An International Journal of Optimization and Control: Theories & Applications
ISSN: 2146-0957 eISSN: 2146-5703
Vol.16, No.5, pp.1903-1926 (2026)
https://doi.org/10.36922/IJOCTA026140049

RESEARCH ARTICLE

Optimal reconfiguration of photovoltaic/wind-based distributed generation systems: A techno-economic analysis using AHP–GA

Manish Kumar Madhav[1], Krishna B. Yadav[1], Akshit Samadhiya[2], Ahmad Taher Azar[3,4], Saim Ahmed[4]*, Walid El-Shafai[4,5], and Chakib Ben Njima[6]

[1]Department of Electrical Engineering, National Institute of Technology, Jamshedpur, Jharkhand, India

[2]Department of Electrical Engineering Harcourt Butler Technical University, Kanpur, India

[3]College of Computer and Information Sciences, Prince Sultan University, Riyadh, Saudi Arabia

[4]Automated Systems and Computing Lab (ASCL), Prince Sultan University, Riyadh, Saudi Arabia

[5]Department of Electronics and Electrical Communications Engineering, Faculty of Electronic Engineering, Menoufia University, Menouf, Egypt

[6]University of Sousse, Sousse, Tunisia

2020rsee006@nitjsr.ac.in; kbyadav.ee@nitjsr.ac.in; akspinnacle1@gmail.com; aazar@psu.edu.sa; sahmed@psu.edu.sa; welshafai@psu.edu.sa; chakib.bennjima@enim.rnu.tn

ARTICLE INFO

Article history:
Received: March 30, 2026
Revised: May 13, 2026
Accepted: May 15, 2026
Published Online: August 24, 2026

Keywords:
Genetic algorithm
Renewable distributed generation
Load flow
Analytic Hierarchy Process
Distribution system
Reliability indices

ABSTRACT

Renewable distributed generation (RDG), notably solar and wind energy, is increasingly integrated into distribution networks (DNs) to enhance sustainability, meet rising demand, and improve grid reliability. This study proposes a coordinated planning framework that jointly optimizes RDG siting/sizing and DN expansion using a hybrid Analytic Hierarchy Process–genetic algorithm (AHP–GA). Multi-objective goals—minimizing active power losses, reliability-related costs, and annual equipment investment—are scalarized using AHP-derived weights and solved through a chromosome-segmentation GA that reduces the search space and accelerates convergence. The method was validated on a modified IEEE 37-node radial distribution system, demonstrating substantial techno-economic benefits: total cost reductions exceeding 25%, approximately 75% reduction in active power losses, and about 40% improvement in reliability indices. A comparative assessment of the IEEE 69-bus system further underscored the approach's efficiency, achieving an active power loss of 16.88 kW (a 92.50% reduction) and 112.67 s of CPU time, outperforming alternative metaheuristics. After the integration of DGs, both reliability indices improved significantly, resulting in reductions of 40.27% in System Average Interruption Duration Index (SAIDI) and 58.84% in Energy Not Served (ENS) annually. The results indicate that coordinated RDG–DN planning yields DNs that are more economical, reliable, and operationally robust than those from sequential or uncoordinated strategies.

1. Introduction

Human lives are becoming increasingly easier and more dependent on technology in almost every area, including entertainment, employment, health, and even interpersonal relationships. This trend is driven by daily advancements in technology and research, leading to a growing

*Corresponding Author

demand for uninterrupted power supply. As a result, distribution engineers face significant challenges in providing a reliable power supply to consumers, a critical issue today.

Renewable distributed generation (RDG) is the localized production of electricity from renewable energy sources, such as solar, wind, biomass, and small hydropower systems. Unlike in central-point power plants, RDG systems are located close to load centers, resulting in lower transmission and distribution losses. By reducing greenhouse gas emissions, they contribute to environmental sustainability, and by enhancing grid resilience and increasing energy efficiency, they increase grid security. RDG is promoting renewable energy adoption to diversify power grid sources and increase energy security. Small-scale RDG systems are now critical components of modern power systems, given the benefits of smart grid technologies and energy storage for providing a decentralized, sustainable form of energy. Distributed generation (DG) has emerged as a key energy source, directly or indirectly connected to the distribution network on the consumer side, and is an essential component of electricity networks. The integration of DG into the distribution network offers numerous benefits, such as reduced network losses, improved system reliability, enhanced voltage profiles, improved power factors, increased network stability, and positive economic and environmental effects.

However, the increasing number of DGs (solar, wind, and small hydro) connected to the distribution network brings both advantages and challenges for grid maintenance and operation. Researchers have addressed optimal DG placement problems using various heuristic and traditional methods. Nevertheless, if the size and placement of DGs are not selected properly, network characteristics, such as stability, voltage profiles, and network losses, can deteriorate to levels worse than those without DG integration.[1-4]

Installing DG provides several technical, financial, and environmental benefits: improved system reliability, reduced transmission losses, reduced energy costs, improved integration with renewable energy sources, and decreased greenhouse gas emissions.[5,6] Studies have focused on reducing active power losses in distribution networks by properly placing multiple DG units, considering different types, such as DGs that deliver both active and reactive power or only active power.[7-9]

A strategy based on a genetic algorithm (GA)[10-14] has been developed to reduce power losses in a radial distribution system while improving voltage stability. This approach focuses on determining the optimal size and location of various types of DG units. Identifying the optimal location and size of DG units is a complex problem involving a nonlinear objective function and nonlinear constraints. Selecting suitable sites for DG installation is essential to achieving multiple objectives, such as voltage regulation, power loss reduction, peak load management, and system reliability and resilience improvement.[15-17] The allocation process considers factors such as load demand, network constraints, environmental considerations, and economic feasibility to identify the most advantageous deployment of DG units. Simultaneously, to effectively integrate DG sources, the network must be restructured to adapt to the existing distribution infrastructure.

The integration of DG in radial networks has gained significant attention in recent years. To accommodate bidirectional power flows and the fluctuations of renewable energy sources, the existing infrastructure must be restructured to facilitate DG integration into electrical distribution networks. This restructuring often involves upgrading distribution lines, transformers, and other equipment; implementing advanced control and monitoring systems; and developing new regulatory frameworks to support the deployment of multiple DGs in radial distribution networks (RDNs). Kaur and Jain[18] proposed a novel approach for the placement of multiple DG units using particle swarm optimization (PSO) combined with a fuzzy decision-making method. This approach addresses multi-objective optimization, balancing competing goals to determine the optimal locations and sizes of DG units for voltage-dependent residential, commercial, and industrial loads. Various soft computing techniques have been successfully applied by researchers to address the optimal DG placement problem. These methods include improved elephant herding optimization (IELHO),[19] nested multi-objective particle swarm optimization (MOPSO),[20] population-based incremental learning (PBIL),[21] harmonic power flow algorithm (HPFA)–PSO,[22] hybrid artificial bee colony (ABC)–cuckoo search,[23] water cycle algorithm (WCA),[24] analytical approaches,[25] lightning search algorithm (LSA)–ABC,[26] GA,[27] Hybrid genetic particle swarm optimization (GPSO),[28] parallel slime mould algorithm,[29] cloud model-based symbolic organism search algorithm,[30] equilibrium optimization algorithm,[31] crow search and black widow hybrid optimization,[32] and whale optimization algorithm (WOA).[33] Additionally, researchers have addressed reliability concerns in DG deployment. The challenges and issues related to power system restructuring have been extensively discussed.[34] A technique for calculating reliability indicators, such as the System Average Interruption Duration Index (SAIDI) and Energy Not Served (ENS), has also been proposed, utilizing Gas.[35]

1.1. Insights from existing research

The improvement in the reliability of estimating off-grid and on-grid individual or blended-agent types of renewable resources has become a crucial research area owing to the electrical power requirement. **Table 1** shows the comparison of different research works with respect to size, location, objective function, and the techniques applied by the researchers.

Table 1. Comparison of numerous recent related works to the proposed work

Reference	Decision variable		Objective function				Optimization algorithm	Distribution network
	Size & location	Multiple DG	Active power losses	Voltage fluctuation	Cost of reliability	Investment cost		
28	✓	✓	✓	✓			GA, PSO	IEEE 33, IEEE 69
26	✓	✓	✓			✓	ABC	38 bus networks
25	✓	✓	✓				Analytical approach	IEEE 33
24	✓	✓	✓	✓		✓	WCA	IEEE 33, IEEE 69
23	✓	✓	✓	✓			GA–PSO	30 node, 141 node
22	✓	✓	✓			✓	PSO	31 bus
21	✓	✓	✓	✓			PBIL	IEEE 33, IEEE 69
20	✓	✓	✓			✓	MOPSO	IEEE 30
19	✓	✓	✓	✓			Improved EHO	IEEE 33
18	✓	✓	✓	✓			MOPSO	IEEE 69
15	✓	✓	✓	✓			Improved ICA	IEEE34, IEEE 69
13	✓	✓	✓				GA	IEEE 31
12	✓	✓	✓	✓			Adaptive GA	IEEE 33
Proposed Technique	✓	✓	✓	✓	✓	✓	AHP–GA	IEEE 37 IEEE 69

Abbreviations: ABC: Artificial bee colony; AHP: Analytic Hierarchy Process; DG: Distributed generation; EHO: Elephant herding optimization; GA: Genetic algorithm; ICA: Imperialist competitive algorithm; MOPSO: Multi-objective particle swarm optimization; PBIL: Population-based incremental learning; PSO: Particle swarm optimization; WCA: Water cycle algorithm.

Although several studies have investigated the optimal placement and sizing of DG units using various heuristic and metaheuristic optimization techniques, significant research gaps remain. Most existing works primarily focus on a single objective, such as minimizing active power loss or improving the voltage profile, while giving limited attention to the simultaneous consideration of technical, economic, and reliability aspects. Furthermore, many studies neglect coordinated distribution network expansion planning along with DG allocation, especially under future load growth conditions. Existing approaches also rarely integrate reliability indices such as SAIDI and ENS directly into the optimization framework. In addition, most previous methods employ standalone optimization techniques without incorporating a structured multi-criteria decision-making process for objective weighting. Therefore, there is a need for a comprehensive multi-objective framework that simultaneously considers DG siting and sizing, network expansion, investment cost, active power loss, and reliability enhancement. To address these limitations, this paper proposes a coordinated AHP–GA based optimization approach for renewable DG allocation and distribution network planning.

1.2. Main contributions and paper organization

The contributions made in this research can be summarized as:

- Optimization of DG size and location: We optimized the size and placement of RDGs, such as solar and wind energy, resulting in reduced system losses and improved voltage profiles.
- Comprehensive consideration of objectives: While most researchers have independently focused on system losses, voltage deviations, reliability costs, and equipment investment costs for DG placement, this work uniquely considers all these objective functions simultaneously, including their technical and economic benefits.
- Incorporation of network expansion: The study also addresses line upgrades and future network expansions to effectively accommodate growing demand.
- Multi-objective framework: This research uses a multi-objective framework that integrates all relevant objectives. The novel AHP–GA methodology is introduced, and its effectiveness is evaluated using the IEEE 37 and IEEE 69 bus test systems.
- Superior performance: Compared to alternative metaheuristic methods, the proposed approach delivers more accurate and satisfactory results.

The paper is organized as follows: Section 1 provides an overview of the study and background, including the research objectives and the theoretical context for this work. Section 2 describes the research methodology, and Section 3 explains the development of the objective function of the model. Sections 4 and 5 present a detailed discussion of the AHP, DG penetration rate, and the optimization method used. Section 6 presents a case study, Section 7 presents the results and discussion, and Section 8 presents a comparative study. Finally, Section 9 concludes with a summary of the overall research findings.

2. Research methodology

Figure 1 outlines the proposed method for determining the optimal location, sizing, and placement of renewable DGs and new load points. This innovative approach introduces autonomous planning for the expansion of distribution networks, identifying candidate positions for DG placement to maximize capacity, facilitate line expansion, and designate locations for new load points.

