

Economic Analysis of Radial Distribution System with Optimally Placed Distributed Generations Using Metaheuristic Optimization Techniques

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DOI: <https://doi.org/10.51244/IJRSI.2026.1305000266>

Received: 18 May 2026; Accepted: 23 May 2026; Published: 13 June 2026

ABSTRACT

Distributed Generation (DG) integration plays a significant role in enhancing the efficiency and reliability of modern Radial Distribution Systems (RDS) such as the IEEE 69-bus network. However, improper placement and sizing of DG units, voltage instability, increased power losses, and lack of coordinated economic analysis vary under load condition remain key limitations in existing approaches. To overcome these challenges, this study proposes an integrated optimization framework for optimal DG placement and sizing using advanced metaheuristic techniques. Initially, the system is analysed using the Backward/Forward Sweep Load Flow (BFSLF) method, followed by a 24-hour load variation analysis to capture realistic demand patterns. The Animated Oat Optimization Algorithm (AOOA) is employed to determine the optimal DG location, while the Plant Rhizome Optimization Algorithm (PROA) is used to obtain the optimal DG size. The proposed model significantly enhances system performance by reducing active power losses from 224.91 kW to 97.59 kW and improving the minimum voltage from 0.9092 p.u. to 0.9567 p.u. In addition, the convergence characteristics indicate fast and stable optimization behaviour with effective exploration and exploitation capability. Finally, the economic evaluation shows that the annual cost is reduced from 11.82 million Rs to 3.13 million Rs (Rs 6/kWh) and from 13.79 million Rs to 3.65 million Rs (Rs 7/kWh), with savings up to 10.14 million Rs and net profit reaching 24.60 million Rs, demonstrating strong economic feasibility.

Keywords: Backward Forward Sweep Load Flow method, Distributed Generation, IEEE 69-bus distribution system, Load flow analysis

INTRODUCTION

Electricity is an important aspect of our everyday existence, serving nearly all of our activities, whether at home or at our workplaces, and its consumption is growing at an alarming rate in the last few years with the increase in population and technological progress [1]. A power system comprises of generation, transmission, and distribution with Distribution System (DS) charged to provide electricity effectively to end users [2]. The RDS is one of the most popular systems due to its simple design, low cost, and ease of use among other configurations [3]. These systems were not originally devised taking into account the current high load requirement which has led to major problems including low voltage profile, high power losses, and low reliability [4]. With the constantly increasing use of electricity these issues become more urgent, which results in higher costs and reduced efficiency of the operations [5]. On the phase power system, the DG has become a viable solution which

is small-scale generation capacity like solar, wind and other renewable sources that are located close to the load centres [6]. The DG units included can aid in minimizing the transmission losses, enhancing the voltage stability, and improving system reliability [7]. Furthermore, DG plays a crucial role in meeting peak load demand and reducing stress on the central grid infrastructure [8]. The integration of DG in RDS faces several technical and operational challenges. One major issue is improper sizing with placement of DG units, which leads to increased power losses and reduced system efficiency. Another challenge is voltage instability, especially at weak buses under varying load conditions. Traditional methods also struggle to handle time-varying load demand, making system planning less accurate. In addition, many existing approaches do not effectively combine technical optimization with economic evaluation, limiting real-world applicability. To overcome these limitations, the motivation of this research is to develop an efficient and reliable optimization framework for optimal DG placement and sizing. The proposed study integrates load flow analysis, 24-hour load variation, and advanced metaheuristic algorithms to improve system performance. It identifies the optimal DG location using the AOOA and optimal sizing using the PROA. This approach ensures reduced power losses, improved voltage profile, and better system stability under dynamic load conditions. Furthermore, it enhances economic benefits by minimizing operating costs and improving overall financial feasibility of the DS. The contribution of the research can be as follow,

- The objective of the study is to develop an optimal DG placement and sizing framework for the IEEE 69-bus RDS to improve technical and economic performance.
- Optimal DG location is determined using the AOOA to minimize power losses with enhanced voltage stability.
- Optimal DG sizing is carried out using the PROA to achieve efficient and economical system operation.
- A 24-hour load variation analysis is incorporated to consider realistic time-varying demand conditions for accurate system evaluation.

The research is organized as follows: Section 2 covers the literature review, Section 3 presents the proposed methodology, Section 4 discusses the results and analysis, and Section 5 concludes the work.

LITERATURE SURVEY

The hybrid optimizer Multi-Objective Particle Swarm Optimization (MOPSO) [9] is for the optimal functioning of DG units and shunt capacitors in RDS. The Revised Coyote Optimization Algorithm (RCOA) [10] for the optimal integration of renewable energy-based DG units in DS. The integration of index techniques with Artificial Optimizer (AO) [11] is introduced for the optimal siting and sizing of biomass-based DG units in RDS. The fuzzy-based African Vulture Optimization (AVO) [12] algorithm is utilized for the simultaneous optimal functioning of DG units, shunt capacitors, and electric vehicle charging stations in RDS. The introduced model introduces a Novel Distribution Voltage Stability Index (NDVSI) [13] for optimal siting and sizing of DG units in RDS.

Problem Formulation

The integration of DG into Radial Distribution Networks (RDN), particularly in standard systems such as the IEEE 69-bus system makes several critical challenges that affect both technical and economic performance. One of the primary issues is the improper placement and sizing of DG units, which can lead to increased power losses, voltage instability, and even reverse power flow conditions. Traditional DS are designed for unidirectional power flow, making them less adaptable to DG penetration. The variations in load demand over a 24-hour period create fluctuating system conditions, complicating optimal planning and operation.

