

Particle Swarm Optimization for Risk-Aware Distributed Generation Planning in Distribution Networks

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Abstract— High penetration of distributed generation (DG) improves distribution network performance but may increase voltage rise and reverse power flow, threatening secure operation. This paper proposes a Particle Swarm Optimization (PSO)-based DG planning framework that simultaneously minimizes active power loss, mitigates voltage risk, suppresses reverse power flow, and maximizes DG penetration. A normalized multi-objective function integrates these criteria into a unified optimization model, while penalty functions enforce network operating constraints. The proposed method is validated on the 33-bus and 69-bus radial distribution systems and compared with GSA, MVM0-SH, and conventional PSO. For the 33-bus system, the proposed approach reduces active power loss by 36.47%, increases the minimum bus voltage from 0.913 p.u. to 0.964 p.u., and limits reverse power flow to 13.2 kW. For the 69-bus system, it achieves a 61.92% reduction in power loss, improves the minimum voltage from 0.909 p.u. to 0.972 p.u., and decreases reverse power flow to 18.9 kW while providing the highest DG penetration among the compared methods. The results demonstrate that explicitly considering voltage risk and reverse power flow enables more effective and reliable DG planning for active distribution networks.

Keywords: Distributed generation, Distribution networks, Multi-objective optimization, Reverse power flow, Voltage stability.



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INTRODUCTION

The rapid deployment of distributed generation (DG), particularly photovoltaic (PV) systems, is fundamentally transforming the operation of modern distribution networks (DNs) [1], [2]. While local generation improves energy efficiency and facilitates the integration of renewable resources, high DG penetration also introduces significant operational challenges [3], [4]. Unlike conventional radial networks designed for unidirectional power delivery, active DNs increasingly experience bidirectional power flows, voltage rise, and reverse power transfer toward upstream substations [5], [6]. These phenomena may reduce voltage security margins, complicate protection coordination, and limit the hosting capacity of renewable energy resources [7], [8].

Optimal DG planning has therefore become an important research topic for improving the technical and economic performance of DNs. Numerous optimization techniques, including Genetic Algorithm (GA) [9], Gravitational Search Algorithm (GSA) [10], Particle Swarm Optimization (PSO) [11], and Mean-Variance Mapping Optimization with Swarm Heuristic (MVM0-SH) [12], have been successfully applied to determine the optimal locations and

capacities of DG units. Most existing studies formulate the planning problem by minimizing network power losses while maintaining voltage and current within prescribed operating limits [13]. Although these approaches effectively improve network efficiency, voltage violations and reverse power flow are generally treated as constraints rather than explicit optimization objectives. Consequently, the obtained DG allocation may satisfy operational limits but still operate close to critical voltage conditions or produce considerable reverse power flow under high renewable penetration [14], [15].

In practical DNs, operating close to the upper voltage limit represents a potential operational risk because relatively small variations in renewable generation or load demand may lead to voltage violations. Likewise, excessive reverse power flow can increase transformer loading, affect voltage regulation equipment, and deteriorate protection coordination. Therefore, DG planning should not only minimize active power loss but also improve voltage security and restrict undesirable upstream power injection. Explicitly incorporating these operational aspects into the optimization objective can produce more reliable and practically applicable planning solutions.

Motivated by these considerations, this paper proposes a PSO-based DG planning framework that simultaneously minimizes active power loss, mitigates voltage risk, suppresses reverse power flow, and promotes higher DG penetration. A normalized multi-objective formulation is developed to balance these conflicting objectives within a unified optimization framework, while Particle Swarm Optimization is employed to efficiently determine the optimal DG locations and capacities. Compared with conventional loss-oriented planning strategies, the proposed formulation provides a more comprehensive assessment of DN operating performance under high renewable penetration.

The main contributions of this work can be summarized as follows. First, a normalized multi-objective function is developed to simultaneously consider active power loss, voltage risk, reverse power flow, and DG penetration within a unified planning framework. Second, voltage risk is explicitly incorporated into the optimization objective to improve voltage security margins rather than merely enforcing voltage constraints. Third, reverse power flow is formulated as an optimization criterion to reduce undesirable upstream power injection while maintaining high renewable energy utilization. Finally, the proposed PSO-based framework is validated on the 33-bus and 69-bus benchmark systems and compared with several existing optimization methods to demonstrate its effectiveness and robustness.

The remainder of this paper is organized as follows. Section II presents the mathematical formulation of the DG planning problem. Section III describes the proposed PSO-based optimization framework. Section IV discusses the simulation results and comparative analysis, and Section V concludes the paper.

