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OPTIMAL SITING AND SIZING OF DISTRIBUTED RENEWABLE GENERATORS IN IEEE-69 BUS RADIAL DISTRIBUTION SYSTEM: A STRATEGIC APPROACH

Kumar Saurabh[1], Dipak Kumar Ghosh[2], B Rajanarayan Prusty[3], Kanhaiya Kumar[4]

[1]Department of Electrical, Electronics and Communication Engineering, Galgotias University, Greater Noida, India

e-mail: saurabhmishram@gmail.com

[2]Department of Electrical, Electronics and Communication Engineering, Galgotias University, Greater Noida, India

e-mail: dipakkumar05.ghosh@gmail.com

[3] Department of Electrical and Electronics Engineering, School of Engineering and Technology, Noida International University, Greater Noida, India

e-mail: b.r.prusty@ieee.org

[4]Department of Electrical and Electronics Engineering, Galgotias College of Engineering and Technology, Greater Noida, India

e-mail: kkanhaiyakumar@gmail.com (Communicating Author)

Abstract:

Growing global concern for sustainable and reliable electricity supply has intensified the deployment of renewable distributed generation (RDG) resources - particularly solar photovoltaic (PV) and wind-based systems - within radial distribution networks. Determining the most suitable locations and capacities of these generators, however, presents a challenging multi-objective optimization task. This research study develops a Quantum-Inspired Particle Swarm Optimization–Gravitational Search Algorithm (QPSOGSA) framework to minimize active power losses, operational cost, and voltage instability simultaneously in the standard IEEE-69 bus radial distribution system. The proposed strategy proceeds in two stages: first, potential RDG installation buses are identified using loss-sensitivity analysis; second, the QPSOGSA algorithm determines the optimal sizing and placement of RDG units at those sites. System losses and voltage performance are evaluated through a Backward/Forward Sweep power-flow model, and the algorithm's outcomes are compared with other metaheuristic techniques such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Bacterial Foraging Optimization (BFOA), and Simulated Annealing (SA).Simulation studies in MATLAB demonstrate that the hybrid QPSOGSA significantly improves network efficiency - achieving lower real-power losses, superior voltage profiles, and reduced operating costs - than the benchmark algorithms. The results indicate that this quantum-inspired hybrid approach offers a robust and scalable tool for DG

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planning, enhancing both the sustainability and reliability of contemporary power-distribution networks.

Keywords: radial distribution system; quantum-inspired PSOGSA algorithm; power loss minimization; wind and solar PV integration

1. Introduction

The global shift toward cleaner energy sources has accelerated the integration of renewable distributed generation (RDG) technologies into existing electrical distribution systems. These RDG units can help stabilize voltage, reduce losses, and make the grid more reliable overall when they are placed in the right places and sized correctly. But if the site and size are not well thought out, it could lead to problems like higher power losses, problems with protection systems working together, and even operational instability. Consequently, efficient RDG planning has emerged as a critical focus of research in contemporary power systems engineering [1–5]. Researchers have increasingly utilized advanced optimization strategies to address this inherently multi-objective problem. Recent endeavors encompass hybrid models that integrate the Grey Wolf Optimization (GWO) algorithm with ETAP-based simulations, demonstrating enhancements in both protection coordination and overall system performance [5]. Quantum annealing has been utilized in the optimization of distribution networks facilitating electric vehicle integration, thereby connecting distributed generation placement strategies with the expansion of e-mobility infrastructure [6].

Simultaneously, advancements in quantum-inspired computational techniques have augmented the solution space for distributed generation (DG) planning. Numerous studies have utilized quantum-inspired evolutionary algorithms to address high-dimensional optimization problems [7]. Also, multi-objective versions of Particle Swarm Optimization (PSO) have been used to find the best places for DGs and capacitor banks at the same time [8]. New methods are becoming more common in this field, such as the Osprey Optimization Algorithm [9] and frameworks that optimize DG units along with flexible loads and energy storage systems [10]. Furthermore, quantum-classical hybrid models utilized in microgrid energy management [11] indicate a future in which decision-making integrates behavioral and socio-economic dynamics alongside technical considerations. Even with these improvements, there is still no one-size-fits-all answer for how to divide DG. Deterministic methods are useful because they are predictable and consistent [12–13]. Stochastic and hybrid metaheuristic algorithms, on the other hand, are more flexible when things are uncertain or change quickly [14–15]. Multi-objective optimization methods try to balance technical, economic, and environmental goals [14], but they often make things more complicated and don't work well on a large scale. Quantum-inspired methods, including chaotic bat algorithms [15] and bounded potential-field swarm strategies [16], exhibit robust global search capabilities yet continue to face challenges related to convergence reliability and practical implementation. Machine learning-based predictive models [17] are also

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promising, but they need a lot of high-quality data to work well. This kind of data isn't always available in real-world power systems.

