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Particle Swarm Optimization Based Optimal Distributed Generation Placement and Sizing in Radial Distribution Network

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Abstract:

This paper presents a Particle Swarm Optimization (PSO)–based approach for the optimal placement and sizing of multiple distributed generation (DG) units in a radial distribution network. The objective is to minimize total real power losses while improving the voltage profile, subject to system operating constraints. A backward–forward sweep (BFS) load flow algorithm is integrated with PSO to accurately model power flow in radial systems. Unlike conventional methods that fix the number or capacity of DG units, the proposed method simultaneously determines the optimal number, locations, and sizes of DGs without predefined restrictions. The methodology is tested on the IEEE 33-bus radial distribution system using MATLAB and validated with ETAP 2021. Simulation results demonstrate a significant reduction in real power losses and notable voltage profile enhancement. Specifically, the optimized allocation of three DG units achieves a loss reduction of approximately 47.05% and raises the minimum bus voltage close to nominal limits. The close agreement between MATLAB and ETAP results confirms the effectiveness and robustness of the proposed PSO-based optimization framework.

***Keywords* — MATLAB, Particle Swarm Optimization, Distributed Generation, ETAP, Simulation.**

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I. INTRODUCTION

Distributed generation refers to decentralized electricity production systems that are installed close to load centers rather than being integrated into conventional centralized transmission networks. These systems supply power directly at or near the point of consumption, thereby minimizing the need for long-distance energy transmission [1, 2]. In practice, distributed generation consists of small- to medium-capacity power units that are connected either to the distribution network or located on the consumer side of the electricity meter. Renewable energy technologies, particularly solar photovoltaic and solar thermal systems, are especially suitable for distributed generation due to their modular design, ease of installation, and reliance on locally available energy resources. By converting solar radiation into electrical and thermal energy, these technologies reduce dependence on fuel transportation and enhance energy accessibility [3]. In addition to solar-based systems, distributed generation frameworks also incorporate other renewable energy sources such as small-scale hydropower plants, wind energy conversion systems, and bioenergy technologies, including biogas and biothermal units. Growing environmental concerns associated with the continued use of fossil fuels particularly issues related to greenhouse gas emissions and global climate change have accelerated the adoption of renewable energy solutions. However, the inherently intermittent and unpredictable nature of solar and other renewable energy sources introduces several operational challenges as their level of integration into power networks increases. These challenges include feeder congestion, power quality degradation due to harmonics, and related system stability concerns. Furthermore, factors such as high initial investment costs, limited operational reliability, and relatively low conversion efficiency continue to restrict the large-scale deployment of these technologies [1].

Moreover, rapid changes in solar irradiance cause voltage flicker and power variability, which represent significant challenges in power systems with high photovoltaic integration [4]. The optimal placement of distributed generation units within a distribution network offers several benefits, including enhanced voltage levels across the system, a significant decrease in overall power losses, improved power quality, and better support for frequency control [7, 8]. Nevertheless, achieving the full advantages of distributed generation requires careful determination of both the capacity and placement of the generators within the distribution network [7, 9, 10].

Several researchers have suggested diverse solution frameworks to meet this objective, which are typically classified by their computational approach as analytical, numerical, or metaheuristic methods. Analytical approaches, in particular, have been utilized to solve the distributed generation siting problem [11–13]. Previous research has investigated the coordinated siting of distributed generators and reactive power support equipment in distribution networks by employing numerical-based optimization approaches [14]. In one study, dynamic programming was applied to solve the problem. Nevertheless, analytical and numerical methods are typically resource-intensive, as they involve assessing every possible combination of DG placement to find the optimal solution. Consequently, most studies using these approaches consider only a limited number of variables [15]. Furthermore, because the problem is inherently non-linear, linear programming techniques frequently struggle to identify the true optimal solutions [16]. Population-based meta-heuristic techniques—such as genetic algorithms, harmony search, bat algorithm, artificial bee colony, particle swarm optimization, and ant colony optimization—offer notable advantages over traditional analytical and numerical methods, as they do not require exhaustive exploration of the entire solution space to obtain satisfactory results. This characteristic significantly reduces computational burden and makes it possible to handle problems involving a large number of decision variables and network buses. In addition, these algorithms are valued for their conceptual simplicity and adaptability to complex optimization problems. Nevertheless, they typically yield approximate rather than exact optimal solutions; however, the accuracy achieved is generally sufficient for most practical engineering applications [17]. A genetic algorithm was employed to determine the optimal locations and capacities of distributed generation units within a distribution network, with the optimization objectives and constraints formulated to account for multiple planning horizons. The problem of distributed generation siting in distribution networks was solved using an optimization framework that merges simulated annealing with genetic algorithm techniques [18]. A technique was developed to minimize real power losses, enhance voltage regulation, and relieve substation loading in an electrical power system through the evaluation of voltage sensitivity indices [19]. To reduce the complexity of the distributed generation placement and sizing problem, many existing studies in the literature typically impose constraints by fixing either the number of DG units or their capacities. In contrast, the approach presented in this work removes such limitations by enabling a heuristic search that explores the full solution space without predefined restrictions on the quantity or rating of DG units. This allows the simultaneous determination of the optimal number, locations, and sizes of DGs required to minimize both real and reactive power losses within the network. Among the available metaheuristic techniques, particle swarm optimization is selected for this study due to its effectiveness in identifying near-global optimal solutions with relatively few iterations and its demonstrated superior performance when compared with other comparable algorithms [20, 21].