System data, including unit costs, branch lengths, maintenance costs, average outage rates, line and load data, fixed investment costs, annual fixed investment cost coefficients from DGs, average outage durations, and decision-maker preferences, were input into the computer program as system information. The program then calculated active power losses and voltage profiles using the forward-backward load flow method. Based on these calculations, potential DG locations were identified.

The AHP method was employed by decision-makers, engineers, or managers to assign reliability parameter weights. Finally, the GA was used to determine the optimal DG placement and capacity by minimizing the objective function. The approach also identified new load points and necessary line upgrades within the distribution network.

In general, existing distribution networks are radial and have a high R/X ratio. As a result, they are in poor condition, making them difficult to solve using traditional Newton-Raphson and fast-decoupled load flow methods. The forward–backward method of load flow is used to determine the electrical parameters for a radial system.[36] The single-line diagram of an RDN with N nodes (node 1 as the source node, with corresponding node voltages V1, V2...VN) is shown in **Figure 2**.

The forward-backward load flow method is applied as follows:

(i) Initialization of voltages at all buses:

$$V_j^{(0)} = V_s \angle 0 \quad \text{for } j = 2,3,4 \ldots \text{N} \tag{1}$$

(ii) The load currents of each phase are computed using the initial voltages for each node, which are calculated as:

$$I_j^{(k)} = \left(\frac{P_{Lj} + jQ_{Lj}}{V_j^{(k-1)}} \right)^* \quad \text{for } j = 2,3,4 \ldots \text{N} \tag{2}$$

where k is the iteration count, P_{Lj} and Q_{Lj} are loads at bus j, and V_j is the voltage at bus j.

(iii) This step, known as the backward sweep, allows the total branch currents from the last bus to the source bus to be computed. The current flowing through the branch mn can

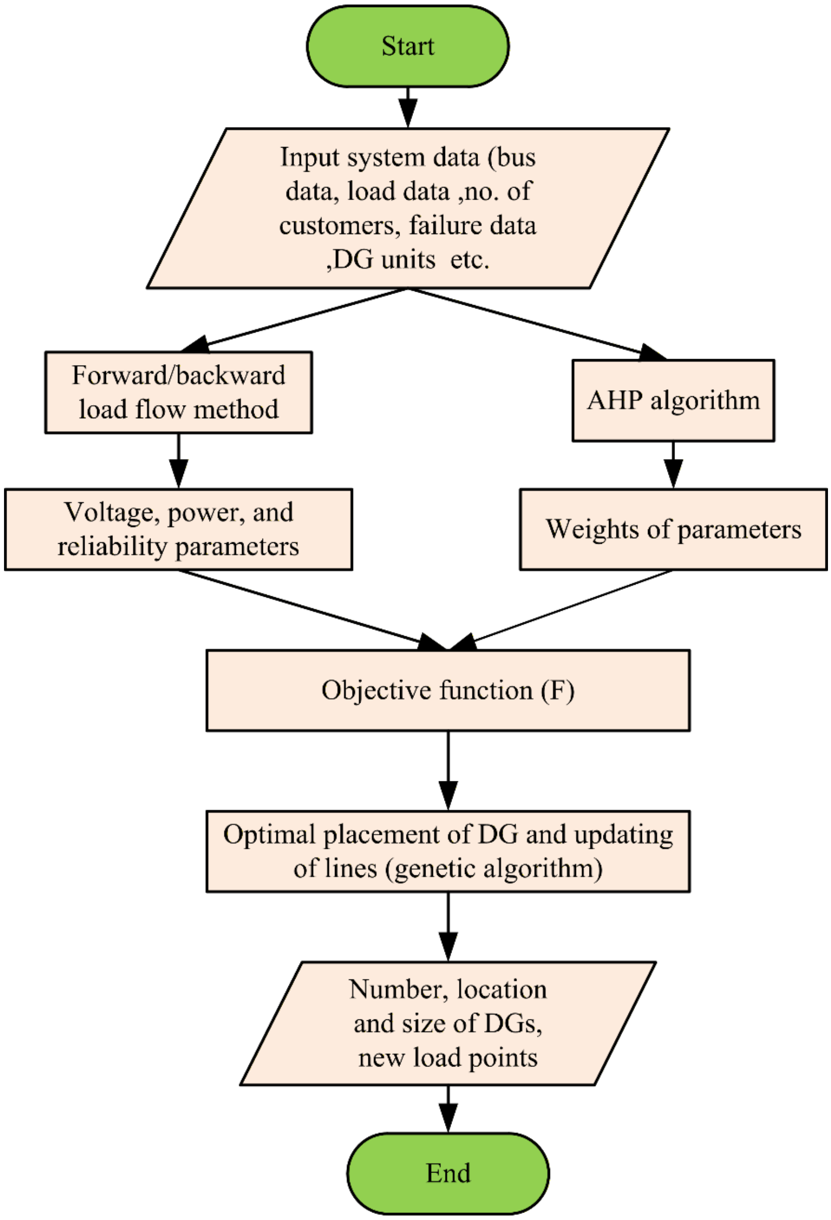

Figure 1. Flowchart of the proposed method
Abbreviations: AHP: Analytic Hierarchy Process; DG: Distributed generation.

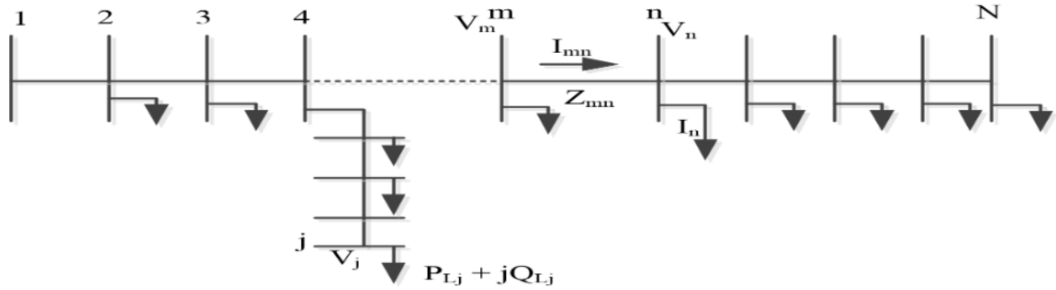

Figure 2. Single-line diagram of a radial distribution network

be calculated as shown below:

$$I_{mn}^{k} = I_{n}^{k} + \sum\nolimits_{p \in N} I_p \tag{3}$$

where I_{mn} is the current through branch mn, I_n is the current drawn by the load connected to bus n, and $\sum\nolimits_{p \in N} I_p$ represents the sum of all the currents of branches entering bus n.

(iv) This step, known as the forward sweep, updates the bus voltage starting from the source node to the last node, as shown below:

$$V_n^{(k)} = V_m^{(k)} - Z_{mn} I_{mn}^{(k)} \tag{4}$$

where V_m and V_n are the corresponding node voltages, and Z_{mn} is the branch impedance.

3. Approach for integrated planning between the distribution network and distributed generation

This study comprehensively considered the optimal configuration and distribution network planning for RDG. A new multi-objective programming model that minimizes the three indicators of system active power loss cost (C_{aploss}), reliability loss cost (C_{rel}), and annual equipment purchase cost (C_{eqp}) as optimization sub-objectives was established. DG access location and capacity, line upgrading and rebuilding, and new load point access locations are the decision variables, and the objective function is:

$$\begin{cases} f_1 = min\left(C_{aploss}\right) \\ f_2 = \min\left(C_{rel}\right) \\ f_3 = \min\left(C_{eqp}\right) \end{cases} \tag{5}$$

3.1. System active power loss cost

If a fault occurs in the system, it is not possible to supply electricity to the connected load until the fault is cleared or the DG is properly connected. Thus, the system reliability is poor due to a fault, so the main work of the discom engineer is to clear the fault and resume supply to the connected load. Minimizing the total active power loss is the primary objective of optimal DG placement in the distribution network.

The power loss in each segment can be calculated as:

$$P_{loss} = \sum_{q}^{T} (I_q)^2 R_q \tag{6}$$

where R_q and I_q represent the resistance and current of the q^{th} branch, respectively, and T is the total number of buses. The cost of active power loss (C_{aploss}) can be calculated as

$$C_{aploss} = P_{loss} T_{\max} R_w \tag{7}$$

where T_{max} is the maximum time during which power is disconnected, and R_w is the per-unit cost due to network loss.

3.2. Annual investment cost for equipment

The annual investment cost for equipment (C_{eqp}) is defined as follows:

$$C_1 = \frac{R_{DG} \sum_{k=1}^{n_{DG}} P_{DGk}}{T_{DG}} \tag{8}$$

where C_1 is the annual capital investments and operational expenditures for DG, R_{DG} is the cost per kW generated by DG, T_{DG} is the total life of DG (in years), n_{DG} is the total number of DG installed, and P_{DGk} is the power generated by the k^{th} DG (in kW).

$$\mathrm{C}_2 = \sum_{t=1}^{N_q} \mathrm{y}_t (\mu_k R_{qt} B_t + M_{qt}) \tag{9}$$

where C_2 is the annual capital investments and operating expenditures for line upgradation,

N_q is the number of present branches, B_t is the length of the t^{th} branch, R_{qt} is the rate of investment per unit length, M_{qt} is the inspection, repair, and maintenance costs of the t^{th} branch, μ_k is the yearly average cost coefficient for fixed investments, and y_t is either 0 (specifies that the t^{th} branch is not selected for upgradation) or 1 (t^{th} branch is selected for upgradation).

$$C_3 = \sum_{s=1}^{N_{new}} (\sigma_s R_{news} B_s + M_{news}) \tag{10}$$

where C_3 is the annual capital and operating costs for new line investment, N_{new} is the new load lines to be formed, σ_s is the annual average fixed investment cost of the s^{th} new line, R_{news} is the rate of investment per unit length for s^{th} new line, B_s is the s^{th} new line length, and M_{news} is the maintenance cost of the s^{th} new line.

Thus, the annual investment cost for equipment of the distribution network is given by:

$$C_{eqp} = C_1 + C_2 + C_3 \tag{11}$$

3.3. Cost of reliability loss

The cost of reliability loss (C_{rel}) is defined as:

$$C_{rel} = \sum_{t=1}^{m_l} \sum_{s=1}^{m_f} W_t R_t U_s \tag{12}$$

$$U_s = \sum_{s=1}^{m_f} r_s . \lambda_s \tag{13}$$

where m_l is the load point; m_f is the number of failure modes, W_t is the load connected to node t, R_t is the cost of supply loss due to fault s with a duration of r_s that causes the loss of customers connected to the load point t, U_s is the unavailability of supply due to fault s, and λ_s is the average failure rate of failure modes.

3.4. Inequality constraints

The objective function, as given in **Equation 5**, has limitations; hence, the objective function must be satisfied within the given range. The limitations are as follows:

$$\begin{cases} N_{DG} \le N_{DG\max} \\ \sum_{t \in \Gamma_g} W_{DGt} \le \xi \sum_{t \in \Gamma_L} W_{Lt} \\ V_{\min} \le V \le V_{\max} \\ W_{st} \le W_{st\max} \\ I_t \le I_{rated} \end{cases} \tag{14}$$

where N_{DG} is the optimal number of final operating DGs, N_{DGmax} indicates the maximum number of candidate locations of DG, W_{Lt} is the load of node t; W_{DGt} is the t^{th} possible contribution of DG, ζ is the penetration rate of DG, Γ_g indicates nodes connected to DG, Γ_L means system load points, V is the voltage vector of all nodes, V_{max} and V_{min} are the voltage range of a particular bus (assumed to be 5% tolerance), W_{st} indicates the active power of branch st and W_{stmax} is its extreme value, I_t is the t^{th} branch current, and I_{rated} is the maximum permissible branch current.