METHOD

A. Problem Formulation

The objective of this study is to determine the optimal siting and sizing of DG units in a DN while explicitly considering voltage risk and reverse power flow. The active power capacity of each DG unit and its installation location are treated as decision variables. Therefore, the problem is formulated as a mixed-integer optimization problem, in which both the placement and the capacity of DG units are optimized simultaneously.

Unlike conventional DG planning approaches that mainly aim to minimize power loss or satisfy voltage constraints, this study proposes a risk-aware objective function. The proposed formulation considers four aspects: power loss reduction, voltage risk mitigation, reverse

power flow limitation, and DG integration enhancement. To avoid scale imbalance among different objective terms, each component is normalized using its corresponding base or reference value. The objective function is expressed as follows:

$$\min F = w_1 \frac{F_{loss}}{F_{loss}^{base}} + w_2 \frac{F_{VRisk}}{F_{VRisk}^{ref}} + w_3 \frac{F_{RPF}}{F_{RPF}^{ref}} - w_4 \frac{F_{DG}}{P_{load}} \quad (1)$$

where w_1 , w_2 , w_3 , and w_4 denote the weighting coefficients associated with active power loss, voltage risk, reverse power flow, and DG penetration, respectively. In this study, the coefficients are selected as $w_1 = 0.4$, $w_2 = 0.3$, $w_3 = 0.2$, and $w_4 = 0.1$, satisfying $\sum_{i=1}^4 w_i = 1.0$. Since all objective components are normalized, these coefficients represent the relative priority assigned to each planning objective rather than compensating for differences in numerical magnitude. Greater emphasis is placed on minimizing active power loss and maintaining voltage security, while reverse power flow mitigation and DG penetration enhancement are incorporated to achieve a balanced and practically feasible DG planning solution. The total active power loss is calculated from the resistive losses of all distribution branches as follows:

$$F_{loss} = \sum_{(i,j) \in \Omega_L} R_{ij} I_{ij}^2 \quad (2)$$

where Ω_L denotes the set of distribution branches, R_{ij} is the resistance of branch $i - j$, and I_{ij} is the corresponding branch current.

To capture the gradual deterioration of voltage conditions, a voltage risk function is introduced. Instead of penalizing only voltage violations, this function assigns a higher penalty when the nodal voltage approaches its upper permissible limit:

$$F_{VRisk} = \sum_{i \in \Omega_N} \frac{1}{V_{max} - V_i + \varepsilon} \quad (3)$$

where Ω_N is the set of buses, V_i is the voltage magnitude at bus i , V_{max} is the upper voltage limit, and ε is a small positive constant used to avoid numerical singularity.

The reverse power flow penalty is defined based on the active power exchange at the substation. When the substation power becomes negative, power is injected from the DN back to the upstream grid and is therefore penalized:

$$F_{RPF} = \sum_{t \in \Omega_T} [\max(0, -P_{sub}(t))]^2 \quad (4)$$

where Ω_T is the set of operating time intervals and $P_{sub}(t)$ is the active power measured at the substation at time t .

To avoid overly conservative DG planning, the DG integration term is included to reward higher installed DG capacity:

$$F_{DG} = \sum_{i \in \Omega_N} P_{DG,i} \quad (5)$$

where $P_{DG,i}$ is the DG capacity installed at bus i .

The proposed optimization model is subject to the standard operating constraints of radial DNs to ensure that the obtained DG planning solution is both technically feasible and operationally secure. The equality constraints are represented by the active and reactive power balance equations, whereas the inequality constraints include the limits on bus voltage magnitude, branch current, and DG capacity.

The active and reactive power balance equations are expressed as

$$P_i^G + P_i^{DG} - P_i^L = \sum_{j \in \Omega_i} P_{ij} \quad (6)$$

$$Q_i^G + Q_i^{DG} - Q_i^L = \sum_{j \in \Omega_i} Q_{ij} \quad (7)$$

where P_i^G and Q_i^G denote the active and reactive power supplied from the upstream network, P_i^{DG} and Q_i^{DG} represent the active and reactive outputs of the DG unit, and P_i^L and Q_i^L are the corresponding load demands at bus i . The operational constraints are defined as

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

$$I_k \leq I_k^{max} \quad (9)$$

$$P_{DG,i}^{min} \leq P_{DG,i} \leq P_{DG,i}^{max} \quad (10)$$

where V_i is the voltage magnitude at bus i , I_k is the current flowing through branch k , and $P_{DG,i}$ denotes the installed DG capacity at candidate bus i .