This work extends the investigation into the practical use of particle swarm optimization by employing it to determine the optimal locations and capacities of distributed generation units in a power distribution network. The objective is to achieve a substantial reduction in total real power losses while simultaneously improving the voltage profile of the system.

Although extensive research has been conducted on DG allocation and sizing using various metaheuristic algorithms, several gaps remain. Many existing studies focus on single DG units or simplified system models, limiting their applicability to real-world distribution networks with multiple DG installations. Additionally, limited attention has been given to combining PSO with realistic load flow techniques such as the backward–forward sweep method for radial systems. The performance of the proposed method was assessed through implementation on the benchmark IEEE 33-bus distribution system using MATLAB codes and validating it using ETAP 2021 software.

II. Mathematical Formulation

1) Bus Load Current Calculation

At iteration k, the injected current at bus i is:

$$i_i^{(k)} = \left(\frac{P_i - jQ_i}{V_i^{(k)}}\right)^*$$

Where:

- $P_i, Q_i =$ active and reactive power demand at bus i
- $V_i^{(k)}$ = bus voltage at iteration k
- $(.)^*$ = complex conjugate

2a) Backward Sweep (Branch Current Calculation)

Starting from the leaf nodes and moving towards the slack bus, branch currents are computed using Kirchhoff's Current Law (KCL). For a branch connecting bus i to bus j:

$$I_{ij}^{(k)} = I_j^{(k)} + \sum_{m \in children(j)} I_{jm}^{(k)}$$

This means each branch current is the sum of:

- Load current at the receiving bus
- Currents of all downstream branches

2b) Forward Sweep (Voltage Update)

Starting from the slack bus and moving outward, bus voltages are updated using Kirchhoff's Voltage Law (KVL):

$$V_j^{(k+1)} = V_i^{(k+1)} + Z_{ij} I_{ij}^{(k)}$$

Where:

- $Z_{ij} = R_{ij} + jX_{ij}$ = branch impedance
- $V_i^{(k+1)}$ = sending − end bus voltage

2c) Convergence Criterion

The iterative process continues until:

$$\mathrm{Max}\left|V_i^{(k+1)} - V_i^{(k)}\right| \le \epsilon$$

where:

- ϵ is the convergence tolerance (typically 10−6)

3) Branch Power Loss Calculation

$$P_{loss,ij} = R_{ij}\left|I_{ij}\right|^2$$

$$Q_{loss,ij} = X_{ij}\left|I_{ij}\right|^2$$

4) PSO Algorithm

High penetration of distributed generation significantly affects power losses and voltage profiles in radial distribution networks. The objective is to optimally determine the location(s) and size(s) of DG units such that total real power loss is minimized while satisfying system operating constraints. Particle Swarm Optimization (PSO) is employed due to its fast convergence, simple implementation, and effectiveness in nonlinear, non-convex power system problems.

Particle Swarm Optimization (PSO) is a stochastic, population-oriented optimization technique motivated by the collective movement patterns observed in natural swarms, such as flocks of birds and schools of fish. In PSO, each candidate solution, referred to as a *particle*, navigates the search space by continuously updating its position based on both its own historical best solution and the globally best solution identified by the swarm. The particle positions, represented by randomly initialized numerical values, define potential solutions within a multi-dimensional optimization space [13].