3.5. Final objective function

For the problem of DG placement and the addition of new load points, the objectives include minimizing network loss costs, equipment purchase costs, and costs associated with reliability losses. To enable meaningful comparison and effective decision-making, these objectives are typically combined into a single objective function. This transformation is achieved using the judgment matrix approach, which assigns weights based on both quantitative and qualitative factors. In this research, the judgment matrix approach was employed to convert the multi-objective function into a single-objective function, facilitating comprehensive optimization. The final objective function for this problem is expressed as follows:[17]

$$F = \min(\omega_1 f_1 + \omega_2 f_2 + \omega_3 f_3) \tag{15}$$

where ω_1, ω_2 and ω_3 are the normalized weights, which are determined with the help of the judgment matrix idea as described in the next section.

4. Analytic hierarchy process

In the 1970s, Saaty[37] introduced the AHP, a decision-making framework for analyzing and prioritizing complex multi-criteria problems. These comparisons are quantified using a numerical scale, such as Saaty's 1–9 scale, which represents the degree of relevance or preference. A judgment matrix, also known as a pairwise comparison matrix, is a decision-making tool for evaluating and ranking multiple options based on criteria. The following steps outline the process for creating a judgment matrix:

(i) Define the criteria/alternatives: Identify the criteria or alternatives that are needed to evaluate and prioritize.
(ii) Pairwise comparisons: Compare the relative weights of each criterion and each potential solution. Assign values to reflect the strength of preference on a numerical scale.
(iii) Complete the matrix: Create a pairwise

comparison matrix, which is a square matrix. N is the number of criteria, and $N \times N$ is the size of the matrix.

(iv) Reciprocal property: Ensure that the reciprocal property is satisfied by the matrix.

Table 2 provides guidance on constructing a judgment matrix.

Table 2. Rules for constructing a judgment matrix

Scaling	Explanation
1	Two criteria have the same status
3	One criterion has a moderate status concerning the second criterion.
5	One criterion has strong significance concerning the second criterion.
7	One criterion has a very strong position concerning the second criterion.
9	One criterion has extreme significance concerning the second criterion.
2, 4, 6, 8	The intermediate status between adjacent decisions.

After forming the judgment matrix, it is essential to solve for the weights. The following steps are used to solve a judgment matrix:[23]

(i) Normalize the matrix: The judgment matrix is normalized across all columns. Each element in a column is divided by the sum of the column elements to normalize it:

$$\overline{b_{mn}} = \frac{b_{mn}}{\sum_{p=1}^{N} b_{pn}}, m, n = 1, 2..., N \tag{16}$$

where N is the number of factors.

(ii) Each element of a normalized matrix of a row is added:

$$R_m = \sum_{n=1}^{N} \bar{b}_{mn}, \text{ m} = 1,2,3...,\text{N} \tag{17}$$

(iii) The vector $\bar{R} = \left[\bar{R}_1, \bar{R}_2, ..., \bar{R}_N\right]^T$ is normalized as:

$$W = \frac{\bar{R}_m}{\sum_{p=1}^{N} R_p}, \text{ m} = 1,2, 3...,\text{N} \tag{18}$$

The final result $W = [W_1, W_2, ..., W_N]^T$ is the desired weight of the system, where $w\_i \geq 0$, and $\sum_{i=1}^{n} w_i = 1$.

To summarize, as far as minimum cost is concerned, the cost of reliability is slightly more important than the equipment purchase cost; and the cost of active power loss is much more important than either reliability cost or equipment purchase cost. The judgment matrix for the final objective function is shown in **Table 3**.

Table 3. Judgment matrix for the final objective function

Target	Active power loss cost	Reliability loss cost	Equipment purchase cost
Active power loss cost	1	5	7
Reliability loss cost	1/5	1	3
Equipment purchase cost	1/7	1/3	1

In this matrix, the first non-trivial comparison (active power loss cost, reliability loss cost) is that "active power loss" cost is strongly preferred (5 times) to "reliability loss cost," so the value 5 enters the (1,2) position. The value 1/5 automatically enters the transpose position (2, 1) for "reliability loss cost, active power loss cost". Similarly, "active power loss cost" is highly preferred over "equipment purchase cost," so the value 7 enters the (1,3) position, while the reciprocal value 1/7 automatically enters the (3,1) position, and so on. The hierarchy of this individual problem is shown in **Figure 3**.

Therefore, the judgment matrix (J) can be written as:

$$J = \begin{bmatrix} 1 & 5 & 7 \\ 1/5 & 1 & 3 \\ 1/7 & 1/3 & 1 \end{bmatrix}$$

Now, using the above steps in the MATLAB program, the normalized matrix and weight vector are given by:

$$J_N = \begin{bmatrix} 0.7447 & 0.7898 & 0.6363 \\ 0.1489 & 0.1579 & 0.2727 \\ 0.1063 & 0.0525 & 0.0909 \end{bmatrix}$$

$$\omega = \begin{bmatrix} 0.7236 & 0.1931 & 0.08323 \end{bmatrix}$$

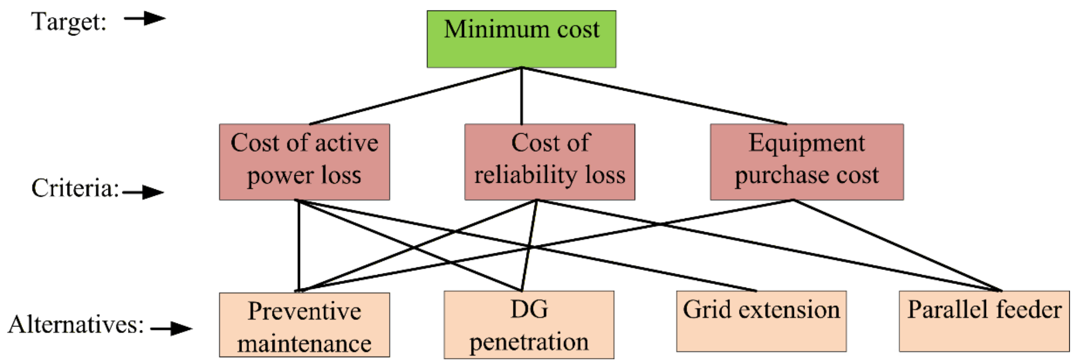

Figure 3. Analytic Hierarchy Process framework
Abbreviation: DG: Distributed generation.

4.1. Establishment of distributed generation candidate positions

The integration of numerous RDGs into a distribution network poses significant challenges, particularly due to the high node density. The presence of multiple DG points across the network adds considerable complexity, hindering the efficiency of computational processes when employing optimization algorithms for power distribution management and voltage control. To mitigate these challenges, we present a practical approach for identifying optimal DG locations to mitigate challenges arising from DG penetration in the distribution network. The IEEE 37-node distribution network, shown in **Figure 4**, is used in the study.

4.2. Limit of distributed generation insertion capability

In a conventional RDN, power flows in a single direction from the substation to the load. However, excessive generation from DGs can cause reverse power flow, potentially affecting transformer operation and grid stability. Improper DG placement can increase network losses rather than reduce them. The *penetration rate* is used to assess the integration of DG into the system relative to the maximum load demand. It indicates the proportion of total load demand met by DG and is defined as the ratio of the total DG capacity in the distribution network to the maximum load of the distribution network. High penetration rates may lead to problems including voltage fluctuations, reverse power flow, coordination challenges with protective systems, and increased network losses. This research used the IEEE 37-node system, in which DGs of varying capacities were installed at different nodes. The network losses of the power distribution system after DG installation were calculated using the power flow method described in Section 2. The effect of DG installation capacity on network losses was then analyzed.

4.3. Selection of the candidate location for renewable distributed generation installation

This study considered the effect of RDG access location on distribution network active power loss and voltage, and combined reliability requirements[13] with the actual distribution network structure to determine DG candidate locations. To quantify the degree of improvement in DG access to network loss,[14] the system active loss improvement rate χ is introduced; it is the ratio of the active power loss after installing DG to the active power loss before installing DG:

$$\chi = \frac{P_{api}}{P_{abpi}} \tag{19}$$

where P_{abpi} is the active power loss before installing DG, and P_{api} is the active power loss after installing DG. **Figure 5** shows the improvement rates in system active power loss after DG was connected to different nodes for six penetration rates: 4%, 9%, 14%, 19%, 24%, and 32%. Comparing the influence of different RDG locations, it was found that installations with higher improvement rates are concentrated in the middle of the entire network, especially when the long branch line was connected to the middle end.

According to the above analysis, combined with active power loss, voltage and reliability indicators, and distribution network load distribution, a practical method for selecting DG candidate locations is proposed. The following steps determine the DG candidate location:

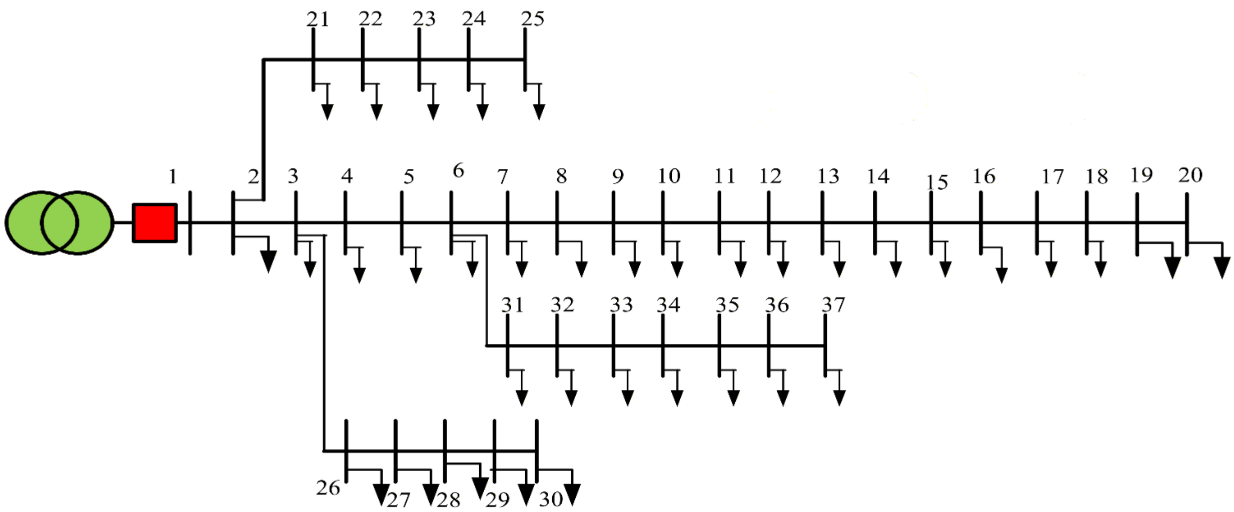

Figure 4. Single-line diagram of a radial network of 37 nodes

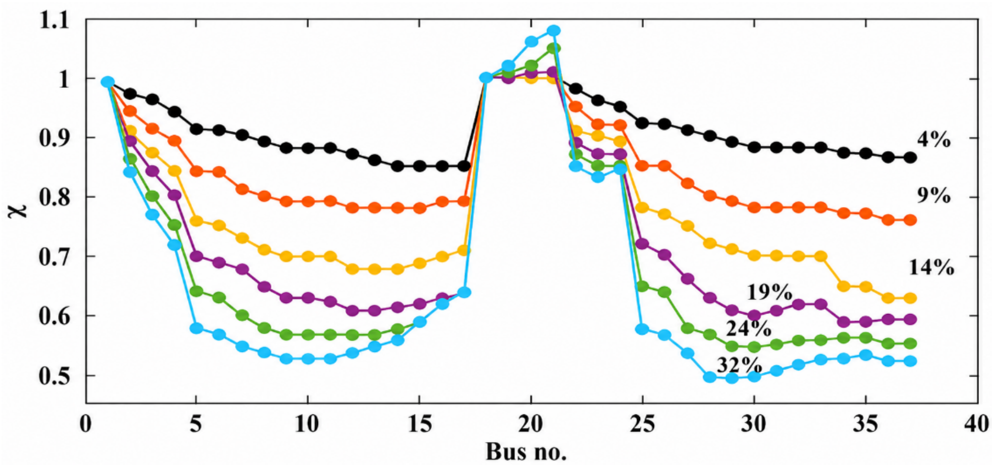

Figure 5. Improvement rates of active power loss at different penetration rates

(i) Sort the injected power of each node based on the improvement rate of the system active power loss, and choose a certain proportion of nodes with a lower improvement rate based on the actual condition of the distribution network, generally taking the top 60%.
(ii) Eliminate the end nodes of the line based on the analysis of the voltage effect.
(iii) Compare improvement rates in system active power loss across nearby nodes and integrate adjacent nodes into a DG candidate site solution space.