Proposed Framework

The proposed framework presents a approach for optimal functioning of DG in the IEEE 69-bus RDS. It integrates load flow analysis, 24-hour load variation, and metaheuristic optimization techniques to improve

system performance. The methodology aims to enhance voltage profile, reduce power losses, and achieve better economic efficiency under varying load conditions. Figure 1 shows the flow of work carried out in this paper.

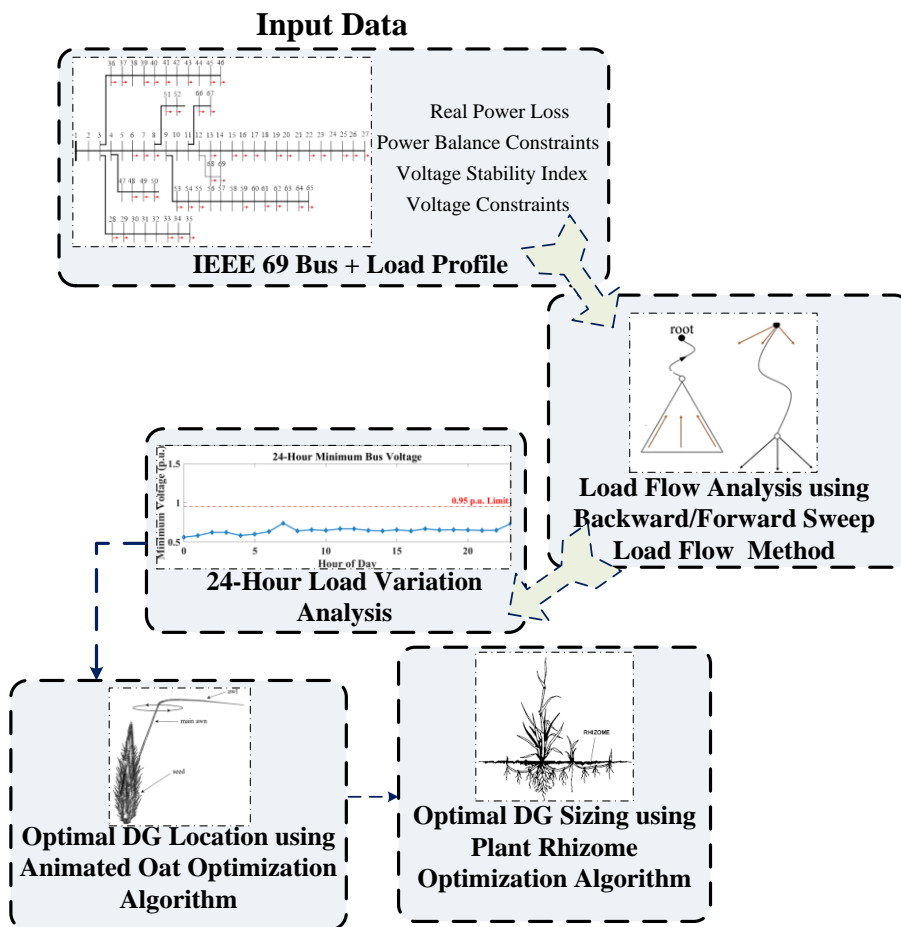


Figure 1: Overall Proposed Framework

System Modelling and Test System Selection

The IEEE 69-bus RDS is represented for modelling and analysis under base conditions without DG integration. Figure 2 presents the Single-line diagram of IEEE 69-bus. The modelling includes the definition of line parameters, bus data (voltage, power demand), and network topology.

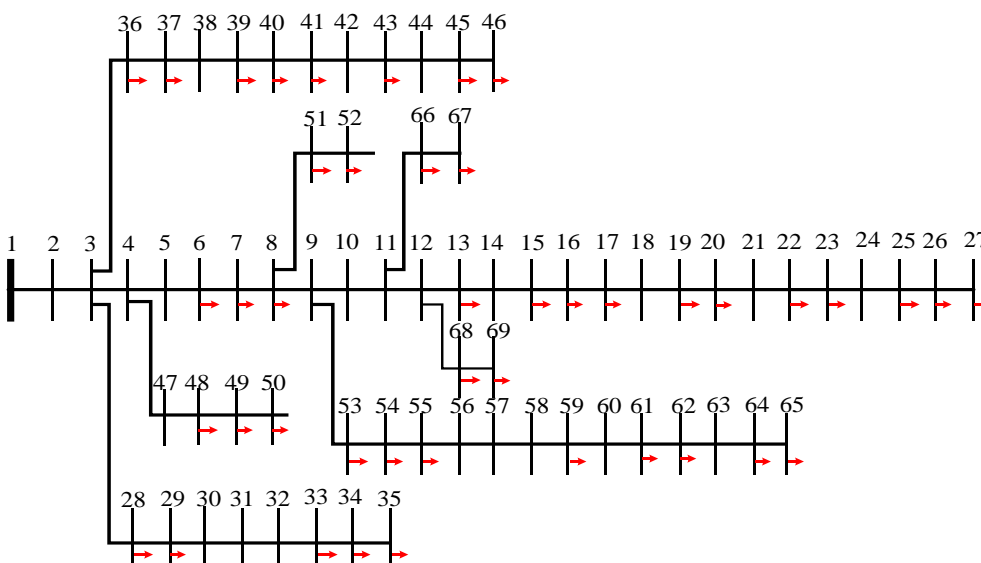


Figure 2: Single-line diagram of IEEE 69-bus RDS

Parameters Analysis

The power loss in the DS occurs due to the resistance of lines and current flowing through them. Minimizing these losses is one of the major objectives in system modelling and DG integration.