5)Decision Variables

For a system with N_{DG} DG units, the particle position vector is defined as:

$$X = \begin{bmatrix} L_1 & L_2 & \dots & L_{N_{DG}} \\ P_{DG_1} & P_{DG_2} & \dots & P_{DG_{DG}} \end{bmatrix}$$

Where:
L_k = location (bus number) of DG unit k
- P_{DGk} =real power rating of DG unit k
 DGs are assumed to operate at unity power factor unless otherwise stated.

6) Objective Function Formulation

6a) Real Power Loss Minimization

The primary objective is to minimize the total real power loss of the distribution system:

$$\min f(X) = P_{loss} = \sum_{i=1}^{N_b} \sum_{j=i+1}^{N_b} R_{ij} \left|I_{ij}\right|^2$$

where:
- R_{ij} = resistance of branch ijijij
- I_{ij} = branch current obtained from BFS load flow

6b) Fitness Function

Including penalty terms for constraint violations:

$$F = P_{loss} + \lambda_1 \sum_{i=1}^{N_b} (\max(0, V_i - V_{max})^2 + max(0, V_{min} - V_i)^2)$$

where:
- λ_1 = penalty coefficient

7) Power Balance with DG Integration

At each bus i:

$$P_i^{net} = P_i^{load} - P_i^{DG}$$
$$Q_i^{net} = Q_i^{load}$$

This modified power demand is used in the BFS load-flow calculation.

8) Constraints

Power Balance Constraint

$$\sum P_{DG} \leq \sum P_{load} + P_{loss}$$

DG Size Limits

$$P_{DG_k}^{min} \leq P_{DG_k} \leq P_{DG_k}^{max}$$

Bus Voltage Limits

$$V_{min} \leq |V_i| \leq V_{max}$$

Typically:

$$0.95 \leq |V_i| \leq 1.05$$

9) PSO Velocity and Position Update Equations

Velocity Update

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

where:
- w = inertia weight
- C_1, C_2 = cognitive and social coefficients
- r1,r2 ∈ [0,1] = random numbers

Position Update

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

Discrete variables (DG locations) are rounded to nearest integer after updating.

III. The IEEE 33-Bus Radial Distribution Test System

The IEEE 33-bus network is a benchmark radial distribution test system that is widely adopted in research studies to enable effective comparison of proposed methods with existing literature. The proposed PSO algorithm was implemented in MATLAB R2022a and executed on an Intel CORE i7 vPro 8th Generation personal computer. The test system carries an aggregate real power demand of 3.715 MW and a total reactive power demand of 2.3 MVar. The load flow analysis was carried out using the Backward Forward Sweep algorithm while the optimal allocation of DG and its sizing to minimize the power loss and improve the voltage profile was done using the PSO algorithm. A comparative performance evaluation of the base case and distributed generation (DG) case on the IEEE-33 bus radial distribution network was carried out in this study. The assessment focuses on voltage profile improvement and real power loss minimization, which are critical indices for evaluating distribution network performance under high penetration of distributed energy resources. Overall, the test network consists of 33 buses interconnected by 32 distribution lines. A schematic diagram is shown in fig 1.

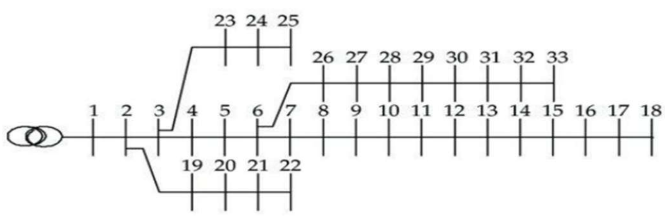

Fig 1: IEEE 33 bus test system

Iv. RESULTS AND DISCUSSION

Base case (without DG) and PSO-DG case results using MATLAB

The voltage magnitude across all the buses in the distribution system before and after PSO optimized multiple DG allocation and siting are presented in Fig. 2. It shows a significant improvement in the system voltage profile. In the base case (no DG), there is a decline in the per unit (pu) voltage magnitude at the buses as we progress along the system from bus 1 to bus 33. However, with the DGs sited at the optimum buses as derived using PSO, there is a significant improvement in the voltage profile of the system with all the buses approaching the nominal voltage.

