

Using Golden Eagle Optimizer: Economic, Environmental and Reliability Assessment

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Abstract Distributed Generation (DG) allocation in Radial Distribution Networks (RDNs) is a nonlinear, constrained planning problem that requires selecting the location, capacity and operating characteristics of the DG. To address the issue of multi-type multi-DG allocation in IEEE 33-bus Radial Distribution Systems (RDS), this paper proposes a system based on the Golden Eagle Optimizer (GEO). There are four possible operating modes for DGs: active-power injection, reactive-power injection, active-power injection with reactive-power absorption, and simultaneous active-and reactive-power injection. The framework allows for a comparison of three different DG configurations based on voltage, capacity, power-balance and operating constraints. Active and Reactive power losses and voltage stability are used for technical performance assessment, while annual Total Owning Cost (TOC), CO₂ emissions and Expected Energy Not Supplied (EENS) are used for economic, environmental and reliability assessments. The evaluated configurations are seen to reduce the active power loss from 0.211 MW to 0.0251 MW, and increase the minimum voltage from 0.9038 p.u. to 0.9865 p.u. for three type-3 DG units at buses 13, 30, and 3, respectively. The TOC diminishes from 22.3546 to 7.2111 Cr/year, CO₂ emissions from 22,354.63 to 6,058.94 tons/year, and EENS from 38.48 to 24.96 MWh/year. The results shown are indicative of effective DG coordination.

Keywords - Distributed Generation (DG); Golden Eagle Optimizer (GEO); Radial Distribution Network; Multi-Type DG Allocation; Voltage Stability.

Introduction

The increasing integration of DG into electrical distribution networks has created opportunities to improve network efficiency, voltage regulation, power-loss performance, environmental sustainability, and supply reliability [1,2]. If the DG units are configured correctly in close proximity of load, transferring power from upstream grid can be minimized, lowering feeder losses and improving voltage profile [3]. DG deployment can also help provide local power support and offset reliance on centralized generation [4]. The improper location, excessive penetration, inappropriate capacities and poorly matched operating characteristics of the DG, however, have the potential to negatively impact the bus voltages, branch loading, power losses, and overall network operation. Thus, the DG planning problem is a constrained, nonlinear and multidimensional optimization problem, which involves the simultaneous determination of the number, type, size and location of the DG, with the aim of meeting the operating requirements of the network.

The simultaneous optimization of the DG number, type, location, and capacity is more complex than more traditional allocation methods that aim to optimize the location and size of a single DG technology [5,6]. The number of DG-units determines the degree of distributed penetration, and the location of these units affects the distribution of power flow, voltage profiles and feeder losses [7]. Likewise, the capacity of the DG unit defines the amount of active-power generation or reactive-power support, while the operating type defines the active and reactive-power characteristics [8]. Therefore, optimizing only for a few planning variables can result in technically viable but not a desired economic, environmental, or reliability performance. A coordinated optimization framework is therefore necessary for a comprehensive assessment of alternative DG configurations and for finding viable solutions in the presence of conflicting network requirements.

The impact of different DG operating characteristics on distribution-network performance is significant, as active-power and reactive-power exchanges affect feeder currents, voltage regulation, power losses, and the amount of power delivered by the main grid [9]. In this study, four operating types of DG are considered under a common allocation framework. The DG operating configurations are categorized into four modes: "Type-1 for active-power delivery, Type-2 for reactive-power provision, Type-3 for combined active- and reactive-power delivery, and Type-4 for active-power generation with reactive-power absorption" [10,11]. These types of operations allow us to systematically study the effect of various P-Q on the technical performance of the network. The framework also considers one, two and three DG configurations, to investigate the impact of increasing DG penetration under the given operating conditions [12].

The multi-dimensionality of DG allocation also demands an optimization method that can search for a nonlinear solution space that includes both discrete bus locations and continuous DG capacities, and incorporates multiple operational constraints [13]. Metaheuristic optimization methods provide a suitable computational approach for such complex planning problems [14]. The GEO is used as the optimization mechanism in this study. GEO is a population-based metaheuristic based on the hunting behaviors of golden eagles in which it combines the exploration and exploitation mechanisms to seek out best regions in the solution space [15]. Using the application in the present framework, the appropriate DG locations and capacities for the targeted DG operating types and numbers can be found without violating the desired network constraints [16].

