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Topology-oriented sensitivity framework for optimal distributed generation planning in active distribution systems

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ABSTRACT

This paper proposes an electrical distance-aware sensitivity planning (EDSP) framework for optimal distributed generation (DG) allocation in active distribution networks (ADNs). EDSP combines electrical distance information with sensitivity-based indicators to identify electrically influential buses and guide DG placement and sizing. A multi-objective planning model is formulated to reduce active power loss, improve voltage profiles, alleviate feeder loading stress, and limit voltage fluctuation under practical operating constraints. Unlike conventional approaches that mainly rely on stochastic search or use topology and sensitivity information separately, EDSP integrates network-wide electrical distance with sensitivity measures to guide both candidate bus prioritization and DG capacity adjustment, thereby improving physical interpretability of the planning process. The framework is validated on the IEEE 33-bus and 69-bus distribution systems and benchmarked against particle swarm optimization (PSO), grey wolf optimization (GWO), whale optimization algorithm (WOA), Harris hawk's optimization (HHO), and multi-objective PSO (MOPSO). Compared with MOPSO, the second-best method, EDSP further reduces active power loss by 4.63% and 4.10% for the 33-bus and 69-bus systems, respectively, while also providing improved voltage regulation and feeder operating performance. These results indicate that EDSP provides an effective and physically interpretable decision-support framework for DG planning in ADNs under the adopted simulation conditions.

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1. INTRODUCTION

Modern active distribution networks (ADNs) have experienced substantial operational changes due to the accelerating adoption of distributed generation (DG) technologies [1], [2]. The integration of renewable DG sources, especially solar photovoltaic and wind-based units, contributes positively to energy sustainability, environmental protection, operational flexibility, and decentralized power supply support [3]. Nevertheless, high DG penetration levels may introduce technical challenges such as voltage instability, feeder overloading, reverse power flow, and operational uncertainty under varying network conditions. Therefore, effective DG planning has become an important issue in modern distribution networks (DNs) [4], [5].

Appropriate DG placement and sizing can substantially improve network operating performance through feeder loss reduction, voltage profile enhancement, operational reliability improvement, and

resilience reinforcement [6], [7]. However, unsuitable DG allocation may lead to voltage rise, feeder instability, branch congestion, and reduced network security. Therefore, optimal DG planning should consider network characteristics, operating constraints, and dynamic system behavior simultaneously [8]. Various optimization techniques have been applied to DG allocation problems in DNs [9], [10]. Conventional analytical approaches provide relatively fast computational performance; however, their effectiveness is often restricted by nonlinear operating conditions and complex network constraints [11]. To address these challenges, various population-oriented optimization techniques have been widely adopted for DG planning problems, including particle swarm optimization (PSO) [12], grey wolf optimization (GWO) [13], whale optimization algorithm (WOA) [14], Harris hawks optimization (HHO) [15], and multi-objective PSO (MOPSO) [16], [17]. Although these methods provide satisfactory optimization performance, most existing approaches still rely heavily on stochastic search behavior with limited consideration of network topology and electrical sensitivity characteristics. Consequently, the obtained solutions may exhibit unstable convergence and limited physical interpretability [18], [19].

Recently, increasing research attention has been directed toward sensitivity-guided and network-aware strategies for DG planning in DNs [20], [21]. Electrical distance analysis provides valuable information regarding electrical coupling relationships among buses and effectively reflects network interaction characteristics within radial DNs [22]. Meanwhile, sensitivity analysis identifies influential buses related to feeder losses, voltage regulation, and branch loading. Combining it with electrical distance therefore provides a physically meaningful basis for DG planning [23]. However, existing topology-based DG planning methods often use network information mainly for candidate screening, while sensitivity-based approaches typically evaluate buses independently. Electrical distance-aware sensitivity planning (EDSP) addresses this limitation by combining network-wide electrical distance with multiple sensitivity measures to guide both candidate prioritization and DG capacity adjustment. Its novelty lies in the coordinated use of topology and sensitivity information throughout the planning process rather than in introducing a new metaheuristic optimizer.

