, the Reactive Power Loss Reduction Index (QLR) is computed using:

$$QLR = \frac{Q_{Loss,Base} - Q_{Loss\,with\,DG}}{Q_{Loss,Base}} \quad (13)$$

where:

$Q_{Loss,Base}$ and $Q_{Loss,Base}$ represent the reactive power losses in the network without and with DGUs optimized, respectively.

Voltage Profile Improvement Index

The voltage profile should remain within acceptable limits for system stability. The Voltage Profile Improvement Index penalizes locations with higher voltage deviations from the base voltage:(Manafi et al., 2013).

$$VPI = \sum_{i=1}^{n} \frac{VD_i - VD_{optmized}}{VD_i} \quad (14)$$

where: VD is the base voltage deviation.

Percentage Voltage Performance (PVP)

The Percentage Voltage Performance (PVP) is defined as:

$$PVP = \frac{VD_{base} - VD_{DG}}{VD_{base}} \times 1OO\% \quad (15)$$

where: VD_{base} is voltage deviation before optimization, VD_{DG} is the voltage deviation after DGUs integration

Multi-Objective Function Formulation

To assess the performance of the system for DG sizing and placement, the Multi-Objective Function (MOF) is given by:(Wong et al., 2019).

$$Min\, F = w_1 \sum P_{loss} + w_2 \sum Q_{loss} + w_3 \sum |V_{deviation}| \quad (16)$$

where: ω_1 , ω_2 and ω_3 are the weights assigned to the respective factors, and the sum of the weights equals 1.

MATERIALS AND METHODS

Description of Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique inspired by natural social behaviors, such as bird flocking and fish schooling. It works by iteratively improving candidate solutions according to a specified quality measure. Each candidate solution, referred to as a particle, adjusts its position in the search space based on its own experience and the experience of neighboring particles. Inherent cooperation and information is sharing between particles in PSO.(Teklu, n.d.) Due to its simplicity, easy implementation, fast convergence, and ability to handle nonlinear, non-differentiable, and multi-modal optimization problems, PSO has become widely used in various fields. However, care must be taken as it can converge prematurely to a local optimum, and its performance may degrade in high-dimensional search spaces. (Van Tran et al., 2024)

PSO Implementation

The steps for implementing PSO for the optimal sizing and placement of DGUs are outlined in the pseudocode below: (Takamatsu et al., 2022).

Pseudocode PSO Algorithm

1. Define parameters.
2. Initialize particles.
3. While the number of iterations is not reached:
    - Evaluate the objective function.
    - Handle constraints using a penalty function.
    - Update the velocity of each particle.
    - Identify the best particle.
    - Update the positions.
4. End while.
5. Display the results.

Initialization:

- Define the objective function: The objective typically aims to minimize active and reactive power losses or improve voltage profiles within the distribution network.
- Initialize the swarm of particles, which represents potential solutions for DG placement and sizing.
- Set PSO parameters: These include the number of particles (swarm size), maximum iterations, inertia weight, and acceleration coefficients. (Weitemeyer et al., 2015)

Fitness Evaluation:

- Calculate the fitness of each particle based on the objective function. This measures how well the configuration of DG placement and sizing meets the optimization criteria (e.g., power loss reduction).
- Update the personal best (pBest) for each particle based on its fitness value.
- Update the global best (gBest), which represents the best solution found by any particle.

Velocity and Position Update:

- Adjust the velocity of each particle based on its previous velocity, the distance from its personal best position, and the distance from the global best position. This guides particles toward the optimal solution.
- Update the position of each particle according to the new velocity, representing a potential new solution (Mojarrad & Ayubi, 2015).

Iteration:

- Repeat the process of fitness evaluation and velocity/position updates until the maximum number of iterations is reached or convergence criteria are met.