Since all objective components are normalized, these coefficients represent the relative importance of each planning objective rather than compensating for differences in numerical magnitude. A higher priority is assigned to active power loss reduction because improving network efficiency remains the primary objective of DG planning. The second-largest weight is allocated to voltage risk mitigation to preserve adequate voltage security under high DG penetration. The remaining weights are assigned to reverse power flow suppression and DG penetration enhancement to achieve a balanced compromise between operational security and renewable energy utilization.

Overall, the proposed formulation provides a comprehensive DG planning framework that simultaneously minimizes active power loss, mitigates voltage risk, suppresses reverse power flow, and promotes higher DG penetration while satisfying all network operating constraints.

B. Proposed DG Planning Framework

The proposed DG planning problem is formulated as a nonlinear mixed-integer optimization problem because the DG locations are discrete variables, whereas the DG capacities are continuous variables. Owing to its simplicity, computational efficiency, and strong global search capability, PSO is adopted to solve the proposed optimization problem. In the PSO framework, each particle represents a candidate DG planning solution consisting of the installation locations and capacities of the DG units.

The PSO parameter settings adopted in this study are summarized in Table 1. These parameters are selected according to commonly recommended values in the literature to provide a suitable balance between global exploration, local exploitation, convergence speed, and computational efficiency. A linearly decreasing inertia weight is employed to enhance the

global search capability during the early iterations and to improve local refinement near the optimal solution in the final search stage. The cognitive and social acceleration coefficients are both assigned a value of 2.0 to ensure stable convergence of the swarm.

Table 1. PSO Parameter Settings

Parameter	Value
Swarm size	40
Maximum iterations	150
Inertia weight (w)	0.9 - 0.4
c_1 ; c_2	2; 2
Velocity limit	$\pm 20\%$ of the search range
Number of DG units	3
Number of independent runs	30

The overall fitness function used in the PSO procedure can be written as:

$$Fit = F + \lambda_V C_V + \lambda_I C_I + \lambda_{DG} C_{DG} \quad (11)$$

where F is the normalized objective function defined in (1), while C_V , C_I , and C_{DG} denote the penalty functions associated with voltage magnitude violations, branch current violations, and DG capacity violations, respectively. The penalty coefficients λ_V , λ_I , and λ_{DG} are assigned sufficiently large values to ensure that infeasible solutions receive lower fitness values than feasible solutions, thereby guiding the optimization process toward technically feasible operating points.

The voltage violation term is defined as:

$$C_V = \sum_{i \in \Omega_N} [\max(0, V_i - V_{max}) + \max(0, V_{min} - V_i)]^2 \quad (12)$$

The branch current violation term is expressed as:

$$C_I = \sum_{(i,j) \in \Omega_L} [\max(0, I_{ij} - I_{ij}^{max})]^2 \quad (13)$$

The DG capacity violation term is given by:

$$C_{DG} = \sum_{i \in \Omega_N} [\max(0, P_{DG,i} - P_{DG,i}^{max}) + \max(0, P_{DG,i}^{min} - P_{DG,i})]^2 \quad (14)$$

During the iterative search process, the velocity and position of each particle are updated according to

$$v_i^{k+1} = w v_i^k + c_1 r_1 (pbest_i - x_i^k) + c_2 r_2 (gbest - x_i^k) \quad (15)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (16)$$

where v_i^k and x_i^k denote the velocity and position of particle i at iteration k , respectively. The variables $pbest_i$ and $gbest$ represent the personal best and global best solutions, whereas r_1 and r_2 are uniformly distributed random numbers within the interval $[0,1]$. The parameters w , c_1 , and c_2 denote the inertia weight, cognitive acceleration coefficient, and social acceleration coefficient, respectively.