The assessment of DG allocation should not be limited to the active power loss or the voltage performance. The implications of alternative DG configurations are also assessed by economic, environmental and reliability considerations [17,18]. The framework of the present invention therefore considers annual TOC, CO₂ emissions and EENS as well as active and reactive power losses and voltage stability [19,20]. These indicators give complementary insight into the impact of DG allocation and can be explored from a technical, economic, environmental and reliability perspective in alternative setups [21].

Accordingly, this study investigates multi-type multi-DG allocation in RDNs using the GEO algorithm. The proposed framework takes into account the type, number, location and capacity of the DG and how they affect the performance of the distribution network. The test network is a 33-bus RDS used by IEEE and the resulting configurations are evaluated under the following operational constraints. The purpose of the study is to determine feasible configurations of the DG allocation and to systematically analyse the technical, economic, environmental and reliability performance of these configurations. Here are the research objectives as shown in given below:

- To develop a Golden Eagle Optimizer (GEO)-based framework for optimal allocation of multiple DG units in radial distribution networks.
- To optimize the location and capacity of different DG operating types for one, two, and three DG configurations under the specified network and operational constraints.
- To evaluate the impact of different DG types and penetration levels on active and reactive power losses, bus voltage profile, and voltage stability.
- To assess the economic, environmental, and reliability performance of the optimized DG configurations using annual total owning cost, CO₂ emissions, and EENS.
- To identify the performance characteristics of the evaluated DG configurations on the IEEE 33-bus RDS and determine the configurations associated with the reported improvements in network performance.

Related Works

Recent research has increasingly focused on metaheuristic optimization for optimal DG allocation in RDNs, particularly for determining suitable DG locations, sizes, operating conditions, and combinations of multiple DG units. The Transient Search Optimization (TSO) method was created by Bhadoriya et al. (2022) [22] to allocate multiple DGs at unity, fixed, and ideal power factors. The approach aims to achieve goals related to active power loss, voltage deviation, and voltage stability. The efficiency of the approach was confirmed by testing it on IEEE 33- and 69-bus systems for both single- and multi-objective issues. This proved that the improved search mechanisms were suitable for the nonlinear DG allocation problem. Similarly, Ahmed et al. (2023) [23] proposed a hybrid SSA-PSO approach for individual and simultaneous multi-DG allocation under time-varying and voltage-dependent loads. The Salp Swarm Algorithm has been combined with the local search capability of Particle Swarm Optimization (PSO) to overcome the premature convergence problem of traditional algorithms, and the performance of the algorithm was tested by benchmark functions and various generation cases. Raza et al. (2023) [24] extended DG planning by integrating multiple DG types with distribution network reconfiguration using Ant Colony Optimization. They both addressed active power loss, voltage deviation, stability and reliability in their approach to energy not-supplied reduction and also preserved the radial structure of IEEE 33- and 69-bus systems. Recently, Salimon et al. (2025) [25] conducted a study on multi-type DG allocation based on the Mountain Gazelle Optimizer, which includes optimization of DG sizing, location, and power factor. The study was conducted on IEEE 33 and 69 bus systems, and included the evaluation of one to three DG units, real and reactive losses, voltage indices, and cost related performance. In a similar way, Roy et al. (2025) [26] used the Artificial Gorilla Troops Optimizer with sensitivity-based bus selection for biomass DG allocation, taking into account real/reactive loss minimization, voltage-profile improvement, voltage stability, composite loads, and load growth. The above studies collectively show the growing trend of using a population-based optimization approach to address the multi-dimension and non-linear nature of a DG allocation.

The economic, environmental, uncertainty, and multi-resource aspects are important issues that have been integrated in distribution-network planning in recent years, in addition to the technical ones. Dash et al. (2024) [27] presented a multi-objective CD-SPBO approach for simultaneous renewable and dispatchable DG allocation with D-STATCOMs, including total active power loss, voltage profile, voltage stability, and