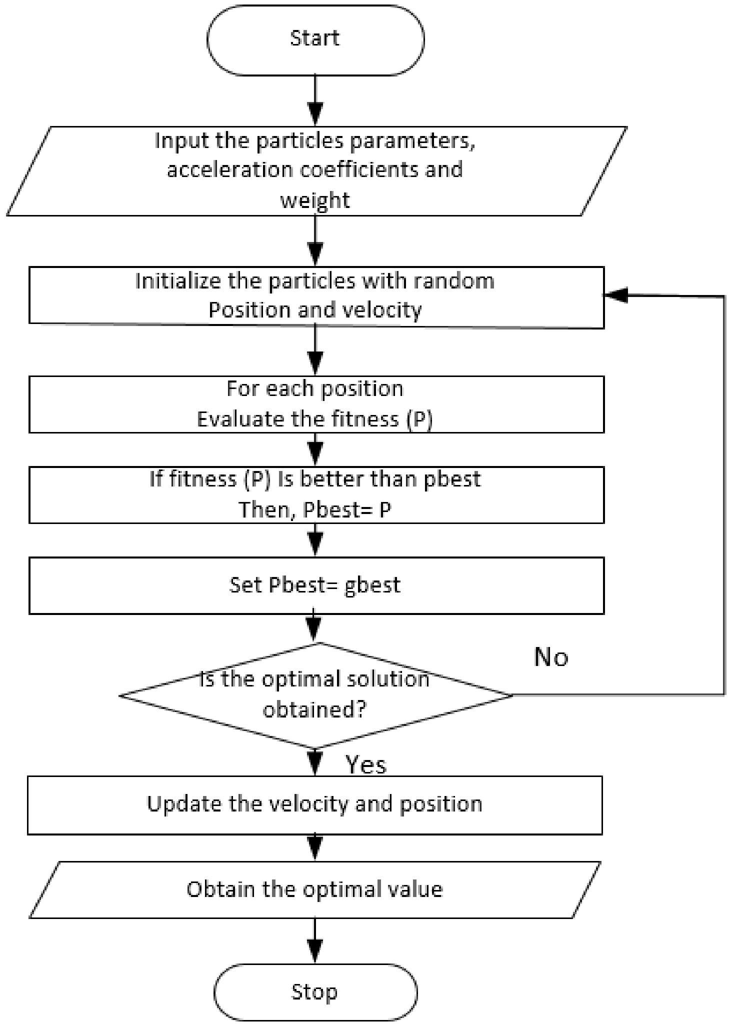

Figure 1: Flow chart of PSO algorithm(Mojarrad & Ayubi, 2015)

Established Objective Function

The performance of PSO depends on the proper setting of its parameters. In this study, the following PSO settings were used:

- Maximum number of iterations: 100
- Swarm size: 50 particles

- Initial inertia weight: 0.9
- Final inertia weight: 0.4
- Acceleration constant: 0.1
- Minimal global error gradient: 1e-10

These parameter values were chosen based on fine-tuning, aiming to achieve a good balance between exploration, exploitation, convergence speed, and solution accuracy for the problem at hand.(Mojarrad & Ayubi, 2015).

RESULTS AND DISCUSSION

For this study, two IEEE 33-bus test systems were used to assess the performance of the PSO algorithm. The system's base voltage is 12.66 kV, and the apparent power is 100 MVA. The approach was implemented in MATLAB R2021b on a PC with an Intel Core i5 processor (2.9 GHz), 8.0 GB RAM, and running Windows 10. Four cases were considered in the IEEE 33-bus test system: (Manafi et al., 2013)

- **Case 1**: Base case (without DGUs).
- **Case 2**: Integration of one DGU.
- **Case 3**: Integration of two DGUs.

In all cases, a forward-backward sweep load flow was conducted using ETAP software to obtain the voltage profile. The system comprises 33 buses and 32 branches, with total active and reactive power loads of 3715 kW and 2300 kVAr, respectively (Sai et al., 2013). The system's single-line diagram is shown in Figure 2.

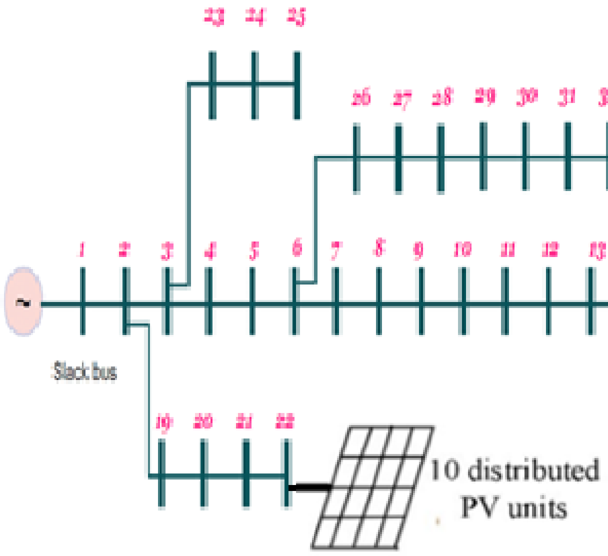

Figure 2: Single line diagram of the IEEE 33-Bus test system, (Nouti et al., 2021).

Case 1: Base Case for 33-Bus System

In the base case, before optimization, the active and reactive power losses were 202.68 kW and 135.14 kVAr, with the minimum voltage recorded at 0.81306 p.u. at bus 18, as shown in the MATLAB simulation results.

