Optimal Allocation and Sizing of Distributed Generation in Radial Distribution Network Using Teaching-Learning Based Optimization

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Abstract: This paper presents a Teaching–Learning Based Optimization (TLBO) approach for optimal allocation and sizing of distributed generation (DG) in a radial distribution network. The DG planning problem is formulated as a constrained nonlinear optimization task aimed at minimizing real power losses and improving voltage profiles. Load flow analysis is performed using the backward–forward sweep method, and the proposed framework is applied to the IEEE 33-bus radial distribution test system. Simulation results show significant reduction in real power losses and substantial improvement in minimum bus voltage compared to the base case without DG. The results confirm that TLBO is a robust, parameter-less, and efficient optimization technique for multi-DG planning in radial distribution networks.

Keywords: *Distributed Generation, Optimization, Real Power, Radial Distribution, Backward-Forward Sweep.*

I. INTRODUCTION

Electrical power distribution systems are highly susceptible to inefficiencies manifested as real power losses, poor voltage profiles, and elevated operational costs when reliant solely on centralized generation and long-distance transmission. These challenges are especially pronounced in radial distribution networks, which are characteristic of many developing and emerging power systems. To address these challenges, Distributed Generation (DG); small-scale energy sources installed near load centers has emerged as a compelling decentralized alternative that can enhance system performance, improve voltage profiles, reduce line losses, and defer infrastructure investments.

Proper integration of DG, however, depends critically on where and how much DG capacity is installed. Optimal allocation and sizing of DG units is a multi-objective problem involving minimization of power losses, improvement of voltage profiles, satisfaction of operational constraints, and cost–benefit considerations. The complexity of this problem arises from its highly nonlinear and non-convex nature, due to intricate power flow relationships and discrete decision variables inherent in placements and capacities.

Traditional analytical methods often fail to find optimal solutions for DG planning due to these complexities. Consequently, the research community has increasingly turned to metaheuristic and nature-inspired optimization methods that are well-suited for such nonlinear problems. One such population-based method is the Teaching and Learning Based Optimization (TLBO) algorithm, inspired by the pedagogical process in classroom learning. TLBO's advantage is its minimal need for algorithm-specific tuning parameters compared to many other evolutionary algorithms, yielding robust performance across a range of optimization scenarios.

II. LITERATURE REVIEW

The integration of distributed generation (DG) into electrical distribution networks has been extensively studied as an effective approach to mitigating real power losses and improving voltage profiles. DG units, when optimally located and sized, supply power closer to load centers, thereby reducing feeder currents and associated I²R losses while enhancing voltage regulation across the network [4]. These benefits are particularly significant in radial distribution systems, which are more vulnerable to voltage drops and high losses due to their structural characteristics. Several methodologies have been proposed for DG allocation and sizing. According to ([9], [10]), FACTS devices such as SVC, capacitor banks and high transformer ratings were used to improve voltage profile and reduce losses in distribution networks. Early works employed analytical and sensitivity-based techniques, such as loss sensitivity factors and voltage stability indices, to identify suitable buses for DG placement

[5]. While these approaches are computationally efficient, they often provide suboptimal solutions due to their inability to fully capture the nonlinear nature of power flow equations and operational constraints.

To overcome these limitations, researchers have increasingly adopted metaheuristic optimization techniques for DG planning. These techniques can simultaneously handle multiple objectives, such as loss minimization and voltage profile improvement, while satisfying system constraints. Studies applying these methods to standard IEEE 33-bus and 69-bus distribution systems consistently demonstrate significant reductions in real power losses and notable voltage profile enhancement when compared to base-case scenarios without DG [10]. Teaching and Learning Based Optimization (TLBO) is a population-based metaheuristic algorithm inspired by the classroom teaching–learning process, where learners improve their knowledge through interaction with a teacher and among themselves. TLBO operates in two primary phases: the teacher phase and the learner phase. A major advantage of TLBO is its parameter-less structure, which eliminates the need for algorithm-specific tuning parameters and enhances robustness and ease of implementation [8].