cost components such as investment, environmental-limit penalties, and energy losses. Zangmo et al. (2024) [28] studied renewable DG and EV integration in a RDS with 24 HR load uncertainty and probabilistic wind and solar characteristics with Beta and Weibull distributions. A multi-population Evolution Whale Optimization Algorithm was applied to a 28-bus Indian system to examine the performance of the power loss, voltage profile, stability, and environmental sustainability. Murali et al. (2025) [29] suggested a consumer-aware multi-objective optimization framework for simultaneous placement of EV charging-station and DG that includes active power loss, voltage variation, and consumer cost using a Modified Weighted TLBO-PSO approach. However, Qian et al. (2025) [30] took a step forward by dealing with the mixed discrete-continuous problem of DG placement and sizing by applying a modified seagull optimization algorithm and then expanded the approach into multi-objective scenarios, including voltage deviation and active/reactive power losses. More recently, Roy et al. (2026) [31] suggested a multi-stage GSA methodology for sizing and placement of solar DG with storage, wind DGs, shunt capacitors, and EV charging stations under different loading and renewable resource conditions. Similarly, Rajkumar et al. (2026) [32] devised an EMALO-based multi-DG system, using sensitivity-based bus preselection and Pareto optimization for real power loss and voltage-profile improvement. In addition, Khoudry et al. (2026) [33] also included deterministic and stochastic DG types and numbers, with techno-economic assessment, in consideration of an Adapted Equilibrium Optimizer. Collectively, these studies indicate a progression toward integrated DG planning; however, the simultaneous optimization of DG number, operating type, location, and capacity with a combined economic, environmental, and reliability assessment remains an important research direction.

Table 1. Existing Blockchain Models

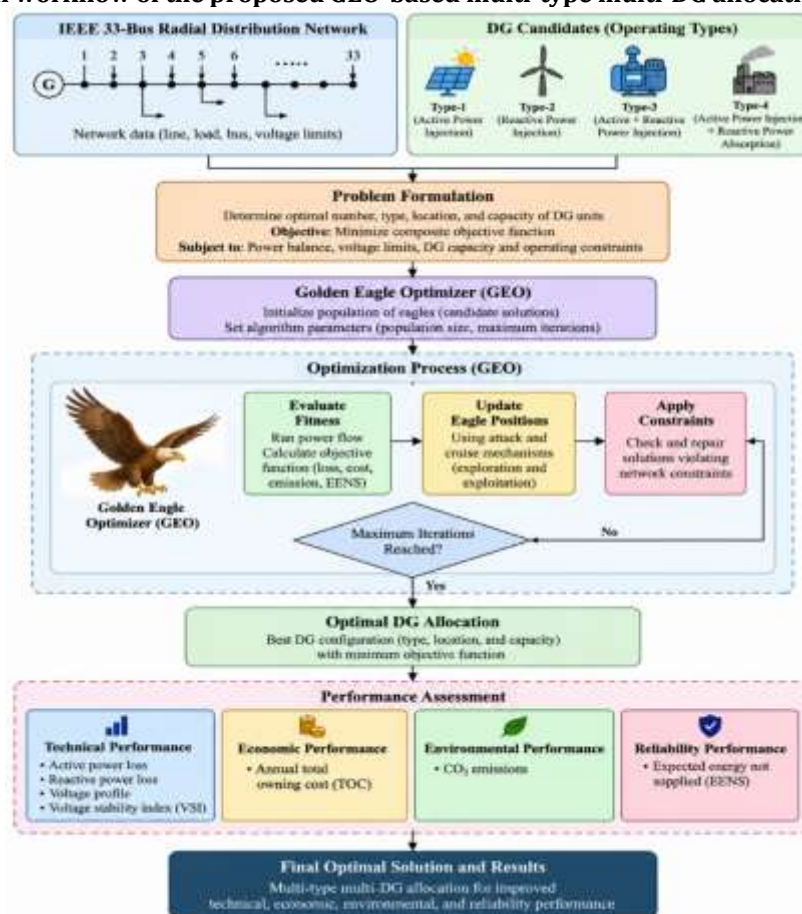
Authors & Year	Optimization / Method	DG / System Considered	Key Findings
Bhadoriya et al. (2022)	Transient Search Optimization (TSO)	Multiple DGs at unity, fixed and optimal power factors	Demonstrated effective DG allocation under single- and multi-objective scenarios through exploration and exploitation mechanisms.
Ahmed et al. (2023)	Hybrid SSA-PSO	Individual and simultaneous multi-DG allocation with TVVD loads	Combined global search of SSA with local search of PSO and addressed premature convergence issues.
Raza et al. (2023)	Ant Colony Optimization Algorithm (ACOA)	Multiple DG types + distribution network reconfiguration	Simultaneous DNR and DG allocation improved network performance and reduced ENS while maintaining radial operation.
Dash et al. (2024)	Continuous-Discrete Student Psychology-Based Optimization (CD-SPBO)	Renewable/dispatchable DGs + D-STATCOMs	Developed a multi-objective framework incorporating technical, economic and environmental criteria for simultaneous device allocation.
Zangmo et al. (2024)	Multipopulation Evolution Whale Optimization Algorithm (MEWOA)	Solar PV, wind DGs and EVs	Incorporated renewable-resource and load uncertainty while demonstrating the technical and environmental benefits of renewable DG integration.
Salimon et al. (2025)	Mountain Gazelle Optimizer (MGO)	Multi-type DGs; 1-3 DG units with different power factors	Optimized DG sizing, location and power factor, highlighting the importance of power-factor optimization in multi-type DG planning.
Roy et al. (2025)	Artificial Gorilla Troops Optimizer (AGTO) + sensitivity index	Biomass DG	Used sensitivity-based severe-bus selection before AGTO-based DG allocation and also considered load growth.
Murali et al. (2025)	Modified Weighted TLBO-PSO	EV charging stations + DGs	Proposed consumer-aware simultaneous optimization of EVCS and DG placement, linking network performance with consumer-oriented cost.
Qian et al. (2025)	Modified Seagull Optimization Algorithm (mSOA-SO / mSOA-MO)	DG location, capacity and power factor	Addressed mixed discrete-continuous DG allocation and extended the method to dual- and triple-objective planning.
Khoudry et al. (2026)	Adapted Equilibrium Optimizer (AEO)	Deterministic and stochastic DG types and numbers	Evaluated different DG types/numbers and incorporated a techno-economic assessment of optimized DG integration.