Thorough reviews [15, 18] show that no one method works best in all situations. This shows how important it is to use hybrid strategies that combine the best parts of different methods. Against this backdrop, the present work introduces a hybrid Quantum-Inspired Particle Swarm Optimization–Gravitational Search Algorithm (QPSOGSA) for optimal DG siting and sizing. The algorithm merges the probabilistic global search capacity of quantum-inspired PSO with the local refinement efficiency of Gravitational Search Algorithm (GSA). This synergy mitigates premature convergence and improves population diversity during optimization. The framework is validated on the IEEE-69 bus radial distribution system (RDS) to assess performance in minimizing losses, improving voltage profiles, and reducing costs. Comparative evaluation with conventional methods demonstrates the superior robustness and scalability of the proposed model. Key Contributions of the Study are given below:

1. Hybrid Quantum-Inspired Optimization Model: A new QPSOGSA framework is developed by fusing the exploratory power of PSO with the exploitation strength of GSA, governed by quantum probabilistic principles.
2. Enhanced Search Balance: The quantum component introduces stochastic transitions that enlarge the search space and prevent early convergence, resulting in better exploration–exploitation equilibrium.
3. Scalable DG Planning Mechanism: Application to the IEEE-69 bus RDS network verifies improved computational stability and scalability over standard GA, PSO, SA, and BFOA algorithms.
4. Multi-Objective Optimization Capability: The proposed model simultaneously minimizes power loss, improves voltage stability, and reduces operational expenditure—demonstrating holistic DG planning performance.
5. Practical Control Efficiency: The algorithm adapts well to varying load and power-factor conditions, ensuring feasible control effort in real-world renewable-integration scenarios.
6. Support for Sustainable Distribution Networks: By delivering accurate and cost-effective DG allocation, the method contributes directly to sustainable and resilient energy-system design.

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2. Problem Formulation

To make a distribution network more technically and economically efficient, you need to find the best place for and capacity of distributed-generation (DG) units. The main goal is to reduce power losses and voltage changes while making sure that the system stays cost-effective and reliable. The task is thus characterized as a multi-objective optimization problem constrained by physical, operational, and design limitations that ensure the network's stability and safety.

2.1 Energy Flow Modeling

This article uses a Backward/Forward Sweep (BFS) power flow algorithm to look at power flow in the RDS. This algorithm was chosen because it is fast and can handle unbalanced loading conditions well. Figure 1 shows a simplified radial feeder segment with two buses (K and B) connected by a line section with impedance Z. The BFS algorithm follows an iterative sequence:

1. Nodal current estimation – currents at every node are calculated based on connected load and DG injection.
2. Backward sweep – branch currents are propagated from the terminal nodes toward the substation to determine line flows.
3. Forward sweep – updating bus voltages from the substation outward using the calculated branch flows.

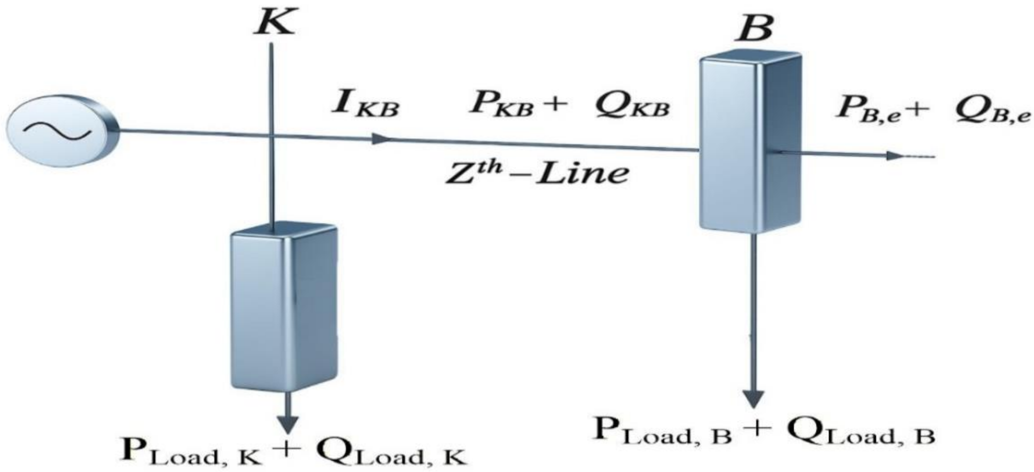

Figure 1. Simplified representation of a radial line section between two buses (K and B) with impedance Z.

This iterative process continues until the maximum bus voltage mismatch falls below a predefined acceptance ($\varepsilon = 1\times10^{-6}$). Upon convergence, the active and reactive power losses across the network are computed.

For a branch connecting node K to node B, the backward sweep calculates the active and reactive power flow as given by Equation (1) and Equation (2), respectively.

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$$P_{KB} = P'_B + R_{KB}\frac{P_B'^2 + Q_B'^2}{V_B^2} \quad (1)$$

$$Q_{KB} = Q'_B + X_{KB}\frac{P_B'^2 + Q_B'^2}{V_B^2} \quad (2)$$

Here, $P'_{KB} = P_B + P_{YB}$ and $Q'_{KB} = Q_B + Q_{YB}$; P_{YB} and Q_{YB} represents the active and reactive load demands at bus B.

$$I_{KB} = \frac{(V_K\angle\partial_K - V_B\angle\partial_B)}{R_{KB} + j\,X_{KB}} \quad (3)$$

$$I_K = \frac{(P_K - j\,Q_K)}{V_K\angle-\partial_K} \quad (4)$$

Here, $V_K\angle\partial_K$ is voltage at node K and $V_B\angle\partial_B$ voltage at node B, the corresponding current injected at bus K through line Z with impedance $Z_{KB} = R_{KB} + j\,X_{KB}$ is represented by Equations (3) and Equation (4) .Subsequently, the receiving-end voltage at bus B is updated using Equation (5).

$$V_B = \left(V_B^2 - 2 * (P_K R_{KB} + j\,Q_K X_{KB}) + (R_{KB}^2 + X_{KB}^2) * \left(\frac{P_K^2 + Q_K^2}{V_K^2}\right)\right)^{\frac{1}{2}} \quad (5)$$

During the forward sweep, bus voltages are updated sequentially along the feeder, yielding the magnitude and phase angle at each node. The active and reactive line losses between buses K and B are determined by Equation (6) and Equation (7), respectively.

$$P_{L(KB)} = R_{KB}\frac{P_{KB}^2 + Q_{KB}^2}{V_K^2} \quad (6)$$

$$Q_{L(KB)} = X_{KB}\frac{P_{KB}^2 + Q_{KB}^2}{V_K^2} \quad (7)$$

The total active power loss of the entire radial system is given by Equation (8):

$$P_{Total_{loss}} = \sum_{B=1}^{NOBR} P_{loss(KB)} \quad (8)$$

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where K = 1..., NOBR indexes each branch (NOBR is the number of branches and NOB is the total number of buses in the system).