Case 2: Installing One DGU for 33-Bus System

The integration of a single DGU resulted in a 34.04% reduction in active power loss and a 33.79% reduction in reactive power loss. Additionally, voltage improvement of 13.4% was achieved when one DGU was added to the system, as shown in Figures 3 to 5. These results were calculated using equations (9), (10), and (11).

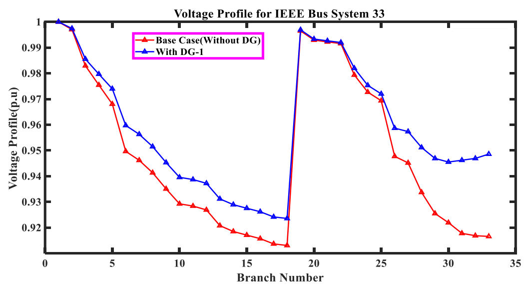

Figure 3: Voltage profile improvement with 1-DGU using PSO.

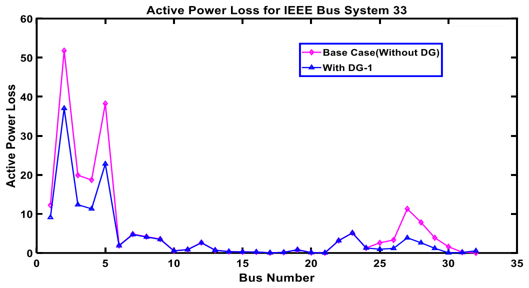

Figure 4: Active power loss reduction with 1-DGU using PSO.

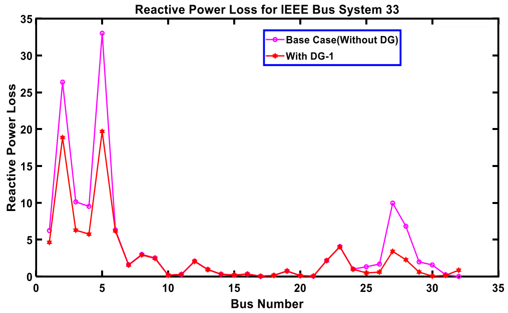

Figure 5: Reactive power loss reduction with 1-DGU using PSO.

Case 3: Installing Two DGUs for 33-Bus System

With two DGUs, the reductions in active and reactive power losses were 42.93% and 43.51%, respectively, and the voltage improvement was 14.62%. Figures 6 to 8 illustrate these results.

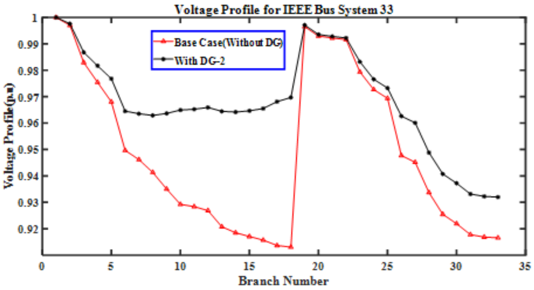

Figure 6: Voltage profile improvement with 2-DGUs using PSO.

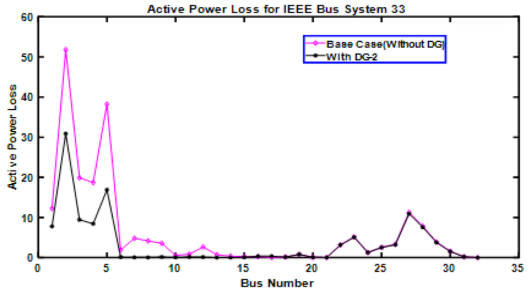

Figure 7: Active Power Loss Reduction with 2-DGUs using PSO.

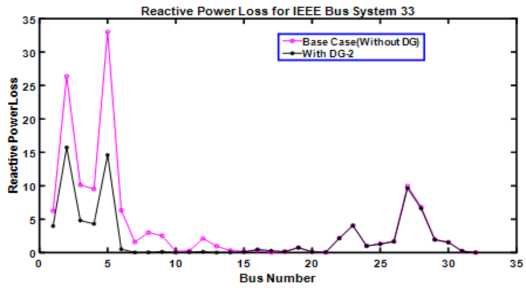

Figure 8: Reactive power loss reduction with 2-DGUs using PSO.

Comparative Analysis

A qualitative comparison revealed that the integration of two DGUs results in better performance than the integration of one DGU. The performance parameters, such as active and reactive power losses, voltage improvement, and optimal sizes and placements, are summarized in Table 1. The parameters Vmin (p.u.), P_{Loss} (kW), Q_{Loss} (kVAr), Opt. Size (kW), and Opt.