This study proposes an EDSP framework for optimal DG allocation in active DNs. EDSP integrates network-wide electrical distance and sensitivity information to guide candidate bus selection and DG capacity adjustment under practical operating constraints. The framework is validated on the IEEE 33-bus and 69-bus systems and compared with PSO, GWO, WOA, HHO, and MOPSO, showing favorable performance in loss reduction, voltage regulation, feeder security, and convergence behavior. Unlike our previous work [24], which focused on renewable energy absorption, the present study emphasizes topology-informed screening, adaptive capacity adjustment, and physical interpretability. The main contributions are summarized as follows: (i) an EDSP framework is developed for intelligent DG allocation in active DNs; (ii) a topology-oriented sensitivity evaluation mechanism is introduced to identify electrically influential buses for effective DG placement and sizing; (iii) a comprehensive multi-objective formulation considering feeder power losses, voltage deviation, feeder loading risk, and dynamic voltage fluctuation is established; and (iv) the proposed EDSP framework is comprehensively validated on 33-bus and 69-bus DNs and compared with several representative optimization techniques.

The remaining sections of this paper are organized as follows. Section 2 introduces the mathematical model, while section 3 presents the proposed EDSP methodology. Simulation results and comparative analyses are discussed in section 4. Finally, the conclusions are provided in section 5.

2. MATHEMATICAL FORMULATION

The growing integration of DG units has considerably influenced the operating characteristics of modern active DNs [25]. Proper DG placement can improve efficiency and voltage regulation, whereas unsuitable allocation may cause feeder overloading and voltage instability. Therefore, the proposed multi-objective model jointly minimizes active power loss, voltage deviation, feeder loading stress, and voltage fluctuation, as follows:

$$F = w_1 L_{loss} + w_2 V_{dev} + w_3 R_{risk} + w_4 S_{dyn} \quad (1)$$

where L_{loss}, V_{dev}, R_{risk}, and S_{dyn} denote the active power loss, voltage deviation, feeder loading risk, and dynamic voltage fluctuation components, respectively.

The weighting coefficients reflect the planning priorities of this study, with active power loss assigned the highest weight, followed by voltage deviation, feeder loading risk, and dynamic voltage fluctuation. These weights are not universally optimal and may be adjusted according to different operational priorities. The active power loss component is defined as (2).

$$L_{loss} = \sum_{b=1}^{N_b} R_b I_b^2 \quad (2)$$

where R_b and I_b denote the resistance and operating current of branch b, respectively, and N_b denotes the total number of branches in the DN. Minimization of this term contributes directly to energy efficiency improvement and thermal loading reduction throughout feeder operation.

Voltage regulation performance is evaluated using the following voltage deviation formulation (3).

$$V_{dev} = \sum_{i=1}^{N_{bus}} | V_i - 1 | \quad (3)$$

where V_i represents the voltage magnitude at bus i, and N_{bus} denotes the total number of buses in the DN. This term penalizes deviations from the nominal operating condition and improves the overall voltage profile quality of the DN. To strengthen feeder operational security and network resilience characteristics, a feeder loading risk index is introduced as (4).

$$R_{risk} = \sum_{b=1}^{N_b} (\frac{I_b}{I_{b,max}}) C_b \quad (4)$$

where I_b and $I_{b,max}$ denote the operating current and maximum allowable current of feeder branch b, respectively. The parameter C_b represents the branch importance coefficient associated with feeder criticality characteristics. In this study, the branch importance coefficient is determined according to the electrical influence of each feeder branch as (5).

$$C_b = \frac{N_{d,b}}{N_{bus}} \quad (5)$$

where $N_{d,b}$ denotes the number of downstream buses supplied through branch b. Consequently, highly influential feeder sections receive larger penalty values under overloaded operating conditions, thereby improving network operational resilience and feeder security performance. To reduce voltage fluctuation under dynamic operating conditions, a dynamic voltage index is introduced as (6).

$$S_{dyn} = \sum_{i=1}^{N_{bus}} | V_i(t+1) - V_i(t) | \quad (6)$$

where $V_i(t)$ and $V_i(t+1)$ represent the voltage magnitudes at bus i during two successive operating intervals. Minimization of this component improves voltage stability behavior and mitigates dynamic voltage variation throughout network operation.