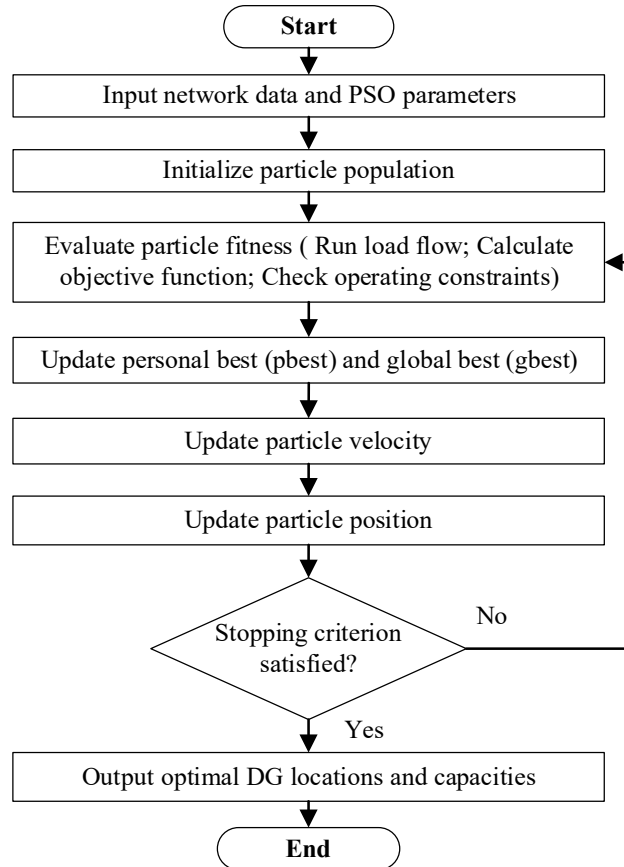


Figure 1. Flowchart of the Proposed PSO-based DG Planning Procedure

The overall optimization procedure is illustrated in Figure 1 and summarized as follows.

Step 1. Input system data and PSO parameters: Read the network data, including line parameters, load demand, operating limits, candidate DG buses, and PSO parameters. Perform the base-case load-flow analysis to obtain the reference values required for objective normalization.

Step 2. Initialize particle population: Randomly generate the initial swarm by assigning feasible DG locations and capacities within the allowable search ranges.

Step 3. Evaluate particle fitness: Perform the load-flow calculation, evaluate the fitness function, and verify all operating constraints for each particle.

Step 4. Update personal and global best solutions: Compare the current fitness value with the stored personal best and global best values, and update them whenever an improved solution is identified.

Step 5. Update particle velocity and position: Update the particle velocity and position using (15) and (16). Any infeasible DG location or capacity is corrected to satisfy the predefined operating limits.

Step 6. Check the stopping criterion: If the maximum number of iterations is reached or the global best solution converges, terminate the optimization; otherwise, return to Step 3.

Step 7. Output the optimal DG planning solution: Report the optimal DG locations and capacities together with the corresponding active power loss, voltage profile, voltage risk, reverse power flow, and DG penetration level.

RESULT AND DISCUSSION

A. Test systems and simulation setup

The proposed DG planning framework was evaluated using the widely adopted 33-bus and 69-bus radial DNs, which are commonly employed as benchmark networks for assessing DG allocation strategies. The 33-bus system consists of 33 buses and 32 distribution branches with a total active and reactive load demand of 3.715 MW and 2.3 MVar, respectively. The 69-bus system comprises 69 buses and 68 branches, supplying a total load of 3.802 MW and 2.694 MVar. These test systems represent medium-scale radial feeders with significant voltage drops toward the end of the feeder, making them suitable for evaluating voltage regulation and power loss reduction through DG integration.

All simulations were carried out in MATLAB R2023a using the backward/forward sweep power-flow algorithm because of its computational efficiency and numerical robustness for radial DNs [16], [17]. DG units were modeled as constant active power sources operating at unity power factor, and the candidate installation buses excluded the substation bus. Network operating constraints included a voltage limit of 0.95–1.05 p.u., branch current limits, and DG capacity limits, as defined in Section II. The weighting coefficients of the objective function were selected as $w_1 = 0.4$, $w_2 = 0.3$, $w_3 = 0.2$, and $w_4 = 0.1$ to balance power loss reduction, voltage risk mitigation, reverse power flow suppression, and DG penetration enhancement.

The proposed PSO algorithm employed a swarm size of 40 particles and a maximum of 150 iterations. A linearly decreasing inertia weight from 0.9 to 0.4 was adopted, while the cognitive and social acceleration coefficients were both set to 2.0. To reduce the influence of stochastic initialization, each optimization method was independently executed 30 times, and the best feasible solution was selected for performance evaluation. The proposed framework was compared with GSA [10], MVMO-SH [18], and a conventional loss-oriented DG planning approach using identical simulation conditions to ensure a fair and consistent comparison. To ensure consistency, all performance indices are defined using standard notations, including P_{loss} , V_{min} , F_{VR} , P_{rev} , and η_{DG} .