2.2 Loss Evaluation with DG Units

When DG units are united into the RDS, they inject active and/or reactive power at specific nodes, altering the net load profile and thus reducing network losses. The branch loss expressions are modified accordingly: the losses on each line with injected DG power can be recalculated using Equation (9), and the overall system losses in the presence of DG are given by Equation (10).

$$P_{DG_{loss}}(KB) = R_{KB} \frac{P^2_{DG(KB)} + Q^2_{DG(KB)}}{V^2_K} \tag{9}$$

$$P_{DG,Total_{loss}} = \sum_{B=1}^{NOBR} P_{DG_{loss}}(KB) \tag{10}$$

2.3 Performance Indices

To evaluate the impact of DG integration, the following performance indices are defined:

- Energy Loss Index ($\Delta\, Ploss_{DG}$): This index quantifies the relative improvement in system efficiency due to DG placement. It is defined as the ratio of the total energy loss with DG units to the total energy loss without DG, as given by Equation (11).

$$\Delta\, Ploss_{DG} = \frac{P_{DG,Total_{loss}}}{P_{Total_{loss}}} \tag{11}$$

- Voltage Deviation Index ($\Delta\, V_{deviation}$): The degree of voltage profile improvement is measured using a voltage deviation index defined by Equation (12). This index captures the magnitude of voltage deviations across all buses (for instance, as the sum of squared deviations from 1.0 p.u.). A smaller $\Delta\, V_{deviation}$ corresponds to a flatter voltage profile (bus voltages closer to the nominal value), indicating improved voltage regulation.

$$\Delta\, V_{deviation} = \text{maximum}\left(\frac{V_1 - V_K}{V_1}\right), \text{for } K = 1,2,3, \dots\dots\dots, NOB \tag{12}$$

- Operational Cost Reduction (Δ OE): The introduction of DG units can reduce operating costs by decreasing network losses and providing local generation. The total operating cost of the system after DG installation is modeled by Equation (13),

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$$\mathrm{ROE} = \left(\mathrm{CC_1 P_{DG,Total_{loss}}} + \mathrm{CC_2 P_{Total,DG}}\right) \tag{13}$$

where CC_1 and CC_2 are pricing coefficients (in $/kW) for the energy lost in the system and the energy supplied by the DG, respectively, and $P_{total,DG}$ is the total energy supplied by the DG units. The net reduction in operating cost achieved by the DG deployment is calculated by Equation (14). A higher cost reduction (or equivalently, a larger negative cost term in the objective) signifies better economic performance.

$$\Delta\ \mathrm{OE} = \frac{\mathrm{ROE}}{\mathrm{P_{Total,DG}^{MAXI}}} \tag{14}$$

2.4 Objective Function

The overall optimization goal is formulated as a multi-objective function that simultaneously seeks to minimize:

- the Energy Loss Index (to reduce power losses),
- the Voltage Deviation Index (to improve the voltage profile), and
- the operating cost (to enhance economic efficiency).

$$\mathrm{minimize(OF)} = \mathrm{minimum}(\gamma_1 \Delta\ \mathrm{Ploss_{DG}} + \gamma_2 \Delta\ \mathrm{V_{deviation}} + \gamma_3 \Delta\ \mathrm{OE}) \tag{15}$$

$$\sum_{x=1}^{3} \gamma_x = 1 \text{ for } \quad 0 \le \gamma_x \le 1 \tag{16}$$

This combined objective is expressed mathematically in Equation (15). In practice, a weighted sum approach is used, and Equation (16) defines the weighting factors γ_x applied to each normalized sub-objective. The weights can be tuned to emphasize certain objectives over others, but in this study, they are chosen to give a balanced importance to losses, voltage profile, and cost.

2.5 Constraints

The optimization is subject to several practical constraints:

- Power balance constraint: Total power generation (including contributions from all DG units) must equal the total load demand plus system losses. This is enforced by the equality in Equation (17).

$$\sum_{K=2}^{NOB} \mathrm{P_{DG(KB)}} = \sum_{K=2}^{NOB} \mathrm{P_K} + \sum_{B=1}^{NOBR} \mathrm{P_{loss(KB)}} \tag{17}$$

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- Voltage limits: Each bus voltage must remain within acceptable limits to maintain power quality and equipment safety, typically between 0.95 p.u. and 1.05 p.u. Equation (18) imposes these lower and upper voltage bounds on every bus.

$$|V_1 - V_B| \leq \Delta V_{DROP}^{MAX} \tag{18}$$

- DG capacity limits: The output of each DG unit is limited by its minimum and maximum capacity ratings. Equation (19) ensures that the power injected by each DG stays within its feasible range (as determined by the DG technology and any operational constraints).

$$P_{Total,DG}^{MINI} \leq P_{Total,DG} \leq P_{Total,DG}^{MAXI} \tag{19}$$

2.6 Sensitivity-Based Candidate Bus Selection

Selecting appropriate candidate buses for DG placement is critical to minimizing losses and preserving voltage stability. In this research work, a loss sensitivity factor (OSF) analysis is used in conjunction with a voltage sensitivity factor (TSF) analysis to identify the most suitable buses for DG integration.