The proposed DG planning model is solved under practical operating constraints. The voltage constraint is expressed as (7).

$$V_{min} \leq V_i \leq V_{max} \quad (7)$$

The allowable voltage range is maintained according to standard DN requirements as (8).

$$0.95 \leq V_i \leq 1.05 \quad (8)$$

The DG operating capacity constraint is formulated as (9).

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

The feeder thermal operating constraint is represented as (10).

$$I_b \leq I_{b,max} \quad (10)$$

In addition, the total DG penetration level is restricted according to network operational capability as (11).

$$\sum P_{DG} \leq \alpha P_{load,total} \quad (11)$$

where $P_{load,total}$ denotes the total active load demand of the DN and α represents the allowable DG penetration level. These operational constraints ensure secure, reliable, and stable operation of the active DN during the DG planning process.

This section defines the objectives and constraints of the DG planning problem. Based on this formulation, the EDSP framework identifies candidate buses and determines DG locations and capacities, as described in the following section.

3. PROPOSED EDSP FRAMEWORK

This section presents the implementation of the EDSP framework. Rather than introducing a new metaheuristic, EDSP integrates electrical distance and sensitivity information to guide candidate bus selection and DG capacity adjustment through an adaptive update strategy. The framework consists of four stages: electrical distance analysis, sensitivity evaluation, candidate bus selection, and constrained DG optimization. The electrical distance is determined as (12).

$$ED_{ij} = | Z_{ii} + Z_{jj} - 2Z_{ij} | \quad (12)$$

where ED_{ij} denotes the electrical distance between buses i and j. The terms Z_{ii}, Z_{jj}, and Z_{ij} are elements of the bus impedance matrix. A lower ED_{ij} value indicates stronger electrical connectivity between buses, whereas larger values represent weaker coupling characteristics.

The electrical distance matrix is computed after the base-case backward/forward sweep load-flow analysis. First, the bus impedance matrix is established from the network topology and branch impedance data. The electrical distance between every pair of buses is then calculated using (12), resulting in a $N \times N$ symmetric electrical distance matrix. Finally, the obtained distances are normalized according to (19) to eliminate the influence of network size and enable fair comparison among candidate buses.

To identify buses with strong influence on network performance, a sensitivity-based ranking index is developed. For each candidate bus, the sensitivity score is defined as (13).

$$SI_i = \lambda_1 LS_i + \lambda_2 VS_i + \lambda_3 RS_i + \lambda_4 DS_i \quad (13)$$

where SI_i represents the overall sensitivity index of bus i. The terms LS_i, VS_i, RS_i, and DS_i denote the loss sensitivity, voltage sensitivity, risk sensitivity, and dynamic voltage sensitivity of bus i, respectively. The coefficients λ_1, λ_2, λ_3, and λ_4 regulate the contribution of each sensitivity component.

The loss sensitivity component evaluates the contribution of DG injection at bus ito active power loss reduction and is expressed as (14).

$$LS_i = | \frac{\partial P_{loss}}{\partial P_{DG,i}} | \quad (14)$$

where P_{loss} represents the total active power loss of the DN and $P_{DG,i}$ represents the active power injection of DG installed at bus i. A higher value of LS_i indicates that DG installation at bus ican provide stronger loss reduction capability.

The voltage sensitivity component is defined as (15).

$$\mathrm{VS}_i = | \frac{\partial V_i}{\partial P_{\mathrm{DG},i}} | \quad (15)$$

where V_i represents the bus voltage magnitude at node i. This term measures the influence of DG injection on voltage improvement. Candidate buses with higher voltage sensitivity are more effective for enhancing voltage regulation performance.

The feeder loading risk sensitivity is defined as (16).

$$RS_i = | \frac{\partial R_{risk}}{\partial P_{DG,i}} | \quad (16)$$

where R_{risk} is the feeder loading risk index defined in section 2. This component identifies buses whose DG injection can effectively reduce loading stress on critical feeder branches.

To account for dynamic voltage behavior, the dynamic sensitivity component is defined as (17).

$$DS_i = | \frac{\partial S_{dyn}}{\partial P_{DG,i}} | \quad (17)$$

where S_{dyn} denotes the dynamic voltage fluctuation index. This term gives higher priority to DG locations that can reduce voltage variation under changing load and renewable generation conditions.