Before DG allocation, the least voltage magnitude across all the buses was obtained at bus 18 with a per unit voltage of 0.87. However, after DG allocation, this value increased to 0.993 per unit. The remote bus; bus 33 has its per unit voltage as 0.886 for the base case while 0.995pu for the DG case. Three DGs were optimized using PSO and the optimal locations are buses 7, 29 and 14 while the sizes are 1.3714MW, 1.6455MW and 0.8597MW respectively. The base case power loss is 0.2959MW and that of the DG case is 0.1567MW with 47.05% loss reduction.

Table 1: Comparative analysis of base case and PSO-DG case using MATLAB

S/N		**Base Case (without DG)**	**PSO-DG case**
1	**Total power loss**	0.2959MW	0.1567MW
2	**Remote bus voltage**	0.886pu	0.995pu
3	**Minimum bus voltage**	0.87pu	0.993pu
4	**Optimal location**	-	7, 29, 14
5	**Optimal size**	-	1.3714, 1.6455, & 0.8597MW

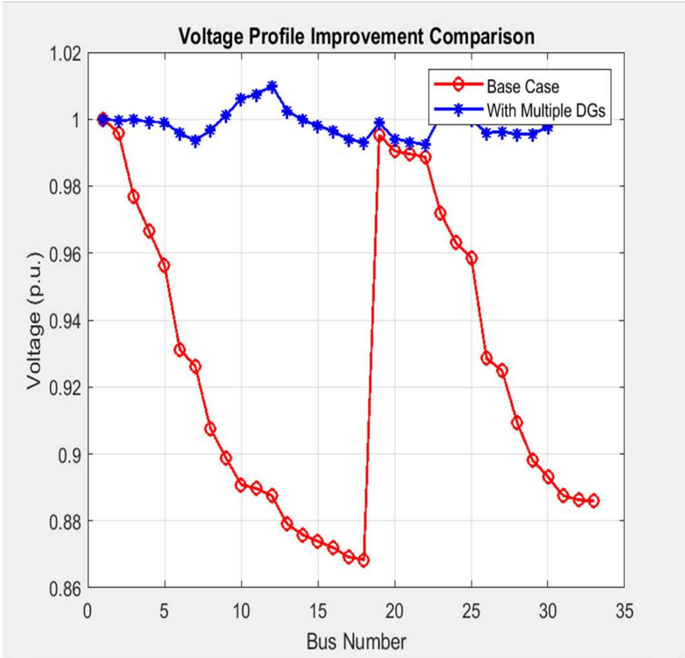

Fig 2: Comparative voltage profile using PSO

Fig 3: Branch power loss for base case and DG case

Comparison of PSO results using MATLAB and ETAP Validation

The analysis of the IEEE 33 bus distribution system voltage profile as derived from ETAP under base case and distributed generation arrangement are illustrated in Fig. 4. The PSO results as presented in table 1 with the obtained results from ETAP shown in Fig. 4 for optimized location plot are in good correlation. It is also shown in Fig. 4 that there is a significant improvement in the voltage profile from bus 1 to bus 33 when the system is fed by DGs compared to the base case (without DG).

From the ETAP model, the base case minimum bus voltage occurred in bus 18 with a value of 0.9057pu and 0.9833pu for the optimized DG case. The remote bus (bus 33) voltage is 0.914pu and that of the optimized DG case is 0.9931pu. The base case total power loss is 0.175MW and that of the optimized DG case is 0.0972MW. The branch power losses are displayed in fig. 5. There is good correlation between the PSO model in fig. 3 and the ETAP model in fig. 5. For the ETAP model, the base case has 21 buses that have their voltages below the minimum acceptable voltage limit of 0.95pu as shown in fig. 6, but after DG allocation at the optimal site, there was significant voltage profile improvement at all the affected buses as shown in fig. 7.