Referring to the feeder model in Figure 1, the active power loss in the line segment between bus K and bus B can be formulated as in equation (20), which depends on the line resistance R_{KB} and the voltage magnitude V_B at bus B.

$$P_{Lloss(KB)} = R_{KB} \frac{(P_{B,e}^2 + Q_{B,e}^2)}{(V_B^2)} \tag{20}$$

Loss Sensitivity Factor (OSF): This factor measures the sensitivity of system losses to an incremental injection of active power at a given bus. It is obtained by differentiating the line loss Equation (20) with respect to $P_{B,e}$, yielding the OSF as shown in Equation (21). A larger OSF value at a particular bus implies that adding a DG unit at that bus would produce a greater reduction in total power losses.

$$OSF_{KB} = \frac{\partial P_{Lloss(KB)}}{\partial P_{B,e}} = \frac{2 * P_{B,e} * R_{K,B}}{V_B^2} \tag{21}$$

- Voltage Sensitivity Factor (TSF): In parallel, the voltage sensitivity factor assesses how close each bus is to violating voltage constraints. It is determined by comparing the base-case voltage magnitude at a bus to the minimum acceptable voltage (e.g., 0.95 p.u.). If a bus's base voltage is only slightly above the minimum limit (indicating TSF < 1.01, or within 1%

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of the lower limit), that bus is considered voltage-sensitive and likely to benefit from support via DG injection. In other words, buses with TSF values below about 1.01 have relatively weak voltage profiles and are good candidates for improvement through local generation, whereas buses with higher TSF are already within comfortable voltage margins.

Candidate Bus Selection Criteria: Finally, the OSF and TSF results are combined to prioritize candidate locations. In general, the buses identified for DG installation should exhibit both:

- High OSF values (indicating substantial potential for loss reduction), and
- Low TSF values (indicating a need for voltage support and only marginal compliance with voltage limits).

Buses that rank highest in OSF and simultaneously have among the lowest TSF values are deemed the most promising sites for DG. This approach balances the technical objective of loss minimization with the operational objective of maintaining acceptable voltage profiles.

3. Proposed Methodology

In order to determine the optimal DG placement and sizing, a hybrid metaheuristic optimization approach is developed. Specifically, a quantum-inspired PSO–GSA algorithm, referred to as QPSOGSA, is employed to enhance global search capabilities and avoid premature convergence, thereby yielding high-quality solutions for the multi-objective problem defined in Section 2.

3.1 Particle Swarm Optimization – Gravitational Search Hybrid

In the PSO–GSA hybrid framework, the solution space is explored by a swarm of agents (particles), where each particle encodes a potential solution defined by a set of DG placement and sizing variables [20]. The movement and updating of these particles are governed by two combined mechanisms:

- PSO component: Each particle is influenced by social (swarm-level) and cognitive (individual memory) behaviors that guide it toward its own best-found position (personal best) and the global best position identified by the swarm. This mirrors the classic PSO approach where particles adjust their velocities based on both their personal experience and the experience of their neighbors.
- GSA component: Particles are also subject to gravitational attraction inspired by the Gravitational Search Algorithm. In this mechanism, all particles are considered as objects with masses, and those with better fitness exert a stronger “gravitational pull” on others. This means high-quality candidate solutions attract other particles, directing the swarm toward promising regions of the search space (analogous to masses attracting each other in Newtonian physics).

Using this hybrid model, the velocity of the k -th particle at iteration p is updated according to Equation (22), and the particle’s position is then updated using Equation (23).

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$$\upsilon_K^p = w * \upsilon_K^{p-1} + c_{1'} * r_{1'} * ac_K^{p-1} + c_{2'} * r_{2'} * \left(g^{best} - \chi_k^{p-1}\right) \quad (22)$$

$$\chi_K^p = \chi_K^{p-1} + \upsilon_K^p \quad (23)$$

Here, υ_K^p denotes the velocity of particle k at iteration p , χ_K^p denotes its position, and the other terms represent acceleration coefficients and weighting factors analogous to standard PSO and GSA parameters (e.g., cognitive and social acceleration constants, inertia weight, and gravitational constants). This formulation ensures that candidate solutions evolve over iterations, being refined by each particle's own experience as well as the swarm's collective intelligence. In essence, solutions are continuously improved through a balance of exploration (via the PSO's stochastic searching and the GSA's global pull towards good regions) and exploitation (via particles converging on known good solutions).

3.2 Quantum-Inspired PSOGSA (QPSOGSA)

Although the PSO–GSA hybrid provides a robust search capability, it can still become trapped in local optima. To mitigate this risk, we incorporate quantum-inspired principles, yielding the QPSOGSA algorithm. In QPSOGSA, each particle is characterized not only by its classical position but also by a quantum state defined by a probability amplitude (often represented using a qubit or an angle in quantum space). This means that each particle can exist in a probabilistic "mixture" of states, rather than a single definitive state, at any given iteration.

$$\rho_{KB}^{p-1} = \Gamma_B^{p-1} * ac_{KB}^{p-1} + \left(1 - \Gamma_B^{p-1}\right) * gbest_B^{p-1} \quad (24)$$

Where

ρ_{KB}^{p-1}= attraction of each particle to its local best value

Γ_B^{p-1} = density function of B^{th} particle

$\Gamma_B^{p-1} = \frac{c_{1'} * r_{1'B}}{c_{1'} * r_{1'B} + c_{1'} * r_{2'B}}$;

$0 \le \Gamma_B^{p-1} \le 1$;

$\left|\Gamma_B^{p-1}\right|^2 = 1$

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The evolution of each particle's state in QPSOGSA follows a modified update rule (given in Equation (24)) that introduces quantum-inspired terms into the motion equations. In practical terms, a particle's position update now has a probabilistic component: the particle can "tunnel" through the solution space, exploring regions that classical particles might miss. Each particle's state is described by a position as well as a probability distribution, enhancing the diversity of the search. Equation (24) encapsulates this quantum state update, involving factors such as an attraction term towards the particle's local best and a probabilistic density function that governs the spread of the particle's quantum position.