B. Results for the 33-bus system

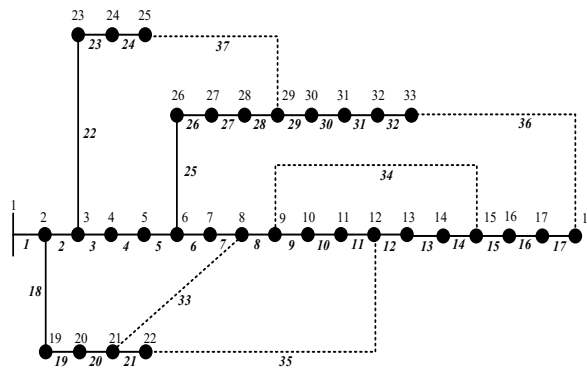


Figure 2. Diagram of the 33-Bus DN

The 33-bus DN consists of 33 buses and 32 branches, as illustrated in Figure 2. The system represents a typical radial configuration comprising the main substation, feeder lines, and load buses, and is widely adopted as a benchmark for evaluating DG planning methods. The system data and technical parameters were obtained from well-established references to ensure the accuracy and reproducibility of the simulation results [19].

Table 2. Performance Comparison for the 33-Bus System

Case	P_{loss} (kW)	ΔP_{loss} (%)	V_{min} (p.u.)	F_{VR}	P_{rev} (kW)	η_{DG} (%)
Base case	202.67	–	0.913	1	0	0
GSA [10]	144.86	28.52	0.946	0.79	95.8	60.4
MVMO-SH [18]	134.81	33.48	0.956	0.66	69.7	64.8
Proposed PSO	128.76	36.47	0.964	0.52	13.2	68.4

The performance of the proposed PSO-based DG planning framework on the 33-bus DN is presented in Table 2 and illustrated in Figure 3. The base case exhibits a relatively high active power loss of 202.67 kW and a minimum bus voltage of 0.913 p.u., indicating that the original radial feeder operates with considerable voltage drop and inefficient power transfer. After DG installation, all optimization methods improved the operating conditions of the network; however, the degree of improvement varies significantly among the compared methods. GSA reduces the power loss to 144.86 kW, while MVMO-SH further decreases it to 134.81 kW. In comparison, the proposed PSO method achieves the lowest power loss of 128.76 kW, corresponding to a 36.47% reduction from the base case. This result confirms that the proposed formulation provides a more effective allocation of DG units by simultaneously considering power loss reduction, voltage risk, and reverse power flow behavior during the optimization process.

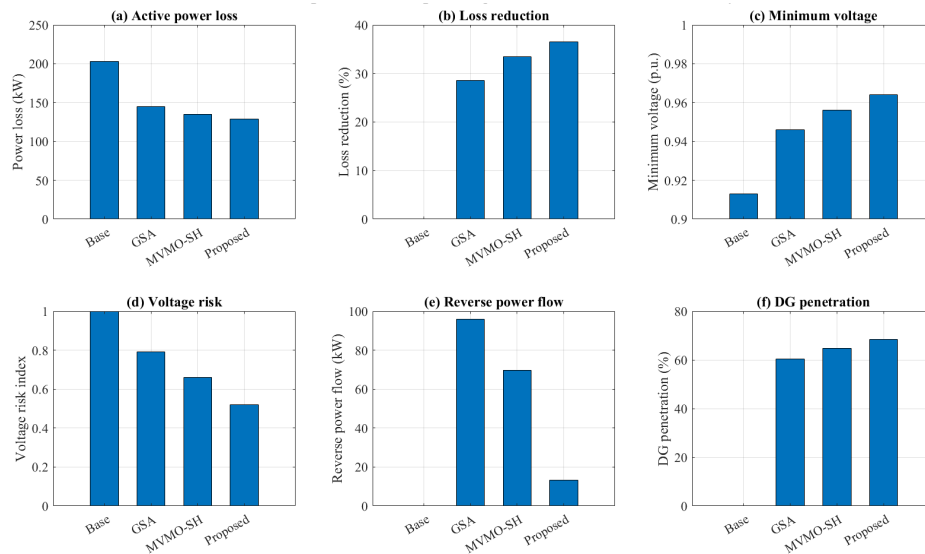


Figure 3. Performance Comparison of Different DG Planning Methods for the 33-Bus DN

In terms of voltage performance, the proposed method also yields the most favorable result. The minimum bus voltage increases from 0.913 p.u. in the base case to 0.964 p.u. after optimization, which is higher than those obtained by GSA and MVMO-SH, indicating superior voltage support capability along the feeder. More importantly, the voltage risk index decreases from 1.00 to 0.52, confirming that the optimized operating point is no longer close to critical voltage conditions. Therefore, the proposed method does not merely satisfy voltage constraints but also enhances the voltage security margin of the DN. A key advantage of the proposed framework is evident in the reverse power flow results. Although GSA and MVMO-SH improve power loss and voltage magnitude, they still produce relatively high reverse power flow values of 95.8 kW and 69.7 kW, respectively. Such upstream power injection may raise operational concerns related to transformer loading, voltage regulation, and protection coordination. By contrast, the proposed PSO method limits reverse power flow to only 13.2 kW while still achieving the highest DG penetration level of 68.4%, indicating that the proposed objective function effectively balances renewable energy utilization with secure feeder

operation.