Optimal Placements and Sizes of DGUs

For the 1-DGU case, the optimal size is 586 kW, and the optimal bus is 33. For the 2-DGU case, the optimal sizes are 344 kW and 412 kW, with optimal bus locations at 33 and 15, respectively. The PSO algorithm determined the most effective buses for placing the DG units, ensuring maximum reduction in power losses and improvement in the voltage profile.

Interpretation

The integration of DGUs, when optimally placed and sized using the PSO algorithm, results in substantial reductions in both active and reactive power losses. The strategic placement of DGUs not only lowers losses but also enhances the voltage profile of the distribution network.

Table 1: Performance Comparison between 1-DGU and 2-DGUs using PSO on IEEE 33-Bus System.

Cases	V_{min} (p.u.)	P_{Loss} (kW)	Q_{Loss} (kVAr)	%*V* Imp	%P_{Loss} *Reduc.*	%Q_{Loss} *Reduc.*	OP opt. size (kW)	Opt. bus Number
Base	0.813	202.68	135.14					
1-DGU	0.922	133.69	89.48	13.4	34.0	33.79	586	33
2-DGUs	0.932	115.66	76.34	14.6	42.9	43.51	344.41	33; 15

Table 2: Performance Comparison and Discussion on Active and Reactive Power Loss, Voltage Profile, Voltage Drops, and Voltage Deviation in the 33-Bus System

scenario	Performance Parameter	Observation	Discussion
System with 1 DGUs:	Active Power Loss	The introduction of a single DGU results in a noticeable reduction in active power losses compared to the base case without any DGUs.	The placement of the DGU contributes to better power distribution and reduces the overall line losses. The specific location of the DGU within the network influences the extent of loss reduction.
	Reactive Power Loss	There is a modest decrease in reactive power losses with the addition of one DGU	While the reactive power loss reduction is not as significant as active power loss, the DGU helps in partially supplying the reactive power demand locally, reducing the burden on the network.
	Voltage Profile:	The voltage profile shows improvement, especially near the DGUs	The local generation enhances the voltage profile, making it more uniform across the buses close to the DGUs.
System with 2 DGUs:	Active Power Loss	Further reduction in active power losses is observed with the integration of two DGUs.	The addition of another DGU helps in distributing the load more evenly, thus reducing the overall active power losses more effectively than a single DGUs
	Reactive Power Loss	Reactive power losses continue to decrease with two DGUs	The presence of two DGUs allows for better local supply of reactive power, reducing the need for reactive power flow over longer distances.
	Voltage Profile:	Voltage deviations decrease further with two DGUs	The voltage profile becomes more stable and uniform with the support of two DGUs, showing less deviation from the nominal value.

CONCLUSION

In conclusion, the optimal integration of DGUs using PSO in the 33-bus system results in notable improvements in network performance, with each additional DGU contributing to reductions in power losses, voltage drops, and deviations. The study emphasizes the importance of optimal DGU placement and sizing to maximize benefits such as loss reduction and voltage profile improvement. The use of PSO proves effective in optimizing the integration of DGUs, ultimately enhancing the reliability and efficiency of power distribution systems. Future work could include considering real-time performance based on weather forecasts for optimal DGU integration in power distribution networks.

LIST OF ACRONYMS / ABBREVIATIONS

Acronym	Full Form
DG	Distributed Generation
DGU	Distributed Generation Unit
DGUs	Distributed Generation Units
ETAP	Electrical Transient Analyzer Program
GHz	Giga Hertz
GA	Genetic Algorithm
GB	Giga Byte
gBest	Global Best
HDPSO	Hybrid Discrete Particle Swarm Optimization
HGAPSO	Hybrid Genetic Algorithm and Particle Swarm Optimization
HT/LT	High Tension/Low Tension
HVDC	High Voltage Direct Current
IEEE	Institute of Electrical and Electronics Engineers
IPSO	Improved Particle Swarm Optimization
kW	Kilo Watt
kVAr	Kilovolt Amperes Reactive
LP	Linear Programming
LVAC	Low Voltage Alternating Current
MATLAB	Matrix Laboratory
MATPOWER	MATLAB Power System
MVAC	Medium Voltage Alternating Current
MVA	Mega Volt Amperes
NLP	Non-Linear Programming
NTL	Non-Technical Losses
OPF	Optimal Power Flow
PLR	Real Power Loss
PSO	Particle Swarm Optimization
PV	Photovoltaic
pBest	Personal Best
PC	Personal Computer
QLR	Reactive Power Loss
RAM	Random Access Memory
REPSO	Ranked Evolutionary Particle Swarm Optimization
SAPSO	Self-Adaptive PSO
VD	Voltage Deviations
VDI	Voltage Deviations Index
VDR	Voltage Deviation Reduction
VI	Voltage Index

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