According to the DG candidate locations established in Step ii, the inserted load points have poor reliability. The placement of RDG should not be overly concentrated due to DG access effects on nearby load nodes. RDG candidate positions are considered for some branch lines based on their load, even though they lack DG candidate roles.

The technique adopted in this research is to estimate the branch-line load proportion relative to the total load. If the proportion exceeds the reciprocal of the maximum number of DG installations, the node with the smallest active network loss improvement rate in the branch is added as the candidate position of the DG. If the final selected DG candidate positions are 3, then there should be at least one DG candidate position on the branch line with a load proportion exceeding 33.33%. For the IEEE 37-node system, seven DG candidate positions were finally determined: 36, 33, 27, 22, 9, 14, and 18 (**Figure 6**).

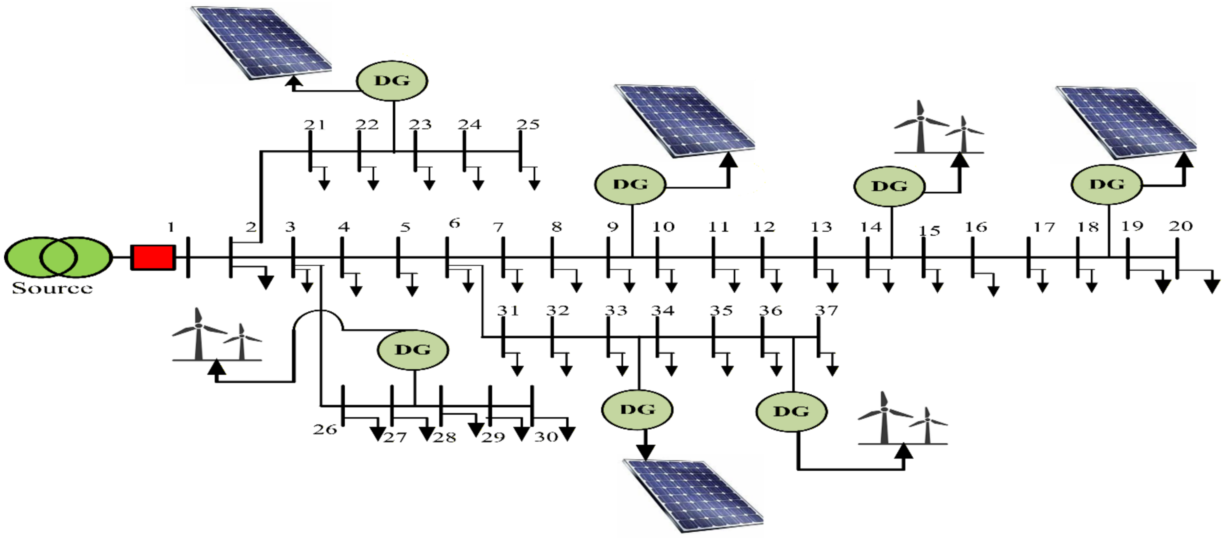

Figure 6. Candidate location of distributed generation (DG)

5. AHP–GA technique

This research employed a coordinated multi-objective optimization methodology integrating AHP and GA for optimal placement and sizing of renewable distributed generators and distribution network expansion planning. The forward–backward load flow method was utilized to analyze the radial distribution system due to its suitability for networks with high R/X ratios. The AHP technique was used to determine the weighting factors for multiple objective functions, including active power loss cost, reliability cost, and equipment investment cost, while the GA was applied to identify optimal DG locations, capacities, line upgrades, and new load access points simultaneously. The effectiveness of the proposed methodology was validated using modified IEEE 37-bus and IEEE 69-bus distribution systems.

Although the proposed approach demonstrated significant improvements in technical and economic performance, certain limitations remain. The study considers static loading conditions and predefined DG penetration levels, but the stochastic nature of renewable energy sources, such as solar and wind generation, is not fully modeled. In addition, uncertainties associated with real-time load variations, weather conditions, and market dynamics are not incorporated into the optimization framework. The analysis is also limited to radial distribution systems and does not consider meshed network configurations or the integration of energy storage systems. These limitations offer opportunities for future research to develop more robust, real-time adaptive planning frameworks for modern smart distribution networks. The detailed flow chart of the AHP–GA method is shown in **Figure 7**.

The genetic chromosome adopts binary code, and each chromosome is divided into three parts—DG, line modification, and new load point:

(i) Coding for part I: It shows the probable installation size of the corresponding RDG node in the access network. In this code, the number of RDGs at each candidate position is represented by a 3-bit binary number, allowing each position to have eight possible capacities. When the code is 0, it indicates that the candidate position is not connected to a DG; when the code is 1–7, it indicates that the corresponding number of DG units are connected to the candidate position.

(ii) Coding for part II: It shows whether the connected line needs to be upgraded. This code uses a single binary integer that represents one of two possibilities: when the code is 0, line k does not require upgrading; when it is 1, line k does.

(iii) Coding for part III: It identifies the node to be selected for connecting to the newly added load point. Each new load point is represented by a two-digit binary number with four access selection locations, and its access position is indicated by the code 0–3.

The steps of DG and distribution network comprehensive coordination planning are as follows:

(i) Enter the original information, *e.g.*, load data and bus data, of the distribution network to be planned.

(ii) Employ the forward–backward method, in accordance with the original network, to calculate the power flow; the initial network branch power and node voltage data are obtained.

(iii) Select the DG candidate position by taking into account the effect of DG access location on distribution network voltage and active power loss, as well as real grid structure and reliability requirements.

(iv) Code each decision variable.

(v) Generate an initial population, and set the number of iterations (iter) to 1.

(vi) Perform power flow calculation.

(vii) Calculate the fitness function, and add a penalty function after the corresponding fitness function for the solution individuals that violate the constraint conditions.

(viii) Perform genetic operations, such as selection, crossover, and mutation, to create new populations.

(ix) Carry out the judgment of the search termination condition; if the minimum retained algebra of the optimal individual or the genetic algebra $G > G_{max}$ is met, the calculation ends, and the result is output; otherwise, set iter = iter + 1, go to Step vi.

6. Case study

To validate the proposed approach discussed in this research paper, three cases were analyzed:

(i) Traditional distribution network planning without considering DG.

(ii) Distribution network planning with DG integration.

(iii) Coordinated planning of DG and distribution grid expansion.

The redesigned IEEE 37-node test system was simulated and computed using the approach described in the study; an example of the calculation is shown in **Figure 8**. The existing line in the figure is shown as solid and does not need to be updated. The line that can be upgraded is shown in dotted lines, and the line chosen for new load access is also shown in dotted lines.

The site selection, capacity setting, and network expansion planning of DG were carried out using the calculation example. The test line included 37 nodes, single feeder, three distributors, 36 branches, and 36 load points; the source reference voltage at node 1 was 12.66 kV; the connected demand was 4,436.98 kVA (3,795 kW, 2,298.86 kVAR); the full installed size of RDG did not exceed 33% of the total load, that is, the extreme access size of DGs in the distribution network was 1,570 kW. Nodes 38–42 in **Figure 8** were new load points with a total capacity of 1,140 kW; the corresponding capacities are listed in **Table 4**. The parameters of initialization are as follows: population size = 50, iteration count = 40, crossover probability = 0.9, mutation probability = 0.08, load power factor = 0.8, efficiency of DG = 0.95, and failure rate of line = 0.1 failure/year/km. It was estimated that the newly added capacity of the original load node in the planned year was 12%, and the total newly added load capacity of the two accounted for 27% of the original load capacity. Among them, the maximum number of planned DG access locations was 3.

The locations of DG candidate installations were 9, 14, 18, 22, 27, 33, and 36; DG capacity selection for each candidate position was 90, 180, 270, 360, 450, 540, and 630 kW. Considering the original load size and operational limits of the line, it was determined that the lines to be upgraded were: 7, 8, 14, 19, 24, 25, 26, 27, 28, 30, and 35. The relevant reference prices are as follows: the price of electricity sold to consumers and the subsidy on renewable energy electricity prices were Indian Rupees (INR) 10.0 and 0.45/kWh, respectively. The capital cost of DGs was INR 60,000.00 kW for photovoltaic and INR 42,000.00 kW for wind turbines. The annual operation and maintenance cost for DG was 1% of the capital investment, and the unit cost of new lines depends on the type of feeder; for an overhead feeder, the cost is approximately INR 1,075,000.00 /km, but for the underground cable line (400 mm^2 cable), the cost is INR 2,100,000.00 /km, and the unit cost of upgrading and transforming the line is INR 700,000.00 /km. All of the pricing listed was obtained from Indian distributors and suppliers.

7. Results and discussion

Three scenarios were investigated using the model and algorithm proposed in this research:

(i) Case 1: Without considering DG.

(ii) Case 2: Planning for both the distribution grid and the DG takes place in stages—DG is planned first, followed by distribution grid expansion planning after DG planning is completed.

(iii) Case 3: Coordinated planning of DG and distribution grid expansion.

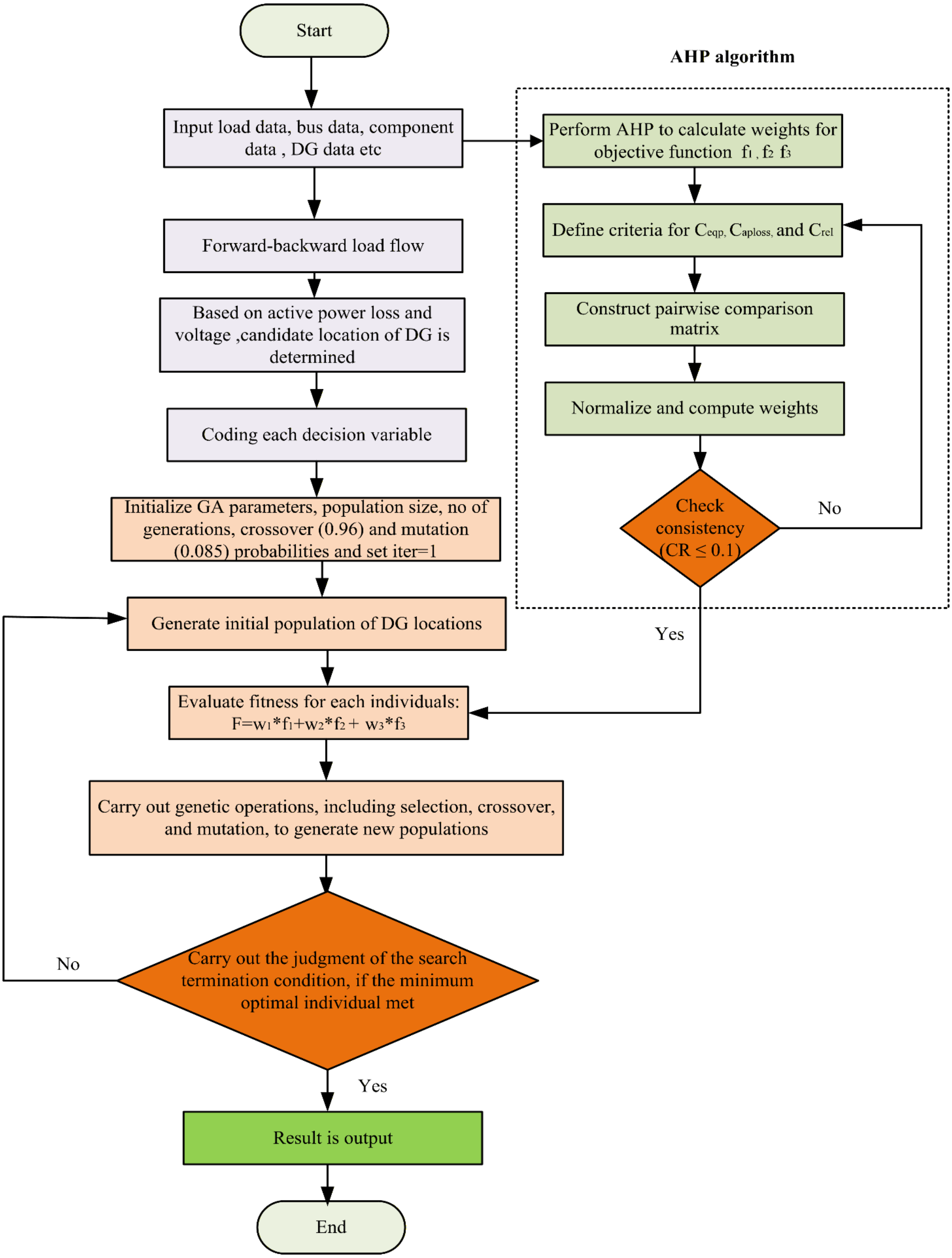

Figure 7. Flow chart of the AHP–GA technique
Abbreviations: AHP: Analytic Hierarchy Process; CR: Consistency ratio; DG: Distributed generation; Genetic algorithm.