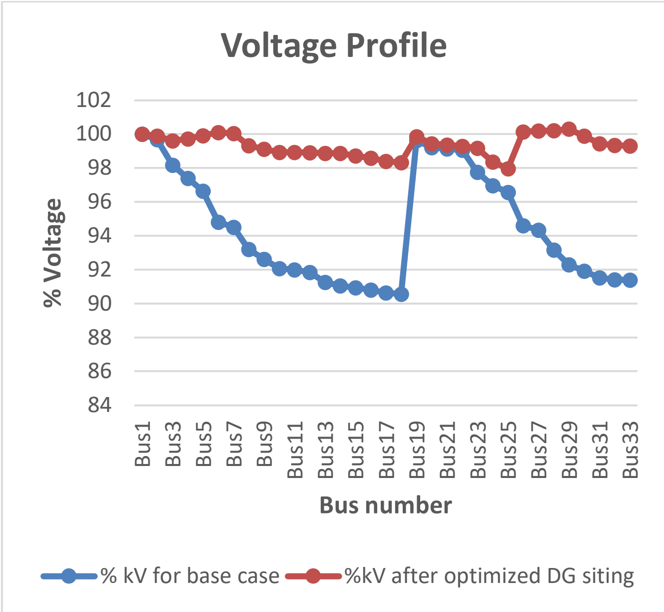

Fig 4: Comparative voltage profile for base case and DG case using ETAP

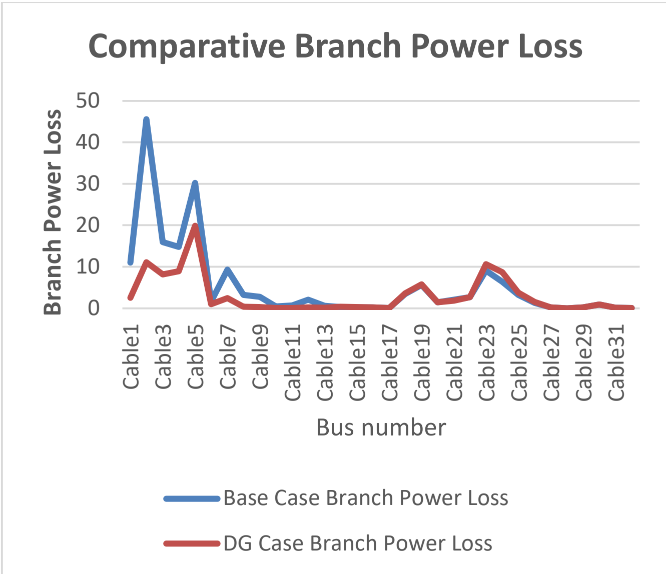

Fig 5: Comparative branch power loss for base case and DG case using ETAP

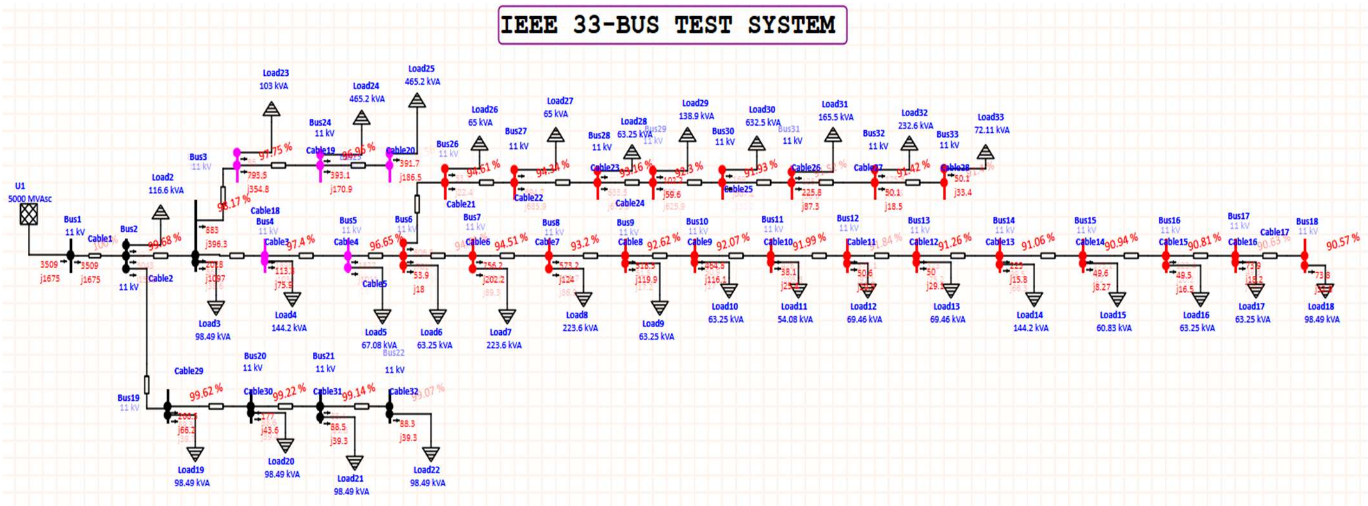

Fig 6: Base case BFS load flow analysis using ETAP

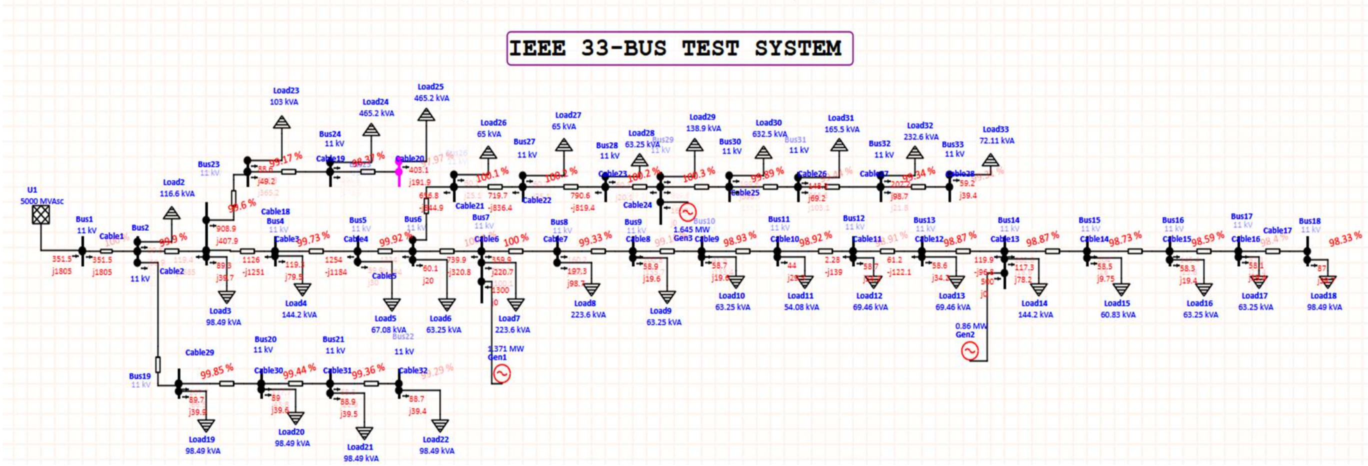

Fig 7: DG case BFS load flow analysis using ETAP