The application of TLBO to optimal DG allocation and sizing has gained increasing attention due to its effectiveness in handling nonlinear, multi-objective optimization problems. Several studies have shown that TLBO can achieve superior loss reduction and voltage profile improvement compared to conventional optimization techniques. [1] demonstrated that TLBO-based DG placement significantly reduces total real power losses while maintaining bus voltages within acceptable limits in radial distribution networks. To further enhance the performance of standard TLBO, numerous improved and hybrid variants have been proposed. Enhanced TLBO versions, such as adaptive TLBO, comprehensive TLBO, and quasi-oppositional TLBO, aim to improve convergence speed and avoid premature stagnation ([9], [3]). Hybrid TLBO approaches combining TLBO with particle swarm optimization (PSO) or simulated annealing have also been reported to provide better exploration–exploitation balance and improved solution quality [7].

Recent studies have extended TLBO-based DG optimization frameworks to include additional objectives such as voltage stability enhancement, emission reduction, and economic cost minimization. Furthermore, uncertainty in load demand and renewable DG output has been incorporated into TLBO formulations, demonstrating the flexibility of the algorithm in addressing realistic power system operating conditions [6]. A substantial number of studies have conducted comparative evaluations of TLBO against other widely used metaheuristic optimization algorithms for DG allocation and sizing. Common benchmark techniques include Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Grey Wolf Optimization (GWO), and Ant Lion Optimization (ALO) ([2], [9]). Comparative results reported in the literature consistently indicate that TLBO performs competitively, and often superiorly, in terms of real

power loss minimization, voltage profile improvement, and convergence characteristics. Unlike PSO and GA, which require careful tuning of multiple control parameters, TLBO's parameter-less nature leads to improved consistency and reduced computational complexity [8]. [9] showed that TLBO achieved lower system losses and better voltage regulation with fewer iterations compared to PSO and GA for standard radial test systems. Hybrid approaches further highlight the strengths of TLBO when integrated with other optimization techniques. Studies combining TLBO with PSO or sensitivity-based methods report enhanced performance over standalone algorithms, particularly in large-scale or multi-DG planning problems [7]. However, some authors note that standard TLBO may suffer from reduced population diversity in later iterations, motivating the development of enhanced and hybrid variants to address this limitation.

The reviewed literature demonstrates that optimal DG allocation and sizing significantly improves distribution system performance, and that TLBO is a powerful optimization technique for addressing this problem. However, many existing studies focus on simplified system models or single DG installations, with limited investigation into multi-DG scenarios and realistic load flow techniques such as the backward–forward sweep method. Additionally, further research is required to evaluate TLBO under high DG penetration levels and practical operating constraints. This study is focused on implementing TLBO and backward-forward sweep load flow algorithm on an IEEE 33 bus radial test network, to determine the optimal location and sizing of multiple DGs for loss minimization and improved voltage profile.

➢ *Load Flow Modeling in Radial Distribution Systems*
For radial distribution networks, the Backward–Forward Sweep (BFS) method is widely used due to its numerical stability and computational efficiency. The branch current and bus voltage calculations are expressed as follows.

• *The Load Current at Bus i is Given by:*

$$I_i = \frac{(P_i - P_{DG,i}) - j(Q_i - Q_{DG,i})}{V_i^*}$$

Where:

✓ P_i, Q_i are the real and reactive power demands at bus i
✓ $P_{DG,i}$, $Q_{DG,i}$ are the DG real and reactive power injections
✓ V_i is the bus voltage

• *The Backward Sweep Computes Branch Currents:*

$$I_{br,k} = \sum_{i \in \Omega_k} I_i$$

Where:

✓ Ω_k represents buses downstream of branch $k.$

- *The Forward Sweep Updates Bus Voltages:*

$$V_{i+1} = V_i - Z_k I_{br}, k$$

Where:

✓ $Z_k = R_k + jX_k$ is the branch impedance.