In practical implementation, the sensitivity components are evaluated by applying the same small DG perturbation at each candidate bus and recalculating the network indices. The resulting changes relative to the base case are normalized to ensure consistent comparison and prevent scale bias. The combined sensitivity score is then weighted by electrical distance, yielding the electrical distance-aware sensitivity index as (18).

$$EDSI_i = SI_i \cdot \left(\frac{1}{1+\bar{ED}_i}\right) \tag{18}$$

where $EDSI_i$ represents the electrical distance-aware sensitivity index of bus i, and ED_i denotes the normalized average electrical distance of bus i relative to the remaining network buses.

The (18) combines the normalized sensitivity score with electrical distance to prioritize buses with strong network response and electrical coupling. This improves the physical interpretability of candidate ranking while reducing exploration of less influential locations. The normalized average electrical distance is calculated as (19).

$$\bar{\mathrm{ED}}_i = \frac{1}{N_{\mathrm{bus}}-1}\sum_{\substack{j=1 \\ j\neq i}}^{N_{\mathrm{bus}}} \frac{\mathrm{ED_{ij}}}{\mathrm{ED_{max}}} \tag{19}$$

where ED_{max} is the maximum electrical distance value in the network. This normalization avoids scale imbalance and allows fair comparison among candidate buses.

After computing $\mathrm{EDSI_i}$, candidate buses are ranked in descending order, with higher values indicating greater suitability for DG installation. The candidate bus set is then defined as (20).

$$\Omega_{DG} = \{i \mid EDSI_i \geq EDSI_{th}\} \tag{20}$$

where Ω_{DG} denotes the candidate DG bus set and $EDSI_{th}$ is the predefined sensitivity threshold. This candidate selection mechanism reduces the search space and improves optimization efficiency.

For each candidate solution, the DG planning vector is defined as (21).

$$X = [B_1, B_2, \ldots, B_{N_{\mathrm{DG}}}, P_{\mathrm{DG},1}, P_{\mathrm{DG},2}, \ldots, P_{\mathrm{DG},N_{\mathrm{DG}}}] \tag{21}$$

where B_k represents the selected bus location of the k-th DG unit, $P_{DG,k}$ denotes its corresponding active power capacity, and N_{DG} is the total number of DG units to be installed.

The DG size is updated within its allowable operating range as (22).

$$P_{DG,k}^{new} = P_{DG,k}^{old} + \eta \cdot EDSI_{B_k} \cdot (P_{DG}^{max} - P_{DG}^{min}) \cdot r \tag{22}$$

where η is the adaptive step coefficient, $EDSI_{B_k}$ is the electrical distance-aware sensitivity value of the selected bus, and ris a random number in the interval $[-1,1]$. The update rule adjusts DG capacity according to the electrical importance of each candidate bus, with larger steps for more influential locations and smaller steps for local refinement. Unlike population-based metaheuristics, EDSP directly uses topology-aware sensitivity information to guide capacity updates and should therefore be viewed as a sensitivity-guided planning framework rather than a standalone optimization algorithm. To maintain feasibility, the updated DG capacity is corrected using (23).

$$P_{DG,k} = min[P_{DG}^{max}, max(P_{DG}^{min} | P_{DG,k})] \tag{23}$$

This correction ensures that all DG capacities remain within their permissible technical limits.

At each iteration, backward/forward sweep load flow analysis is performed to update bus voltages, branch currents, and power losses. The fitness value is then evaluated using the objective function, while penalty terms are added for constraint violations as (24).

$$F_{pen} = F + \mu_1 \sum_{i=1}^{N_{bus}} max(0, V_i - V_{max})^2 + \mu_2 \sum_{i=1}^{N_{bus}} max(0, V_{min} - V_i)^2 + \mu_3 \sum_{b=1}^{N_b} max(0, I_b - I_{b,max})^2 \tag{24}$$

where F_{pen} is the penalized objective value. The parameters μ_1, μ_2, and μ_3 are penalty coefficients for voltage upper limit violation, voltage lower limit violation, and branch current violation, respectively. This mechanism guides the search process toward feasible and secure operating solutions.