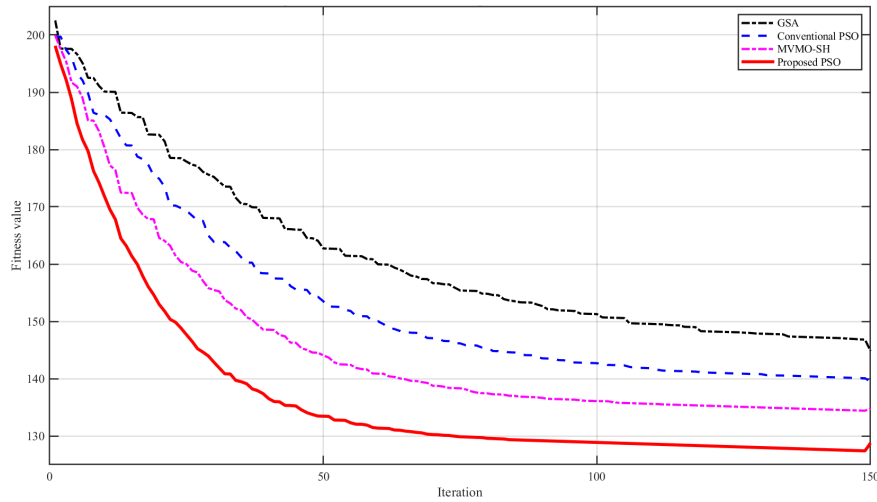


Figure 4. Convergence Curves of Different Optimization Methods for the 33-Bus System

The convergence behavior shown in Figure 4 further supports the effectiveness of the proposed optimization strategy. Compared with GSA, MVMO-SH, and conventional PSO, the proposed method converges more rapidly and reaches the lowest final fitness value. The fitness curve decreases sharply during the early iterations and stabilizes after approximately 80 iterations, reflecting a smooth transition from global exploration to local exploitation. This behavior demonstrates that the proposed PSO-based framework is not only effective in obtaining a high-quality DG planning solution but also computationally stable when applied to the 33-bus system. Overall, the results presented in Table 2, Figure 3, and Figure 4 confirm that the proposed method offers a superior balance among power loss reduction, voltage improvement, reverse power flow mitigation, and DG penetration enhancement.

C. Results for the 69-Bus System

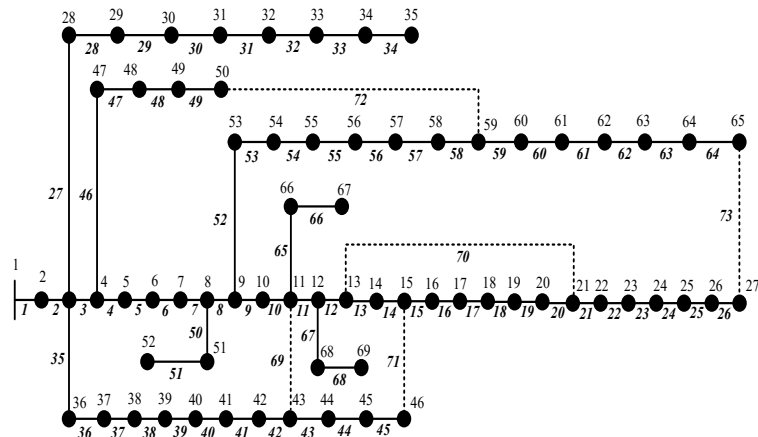


Figure 5. Diagram of the 69-Bus DN

The 69-bus DN consists of 69 buses and 68 branches, as shown in Figure 5. The system represents a larger radial configuration with longer feeder sections and higher impedance, making it more suitable for evaluating DG integration under more challenging operating conditions. The system data and technical parameters were obtained from well-established references to ensure the accuracy and reproducibility of the simulation results [20].

The proposed DG planning framework was further validated using the 69-bus radial distribution system, which represents a larger and more heavily loaded distribution network than the 33-bus system. Owing to its longer feeder length and higher branch impedance, the 69-bus network is more susceptible to voltage degradation and reverse power transfer under high DG penetration. The comparative results summarized in Table 3 and illustrated in Figure 6 demonstrate that all optimization methods improve the operating performance of the distribution system; however, noticeable differences are observed in their ability to simultaneously satisfy multiple planning objectives.