To implement the quantum update, Monte Carlo (MC) [19] sampling is employed to generate random variations in accordance with the quantum state equation as in Equation (25) and Equation (26).

$$\chi_{KB}^{p} = \rho_{KB}^{p-1} + \varsigma * \left|\mathcal{H}_{B}^{p-1} - \chi_{KB}^{p}\right| * \log_e {}^{1}/_{\varrho}\,;\ \text{if}\ ב \geq 0 \tag{25}$$

$$\chi_{KB}^{p} = \rho_{KB}^{p-1} - \varsigma * \left|\mathcal{H}_{B}^{p-1} - \chi_{KB}^{p}\right| * \log_e {}^{1}/_{\varrho}\,;\ \text{if}\ ב \leq 0 \tag{26}$$

Where

χ_{KB}^{p}= updated position of K^{th} particle towards B^{th} particle at p^{th} iteration

ς= convergence controller

$\varsigma, ב \in (0,1)$= random variables

$\mathcal{H}_{B}^{p-1}$= average best acceleration factor

The overall average acceleration factor is given by Equation 27.

$$\mathcal{H}_{B}^{p-1} = \frac{1}{NOB} \sum_{K=1}^{NOB} ac_{KB}^{p-1} \tag{27}$$

Specifically, as shown in equations (25-26), random samples are drawn for each particle based on its probability amplitude, and these samples dictate the particle's new position (within the quantum-defined range) at the next iteration [15]. In these expressions, the terms represent the updated particle position moving toward a target (e.g., a global best particle), a

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convergence control parameter, random variables introduced by the MC process, and the swarm's average best acceleration factor, respectively. Equation (27) provides the formula for this overall average acceleration factor, which reflects the mean pull exerted by the best-performing particles on the swarm.

3.3 Application to DG Allocation and Sizing

The QPSOGSA algorithm is applied to the DG placement and sizing problem by simultaneously optimizing two decision vectors:

- The locations of DG units (i.e. selecting which bus indices will host DG installations).
- The sizes or capacities of the DG units at those chosen locations.

In this implementation, the quantum-inspired search (governed by equation (24)) primarily drives the exploration of different possible DG sizes, allowing the algorithm to consider a wide range of generation capacity combinations. Meanwhile, the position update Equations (25) & Equations (26) control how candidate bus locations for DG are explored and updated throughout the optimization process.

By incorporating the multi-objective fitness function defined in Section 2 (equation (15)) into the algorithm's evaluation step, QPSOGSA ensures that each potential solution is assessed on its combined technical and economic performance. In other words, the algorithm balances trade-offs between minimizing system losses, improving the voltage profile, and reducing operational costs as it searches for the optimal DG deployment strategy. This allows QPSOGSA to guide the solution toward configurations that offer a well-rounded improvement across all objectives rather than excelling in only one dimension.

4. Results

4.1 Simulation Setup

The proposed QPSOGSA framework was implemented in MATLAB and tested on the standard IEEE 69-bus RDS (operating at 12.66 kV) [15]. All bus voltage magnitudes were constrained between 0.95 p.u. and 1.05 p.u. during the optimization. Two types of renewable distributed generators (RDGs) were considered in the simulations:

- Type I: Photovoltaic (PV) generators operating at unity power factor (PF = 1.0), which inject only active power into the system.
- Type II: Wind turbine generators operating at PF = 0.866 lagging, capable of supplying both active and reactive power (this power factor reflects typical operation where the wind turbine provides some reactive support).

The performance of the QPSOGSA optimizer was benchmarked against two other optimization methods widely used for DG planning: Simulated Annealing (SA) and the Bacterial Foraging Optimization Algorithm (BFOA). By comparing against these established

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metaheuristics, we can evaluate the relative effectiveness of QPSOGSA in finding high-quality solutions for the DG placement and sizing problem.

4.2 Results on IEEE 69-Bus RDS

In the case study, candidate buses for DG installation were first identified through the OSF and TSF analyses described in Section 2. Figure 2 illustrates the calculated OSF and TSF values for each bus in the 69-bus system. The OSF curve quantifies how additional active power injection at each bus would affect total system losses, whereas the TSF values indicate each bus's steady-state voltage (relative to the nominal voltage) and hence its voltage stability margin. By examining both indices together, it is possible to pinpoint the buses where installing DG offers the greatest combined benefit in terms of loss reduction and voltage support.

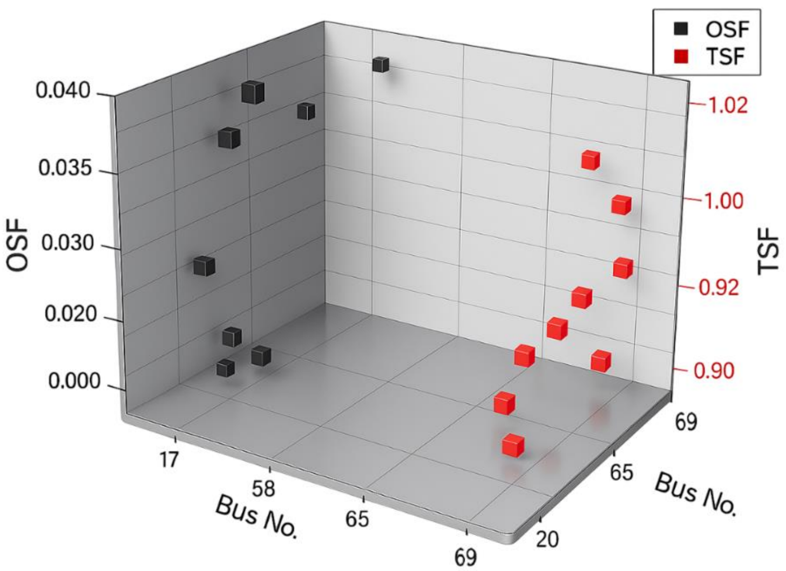

Figure 2. OSF and TSF analysis of the IEEE 69-bus RDS showing prioritized DG candidate buses characterized by high OSF and low TSF values.