➢ *Objective Function Formulation*

- *Real Power Loss Minimization*
  The total real power loss in the distribution system is expressed as:

$$P_{loss} = \sum_{k=1}^{N_{br}} R_k |I_{br,k}|^2$$

✓ *The Primary Objective Function is:*

$$min f_1 = P_{loss}$$

This objective has been widely adopted in DG planning studies due to its direct impact on system efficiency (Mohanty and Tripathy, 2014; Abdelsalam *et al.,* 2017).

➢ *Voltage Profile Improvement*
  Voltage profile improvement is typically achieved by minimizing the Voltage Deviation Index (VDI):

$$VDI = \sum_{i=1}^{N_b} (V_i - V_{ref})^2$$

Where:

V_{ref} is usually set to 1.0 p.u.

- *The Second Objective Function is:*

$$min f_2 = VDI$$

This formulation ensures voltage magnitudes remain close to their nominal values (Sultana and Roy, 2014).

➢ *Multi-Objective Optimization Function*
  To simultaneously minimize losses and improve voltage profile, a weighted objective function is commonly employed:

$$min F = w_1 \frac{P_{loss}}{P_{loss}^{base}} + w_2 \frac{VDI}{VDI^{base}}$$

Where:

$$w_1 + w_2 = 1.$$

➢ *System Constraints*

- *Power Balance Constraint*

$$\sum P_{DG} + P_{sub} = \sum P_{load} + P_{loss}$$

This ensures system power equilibrium.

- *Voltage Constraints*

$$V_i^{min} \leq V_i \leq V_i^{max}$$

✓ *Typically:*

$$0.95 \leq V_i \leq 1.05 \, p.u.$$

- *DG Capacity Constraints*

$$P_{DG,i}^{min} \leq P_{DG,i} \leq P_{DG,i}^{max}$$

$$Q_{DG,i}^{min} \leq Q_{DG,i} \leq Q_{DG,i}^{max}$$

These limits reflect DG technology ratings.

- *Line Thermal Limits*

$$|I_{br,k}| \leq I_{br,k}^{max}$$

This prevents branch overloading.

➢ *Teaching and Learning Based Optimization (TLBO) Algorithm for DG Planning*
  In TLBO, each learner represents a candidate DG allocation and sizing solution:

$$X = [Bus_{DG1}, P_{DG1,...,} Bus_{DGn}, P_{DGn}]$$

- *Teacher Phase*
  The mean of the population is updated as:

$$M_{new} = M + r(M_{teacher} - T_f M)$$

Where:

✓ r is a random number in [0,1]
✓ T_f is the teaching factor (1 or 2)

- *Learner Phase*
  Learners interact pairwise:

$$X_i^{new} = \begin{cases} X_i + r(X_j - X_i), if \, f(X_j) < f(X_i) \\ X_i + r(X_i - X_j), \quad otherwise \end{cases}$$

This phase improves solution diversity and convergence.