$$P_{loss} = \sum_{i=1}^N S_j |J_j|^2 \quad (1)$$

where, S_j denotes j branch resistance, J_j is the current that flowing through branch j , and N is total count of branches. Voltage stability indicates the system ability to maintain voltage levels under varying load conditions. Improving essential voltage stability for reliable system operation.

$$S_j = |W_j|^4 - 4(Q_j S_j + R_j Y_j) |W_j|^2 - 4(Q_j R_j + R_j Y_j)^2 \quad (2)$$

where, W_j denotes buses voltage magnitude, Q_j represents real power at bus, R_j is the reactive power at bus, and S_j is the resistance of line. Power balance ensure that generated power meets the load demand at each bus while satisfying network conditions.

$$Q_{hj} - Q_{ej} = W_j \sum_{k=1}^N W_k Z_{jk} \cos(\delta_j - \delta_k + \theta_{jk}) \quad (3)$$

$$R_{hj} - R_{ej} = W_j \sum_{k=1}^N W_k Z_{jk} \cos(\delta_j - \delta_k + \theta_{jk}) \quad (4)$$

where, W_j, W_k denotes the voltage magnitudes, δ_j, δ_k is the voltage angles, and θ_{jk} is the admittance angle. Voltage limits are imposed to ensure safe and stable operation of the DS. Maintaining these limits prevents voltage instability and equipment damage.

$$V_{min} \leq V_j \leq V_{max} \quad (5)$$

where, V_{min} is the low allowable voltage, V_j represents voltage at bus j and V_{max} is the maximum allowable voltage.

Load Flow Analysis using BFSLF Method

The system is analysed using the BFSLF [14] method, which is a fixed-point iterative technique suitable for RDN. For load flow analysis, the relationship between variables is expressed as a fixed-point problem:

$$(y, z) = (g(y, z), h(y, z)) \quad (6)$$

$$y_k = g_k(y, z), \quad \forall_k = p_1, \dots, p_1 \quad (7)$$

$$z_k = h_k(y, z), \quad \forall_k = 1, \dots, p_2 \quad (8)$$

where, y is the vector of line variables, z denotes the vector of bus voltage, $g(\cdot)$ is the function updating line variables, and $h(\cdot)$ is the function updating bus voltages. The iterative update follows a Gauss–Seidel type approach. Due to the radial structure, the equations follow a recursive form. The backward sweep computes line variables from leaf buses to the root:

$$y_k = g_k(y \Gamma_k^o, z), \quad \forall_k \in P \quad (9)$$

where, Γ_k° denotes the set of downstream buses of bus k , and P is the total number buses. The forward sweep updates bus voltages from the root to the leaf buses:

$$z_k = h_k(y, P_k^\circ), \quad \forall_k \in P \tag{10}$$

where, P_k° denotes the set of upstream buses from root to bus k , and y, P_k° is the voltage of upstream buses.

24-Hour Load Variation Analysis

A time-series load variation analysis is carried out using a 24-hour load profile to represent realistic operating conditions of the DS. To capture this variation, load factors are applied to the base load at each hour. For each time interval, the load demand is modified as:

$$Q_j^{(u)} = \lambda_u \cdot Q_j, \quad R_j^{(u)} = \lambda_u \cdot R_j \tag{11}$$

where, Q_j, R_j nis the base load values and λ_u is the load factor at time. This allows evaluation of voltage profile, branch currents, and power losses across different time periods. Through this analysis, peak load and off-peak conditions are identified with their voltage impacts deviations and system losses.

Optimal DG Location using AOOA

The AOOA [15] is a nature-inspired metaheuristic developed based on the seed dispersal mechanism of the Animated Oat plant (*Avena sterilis*), which exhibits adaptive exploration through random dispersal and efficient exploitation via hygroscopic motion and obstacle-driven ejection. AOOA is used after the 24-hour load variation analysis to identify the optimal DG location by minimizing real power losses in the DS. Figure 3 presents the flowchart for AOOA.