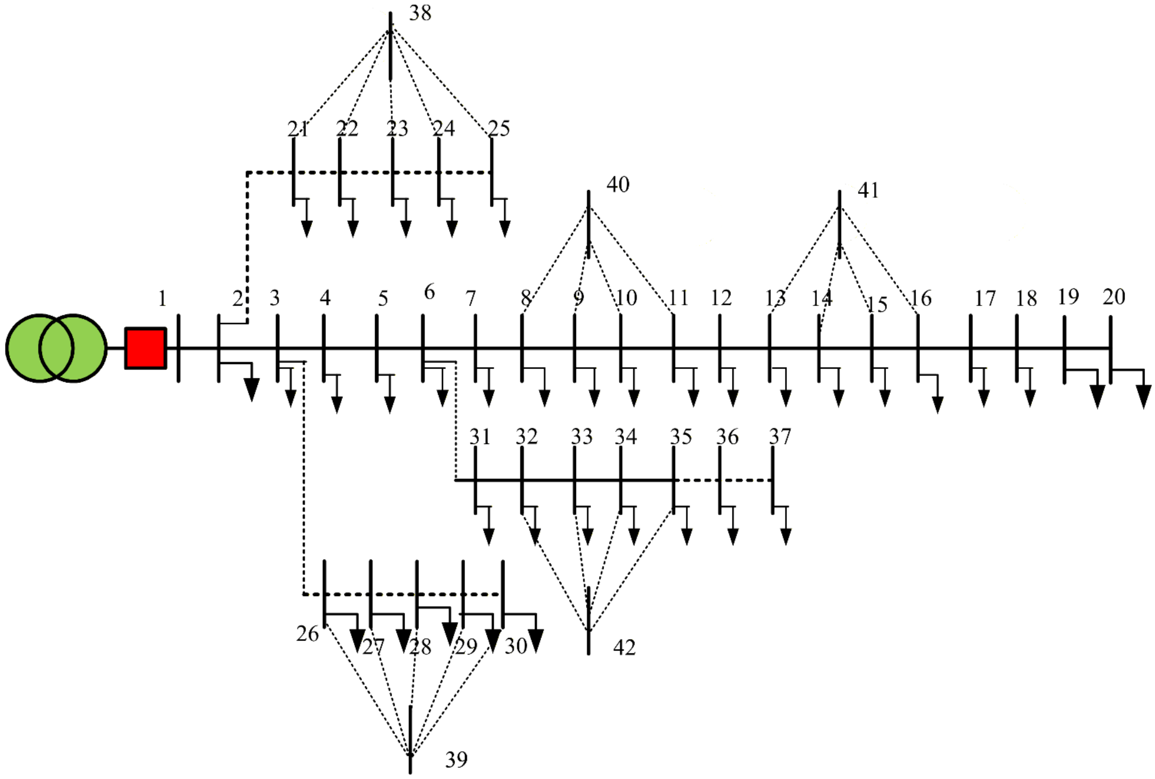

Figure 8. Restructuring of radial distribution network

Table 4. Data of new load points and possible connection points

Load point	Active load (kW)	Reactive load (kVAR)	Possible access location
38	320	240	21, 22, 23, 25
39	200	150	26, 27, 29, 30
40	400	300	8, 9, 10, 11
41	120	90	13, 14, 15, 16
42	100	75	32, 33, 34, 35

When we applied the proposed method to the IEEE 37-load point distribution network in MATLAB R2016a (MathWorks, United States of America), three RDGs were required in two cases (**Table 5**). The optimal locations and capacities of the three RDGs for both cases are presented in **Table 5**. The upgraded branches in both cases were 21, 22, and 26. The new load point access locations were 9, 13, 21, 26, and 32.

The distribution grid extension and optimization results for Case 3 are shown in **Figure 9**, where the dotted line denotes the lines to be upgraded. The branches 21, 22, and 26 required upgrades to improve power supply and reliability. The final locations of DG were 9, 17, and 32. When we analyzed the optimization results for each case in **Table 5**, we found that Case 1 requires five additional lines to be upgraded compared with Cases 2 and 3, indicating that DG has a delaying effect on the transformation of the distribution grid. When we compared Cases 2 and 3, the DG access position was midway along the branch line. The placement of the newly added load nodes differed between Case 3 and Case 2, and Case 3 had a marginally higher penetration rate. We assumed a 75% load factor for this technique. The newly added load points 38, 39, 40, 41, and 42 can be accessed from 21, 26, 9, 13, and 31, respectively.

For the given system, the planning results of each case are shown in **Table 6**. It was assumed that all the branches had a uniform length of 1 km, a failure rate of 0.1 failure/year/km, and a repair time of 4 h. It was observed that, in Cases

Table 5. Distributed generation (DG) final planning results

Case	DG access location	DG capacity (kVA)	Penetration rate (%)	Upgraded branch numbers	Added load point access locations
1	–	–	–	7, 8, 14, 19, 24, 25, 30, 35	8, 13, 21, 26, 32
2	9, 17, 34	180, 360, 360	23.17	21, 22, 26	8, 13, 21, 26, 32
3	9, 17, 32	90, 450, 450	26.08	21, 22, 26	9, 13, 21, 26, 32

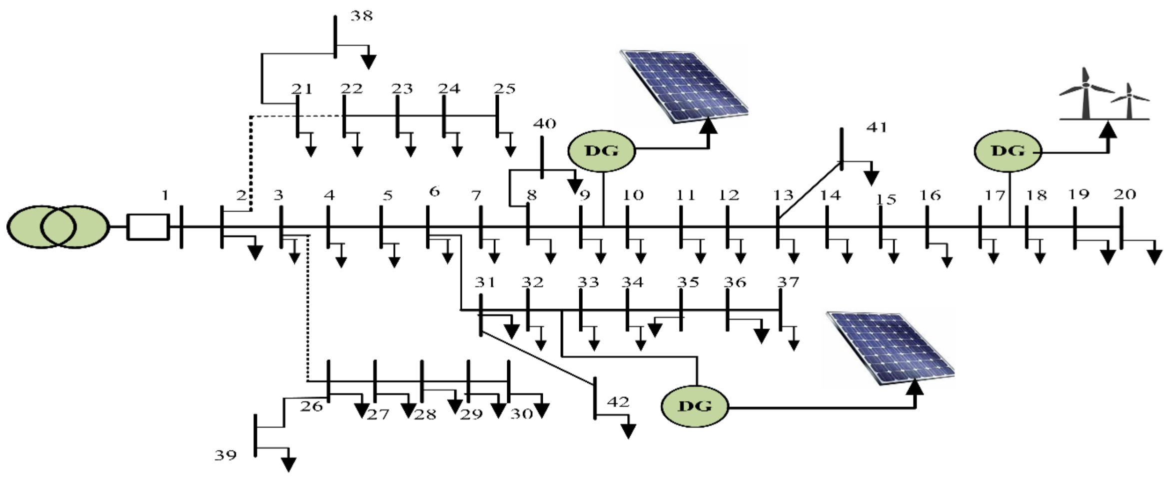

Figure 9. Optimization results of distributed generation (DG) candidate positions and distribution network grid expansion

2 and 3, except for the increase in equipment investment cost after DG investment, the other two indicators were significantly better than in Case 1, and the total cost reduction exceeded 25%. Comparing Cases 2 and 3, since Case 3 simultaneously decided the location and DG capacity, the line to be transformed, and the newly added load points, the configuration scheme obtained was more reasonable. Furthermore, it was observed that Case 3 had the smallest line loss, the least power shortage cost, and the smallest comprehensive cost. The annual operation and maintenance costs for Cases 2 and 3 were INR 0.486 million and INR 0.5418 million, respectively. When analyzed from the second year onward, the total cost of Case 3 was 3.5% less than that of Case 2. As shown in **Figure 10**, the voltage profile improved significantly with DG. The voltage at node 21 peaked, approaching the safe operating lower limit of 0.95 p.u., without DG. The distribution system's performance, particularly feeder voltage, was markedly influenced by the distance between the RDG and the terminal node. Graphical analysis shows that the closer the DG connection is to the terminal node, the greater the improvement in voltage distribution within the feeder.

From **Figure 11**, the total loss without installing renewable DG was INR 125.628 million per year, while with DG installed at the provided location, the loss was INR 89.807 million, resulting in a reduction of INR 35.821 million per year. When considering expansion and DG installation, this reduction was INR 31.685 million. The active power losses with and without DG were 142.1918 kW and 600.1952 kW, respectively.

Table 7 presents an analysis of active power losses at various load points in a distribution network for different DG capacities. It demonstrates how RDG placement can drastically reduce power loss: for DG (990 kW), the total power loss was reduced by 9.85% compared to DG (960 kW) (151.75 kW → 142.20 kW) and 20.36% compared to DG (510 kW) (178.64 kW → 142.20 kW). At load point 2, power loss decreased by 9.27% from DG (900 kW) to DG (990 kW), and at load point 4, power loss decreased by 14.91%.

Table 6. Cost comparison of distribution network expansion planning with or without distributed generation (DG) access

Case	Equipment investment cost	Network loss cost	Power shortage cost	Total cost	Percentage reduction (%)
1	5.600	52.204	67.824	125.628	–
2	50.700	13.199	25.908	89.807	28.51
3	56.280	12.367	25.296	93.943	25.22

Note: Cost in million Indian Rupees (INR) per year.