The adaptive step coefficient is gradually reduced during the optimization process to balance exploration and exploitation:

$$\eta_{max} - (\frac{\eta_{max}-\eta_{min}}{T_{max}})t \tag{25}$$

where $\eta(t)$ is the step coefficient at iteration t, η_{max} and η_{min} are the maximum and minimum step coefficients, respectively, and T_{max} is the maximum number of iterations. A larger step size promotes exploration in early iterations, whereas a smaller step size improves local refinement near convergence. This gradual reduction balances exploration and exploitation while maintaining the simplicity and stability of the EDSP framework.

The implementation procedure of the proposed EDSP method is summarized as follows. Figure 1 illustrates the overall workflow of the proposed EDSP framework for optimal DG planning.

- Step 1: import network data and operating constraints.
- Step 2: perform backward/forward sweep load flow analysis to obtain the initial operating condition.
- Step 3: calculate the electrical distance matrix using the bus impedance matrix.
- Step 4: evaluate network sensitivity indices for all candidate buses.
- Step 5: identify candidate buses. Electrical distance-aware sensitivity indices are calculated to prioritize influential buses for DG integration.
- Step 6: generate initial DG solution. DG locations and capacities are initialized within allowable operating limits.
- Step 7: perform load flow analysis. Network operating conditions are updated using backward/forward sweep load flow analysis.
- Step 8: evaluate fitness and constraints. The objective function and operational constraints are evaluated, and penalty terms are added if violations occur.
- Step 9: update DG variables. DG locations and capacities are updated according to the adaptive electrical distance-aware sensitivity strategy, and the objective function is re-evaluated after each update.
- Step 10: retain the best solution. The solution with the lowest objective value is preserved.
- Step 11: check stopping criterion. The optimization continues until the maximum iteration number is reached.
- Step 12: obtain optimal solution. Final DG locations, capacities, network losses, voltage profiles, and convergence characteristics are reported.

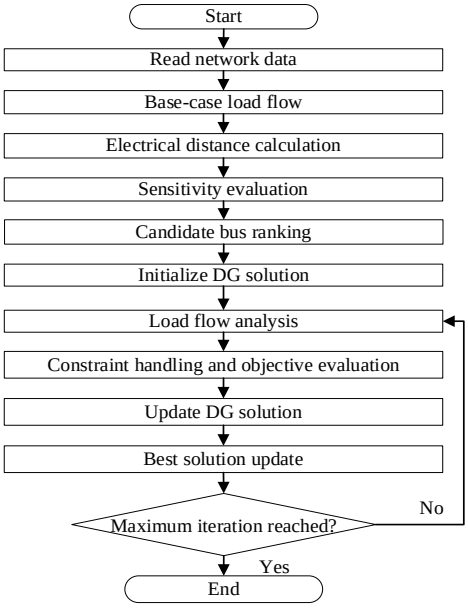


Figure 1. Flowchart of the proposed EDSP framework for DG planning in active DNs

The EDSP framework improves search efficiency and physical interpretability by restricting the search to electrically influential candidate buses identified through electrical distance-aware sensitivity ranking. Its twelve-step implementation procedure is summarized in Figure 1, from network initialization to the final DG planning solution.

4. RESULTS AND DISCUSSION

The IEEE 33-bus and 69-bus systems are used as representative radial distribution benchmarks with different network sizes and operating characteristics. They enable EDSP to be evaluated under different levels of network complexity while maintaining comparability with existing studies. Further validation on larger practical networks remains necessary. The simulation parameters are listed in Table 1.

Table 1. Simulation parameters

Parameter	Value
Simulation environment	MATLAB
Load flow technique	Backward/forward sweep [26]
Test systems	IEEE 33-bus and 69-bus systems
Number of DG units	3
Voltage operating range	0.95 - 1.05 p.u.
Maximum DG penetration	70% of total active load
Population size of benchmark algorithms; maximum iterations	30; 100
Compared methods	PSO, GWO, WOA, HHO, MOPSO, EDSP
Objective weights	$w_1 = 0.4$, $w_2 = 0.25$, $w_3 = 0.20$, $w_4 = 0.15$
Performance indices	$L_{loss}, V_{dev}, R_{risk}, S_{dyn}, V_{min}$

4.1. 33-bus distribution power system

Figure 2 shows the 33-bus radial DN, consisting of 33 buses and 32 feeder branches. Under the adopted simulation settings, EDSP achieves the lowest power loss, the highest minimum bus voltage, reduced feeder loading stress, and improved voltage stability. Detailed results are presented in Table 2.