Roy et al. (2026)	Gravitational Search Algorithm (GSA)	Solar DG + BSS, wind DGs, shunt capacitors and EVCSs	Proposed a multi-stage framework integrating DER sizing/placement, EVCS allocation and network reinforcement under varying operating conditions.
Rajkumar et al. (2026)	Enhanced Modified Ant Lion Optimizer (EMALO) + APLS/VSI	Multi-DG allocation; PV and WT scenarios	Combined sensitivity-based bus preselection with enhanced search mechanisms and Pareto optimization for multi-DG allocation.

Research Methodology

Fig. 1 illustrates the overall workflow of the proposed GEO-based multi-type multi-DG allocation framework. The process begins with the IEEE 33-bus RDN and specification of four DG operating types. The optimization problem is then formulated by defining DG number, type, location, and capacity under the specified network and operating constraints. The Golden Eagle Optimizer initializes candidate solutions and iteratively performs fitness evaluation, eagle-position updates, and constraint handling until the stopping criterion is satisfied. The optimal DG configuration is subsequently obtained and evaluated in terms of technical performance, annual total owning cost, CO₂ emissions, and EENS.

Fig. 1: Overall workflow of the proposed GEO-based multi-type multi-DG allocation framework.



3.1. Distribution Network and DG Allocation Framework

The proposed DG allocation framework is tested on the IEEE 33-bus RDN. Bus 1 is considered the slack/reference bus, while DG units are installed only at candidate buses 2–33. N_{DG} is the number of installed DG unit in each optimization case; each DG unit is defined by the installation bus and the generation capacity. There are four different types of DG operation and varying numbers of DG units. Duplicate DG locations are not permitted. Active-DG capacity is limited to 0.1–2.0 MW for each DG and 3.0 MW for the total active-DG capacity when applicable. The respective active- and reactive-power characteristic is included in the power-flow analysis. Therefore, DG allocation is a nonlinear mixed-variable optimization problem, as it consists of both discrete bus locations and continuous capacity variables.

3.2. Multi-Type DG Operating Models

DG units are classified based on how much active and reactive power they exchange with distribution network. Four operating types are considered in the study.

3.2.1 Type-1 DG

A Type-1 DG injects active power into the distribution network while maintaining zero reactive-power exchange. Its operating condition can be represented as

$$P_{DG,i} > 0, \quad Q_{DG,i} = 0$$

This type mainly provides active power support and may also contribute to the reduction of upstream active power supply.

3.2.2 Type-2 DG

A Type-2 DG supplies reactive power without active-power generation. Its operating condition is represented as

$$P_{DG,i} = 0, \quad Q_{DG,i} > 0$$

This class of contribution is mainly reactive-power support, which can affect bus-voltage magnitudes, reactive-power losses, and voltage stability.

3.2.3 Type-3 DG

A Type-3 DG simultaneously supplies active and reactive power. Therefore,

$$P_{DG,i} > 0, \quad Q_{DG,i} > 0$$

In this operating mode, the reactive-power output is calculated based on a specified power-factor condition in the associated optimization scenario.