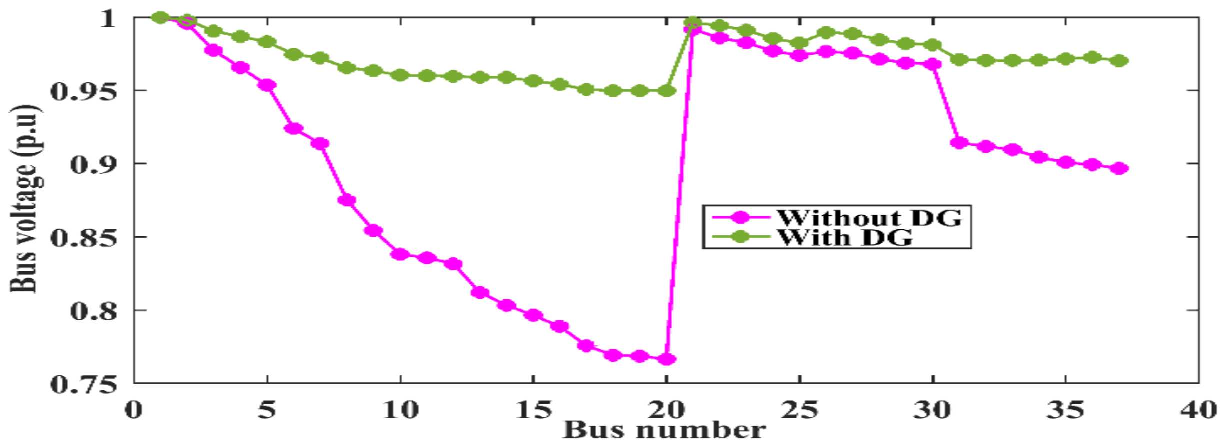

Figure 10. Voltage profile with and without distributed generation (DG)

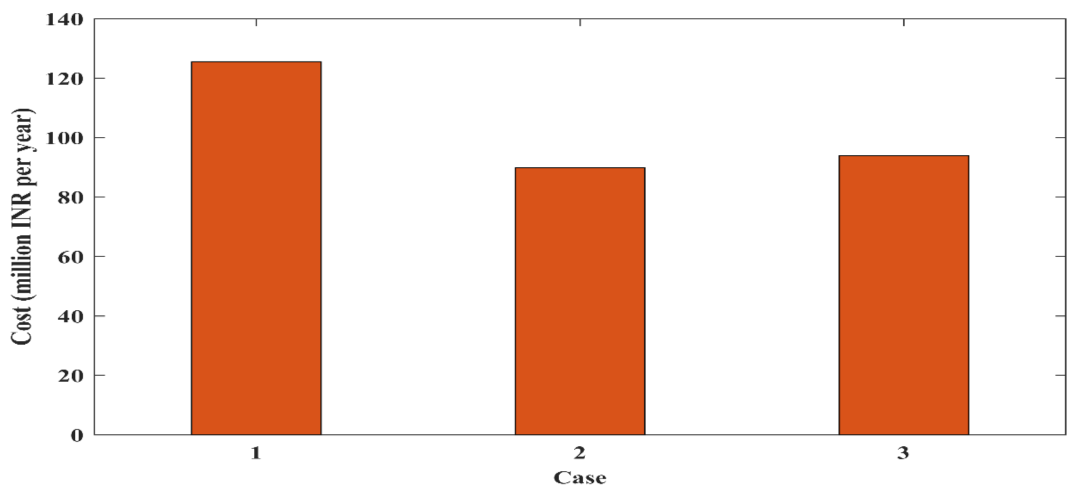

Figure 11. Variation of cost for all cases

Figure 12 shows the comparison of active power loss with DG size. As DG size increased, the active power loss decreased.

With a load factor of 75%, in Case 2, we provided power to load points 10, 11, 12, 13, 14, 15, 16, 17, 19, 20, 31, 32, 33 and 34, while in Case 3, these were load points 10, 11, 13, 14, 15, 16, 17, 18, 19, 20, 31, 32, 33, 34, 41, 42.

When there was no DG in the system, the SAIDI (**Figure 13**) and ENS (**Figure 14**) were 14.4 and 67,824, respectively. In contrast, when DGs were connected, SAIDI and ENS decreased sharply. The reduction in SAIDI and ENS was 40.27% and 58.84% per year, respectively.

Table 7. Variation of active power loss (P_{loss}) across distributed generation (DG) sizes

Load points	**P_{loss} (kW)**					
	DG = 900	**DG = 960**	**DG = 990**	**DG = 840**	**DG = 750**	**DG = 510**
2	14.5800	13.9800	13.2300	15.0600	15.9300	18.4300
3	44.0800	41.7000	38.7300	46.0500	49.5700	59.8900
4	21.3400	19.9200	18.1700	22.5200	24.6400	30.9600
5	20.0500	18.6500	16.9100	21.2100	23.3100	29.5900
6	38.8400	37.8900	34.2800	35.7200	30.6316	18.7000
7	1.0900	1.0600	1.5800	1.2000	1.4100	2.0580
8	0.0067	0.0054	0.0044	0.0074	0.0090	0.0145
9	0.0033	0.0025	0.0019	0.0037	0.0040	0.0081
10	0.0015	0.0009	0.0005	0.0019	0.0028	0.0064
11	0.0279	0.0175	0.0078	0.0376	0.0585	0.1391
12	0.0226	0.0106	0.0018	0.0352	0.0640	0.1868
13	0.0018	0.0016	0.0011	0.0022	0.0029	0.0049
14	0.0771	0.0593	0.0402	0.0923	0.1231	0.2298
15	0.0037	0.0026	0.0014	0.0048	0.0070	0.0153
16	0.0004	0.0000	0.0000	0.0001	0.0001	0.0004
17	0.0307	0.0017	0.0003	0.0054	0.0097	0.0276
18	0.0005	0.0000	0.0000	0.0001	0.0007	0.0004
19	0.0000	0.0000	0.0045	0.0021	0.0024	0.0004
20	0.0065	0.0011	0.0096	0.0053	0.0012	0.0010
21	3.2200	3.2200	3.2100	3.2200	3.2210	3.2200
22	4.5000	4.5000	4.5000	4.5000	4.5000	4.5100
23	2.2500	2.2500	2.2500	2.2500	2.2500	2.2500
24	3.7600	3.7500	3.7500	3.7600	3.7600	3.7600
25	0.9400	0.9405	0.9400	0.9408	0.9400	0.9400
26	0.4700	0.4771	0.4766	0.4778	0.4700	0.4800
27	0.5100	0.5123	0.5117	0.5131	0.5137	0.5100
28	1.4000	1.4000	1.4000	1.4000	1.4000	1.4200
29	0.7425	0.7419	0.7410	0.7430	0.7439	0.7460
30	0.2083	0.2082	0.2079	0.2080	0.2087	0.2094
31	0.1423	0.2561	1.0400	0.1420	0.1440	0.1471
32	0.0661	0.0658	0.0654	0.0660	0.0668	0.0680
33	0.0181	0.0180	0.0178	0.0180	0.0183	0.0180
34	0.0294	0.0292	0.0290	0.0290	0.0297	0.0304
35	0.0079	0.0079	0.0078	0.0080	0.0080	0.0083
36	0.0037	0.0037	0.0037	0.0037	0.0038	0.0040
37	0.0032	0.0032	0.0032	0.0033	0.0033	0.0034
Total power loss (kW)	158.4800	151.7500	142.2000	160.3000	164.1100	178.6400

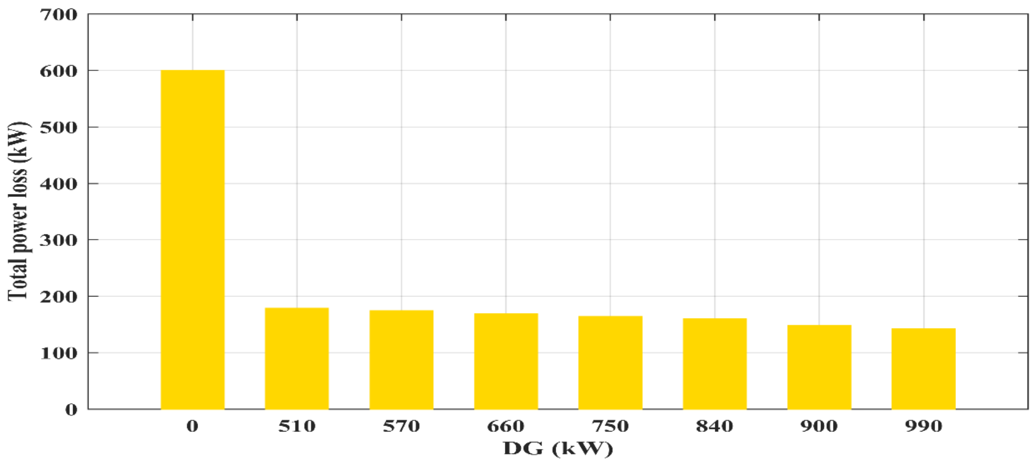

Figure 12. Comparison of active power loss (in kW) across distributed generation (DG) sizes

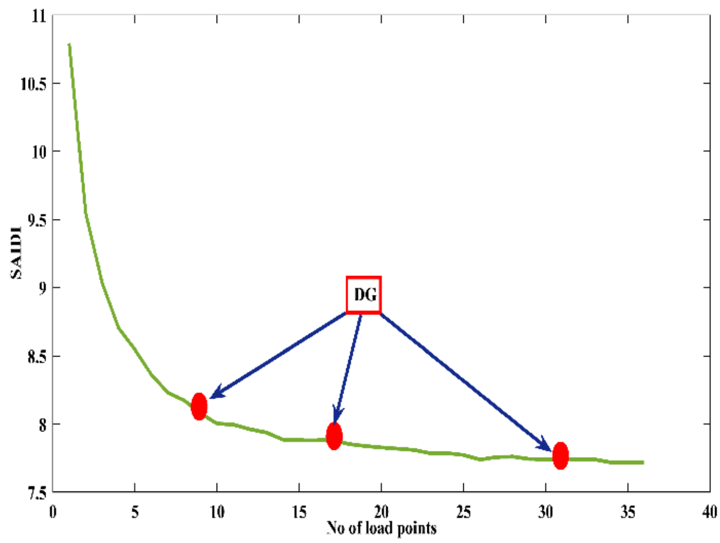

Figure 13. SAIDI across the number of load points
Abbreviations: DG: Distributed generation; SAIDI: System Average Interruption Duration Index.

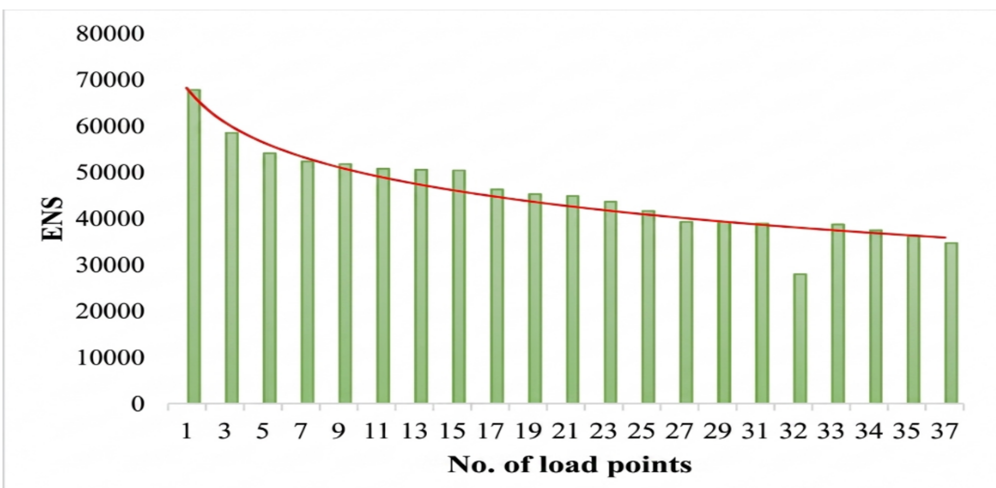

Figure 14. Energy not served (ENS) across the number of load points

8. Comparative study

Figure 15 shows the results for the 69-bus system using the bacterial foraging algorithm (BFA), ant colony optimization (ACO), and GA. GA consistently outperformed the other methods. The active power loss without DG was 225.050 kW; with DGs, it depended on the location and size (**Table 8**). The active power losses from ACO, BFA, and GA were 124.368 kW, 83.770 kW, and 16.680 kW, respectively, due to the location and size of the DG. **Figures 16** and **17** show the comparisons of the voltage profile and convergence plot, respectively. The optimal location and size improved the voltage profile, and GA also yielded better overall results. From the convergence plot, GA yielded the lowest fitness value and the best convergence. The CPU times for ACO, BFA, and GA were 210.50, 160.33, and 112.67 s, respectively. The proposed technique achieved the highest active power loss improvement rate (χ).