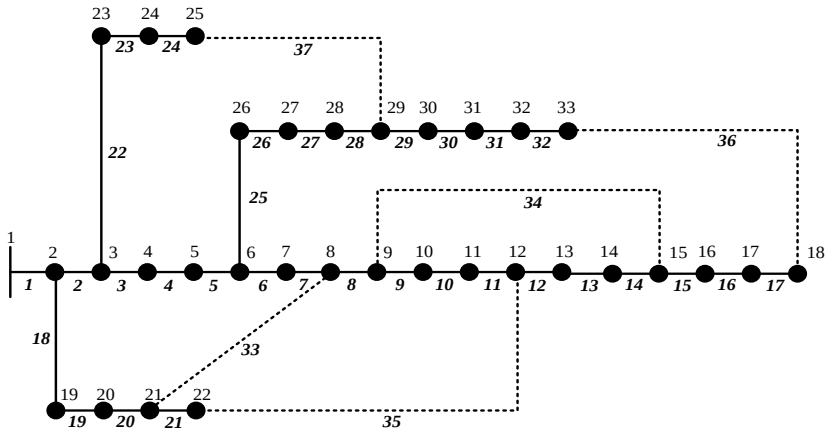


Figure 2. Single-line configuration of the IEEE 33-bus distribution system [27]

Table 2. Optimal DG allocation results for the IEEE 33-bus distribution network

Method	DG locations	DG sizes (kW)	L_{loss}	V_{dev}	R_{risk}	S_{dyn}	V_{min} (p.u.)
Base case	-	-	210.98	1.8426	5.2164	0.1845	0.9038
PSO	13, 24, 30	720, 860, 780	78.63	0.6241	2.3187	0.0816	0.9715
GWO	13, 24, 30	745, 890, 805	74.82	0.5714	2.1063	0.0732	0.9741
WOA	13, 24, 30	752, 902, 815	72.94	0.5487	1.9846	0.0694	0.9756
HHO	13, 24, 30	760, 915, 828	71.45	0.5218	1.8735	0.0648	0.9768
MOPSO	13, 24, 30	772, 926, 841	69.36	0.4862	1.7461	0.0587	0.9781
EDSP	13, 24, 30	795, 948, 867	66.15	0.4516	1.5824	0.0513	0.9794

Table 2 and Figures 3(a) to (d) present the comparative performance of the proposed EDSP framework and the benchmark methods for the 33-bus DN. In the base operating condition, the system experiences an active power loss of 210.98 kW with a minimum voltage of 0.9038 p.u., indicating considerable feeder loss and poor voltage quality before DG installation. After DG integration, all investigated methods improve network performance, while EDSP provides the most favorable numerical results under the adopted simulation settings. The proposed method decreases the active power loss to 66.15 kW, corresponding to a reduction of 68.64% relative to the base case. This value is lower than those obtained by PSO, GWO, WOA, HHO, and MOPSO. Compared with PSO and MOPSO, EDSP further reduces the power loss by 15.87% and 4.63%, respectively. These results indicate that the electrical distance-aware sensitivity strategy can effectively identify suitable DG locations and capacities for loss minimization.

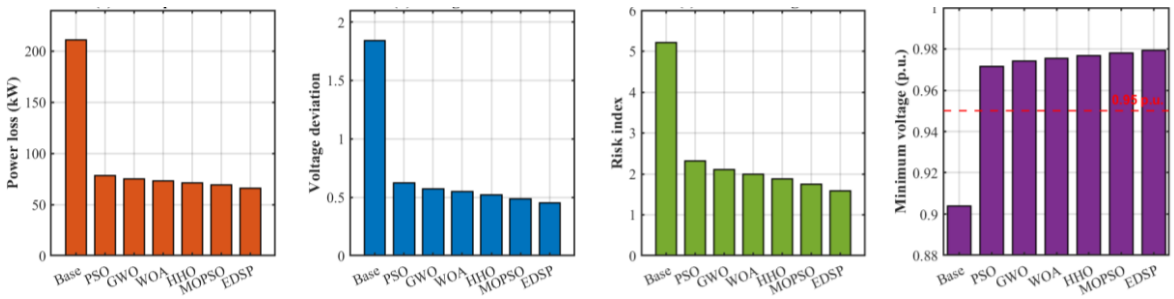


Figure 3. Performance comparison for the 33-bus system: (a) active power loss, (b) voltage deviation, (c) feeder loading risk, and (d) minimum bus voltage