➢ *The IEEE 33-Bus Radial Distribution Test Network*
  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 TLBO 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. The assessment focused 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.
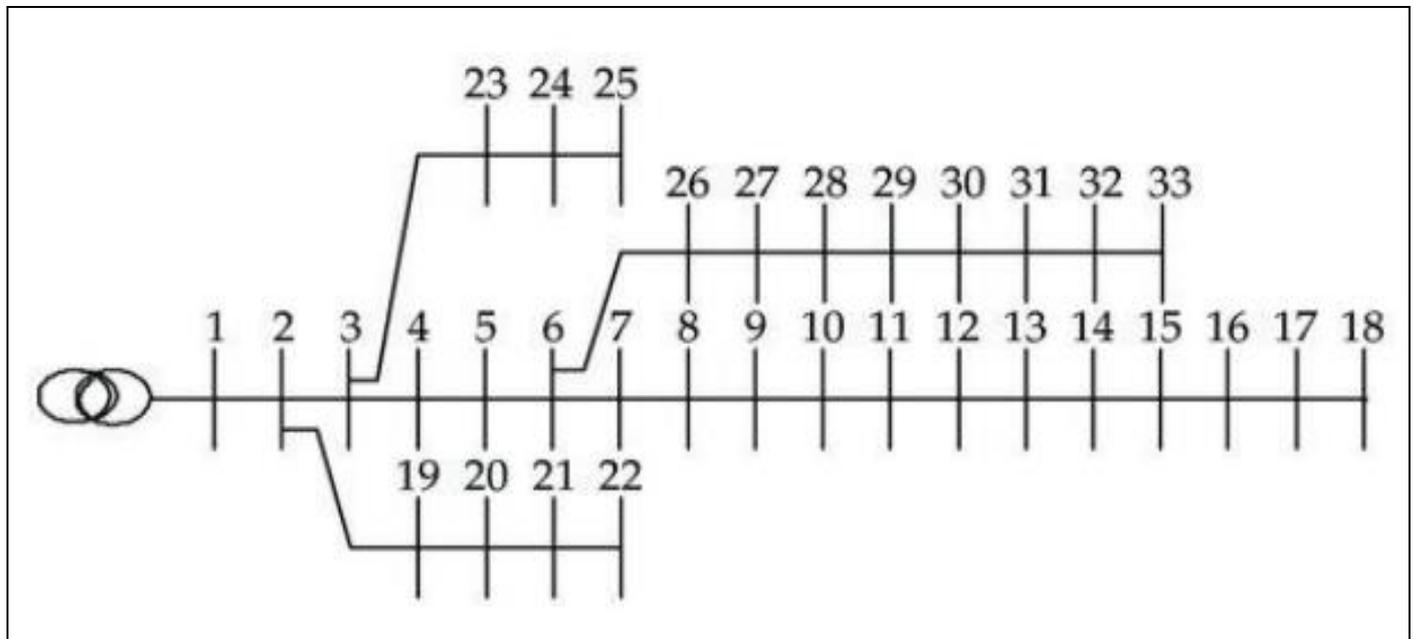

Fig 1 11kV IEEE 33 Bus Radial Test Network

III. RESULT AND DISCUSSION

➤ *Base Case (Without DG) and TLBO-DG Case Results*

The voltage magnitude across all the buses in the distribution system before and after TLBO 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 multiple DGs sited at the optimum buses as derived using TLBO, there is a significant reduction in the total power loss and an improvement in the voltage profile of the system with all the buses approaching the nominal voltage.

Before DG allocation, the minimum bus voltage magnitude across all the buses was obtained at bus 18 with a per unit voltage of 0.6678pu. However, after multiple DG allocation, this value increased to 0.8894pu. The minimum

bus voltage for the DG case is 0.8838pu at bus 33. The remote bus; bus 33 has its per unit voltage as -0.4069pu for the base case while 0.8415pu for the DG case. Three DGs were optimized using Backward-Forward Sweep load flow algorithm and TLBO and the optimal locations are buses 6, 5and 7 while the sizes are 0.02MW, 0.036MW and 0.066MW respectively. From buses 17 to 21 were a little below the acceptable minimum voltage limit of 0.95pu for the DG case. The base case power loss is 0.1466MW and that of the DG case is 0.0199MW with 86.41% loss reduction. The base case voltage deviation index was massive from bus 5 to bus 30 compared to the voltage deviation index for the DG case which was minimal as shown in fig. 4. The voltage profile improvement comparison for base case and DG case is shown in fig. 2. The base case total power loss compared with the DG case total power loss is shown in fig. 3. The TLBO convergence curve is shown in fig. 5. This curve shows that the best total power loss was obtained at the 50th iteration.