Table 9 presents a comparative analysis of the proposed method and various existing methods from the literature.[38-41] The proposed method demonstrated both efficacy and robust performance. The line losses, reactive power losses, and voltage profile also improved significantly. The proposed method achieved a 79.73% reduction in line losses and 76.83% in reactive power losses. The penetration rate of the proposed model was 30–35%, which is suitable for distribution network configuration.

Table 8. Comparison of active power loss percentage

Optimization technique	Power loss (kW)	Percentage reduction (%)	DG location	DG size (kW)	Total DG size (kW)	χ
Without DG	225.050	–	–	–	–	–
With DG (ACO)	124.368	44.74	18, 46, 61, 63	652, 755, 1,118, 658	3,183	0.552
With DG (BFA)	83.770	62.77	24, 40, 61, 65	463, 802, 820, 734	2,819	0.370
With DG (GA)	16.880	92.50	8, 38, 52, 62	1,054, 781, 432, 897	3,164	0.075

Abbreviations: ACO: Ant colony optimization; BFA: Bacterial foraging algorithm; DG: Distributed generation; GA: Genetic algorithm.

Table 9. Comparison of the output across the proposed and existing methods

Reference	No. of buses with under-voltage	Real power loss (kW)	Reactive power loss (kVAR)	DG capacity (kW)	No. of DG	Reduction in active power loss (%)
Without DG	22	224.960	102.15	–	–	–
38	13	113.570	79.43	1,000	1	43.75
39	–	70.560	50.30	2,736	3	59.65
40	–	87.523	–	3,130	3	49.95
41	–	78.659	57.17	2,910	3	55.00
Proposed method	8	62.456	31.47	1,398	4	72.24
		45.596	23.66	1,620	6	79.73

Abbreviation: DG: Distributed generation.

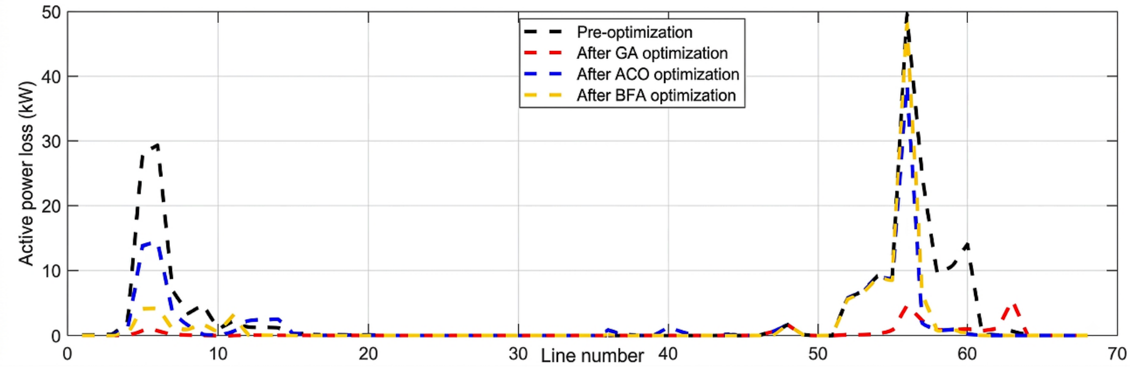

Figure 15. Comparison of active power loss for 69-bus system

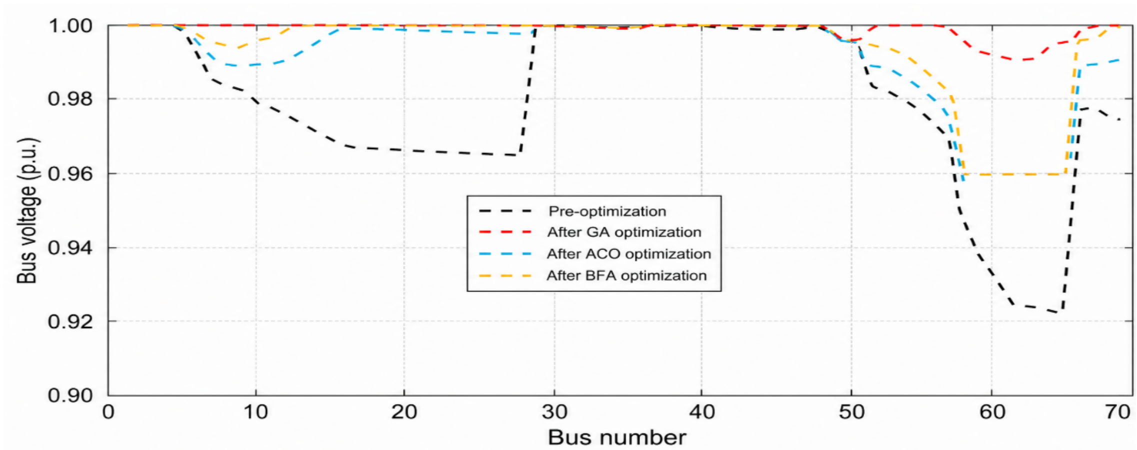

Figure 16. Voltage profile for 69- bus system

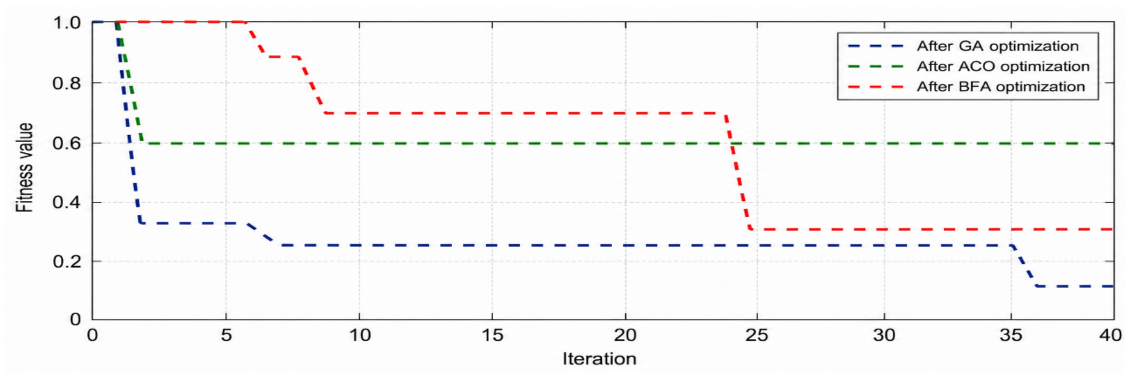

Figure 17. Convergence plot for 69- bus system

9. Conclusion

This research proposes a coordinated AHP–GA-based approach for optimal placement and sizing of renewable distributed generators and distribution network expansion planning. The proposed approach determined the optimal locations of DGs at buses 9, 17, and 32 to minimize active power loss, voltage profile, reliability indices, and network structure. The results show that there is ample technical and economic improvement in the distribution network performance. The active power loss was reduced by almost 75%, and the reliability indices SAIDI and ENS were reduced by 40.27% and 58.84% per year, respectively, by the proposed approach. The superiority of the proposed method is confirmed through a comparative study with ACO and BFA, focusing on power loss minimization, convergence characteristics, and computational efficiency. The proposed GA technique achieved an active power loss of 16.68 kW (92.50% reduction) and 112.67 s of CPU time, both of which are better than those of other existing techniques. The study also shows that the proposed coordinated planning method for DG integration and network expansion is more reliable, economical, and efficient than traditional planning strategies. The proposed framework also has strong potential for practical implementation in modern distribution systems, where the penetration of renewable energy is increasing. Future research could integrate stochastic renewable generation functions, energy storage systems, and real-time uncertainties into the operation of these systems to further enhance the robustness and applicability of the proposed methodology.

Acknowledgments

This paper is derived from a research grant funded by the Research, Development, and Innovation Authority (RDIA), Kingdom of Saudi Arabia, with grant number 13382-psu-2023-PSNU-R-3-1-EI-. The authors would like to acknowledge the support of Prince Sultan University, Riyadh, Saudi Arabia, in covering the article processing charges for this publication. This research is supported by the Automated Systems and Computing Lab (ASCL), Prince Sultan University, Riyadh, Saudi Arabia.

Funding

This work is funded by Prince Sultan University, Riyadh, Saudi Arabia.

Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Manish Kumar Madhav, Krishna B. Yadav, Akshit Samadhiya, Ahmad Taher Azar
Formal analysis: All authors
Funding acquisition: Ahmad Taher Azar, Saim Ahmed
Investigation: Manish Kumar Madhav, Krishna B. Yadav, Akshit Samadhiya, Ahmad Taher Azar
Methodology: Manish Kumar Madhav, Krishna B. Yadav, Akshit Samadhiya
Supervision: Ahmad Taher Azar, Saim Ahmed, Walid El-Shafai, Chakib Ben Njima
Writing–original draft: Manish Kumar Madhav, Krishna B. Yadav, Akshit Samadhiya
Writing–review & editing: All authors

Availability of data

The data are available from the corresponding author upon reasonable request.

References

1. Zhu D, Broadwater RP, Tam KS, Seguin R, Asgeirsson H. Impact of DG placement on reliability and efficiency with time-varying loads. *IEEE Trans Power Syst.* 2006;21(1):419-427.

   https://doi.org/10.1109/TPWRS.2005.860943

2. Fergany AE. Optimal allocation of multi-type distributed generators using backtracking search optimization algorithm. *Int J Electr Power Energy Syst.* 2015;64:1197-1205.

   https://doi.org/10.1016/j.ijepes.2014.09.020

3. Ismael SM, Abdel Aleem SHE, Abdelaziz AY, Zobaa AF. State-of-the-art of hosting capacity in modern power systems with distributed generation. *Renew Energy.* 2019;130:1002-1020.

   https://doi.org/10.1016/j.renene.2018.07.008

4. Lee SH, Park JW. Optimal placement and sizing of multiple DGs in a practical distribution system by considering power loss. *IEEE Trans Ind Appl.* 2013;49(5):2262-2270.

   https://doi.org/10.1109/TIA.2013.2260117

5. Georgilakis PS, Hatziargyriou ND. Optimal distributed generation placement in power distribution networks: models, methods, and future research. *IEEE Trans Power Syst.* 2013;28(3):3420-3428.

   https://doi.org/10.1109/TPWRS.2012.2237043

6. Nekooei K, Farsangi MM, Nezamabadi H, Lee KY. An improved multi-objective harmony search for optimal placement of DGs in distribution systems. *IEEE Trans Smart Grid.* 2013;4(1):557-567.

   https://doi.org/10.1109/TSG.2012.2237420

7. Hung DQ, Mithulananthan N. Multiple distributed generator placement in primary distribution networks for loss reduction. *IEEE Trans Ind Electron.* 2013;60(4):1700-1708.

https://doi.org/10.1109/TIE.2011.2112316

8. Kansal S, Kumar V, Tyagi B. Optimal placement of different type of DG sources in distribution networks. *Int J Electr Power Energy Syst.* 2013;53:752-760.

   https://doi.org/10.1016/j.ijepes.2013.05.040

9. Kaur S, Kumbhar G, Sharma JD. A MINLP technique for optimal placement of multiple DG units in distribution systems. *Int J Electr Power Energy Syst.* 2014;63:609-617.

   https://doi.org/10.1016/j.ijepes.2014.06.023

10. Sheng W, Liu KY, Meng X, Li Y. Optimal placement and sizing of distributed generation via an improved nondominated sorting genetic algorithm II. *IEEE Trans Power Deliv.* 2015;30(2):569-578.

    https://doi.org/10.1109/TPWRD.2014.2325938

11. Heidari A, Agelidis VG, Kia M. Considerations of sectionalizing switches in distribution networks with distributed generation. *IEEE Trans Power Deliv.* 2015;30(3):1401-1409.