Table 3. Performance Comparison for the 69-Bus System

Case	P_{loss} (kW)	ΔP_{loss} (%)	V_{min} (p.u.)	F_{VR}	P_{rev} (kW)	η_{DG} (%)
Base case	224.95	—	0.909	1	0	0
GSA [10]	106.82	52.51	0.955	0.73	126.8	62.7
MVMO-SH [18]	93.58	58.4	0.966	0.59	82.6	68.1
Proposed PSO	85.63	61.92	0.972	0.45	18.9	71.2

The base-case network exhibits an active power loss of 224.95 kW with a minimum bus voltage of 0.909 p.u., as presented in Table 3, indicating a relatively weak voltage profile along the downstream buses. The implementation of GSA and MVMO-SH significantly reduces feeder losses to 106.82 kW and 93.58 kW, corresponding to loss reductions of 52.51% and 58.40%, respectively. Nevertheless, the proposed PSO framework further decreases the active power loss to 85.63 kW, achieving the highest reduction of 61.92% among all compared methods. This additional improvement indicates that the proposed objective function guides the optimization process toward DG configurations that more effectively redistribute feeder power flows and reduce branch current magnitudes throughout the network.

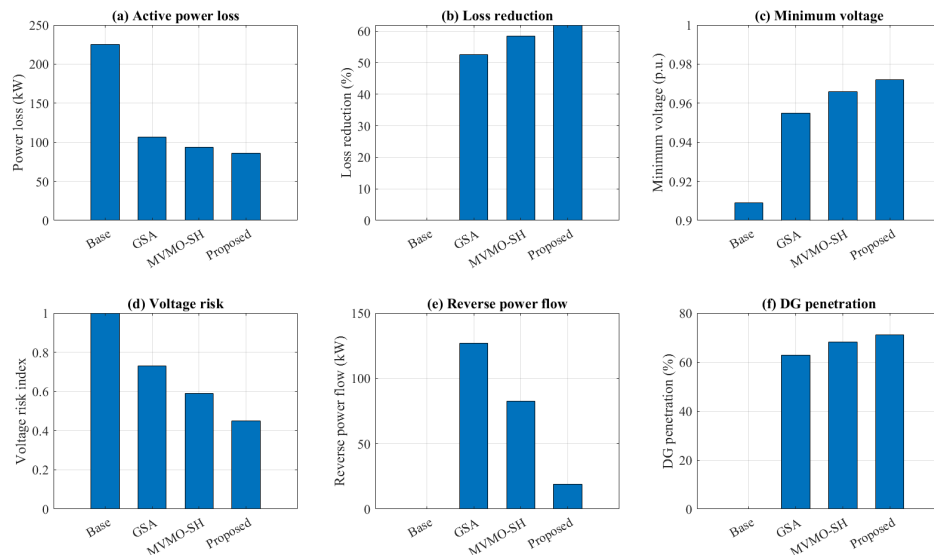


Figure 6. Performance Comparison of Different DG Planning Methods for the 69-Bus System

Voltage performance is also substantially enhanced after DG installation. The minimum bus voltage increases from 0.909 p.u. in the base case to 0.972 p.u. with the proposed method, whereas GSA and MVMO-SH achieve minimum voltages of 0.955 p.u. and 0.966 p.u., respectively. These results demonstrate that the optimized DG allocation not only compensates for voltage drops at remote buses but also improves the overall voltage distribution along the feeder. Consistent with this observation, the voltage risk index decreases from 1.00 to 0.45, representing the lowest value among all investigated methods. This reduction confirms that the proposed planning strategy increases the operational voltage

margin and decreases the likelihood of buses approaching critical voltage conditions under high renewable penetration.

Another important observation is the significant reduction in reverse power flow. Although GSA and MVMO-SH effectively minimize feeder losses, they allow considerable upstream power injection of 126.8 kW and 82.6 kW, respectively. Such operating conditions may adversely affect transformer loading, voltage regulation devices, and protection coordination in practical distribution systems. By explicitly incorporating reverse power flow into the optimization objective, the proposed PSO framework limits the reverse power flow to only 18.9 kW, representing a reduction of more than 77% compared with MVMO-SH and approximately 85% compared with GSA. This result demonstrates that the proposed formulation achieves a more practical DG planning solution by balancing energy efficiency with secure network operation. Furthermore, the comparison of DG penetration levels highlights the effectiveness of the proposed framework. While GSA and MVMO-SH accommodate DG penetration levels of 62.7% and 68.1%, respectively, the proposed method increases renewable integration to 71.2% without compromising voltage quality or operational security. This finding indicates that a higher penetration of distributed generation can be achieved when voltage risk assessment and reverse power flow mitigation are considered simultaneously during the optimization process, rather than relying solely on conventional loss minimization.