Table 1 Comparative Analysis of Base Case and TLBO-DG Case Using MATLAB

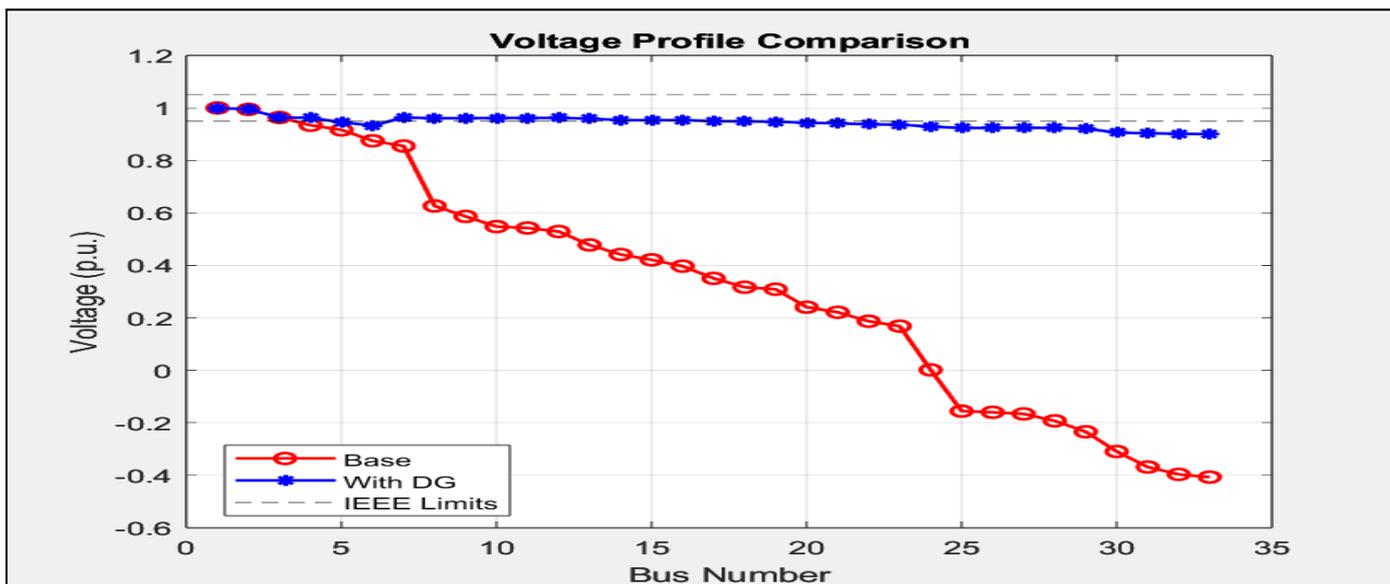| S/N		Base Case (without DG)	TLBO-DG case
1	Total power loss	0.1466MW	0.0178MW
2	Loss reduction	-	87.85%
2	Remote bus voltage	-0.4069pu	0.9pu
3	Minimum bus voltage	0.6678pu at bus 18	0.9041pu at bus 33
4	Optimal location	-	7, 6, 4
5	Optimal size	-	0.02, 0.036, & 0.083MW