From these results, bus 58 stands out as a particularly weak node, with one of the highest OSF values (0.0302) and one of the lowest base voltages (0.908 p.u.). This indicates that bus 58 is near the end of the feeder, experiencing a significant voltage drop and heavy loading. Placing a DG unit at bus 58 would therefore be highly effective: it would substantially raise the local voltage and markedly reduce line losses in that segment of the network.

Bus 61 is another critical downstream location, with an OSF of 0.02186 and a base voltage of 0.9311 p.u. Although its voltage is slightly higher than that of bus 58, bus 61 still operates below the 0.95 p.u. threshold, underscoring the need for additional voltage support at that node. The relatively high OSF for bus 61 suggests that injecting active power here can significantly alleviate losses in the lower part of the feeder, similar to bus 58.

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In contrast, bus 22 (located in the mid-feeder region) shows a moderate OSF (8.0×10^{-4}) but a healthy base voltage slightly above unity (1.0174 p.u.). Despite its higher voltage, bus 22 carries substantial current due to the large cumulative load downstream. Installing a DG at this mid-feeder position helps to offload the upstream sections by locally supplying some of the demand, thereby reducing overall feeder losses. The QPSOGSA algorithm indeed selected bus 22 as an optimal DG site because it provides strategic relief in the middle of the feeder, complementing the loss reduction and voltage improvement achieved by DGs at the far-end buses 58 and 61.

Taken together, the chosen set of buses (22, 58, 61) covers the mid, lower, and end sections of the feeder. This combination effectively addresses both objectives of the problem: minimizing total power losses and enhancing voltage stability across the network. By identifying nodes that span different segments of the feeder, QPSOGSA ensured a more uniform voltage profile and improved power quality throughout the distribution system.

For the identified optimal locations, the QPSOGSA algorithm determined the following DG sizes under the two scenarios: -

- At PF = 1.0 (Type I PV units): the optimal DG capacities were approximately 290 kW at bus 22, 1430 kW at bus 58, and 330 kW at bus 61.
- At PF = 0.866 (Type II wind units): the optimal capacities at the same buses were about 370 kW (bus 22), 1230 kW (bus 58), and 420 kW (bus 61).

Figure 3 and Figure 4 compare the performance of the proposed QPSOGSA with that of other algorithms for the Type I (PF = 1.0) and Type II (PF = 0.866) scenarios, respectively. Prior to optimization, the total active power loss in the system was 224.98 kW. After optimally placing and sizing DGs, all algorithms achieved substantial loss reductions, but the extent of improvement varied. The classical Genetic Algorithm (GA) reduced the losses to about 89.0 kW (approximately a 60.5% reduction), while Particle Swarm Optimization (PSO) brought losses down to 83.2 kW (~63.0% reduction). The hybrid GA/PSO approach performed slightly better, yielding 81.1 kW (63.95% reduction). Simulated Annealing (SA) achieved 77.1 kW (65.7% reduction), and BFOA reduced losses to 75.23 kW (a 66.6% reduction). Notably, the hybrid PSOGSA and the proposed QPSOGSA outperformed all these methods. QPSOGSA achieved the lowest loss of 73.47 kW, corresponding to a 68.0% reduction, marginally better than the hybrid-PSOGSA result of 73.58 kW (67.3% reduction). These results highlight the efficacy of QPSOGSA in balancing exploration and exploitation to find high-quality solutions that significantly cut losses.

QPSOGSA also provided a more balanced DG sizing solution for the Type I case. It allocated generation capacities of approximately 290 kW, 1430 kW, and 330 kW at buses 22, 58, and 61, respectively. This distribution of DG sizes is more realistic compared to some of the other algorithms, which tended to propose one or two excessively large units. For instance, the pure GA solution assigned an overly large 929.7 kW unit at one location (bus 58), and even the GA/PSO hybrid suggested a 1192.6 kW unit for one site. In contrast, the total

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installed DG capacity under QPSOGSA's solution was about 2050 kVA, significantly lower than the 2990 kVA combined capacity required by the GA/PSO or PSO solutions. Despite using less total capacity, QPSOGSA achieved greater loss reduction, indicating a more efficient utilization of the DG resources.