A random DG allocation at buses 5, 31 and 11 shown in fig. 10, were done to compare its impact on the voltage profile and branch power loss with those of the optimized and base cases to show the impact of optimizing the system. Figure 8 and 9 shows the voltage profile and branch power loss for base case, optimized case and random case. The results show that PSO optimized DG case performed better than the base case and random case.

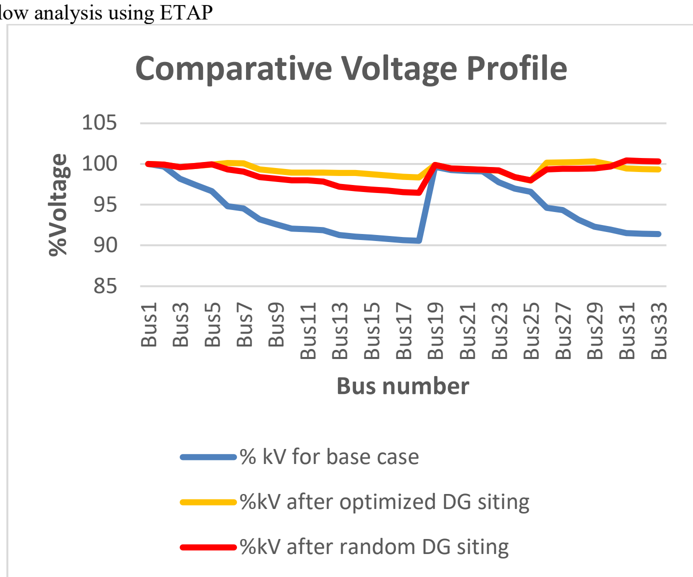

Fig. 8: Comparative voltage profile for base case, optimized case and random case