    https://doi.org/10.1109/TPWRD.2014.2385654

12. Ganguly S, Yokota H. Distributed generation allocation on radial distribution networks under uncertainties of load and generation using genetic algorithm. *IEEE Trans Sustain Energy.* 2015;6(3):688-697.

    https://doi.org/10.1109/TSTE.2015.2406915

13. Abdelsalam A, Zidan A, El-Saadany A. Optimal DG allocation in radial distribution systems with high penetration of non-linear loads. *Electr Power Compon Syst.* 2015;43(13):1487-1497.

    https://doi.org/10.1080/15325008.2015.1043601

14. Narayanan K, Siddiqui SA, Fozdar M. Optimal placement of distributed generators in radial distribution system for reducing the effect of islanding. *J Electr Eng Technol.* 2016;11(3):551-559.

    https://doi.org/10.5370/JEET.2016.11.3.551

15. Poornazaryan B, Karimyan P, Gharehpetian G, Abedi M. Optimal allocation and sizing of DG units considering voltage stability, losses and load variations. *Int J Electr Power Energy Syst.* 2016;79:42-52.

    https://doi.org/10.1016/j.ijepes.2015.12.034

16. Pereira B, Martin G, da Costa R, Contreras J, Mantovani JRS. Optimal distributed generation and reactive power allocation in electrical distribution systems. *IEEE Trans Sustain Energy.* 2016;7(3):975-984.

    https://doi.org/10.1109/TSTE.2015.2512819

17. Amohadi M, Firuzabad MF. Optimal placement of switching and protection devices in radial distribution networks to enhance system reliability using the AHP-PSO method. *Turk J Electr Eng Comput Sci.* 2019;27(1):181-196.

    https://doi.org/10.3906/elk-1806-130

18. Kaur N, Jain SK. Multi-objective optimization approach for placement of multiple DGs for voltage sensitive loads. *Energies.* 2017;10(11):1733.

    https://doi.org/10.3390/en10111733

19. Meena NK, Parashar S, Swarnkar A, Gupta N, Niazi KR. Improved elephant herding optimization for multiobjective DER accommodation in distribution systems. *IEEE Trans Ind Inform.* 2018;14(3):1029-1039.

    https://doi.org/10.1109/TII.2017.2748220

20. Eltamaly AM, Al-Saud MS. Nested multi-objective PSO for optimal allocation and sizing of renewable energy distributed generation. *J Renew Sustain Energy.* 2018;10(3):035302.

    https://doi.org/10.1063/1.5028484

21. Grisales-Noreña LF, Montoya DG, Ramos-Paja CA. Optimal sizing and location of distributed generators based on PBIL and PSO techniques. *Energies.* 2018;11(4):1018.

    https://doi.org/10.3390/en11041018

22. HassanzadehFard H, Jalilian A. Optimal sizing and location of renewable energy-based DG units in distribution systems considering load growth. *Int J Electr Power Energy Syst.* 2018;101:356-370.

    https://doi.org/10.1016/j.ijepes.2018.03.038

23. Bhullar S, Ghosh S. Optimal integration of multi distributed generation sources in radial distribution networks using a hybrid algorithm. *Energies.* 2018;11(3):628.

    https://doi.org/10.3390/en11030628

24. El-Ela AAA, El-Sehiemy RA, Abbas AS. Optimal placement and sizing of distributed generation and capacitor banks in distribution systems using water cycle algorithm. *IEEE Syst J.* 2018;12(4):3629-3636.

    https://doi.org/10.1109/JSYST.2018.2796847

25. Khoubseresht O, Shayanfar H. The role of demand response in optimal sizing and siting of distribution energy resources in distribution network with time-varying load: an analytical approach. *Electr Power Syst Res.* 2020;180:106100.

    https://doi.org/10.1016/j.epsr.2019.106100

26. Manna DK, Goswami SK. Optimum placement of distributed generation considering economics as well as operational issues. *Int Trans Electr Energy Syst.* 2020;30(3):e12246.

    https://doi.org/10.1002/2050-7038.12246

27. Madhav MK, Yadav KB. Economic analysis of isolator placement in the radial network for enhancement of reliability indicators. *Electr Eng.* 2024;106(1):891-904.

https://doi.org/10.1007/s00202-023-02013-z

28. Pesaran HM, Nazari-Heris M, Mohammadi-Ivatloo B, Seyedi H. A hybrid genetic particle swarm optimization for distributed generation allocation in power distribution networks. *Energy.* 2020;209:118218.

https://doi.org/10.1016/j.energy.2020.118218

29. Wang HJ, Pan JS, Nguyen TT, Weng S. Distribution network reconfiguration with distributed generation based on parallel slime mould algorithm. *Energy.* 2022;244:123011.

https://doi.org/10.1016/j.energy.2021.123011

30. Kawambwa S, Hamisi N, Mafole P, Kundaeli H. A cloud model based symbiotic organism search algorithm for DG allocation in radial distribution network. *Evol Intell.* 2022;15:545-562.

https://doi.org/10.1007/s12065-020-00529-y

31. Shaheen AM, Elsayed AM, Ragab A, El-Sehiemy AY. Equilibrium optimization algorithm for network reconfiguration and distributed generation allocation in power systems. *Appl Soft Comput.* 2021;98:106867.

https://doi.org/10.1016/j.asoc.2020.106867

32. Rafi V, Dhal PK, Rajesh M, Srinivasan DR, Chandrashekhar M, Reddy NM. Optimal placement of time-varying distributed generators by using crow search and black widow-hybrid optimization. *Meas Sens.* 2023;30:100900.

https://doi.org/10.1016/j.measen.2023.100900

33. Subbaramaiah K, Sujatha P. Optimal DG unit placement in distribution networks by multi-objective whale optimization algorithm and its techno-economic analysis. *Electr Power Syst Res.* 2023;214:108869.

https://doi.org/10.1016/j.epsr.2022.108869

34. Aishvarya N, Srivastava SK, Singh SN. Congestion management approaches in restructured power system: key issues and challenges. *Electr J.* 2020;33(3):106715.

https://doi.org/10.1016/j.tej.2020.106715

35. Madhav MK, Yadav KB. Optimum location of isolator in radial distribution system using genetic algorithm to improve the system reliability. In: Kumar J, Tripathy M, Jena P, eds. *Control Applications in Modern Power Systems.* Lecture Notes in Electrical Engineering. Vol 870. Singapore: Springer; 2022:177-188.

https://doi.org/10.1007/978-981-19-0193-5_15

36. Selim A, Akher MA, Aly MM, Kamel S, Seniyu T. Fast quasi-static time-series analysis and reactive power control of unbalanced distribution systems. *Int Trans Electr Energy Syst.* 2019;29(1):e2673.

https://doi.org/10.1002/etep.2673

37. Saaty TL. A scaling method for priorities in hierarchical structures. *J Math Psychol.* 1977;15(3):234-281.

https://doi.org/10.1016/0022-2496(77)90033-5

38. Shaik MA, Mareddy PL, Visali N. Enhancement of voltage profile in distribution system by reconfiguring with DG placement using equilibrium optimizer. *Alex Eng J.* 2022;61(5):4081-4093.

https://doi.org/10.1016/j.aej.2021.09.063

39. Dashtdar M, Najafi M, Esmaeilbeig M, Bajaj M. Placement and optimal size of DG in the distribution network based on nodal pricing reduction with nonlinear load model using the IABC algorithm. *Sadhana.* 2022;47(2):73.

https://doi.org/10.1007/s12046-022-01850-1

40. Veeramsetty V, Venkaiah C, Kumar DMV. Hybrid genetic dragonfly algorithm based optimal power flow for computing LMP at DG buses for reliability improvement. *Energy Syst.* 2018;9(3):709-757.

https://doi.org/10.1007/s12667-017-0268-2

41. Rezvanfara R, Hagha MT, Zarea K. Power-based distribution locational marginal pricing under high penetration of distributed energy resources. *Int J Electr Power Energy Syst.* 2020;123:106303.

https://doi.org/10.1016/j.ijepes.2020.106303

Manish Kumar Madhav *received his M. Tech. degree in Power System from IIT Roorkee, India, in 2013, and his PhD in Electrical Engineering from NIT Jamshedpur in 2026.*
https://orcid.org/0000-0002-5778-9802

Krishna B. Yadav *received a PhD in Electrical Engineering from IIT Roorkee in 2007. He is a Professor in the Department of Electrical Engineering, NIT Jamshedpur, India. His research areas are power systems, renewable energy, and electrical drives.*
https://orcid.org/0000-0002-9424-7666

Akshit Samadhiya *graduated from S.R.M. University, Chennai, in 2013 with a B. Tech degree in Electrical and Electronics Engineering. He received an M. Tech degree in Power Electronics and Drives from the National Institute of Technology, Jamshedpur, in 2017. He received a PhD in Electrical Engineering from the National Institute of Technology, Jamshedpur, in 2023. Currently, he is an Assistant Professor in the Electrical Engineering Department at Harcourt Butler Technical University, Kanpur. His research*

interests include power and renewable energy system planning, techno-economic analysis of renewable-based energy systems, renewable energy forecasting, electrical/hybrid vehicles, microgrid planning and control, and control, design, and optimization of power electronics. He has authored research papers in renowned SCI/SCOPUS-indexed international journals and SCOPUS-indexed conferences. He has reviewed research papers in SCI/SCOPUS-indexed journals, such as IEEE Access, Optimal Control Applications and Methods (Wiley), and Arabian Journal of Science and Engineering (Springer).
https://orcid.org/0000-0002-8512-4912

Ahmad Taher Azar *is currently a Full Professor with the College of Computer and Information Sciences (CCIS), Prince Sultan University, Riyadh, Saudi Arabia. He is also the leader of the Automated Systems and Computing Lab (ASCL), Prince Sultan University. He has expertise in artificial intelligence, control theory and applications, robotics, machine learning, computational intelligence, and dynamical system modeling. He has authored/co-authored over 500 research articles in prestigious peer-reviewed journals, book chapters, and conference proceedings. He is an Editor of IEEE Systems Journal, IEEE Transactions on Neural Networks and Learning Systems, Human-Centric Computing and Information Sciences (Springer), and Engineering Applications of Artificial Intelligence (Elsevier).*
https://orcid.org/0000-0002-7869-6373

Saim Ahmed *received the B. S. degree in Electronics from the Sir Syed University of Science and Technology, Pakistan, in 2009; the M. E. degree in Industrial Control and Automation from Hamdard University, Pakistan, in 2013; and the PhD in Control Science and Engineering from Nanjing University of Science and Technology, China, in 2019. He is currently a Postdoctoral Researcher at the Automated Systems and Computing Laboratory (ASCL), Prince Sultan University, Saudi Arabia. His research interests include the theory and applications of adaptive control, sliding mode control, time-delay control, robotic manipulators, and nonlinearities and their compensation.*
https://orcid.org/0000-0002-2302-705X

Walid El-Shafai *research interests encompass a range of areas, including cybersecurity applications, applied artificial intelligence, forensics of malware, systems for multimedia communication, the application of signal processing in images and videos, Internet of Things (IoT), digital data protection such as watermarking, steganography, and encryption, development of applications for medical diagnoses, cancellable biometrics and pattern recognition, and analysis and detection of malware and ransomware.*
https://orcid.org/0000-0001-7509-2120

Chakib Ben Njima *is a Tunisian researcher and professor in automation, control systems, and industrial engineering affiliated with the University of Sousse. He received his Master's degree in 2007 from the National School of Engineers of Monastir, Tunisia. He obtained his PhD in 2013 and his HDR in Automatic Control from the University of Monastir in 2021. He is the President (Founder) of the Tunisian Association of Technology and Sustainable Development (ATTeDD). He is the Founder of the International Conference on Control, Automation, and Diagnosis (ICCAD).*
https://orcid.org/0000-0003-4160-8453

An International Journal of Optimization and Control: Theories & Applications (https://accscience.com/journal/ijocta)