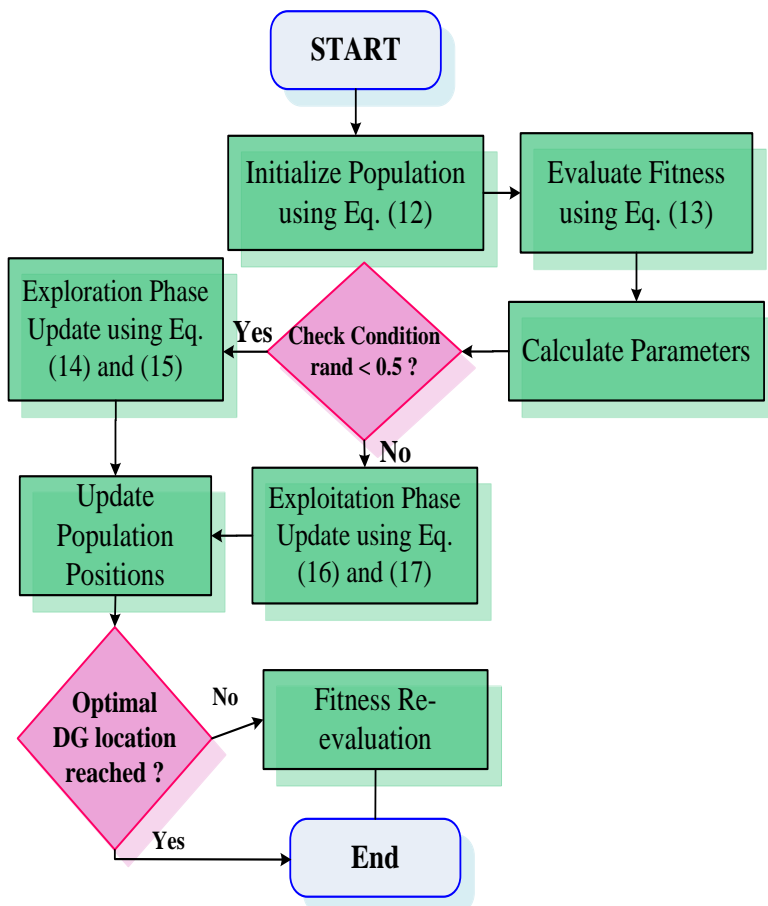


Figure 3: AOOA flowchart

Initialization

In this stage, an initial population of candidate solutions is generated randomly within the defined search space. Each individual represents a possible DG location in the system. This step ensures diversity in the population and provides a good starting point for the optimization process.

$$y_{jk} = s \times (WC_k - MC_k) + MC_k \tag{12}$$

where, WC_k, MC_k denotes the Upper and lower bounds (bus limits) and s is the random number.

Fitness Evaluation

The objective is to minimize total real power loss in the system:

$$g(Y) = \sum_{l=1}^{pc} Q_{loss,l} \tag{13}$$

where, $\sum_{l=1}^{pc} Q_{loss,l}$ denotes the real power loss in branch, and pc is the total number of branches.

Exploration phase

In this phase, AOOA performs global search inspired by random seed dispersal due to environmental factors like wind and water. It enhances diversity and avoids local minima.

$$X = \frac{d}{\pi} \times (2 \times s_{dim} - 1) \otimes VC \tag{14}$$

$$\begin{cases} Y_{u+1}(j) = \frac{1}{P} \times \sum_{j=1}^P Y_u(j) + X, \text{ if } \text{mod}(j, P/10) = 0, \\ Y_{u+1}(j) = Y_{best} + X, \text{ if } \text{mod}(j, P/10) = 1, \\ Y_{u+1}(j) = Y_u(j) + X, \text{ else} \end{cases} \tag{15}$$

where, X denotes the step wise vector, d is the dynamic control parameter, and s is the random number. This phase ensures global exploration and identification of promising regions.

Exploitation Phase

The exploitation phase focuses on refining the solutions obtained during exploration. It is based on two mechanisms: rolling motion (when no obstacle is encountered) and ejection motion (when obstacles are present). These mechanisms help in fine-tuning the candidate solutions and accelerating convergence toward the optimal DG location.

$$Y_u(j) = Y_{best} + S + d \times Levy(dim) \otimes Y_{best} \tag{16}$$

$$Y_u(j) = Y_{best} + K + d \times Levy \otimes Y_{best} \tag{17}$$

where, S denotes the rolling movement component, K is the ejection movement component, and d is the control parameter. The rolling mechanism improves local search, while the ejection mechanism helps escape local minima, ensuring better convergence.

Reevaluating Fitness and Termination

The fitness of updated solutions is recalculated in each iteration based on power loss. Better solutions replace poorer ones, and this process continues until convergence. The process get terminated when the maximum number of iterations is reached.

Optimal DG Sizing using PROA

The PROA [16] is a bio-inspired optimization technique based on the growth behaviour of plant root systems, including fibrous, lateral, and primary roots. It effectively balances exploration and exploitation by simulating nutrient search and diffusion in soil space. The fitness of each solution $F(y_j)$ is then evaluated based on real power loss. The algorithm proceeds with exploration through fibrous root growth to search diverse regions and exploitation through primary and lateral root growth to refine solutions toward optimal DG sizing. During each iteration, the fitness of updated solutions is re-evaluated and compared, allowing better solutions to replace inferior ones.

Experimental Outcome

The proposed system is analysed under the Windows 11 environment using the MATLAB simulator. The performance of the RDS is evaluated for both cases, with and without DG. The analysis includes technical parameters such as voltage profile and power losses, as well as economic factors like operating cost and savings. The optimization process using AOOA and PROA is carried out to determine the optimal DG location and size. The results demonstrate that the optimized system provides improved performance compared to the base case. Both technical and economic aspects are thoroughly analysed, confirming the effectiveness of the proposed methodology under varying load conditions. Tabel 1 presents the network configuration of IEEE 69-Bus RDS. Table 2 presents the base case load flow results of the IEEE 69-bus system without DG integration.

Table 1: Network Configuration of IEEE 69-Bus RDS

Parameter	Value
Test System	IEEE 69-Bus RDS
Total Number of Buses	69
Total Number of Branches	68
System Type	Radial Distribution Network
Nominal Voltage	12.66 kV
Base Power	100 MVA
Slack Bus	Bus 1
Bus Type	PQ Buses (except slack bus)
Load Type	Constant PQ Loads
Base Case Operation	Without DG
Voltage Limits	0.9 p.u. to 1.1 p.u.
Load Profile	24-Hour Time-Varying Load
Optimization Methods	AOOA (DG Location), PROA (DG Sizing)

Table 2: Base Load Flow Results (Without DG) - IEEE 69-Bus System

Bus No.	Voltage (p.u.)	Voltage (kV)	Bus No.	Voltage (p.u.)	Voltage (kV)
1	1.000000	12.6600	13	0.965281	12.2205
2	0.999967	12.6596
3	0.999933	12.6592	60	0.919743	11.6439
4	0.999840	12.6580	61	0.912346	11.5503
5	0.999021	12.6476	62	0.912056	11.5466
6	0.990088	12.5345	63	0.911668	11.5417
7	0.980798	12.4169	64	0.909768	11.5177
8	0.978583	12.3889	65	0.909194	11.5104
9	0.977450	12.3745	66	0.971299	12.2966
10	0.972456	12.3113	67	0.971298	12.2966
11	0.971355	12.2974	68	0.967869	12.2532
12	0.968199	12.2574	69	0.967868	12.2532