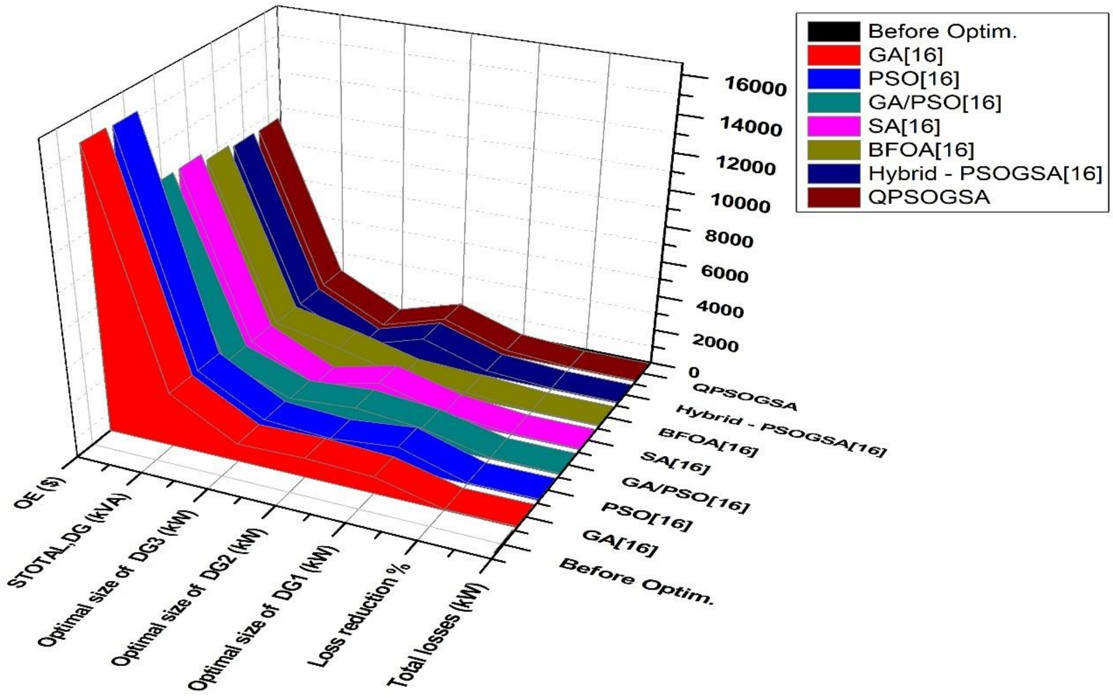

Figure 3. Performance comparison of optimization algorithms on the IEEE 69-bus system for Type I DG (PV at PF = 1.0).

From an economic perspective, QPSOGSA's solution led to the lowest operating expense (OE) among the compared algorithms for the Type I scenario. The annual OE associated with QPSOGSA was approximately \$10,498. This was slightly better than the hybrid-PSOGSA result of \$10,544, and considerably better than the OEs for BFOA (\$10,741), GA (\$15,343), and PSO (\$15,272). The significantly higher costs in the GA and PSO cases reflect their larger installed DG sizes (and hence higher capital or operating costs), whereas QPSOGSA's cost is lower due to its more optimal sizing and loss reduction. The reduction in operating cost confirms that QPSOGSA not only improves the technical performance of the system but also yields economic benefits, making it a very attractive solution overall.

For the Type II scenario (wind-based DG with PF = 0.866), a similar pattern was observed. Before optimization, the system's active power losses were 224.98 kW. After deploying optimally sized DGs, all algorithms achieved dramatic loss reductions, but QPSOGSA again delivered the best outcome. QPSOGSA reduced the losses to about 12.45 kW, which represents a 95.34% reduction from the base case. This outperforms the loss reductions achieved by SA (92.77%), BFOA (94.26%), and hybrid PSOGSA (94.27%). Essentially, QPSOGSA was able to eliminate the vast majority of losses in the system for the Type II case, performing slightly better than even the advanced hybrid PSOGSA.

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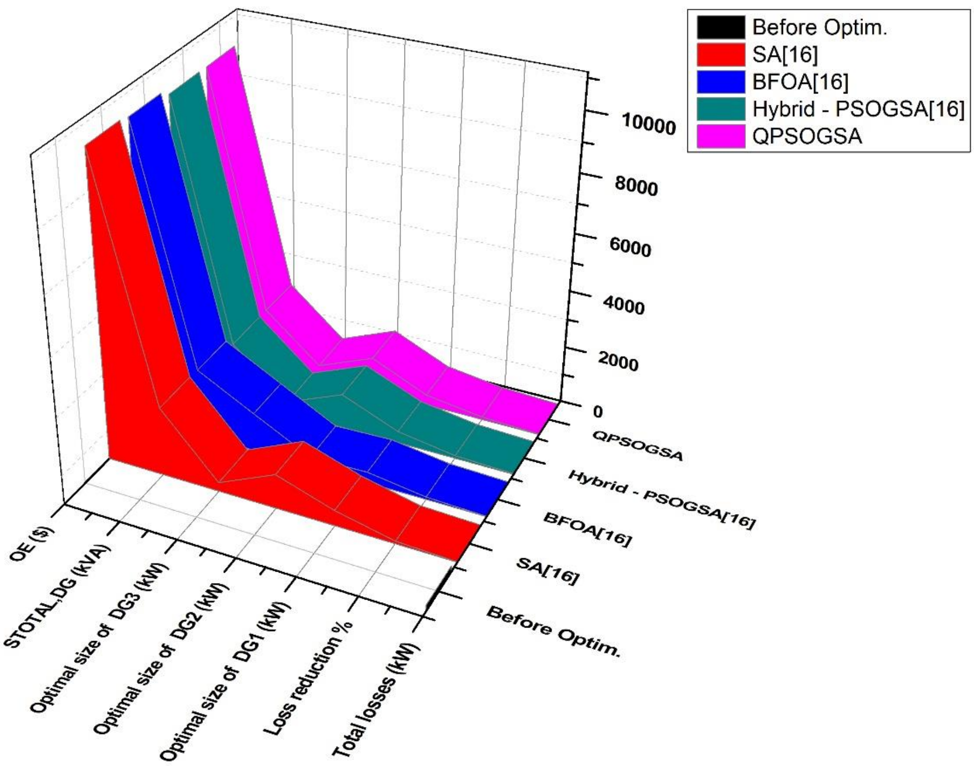

Figure 4. Performance comparison of optimization algorithms on the IEEE 69-bus system for Type II DG (WT at PF = 0.866).