Voltage regulation performance is improved after DG integration using the proposed EDSP framework. The minimum bus voltage increases from 0.9038 p.u. in the base condition to 0.9794 p.u., which is higher than the values achieved by PSO, GWO, WOA, HHO, and MOPSO. In addition, EDSP obtains the lowest voltage deviation index of 0.4516, indicating improved voltage profile performance throughout the network. The proposed method also achieves the minimum feeder loading risk value of 1.5824 and the lowest dynamic voltage fluctuation index of 0.0513, demonstrating its effectiveness in reducing feeder stress and improving voltage stability under varying operating conditions. Overall, the obtained results indicate that EDSP provides a favorable and physically meaningful DG planning solution by integrating electrical distance characteristics with sensitivity-guided search capability.

4.2. 69-bus distribution power system

Figure 4 presents the single-line configuration of the 69-bus radial DN considered in this study. Compared with the 33-bus system, the 69-bus network has a larger and more complex feeder structure consisting of 69 buses and 68 radial branches.

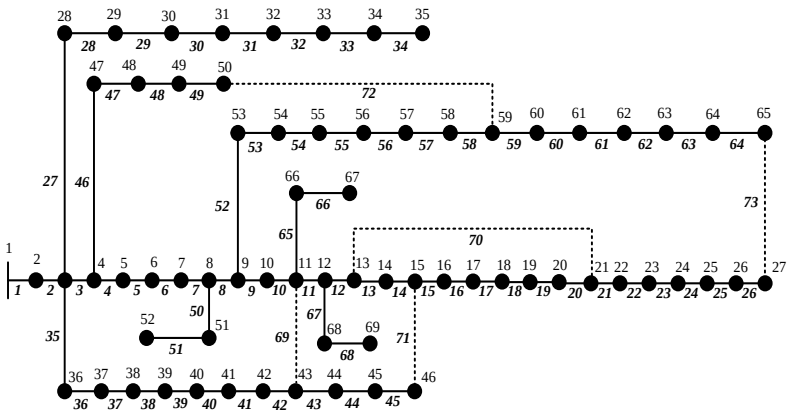


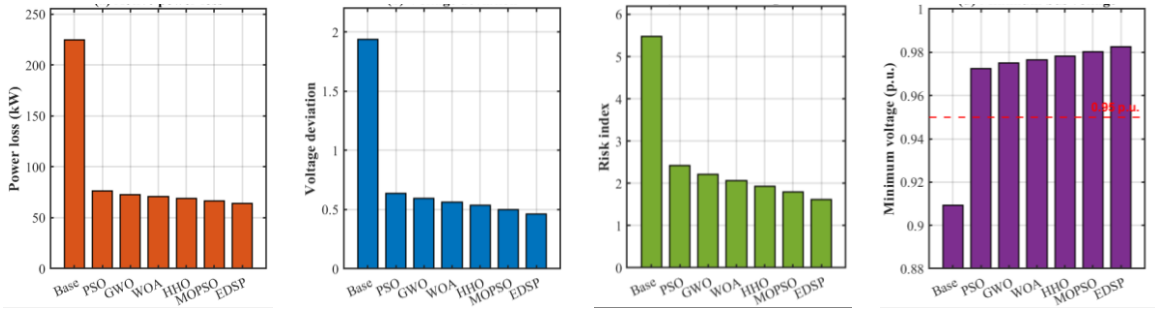
Figure 4. Single-line configuration of the IEEE 69-bus distribution system [27]

A similar performance trend is observed in the 69-bus system. EDSP continues to provide favorable overall planning performance by simultaneously reducing network losses, improving voltage regulation, and enhancing voltage stability. The comparative results are summarized in Table 3.