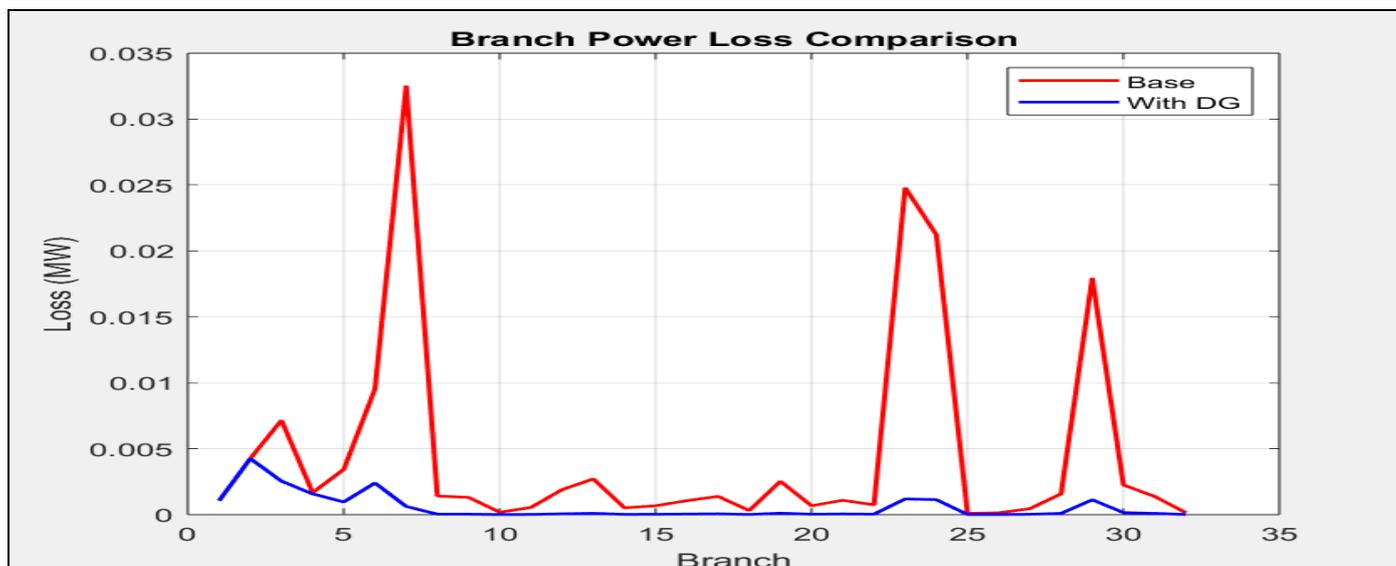Fig 2 Comparative Voltage Profile Improvement Using BFS and TLBO Algorithm
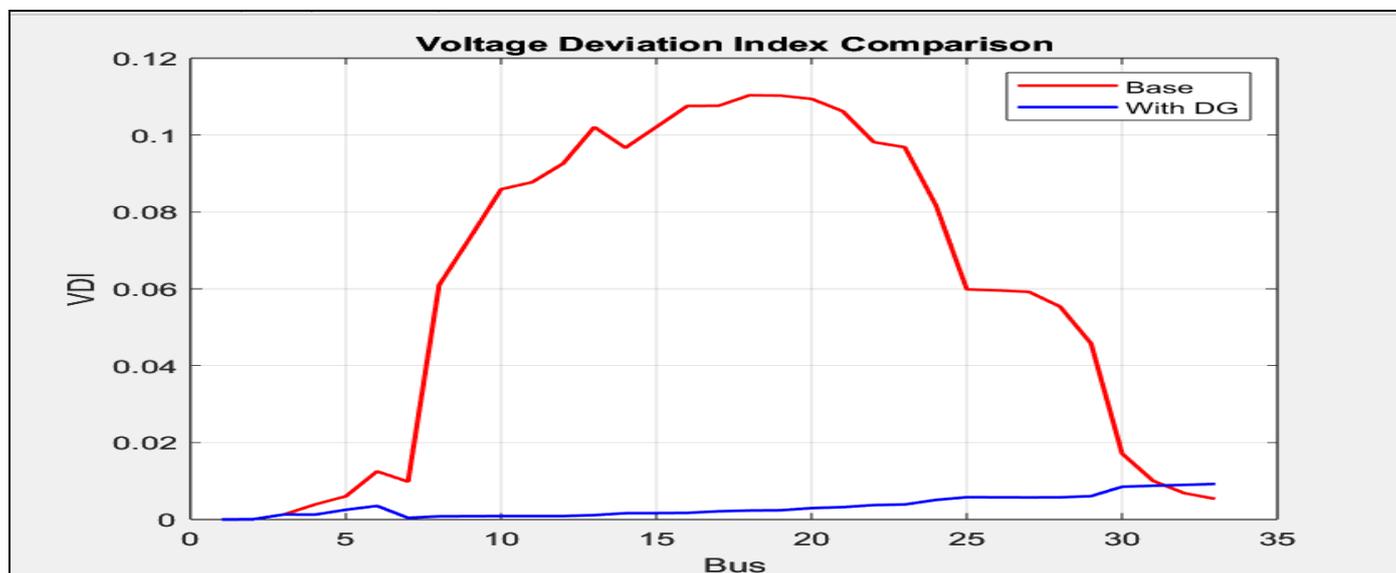