In terms of DG sizing for the Type II case, QPSOGSA determined optimal capacities of roughly 370 kW, 1210 kW, and 420 kW for the DG units at buses 22, 58, and 61, respectively. These values are well-balanced, especially when compared to the allocations from other techniques which sometimes oversized one of the units. For example, BFOA proposed a 1336.1 kW DG at one bus, and SA suggested a 1195.4 kW unit, indicating a less even distribution of generation. QPSOGSA's total installed capacity was about 2000 kVA (similar to that of hybrid PSOGSA), but it achieved greater loss reduction with that capacity by distributing it more effectively across the network.

Economically, QPSOGSA also provided the most cost-effective solution in the Type II scenario. The annual operating cost with QPSOGSA optimization was approximately $10,040. This was marginally lower than the cost with hybrid PSOGSA ($10,052), and noticeably lower than the costs resulting from SA ($10,352) or BFOA ($10,265). Once again, the lower operating cost reflects both the reduced losses (less wasted energy) and the efficient sizing of DG units (avoiding excessive capacity that does not contribute proportionally to loss reduction). These results reinforce that QPSOGSA not only minimizes technical losses and maintains voltages within desired limits, but also ensures a more cost-effective operation of the distribution system compared to other optimization strategies.

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5. Discussion

Renewable energy integration has consistently required innovative approaches for maximizing efficiency and reliability, ranging from advanced strategies [21-23]. The simulation outcomes for the IEEE-69-bus RDS confirm that appropriate integration of DG through the proposed Quantum-Inspired Particle Swarm Optimization–Gravitational Search Algorithm (QPSOGSA) can substantially enhance both the technical and economic performance of radial distribution systems. Compared with SA, BFOA, and conventional PSO-based hybrids, the QPSOGSA configuration achieved the lowest active-power losses, higher minimum-bus voltages, and noticeably lower operating expenditure.

The hybrid framework makes it possible for global exploration and local exploitation to work together in a balanced way, which leads to these improvements. The quantum-inspired part of the algorithm adds probabilistic movement strategies that let the search agents avoid local optima, which makes it easier for them to explore the solution space. At the same time, the gravitational search mechanism guides particles toward high-quality solution zones. This creates a synergy that stops the tendency for early convergence, which is a common problem with many current metaheuristic techniques. This dynamic interaction makes the search process more thorough and balanced.

One of the best things about QPSOGSA is its quick convergence. Because the quantum-based position updating keeps particles from being too similar, the algorithm often finds solutions that are close to the global optimum in fewer iterations. This helps the algorithm run faster and shows that it is a good choice for applications that need to make quick decisions, especially when dealing with large-scale distribution networks. The method's ability to lower yearly operating costs is especially important when it comes to operational performance. Decreasing power losses has a direct effect on the cost of buying energy and cuts down on costs related to transmission. In the case study, QPSOGSA consistently produced lower annual costs than other optimization methods. For distribution system operators, these savings not only improve their bottom line, but they also give them the chance to put off expensive infrastructure investments by making the most of their current network assets.

The suggested model also shows that it can easily adapt to different DG setups and power factor conditions. The algorithm kept voltage levels within regulatory limits while minimizing losses, whether it was used on solar PV systems with a unity power factor or wind generators with a lagging power factor. This flexibility makes the framework a good fit for renewable energy systems that are not all the same and need to be able to handle different types of generation. In conclusion, the hybrid quantum-inspired optimization method is a strong and flexible tool for planning modern distribution systems. It has clear technical benefits, like lower losses, better voltage control, and faster convergence, as well as being cost-effective and useful in the real world. This framework could become a basic way to build smart, self-optimizing distribution networks if future improvements include uncertainty modeling and considerations for ancillary services.

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6. Conclusions

This research study presents a comprehensive framework for determining the optimal placement and sizing of distributed generation (DG) units in radial distribution systems, employing a hybrid Quantum-Inspired Particle Swarm Optimization integrated with the Gravitational Search Algorithm (QPSOGSA). When used on the IEEE 69-bus radial distribution system, the model showed significant improvements in both technical and economic performance compared to traditional optimization methods. The results show that strategically combining renewable distributed generation sources like solar photovoltaic systems and wind turbines can greatly lower active power losses, make voltage stability better, and lower overall operating costs. When compared to other metaheuristic methods like PSOGSA, Simulated Annealing (SA), and Bacterial Foraging Optimization Algorithm (BFOA), the proposed QPSOGSA always gave better results. These included less power loss, faster convergence rates, and more stable voltage profiles, whether the power factor was unity or lagging.

The quantum-inspired design of the algorithm helped keep the solutions diverse and lower the risk of premature convergence. The gravitational search part made local search more efficient. This synergy led to a more stable and balanced optimization process. The method also showed great computational performance, getting close to optimal results with fewer iterations. This means it is good for planning tasks that need to be done quickly or on a large scale. Economic evaluation further revealed considerable annual cost savings, underlining the dual advantage of the approach: strengthening system performance and offering clear financial benefits to distribution network operators and planners.

Overall, the developed QPSOGSA-based strategy provides a robust, scalable, and adaptable tool for distributed-generation planning in modern distribution networks. Its ability to handle multiple objectives simultaneously - loss minimization, voltage improvement, and cost reduction - positions it as a strong candidate for sustainable grid-modernization programs. Future work can extend this framework by incorporating stochastic modeling of renewable variability, energy-storage coordination, and demand-response mechanisms, leading toward an integrated, intelligent, and resilient energy-distribution environment.

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