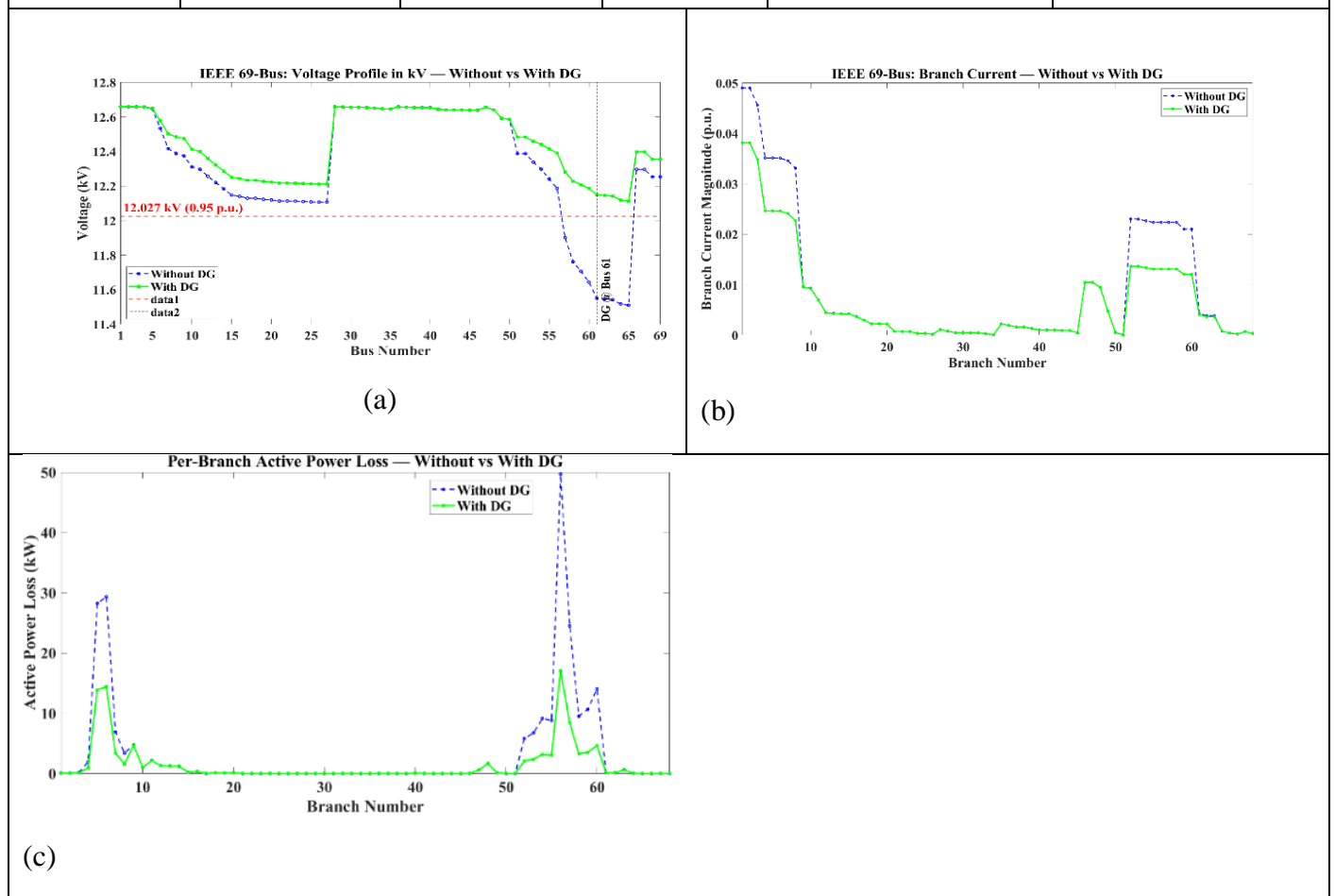


Figure 4: With and Without DG Analysis in IEEE 69-Bus System (a) Voltage (kV) (b) Branch Current Magnitude (c) Active Power Loss

Figure 4 presents the comparative analysis of the IEEE 69-bus system under without DG and with DG conditions. In Figure 4(a) illustrates Voltage (kV), the voltage profile is improved after DG integration, where the voltage remains around 12.6 kV near bus 30 for both cases, while at the end bus (bus 69), the voltage improves from approximately 12.4 kV (without DG) to about 12.3–12.35 kV (with DG), indicating better voltage support along the feeder. In Figure 4(b) presents the Branch Current Magnitude, the branch currents are reduced after DG integration due to local power support, which decreases the current flowing from the substation to load buses. In Figure 4(c) shows the Active Power Loss, a significant reduction in power loss is observed with DG integration compared to the base case. Table 3 presents the economic analysis of the system with and without DG.