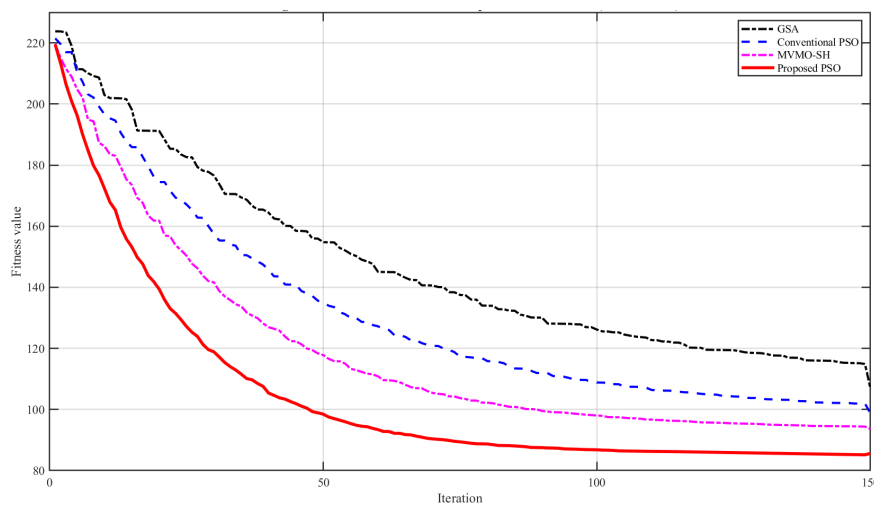


Figure 7. Convergence Curves of Different Optimization Methods for the 69-Bus System

The convergence characteristics of all compared methods are illustrated in Figure 7. The proposed method exhibits the fastest convergence rate and reaches the lowest fitness value after approximately 90 iterations, outperforming GSA, MVMO-SH, and conventional PSO. The rapid reduction of the objective function during the initial search stage indicates strong global exploration capability, whereas the stable convergence observed in the later iterations reflects effective local exploitation around the optimal solution. The absence of noticeable oscillations near convergence further demonstrates that the selected PSO parameter settings provide stable optimization behavior for large-scale DNs. Overall, the combined results presented in Table 3, Figure 6, and Figure 7 confirm that the proposed PSO-based DG planning framework consistently outperforms the existing methods by simultaneously reducing network losses, improving voltage security, suppressing reverse power flow, and increasing renewable energy penetration in the 69-bus DN.

Although the proposed PSO-based DG planning framework demonstrates promising performance on the 33-bus and 69-bus benchmark systems, several limitations should be acknowledged. The present study considers deterministic operating conditions with constant

load demand and DG output operating at unity power factor. In addition, only radial distribution networks are investigated, and uncertainties associated with renewable generation, load variations, and energy storage systems are not explicitly considered. These assumptions may influence the applicability of the proposed framework under practical operating conditions. Future work will extend the proposed method to stochastic DG planning, multi-period operation, and active DNs with coordinated voltage control and energy storage integration.

CONCLUSION

This paper proposed a PSO-based DG planning framework that simultaneously minimizes active power loss, mitigates voltage risk, suppresses reverse power flow, and enhances DG penetration in radial DNs. By explicitly incorporating voltage risk and reverse power flow into the objective function, the proposed method provides a more balanced and practical planning strategy than conventional loss-oriented optimization. Simulation results on the 33-bus and 69-bus benchmark systems demonstrated the effectiveness of the proposed framework. For the 33-bus system, active power loss was reduced by 36.47%, the minimum bus voltage increased from 0.913 p.u. to 0.964 p.u., the voltage risk index decreased to 0.52, and reverse power flow was limited to 13.2 kW. For the 69-bus system, the proposed method achieved a 61.92% reduction in power loss, improved the minimum bus voltage from 0.909 p.u. to 0.972 p.u., reduced the voltage risk index to 0.45, and limited reverse power flow to 18.9 kW, while maintaining the highest DG penetration level among the compared methods. Future work will extend the proposed framework by considering renewable generation uncertainty, time-varying load conditions, energy storage systems, and coordinated operation of active DNs, in order to further enhance planning flexibility and operational reliability.

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