Fig 3 Branch Power Loss for Base Case and DG Case

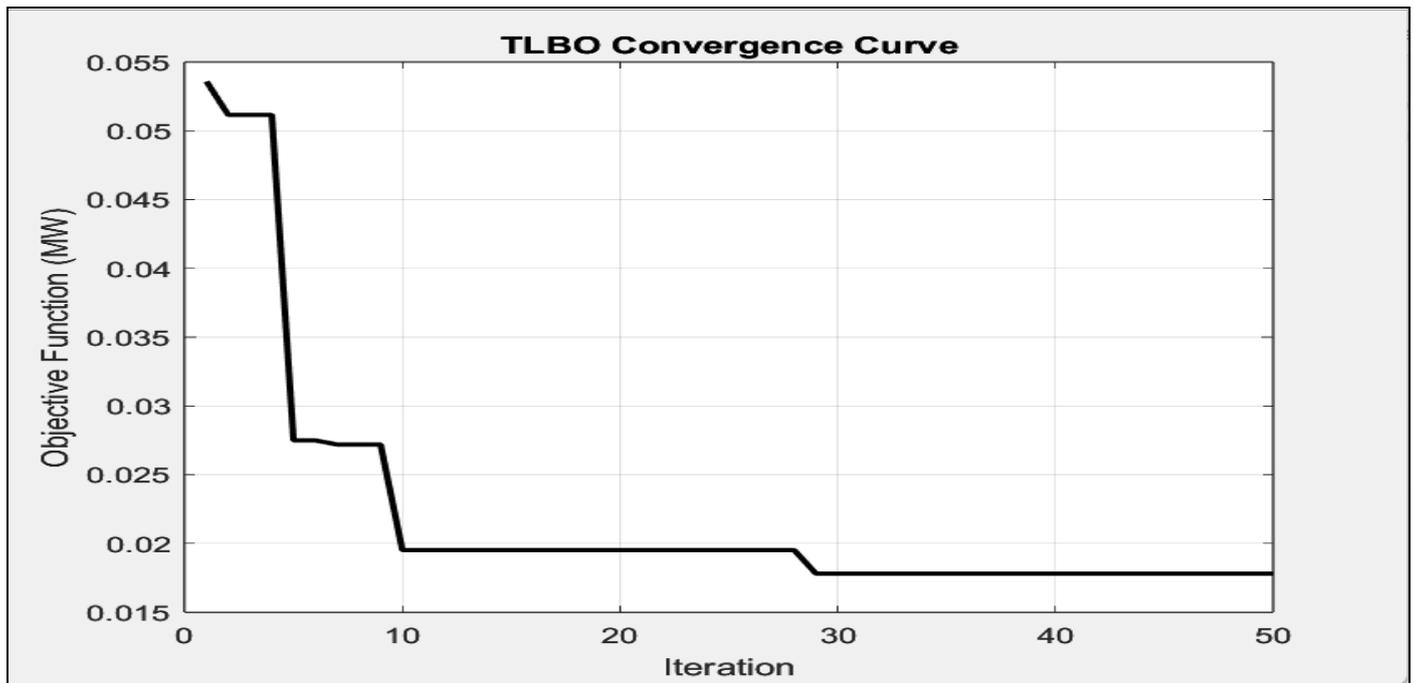Fig 4 Voltage Deviation Index Comparison for Base Case and DG Case

Fig 5 TLBO Convergence Curve

IV. CONCLUSION

The study demonstrates that strategic placement and sizing of DGs in a radial distribution network can significantly improve efficiency, reduce losses, and enhance voltage stability. This provides a practical approach for planning future distributed generation integration in unbalanced distribution networks.

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