Table 3: Economic analysis

Parameter	Rs 6/kWh	Rs 7/kWh
Annual Cost without DG (Million Rs)	11.82	13.79
Annual Cost with DG (Million Rs)	3.13	3.65
Annual Saving (Million Rs)	8.69	10.14
Present Worth Factor (PWF)	8.5136	8.5136
Present Worth of Saving (Million Rs)	80.30	86.30
DG Investment Cost (Million Rs)	62.20	62.20
Net Profit (Million Rs)	11.82	24.60
Payback Period (years)	7.15	6.13

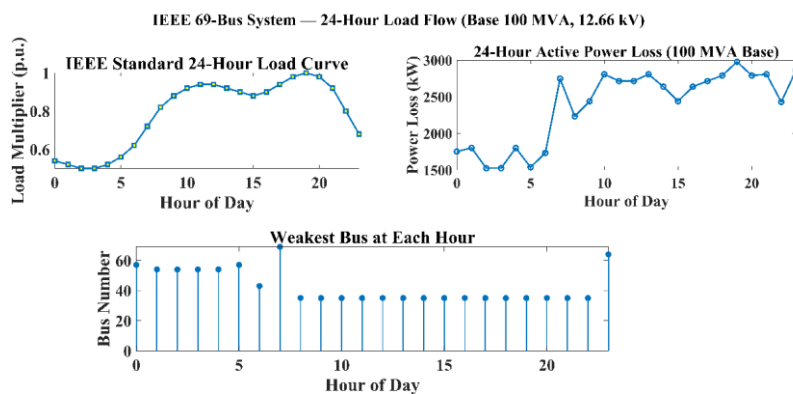


Figure 5: 24-Hour Load Flow Analysis (a) Load Multiplier (b) Power Loss (c) Minimum Bus Voltage

Figure 5 presents the 24-hour load flow of system performance under changing load conditions throughout the day. In Figure 5(a), the load multiplier variation over 24 hours is presented, where the load increases from 0.50–0.54 during off-peak hours (Hr 02–03) to a maximum of 1.00 at Hr 19, indicating peak demand conditions. In Figure 5(b), the corresponding power loss profile is shown, where losses rise from a minimum of 51.6 kW at low load to a maximum of 224.9 kW at peak load, clearly reflecting the impact of load variation on system losses. In Figure 5(c), the minimum voltage bus is illustrated, where Bus 65 remains the critical bus throughout the day, with voltage varying from a higher value of 0.9567 p.u. during off-peak hours to a minimum of 0.9092 p.u. at peak load. Overall, the figure demonstrates that increasing load demand leads to higher power losses and reduced voltage levels, emphasizing the importance of optimal DG integration for improved system performance.

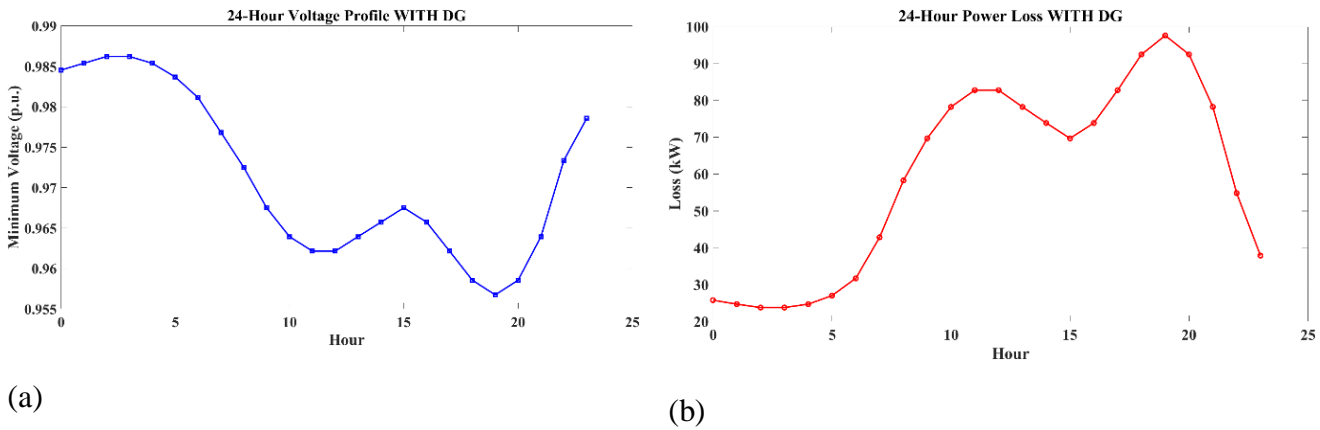


Figure 6: IEEE 69-Bus System with DG - 24-Hour Analysis (a) Minimum Voltage (p.u.) (b) Power Loss (kW)

Figure 6 presents the 24-hour performance of the IEEE 69-bus system after DG integration. In Figure 6(a) presents the Minimum Voltage, the voltage profile shows improved stability throughout the day, with values around 0.985 p.u. at Hour 5 and approximately 0.98 p.u. at Hour 24, indicating better voltage regulation under varying load conditions. In Figure 6(b) shows the Power Loss (kW), the loss variation over 24 hours is illustrated, where losses are reduced significantly compared to the base case. The power loss is about 25 kW at Hour 5, increases to around 80 kW at Hour 20 during higher load demand, and reduces to nearly 40 kW at Hour 24, following the load pattern.

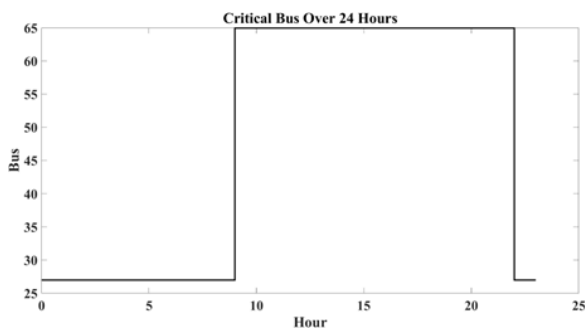


Figure 7: Critical Bus Analysis over 24 Hours

Figure 7 presents the variation of the critical (minimum voltage) bus over a 24-hour period. It is observed that the critical bus is around Bus 27 during initial low-load hours, then shifts to Bus 65 from approximately Hour 10 to Hour 22 under higher load conditions, indicating increased system stress. After peak hours, the critical bus shifts back toward lower-numbered buses, showing recovery in voltage profile during reduced load.