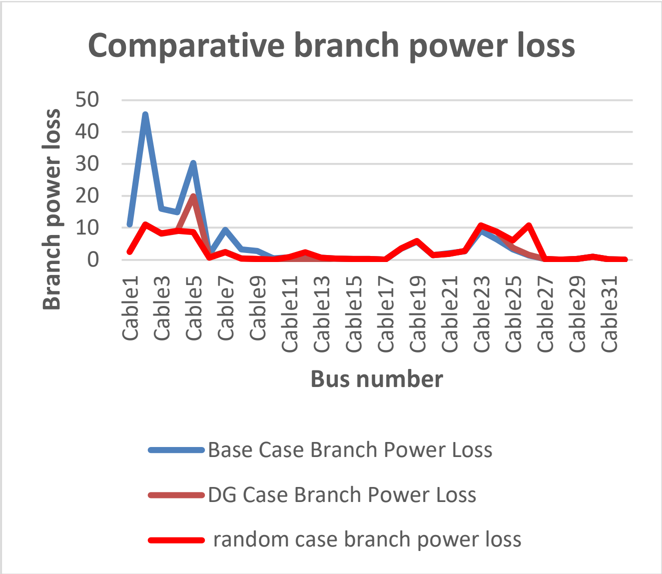

Fig. 9: Comparative branch power loss for base case, optimized case and random cas

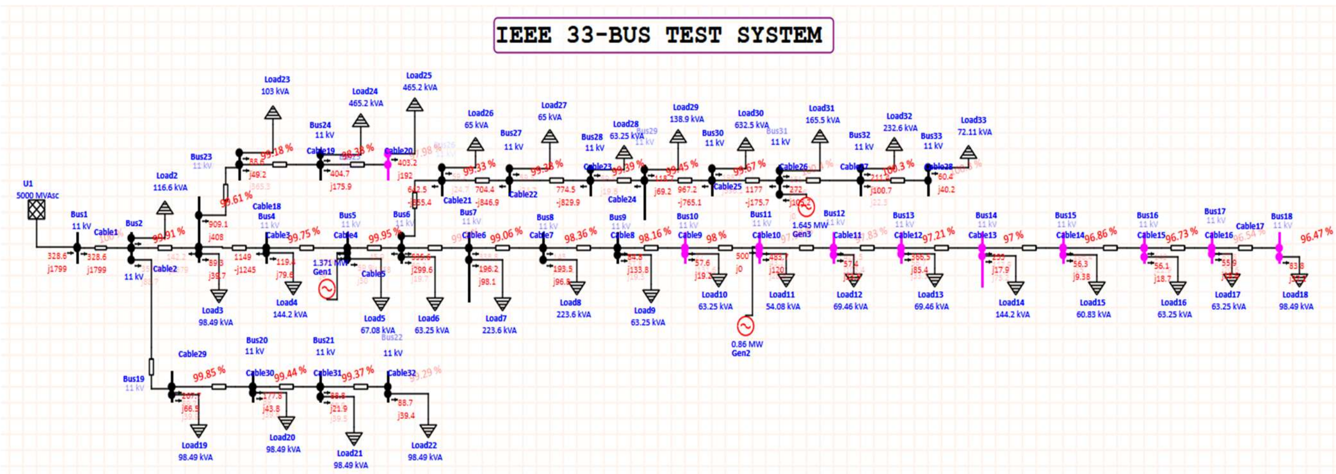

Fig 10: Random case BFS load flow analysis using ETAP

CONCLUSION

This study has successfully demonstrated the effectiveness of Particle Swarm Optimization for the optimal placement and sizing of multiple distributed generation units in a radial distribution network. By integrating PSO with the backward–forward sweep load flow method, the proposed approach efficiently addresses the nonlinear and non-convex nature of the DG allocation problem. Application to the IEEE 33-bus test system shows that optimal DG integration leads to substantial real power loss reduction and significant improvement in voltage profiles across all buses. Compared with the base case and random DG placement, the PSO-optimized solution achieved superior system performance, confirming the importance of optimization-based planning. Validation using ETAP further reinforces the reliability of the results obtained from the MATLAB implementation. Overall, the proposed method provides a practical and effective tool for distribution network planners seeking to enhance efficiency, voltage stability, and operational performance under high penetration of distributed generation.

REFERENCE

[1] B.H. Chowdhury & C.-L. Tseng. Distributed energy resources: issues and challenges. *J Energy Eng*, 109–110, 2007.