Table 3. Optimal DG allocation results for the IEEE 69-bus distribution network

Method	DG locations	DG sizes (kW)	L_{loss}	V_{dev}	R_{risk}	S_{dyn}	V_{min} (p.u.)
Base case	-	-	224.95	1.9368	5.4821	0.1964	0.9092
PSO	17, 50, 61	690, 940, 820	76.45	0.6382	2.4215	0.0863	0.9724
GWO	18, 50, 61	715, 965, 842	72.48	0.5967	2.2138	0.0785	0.9751
WOA	18, 49, 61	724, 978, 855	70.62	0.5634	2.0712	0.0734	0.9764
HHO	18, 50, 61	736, 991, 866	68.79	0.5348	1.9286	0.0681	0.9782
MOPSO	18, 50, 61	748, 1005, 879	66.57	0.5013	1.7925	0.0618	0.9801
EDSP	18, 50, 61	766, 1028, 897	63.84	0.4629	1.6147	0.0542	0.9826

For the 69-bus DN, the results in Table 3 and Figures 5(a) to (d) further illustrate the performance of the proposed EDSP framework on a larger benchmark network. The base-case network has an active power loss of 224.95 kW and a minimum voltage of 0.9092 p.u., reflecting a relatively stressed operating condition before DG integration. After optimization, EDSP achieves the lowest power loss of 63.84 kW, corresponding to a loss reduction of 71.62% compared with the base case.



(a) (b) (c) (d)

Figure 5. Performance comparison for the 69-bus system: (a) active power loss, (b) voltage deviation, (c) feeder loading risk, and (d) minimum bus voltage

Under the adopted simulation settings, EDSP yields the lowest reported objective values among the investigated methods for the 69-bus DN. In particular, the active power loss is reduced to 63.84 kW, which is lower than the values obtained by PSO, GWO, WOA, HHO, and MOPSO. Compared with MOPSO, the second-best method, EDSP further reduces active power loss by 4.10%, indicating the effectiveness of the proposed sensitivity-guided planning strategy for the larger radial network. Voltage regulation performance is also improved, with the minimum bus voltage increasing from 0.9092 p.u. in the base case to 0.9826 p.u. using EDSP. In addition, the proposed method achieves the lowest values of V_{dev}, R_{risk}, and S_{dyn}, indicating improved voltage quality, lower feeder loading stress, and improved dynamic voltage stability. The favorable performance of EDSP results from combining network-wide electrical distance with local sensitivity information. This enables the framework to prioritize buses that are both electrically influential and responsive to DG injection, thereby focusing capacity adjustment on more promising locations and improving the physical interpretability of the planning process.

Overall, EDSP achieves favorable performance by combining electrical distance and sensitivity information to focus the search on electrically influential locations. The reported results provide comparative numerical evidence under common simulation conditions rather than a formal statistical demonstration of superiority. Full multi-run statistical analysis is left for future work. The main limitations include sensitivity to parameter selection, validation only on the 33-bus and 69-bus systems, and the absence of uncertainty and time-varying operating conditions. Future work will address repeated simulations, parameter sensitivity, larger practical networks, and uncertainty-aware multi-period planning.

5. CONCLUSION

The obtained results indicate that EDSP provides a topology-guided and physically interpretable approach to DG planning by combining electrical distance information with sensitivity-based candidate screening and adaptive capacity adjustment. Rather than relying solely on stochastic population search, the framework narrows the planning space toward electrically influential locations, improving the transparency and efficiency of the decision process. The results obtained on the IEEE 33-bus and 69-bus systems indicate that EDSP can support DN planners in screening promising DG locations before detailed sizing and evaluation, thereby reducing unnecessary candidate assessments under the considered simulation conditions. The present study is limited to deterministic benchmark networks and therefore does not fully represent uncertainty, temporal variability, or large-scale practical operating conditions. Future research will extend EDSP to uncertainty-aware and multi-period planning with renewable generation, battery energy storage systems, electric vehicles, and real-time DN applications.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Trieu Ngoc Ton	✓	✓		✓		✓	✓		✓	✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest that could have influenced the objectivity of this research or its publication.

DATA AVAILABILITY

The data generated and analyzed during this study are available from the corresponding author upon reasonable request.

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