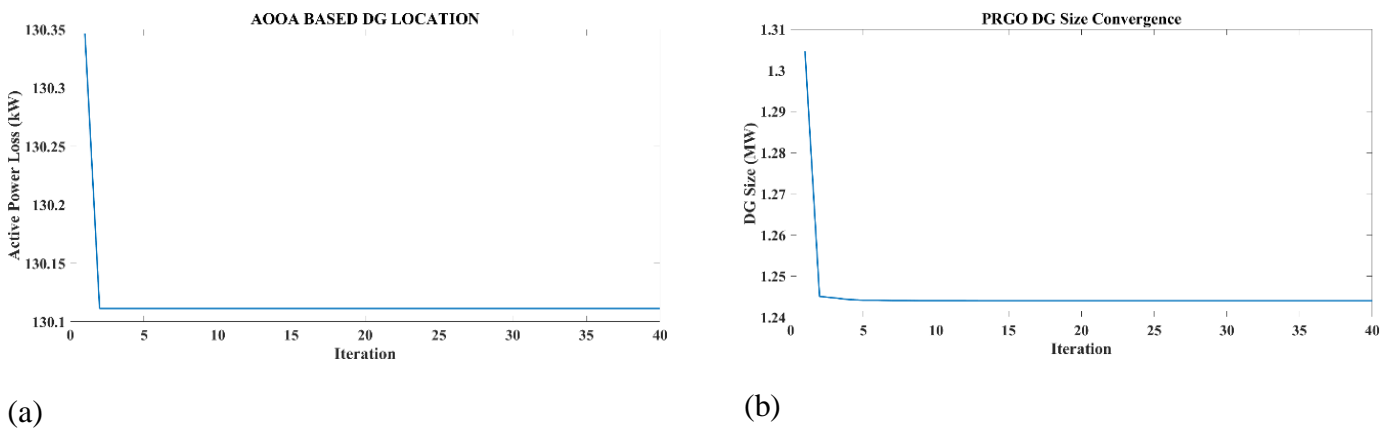


Figure 8: Optimization model convergence analysis (a) AOOA-based active power loss (b) PRGO convergence

Figure 8 presents the convergence behaviour of the proposed optimization model over 40 iterations. In Figure 8(a) shows the AOOA-based DG Location Convergence, the active power loss initially starts at around 130.35

kW in the first iteration and rapidly decreases to below 130.15 kW by the third iteration, after which it remains stable up to the 40th iteration, indicating fast convergence and solution stability. In Figure 8(b) shows the PROA-based DG Sizing Convergence, the DG size begins at approximately 1.3 MW in the initial iteration and converges to the optimal DG size of 1.244 MW by the third iteration, maintaining a consistent value for the remaining iterations.

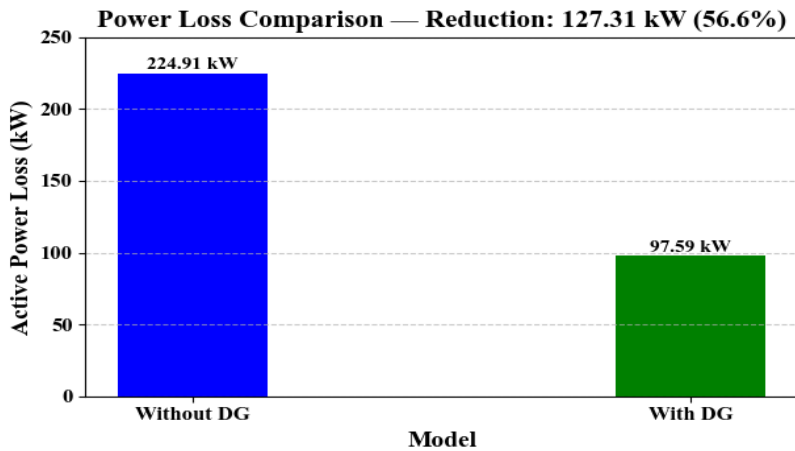


Figure 9: Power Loss Comparison (With and Without DG)

Figure 9 presents the comparison of active power losses in the IEEE 69-bus system before and after DG integration. The 10-Fold Cross-Validation Results of Proposed AOOA-PROA Model is tabulated in Table 4.

Table 4: 10-Fold Cross-Validation Results of Proposed AOOA-PROA Model

Fold No.	Power Loss (kW)	Minimum Voltage (p.u.)	Remarks
1	98.12	0.9558	Stable
2	97.85	0.9561	Stable
3	97.63	0.9565	Stable
4	97.91	0.9560	Stable
5	97.59	0.9567	Best
6	97.88	0.9562	Stable
7	97.74	0.9564	Stable
8	97.66	0.9566	Stable
9	97.83	0.9563	Stable
10	97.70	0.9565	Stable

The approach focuses on improving both technical efficiency and economic feasibility of DG integration. Significant improvements are observed after optimization. This accurate identification of the optimal DG functioning of 1.244 MW, which ensures better power flow distribution. This is mainly due to accurate identification of the optimal DG functions, which ensures better power flow distribution. The inclusion of time-varying load analysis further strengthens the reliability of the results by capturing real operating conditions. The coordinated use of optimization algorithms enhances convergence and solution quality.