[2] V.S. Galgali, M. Ramachandran & G.A. Vaidya. Multi-objective optimal sizing of distributed generation by application of Taguchi desirability function analysis. *SN Appl Sci*, 1:1–14, 2019.

[3] V. Kalkhambkar, B. Rawat, R. Kumar & R. Bhakar. Optimal allocation of renewable energy sources for energy loss minimization. *J Electr Syst*, 113:115–130, 2017.

[4] E. Caamaño-Martín, H. Laukamp, M. Jantsch, T. Erge, J. Thornycroft, H. De Moor, S. Cobben, D. Suna & B. Gaiddon. Interaction between photovoltaic distributed generation and electricity networks. *Prog Photovoltaics Res Appl*, 16:629–643, 2008.

[5] A. Kazemi & M. Sadeghi. Sitting and sizing of distributed generation for loss reduction. In *Proceedings of the Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, pp. 1–6, 2009.

[6] N. Ghosh, S. Sharma & S. Bhattacharjee. A load flow based approach for optimum allocation of distributed generation units in the distribution network for voltage improvement and loss minimization. *Int J Comput Appl*, 50:15–22, 2012.

[7] Y.M. Arjun & B.R. Suresh. Impact of distributed generation on three feeder radial distribution system. *Int J Eng Res Appl*, 3:983–988, 2013.

[8] L. Ramesh, S.P. Chowdhury, S. Chowdhury, A.A. Natarajan & C.T. Gaunt. Minimization of power loss in distribution networks by different techniques. *Int J Electr Electron Eng*, 2:521–527, 2009.

[9] K. Mahmoud & M. Lehtonen. Direct approach for optimal allocation of multiple capacitors in distribution systems using novel analytical closed-form expressions. *Electr Eng*, 2020.

[10] K. Mahmoud & M. Lehtonen. Simultaneous allocation of multi-type distributed generations and capacitors using generic analytical expressions. *IEEE Access*, 7:182701–182710, 2019.

[11] K. Mahmoud & A. Ahmed. Power loss minimization in distribution systems using multiple distributed generations. *IEEJ Trans Electr Electron Eng*, 10:521–526, 2015.

[12] J.O. Petinrin & M. Shaaban. Multiperiod coordination of local voltage controllers and energy storage for voltage regulation in distribution feeder-connected renewable energy sources. *Iran J Sci Technol Trans Electr Eng*, 2018.

[13] T.H. Fawzi, S.M. El-Sobki & M.A. Abdel-Halim. New approach for the application of shunt capacitors to the primary distribution feeders. *IEEE Trans Power Appar Syst*, 102:10–13, 1983.

[14] M. Janga Reddy & D. Nagesh Kumar. Evolutionary algorithms, swarm intelligence methods, and their applications in water resources engineering: a state-of-the-art review. *H2Open J*, 3:135–188, 2020.

[15] D. Das, D. Kothari & A. Kalam. Simple and efficient method for load flow solution of radial distribution network. *Int J Electr Power Energy Syst*, 17(5):335–346, 1995.

[16] Z. Abdmouleh, A. Gastli, L. Ben-Brahim, M. Haouari & N.A. Al-Emadi. Review of optimization techniques applied for the integration of distributed generation from renewable energy sources. *Renew Energy*, 113:266–280, 2017.

[17] B. Kuri, M.A. Redfern & F. Li. Optimisation of rating and positioning of dispersed generation with minimum network disruption. In *Proceedings of the 2004 IEEE Power Engineering Society General Meeting*, 2:2074–2078, 2004.

[18] M. Gandomkar, M. Vakilian & M. Ehsan. A combination of genetic algorithm and simulated annealing for optimal DG allocation in distribution networks. In *Proc*

Can Conf Electr Comput Eng, pp. 645–648, 2005.
[19] N.S. Gopiya, D.K. Khatod & M.P. Sharma. Optimal allocation of distributed generation in distribution system for loss reduction. In *IACSIT Coimbatore Conf*, 28:42–46, 2012.
[20] A. Gupta & S. Srivastava. Comparative analysis of ant colony and particle swarm optimization algorithms for distance optimization. *Procedia Comput Sci*, 173:245–253, 2020.
[21] H.H.A. Mukhairez & A.Y.A. Maghari. Performance comparison of simulated annealing, GA and ACO applied to TSP. *Int J Intell Comput Res*, 6:647–654, 2015.