CONCLUSION

This study presents an effective optimization framework for optimal DG placement and sizing in the IEEE 69-bus RDS. The proposed methodology integrates BFS LF analysis, 24-hour load variation modeling, and advanced metaheuristic techniques to improve both technical and economic performance. The proposed AOOA–PROA model achieves superior results compared to existing methods. The active power loss is reduced to 97.59 kW, and the minimum voltage is improved to 0.9567 p.u., confirming enhanced system performance and stability. Future research can further enhance the proposed framework by incorporating stochastic and probabilistic uncertainty modelling of renewable energy-based DG sources, such as solar photovoltaic and wind systems, to improve operational robustness under real-time fluctuating conditions. The extension of the proposed methodology to large-scale and complex distribution networks with different topologies can improve the scalability and generalization capability of the model. In addition, hybrid metaheuristic optimization approaches integrating multiple intelligent algorithms may be explored to achieve improved convergence speed, global search capability, and solution accuracy. Real-time implementation through Hardware-In-the-Loop (HIL) simulations and smart grid platforms can provide practical validation of the proposed strategy under dynamic operating environments. Moreover, future work can focus on multi-objective optimization considering technical, economic, reliability, emission reduction, power quality, and environmental sustainability indices to develop a comprehensive and sustainable DG planning framework for modern power distribution systems.

REFERENCES

1. Roy, S. and Singh, R., 2025. Distributed energy procurement with renewable energy sources in a radial distribution system. *Computers and Electrical Engineering*, 123, p.110268.
2. Šehić, F., Konjić, T., Čalasan, M. and Rakočević, S., 2025. A new approach for optimal allocation and sizing a distributive energy source or a parallel compensation device in radial distribution networks. *Electrical Engineering*, 107(6), pp.8171-8188.
3. Abera, A.G., Yetayew, T.T. and Alyu, A.B., 2025. Optimized solar PV integration for voltage enhancement and loss reduction in the Kombolcha distribution system using hybrid grey wolf-particle swarm optimization. *Results in Engineering*, 26, p.105484.
4. Sahay, S., Biswal, S.R., Shankar, G., Jha, A.V., Appasani, B., Srinivasulu, A. and Nsengiyumva, P., 2025. Optimized placement of distributed generators, capacitors, and EV charging stations in reconfigured radial distribution networks using enhanced artificial hummingbird algorithm. *Scientific Reports*, 15(1), p.11144.
5. Maurya, P., Tiwari, P. and Pratap, A., 2025. Application of the hippopotamus optimization algorithm for distribution network reconfiguration with distributed generation considering different load models for enhancement of power system performance. *Electrical Engineering*, 107(4), pp.3909-3946.
6. Soliman, I.A., Tulskey, V., Abd el-Ghany, H.A. and ElGebaly, A.E., 2025. Efficient allocation of capacitors and vehicle-to-grid integration with electric vehicle charging stations in radial distribution networks. *Applied Energy*, 377, p.124745.
7. Shams, H., Rostami, N. and Mohammadi Ivatloo, B., 2025. A clustering-based co-allocation of battery swapping stations and wind-photovoltaic plants in radial distribution systems. *Scientific Reports*, 15(1), p.22486.
8. Debbarman, S., Namrata, K., Samadhiya, A., Azar, A.T., Ahmed, S., Mahlous, A.R. and El-Shafai, W., 2025. Modified cheetah optimizer for optimal techno-economic placement of distributed energy source planning. *Discover Sustainability*, 6(1), p.1120.
9. Patel, P., Patil, N., Mohsen, A., Kashyap, A., Hasan, N.A., Thatoi, D.N. and Gupta, D., 2025. Multi-objective particle swarm optimization algorithm-based method for optimal placement and sizing of distributed generations and shunt capacitors in a radial distribution network. *Results in Engineering*, p.106514.
10. Kien, L.C., Van Hien, T., Ngoc Tram, H.D. and Pham, T.D., 2025. Optimal Integration of Renewable Energy–Based Distributed Generation Units in Radial Distribution System. *International Transactions on Electrical Energy Systems*, 2025(1), p.8694811.
11. Roy, K., Bansal, S.K. and Bansal, R.C., 2025. Performance enhancement of radial distribution system with optimal DG allocation. *International Journal of Modelling and Simulation*, 45(1), pp.245-263.

12. Maurya, P., Tiwari, P. and Pratap, A., 2025. Puma optimizer technique for optimal planning of different types of distributed generation units in radial distribution network considering different load models. *Electrical Engineering*, 107(3), pp.2777-2828.
13. Mokred, S., Wang, Y., Alruwaili, M. and Ibrahim, M.A., 2025. A novel approach for voltage stability assessment and optimal siting and sizing of DGs in radial power distribution networks. *Processes*, 13(7), p.2239.
14. Fang, B., Zhao, C. and Low, S.H., 2025. Convergence of backward/forward sweep for power flow solution in radial networks. *IEEE Transactions on Control of Network Systems*, 12(2), pp.1780-1792.
15. Wang, R.B., Hu, R.B., Geng, F.D., Xu, L., Chu, S.C., Pan, J.S., Meng, Z.Y. and Mirjalili, S., 2025. The Animated Oat Optimization Algorithm: A nature-inspired metaheuristic for engineering optimization and a case study on Wireless Sensor Networks. *Knowledge-Based Systems*, 318, p.113589.
16. Zhang, J., Yan, F. and Yang, J., 2025. Binary plant rhizome growth-based optimization algorithm: An efficient high-dimensional feature selection approach. *Journal of Big Data*, 12(1), p.13.