3.2.4 Type-4 DG

A Type-4 DG supplies active power while absorbing reactive power from the distribution network. Hence,

$$P_{DG,i} > 0, \quad Q_{DG,i} < 0$$

The power factor condition is used to calculate the reactive-power absorption. The effect of the active-power generation and reactive-power demand can thus be studied in the case of inclusion of Type-4 DG.

The four DG types are tested under their different operating characteristics, and thereby the impact of varying (P-Q) behaviours can be studied in a systematic way on losses, voltage performance, cost, emissions and reliability. The four types of DG are considered as 4 different optimization scenarios, whereas the GEO is used to find the location and capacity of the DGs for each specified DG type and DG number.

3.3. Objective Function Development

DG optimal siting needs to consider technical, economic, environmental and reliability characteristics of the distribution network all together. The goal function is designed to measure the performance of various DG allocation configurations, including active and reactive power losses, voltage stability, annual total owning cost, CO₂ emissions, and EENS. These parameters are measured on different scales and vary in their numerical range and values, so the individual objective components are scaled before they are combined in the fitness function. The general composite objective function can be expressed as:

$$F_{obj}(x) = w_1 f_{loss}(x) + w_2 f_{cost}(x) + w_3 f_{CO_2}(x) + w_4 f_{EENS}(x) + w_5 f_{VSI}(x)$$

where F_{obj} represents the overall objective value for a candidate DG configuration x , while f_{loss} , f_{cost} , f_{CO_2} , f_{EENS} , and f_{VSI} denote the normalized technical, economic, environmental, reliability, and voltage-stability components, respectively. The parameters w_1 – w_5 represent the corresponding weighting factors. A lower value of the composite objective indicates improved overall network performance when the individual components are formulated as minimization objectives.

3.3.1 Technical Performance

A technical performance assessment of the distribution network is based on the losses of active power, reactive power and voltage stability. By optimizing the placement of DG, branch currents can be minimized, leading to lower power losses and better voltage profile. The total active power loss is calculated as:

$$P_{loss} = \sum_{i=1}^{N_l} I_i^2 R_i$$

where I_i is the current flowing through branch i , R_i is the resistance of branch i , and N_l represents the total number of distribution branches.

The corresponding reactive power loss is expressed as:

$$Q_{loss} = \sum_{i=1}^{N_l} I_i^2 X_i$$

where X_i denotes the reactance of branch i . For optimization to be dimensionless, the active power loss can be expressed as a percentage of the active power loss in a base case network:

$$P_{loss,norm} = \frac{P_{loss}}{P_{loss,base}}$$

where $P_{loss,base}$ represents the active power loss obtained before DG integration.

The Voltage Stability Index (VSI) is employed to evaluate the voltage stability of the distribution network. For each branch linking the sending bus i to the receiving bus j , the VSI is determined from the corresponding voltage and power-flow parameters as follows:

$$VSI_j = f(V_i, P_j, Q_j, R_{ij}, X_{ij})$$

where V_i is the sending-end voltage, P_j and Q_j are the active and reactive powers at the receiving bus, and R_{ij} and X_{ij} are the branch resistance and reactance, respectively. The VSI is added to the objective formulation to achieve a stable voltage profile in the RDN.

3.3.2 Economic and Environmental Performance

The economic efficiency of the DG allocation is assessed based on the annual TOC of the DG allocation. The

cost assessment takes into account investment and operation needs of DG units during the defined planning period. For a planning period of N years and discount rate d , the capital recovery factor is expressed as:

$$CRF = \frac{d(1+d)^N}{(1+d)^N - 1}$$

The annual total owning cost can generally be represented as:

$$TOC = C_{\text{annualized}} + C_{\text{O\&M}} + C_{\text{energy}}$$

where $C_{\text{annualized}}$ represents the annualized investment cost, $C_{\text{O\&M}}$ denotes the operation and maintenance cost, and C_{energy} represents the associated energy cost.

Environmental performance is measured by the annual CO₂ emissions from electricity supplied by the grid and DG sources. The total emissions can be expressed as:

$$E_{\text{CO}_2} = E_{\text{grid}}EF_{\text{grid}} + E_{\text{DG}}EF_{\text{DG}}$$

where E_{grid} and E_{DG} are the annual energy supplied by the grid and DG units, respectively, while EF_{grid} and EF_{DG} represent their respective emission factors. Minimizing this component supports DG configurations with lower environmental impact.

3.3.3 Reliability Performance

The reliability of the distribution network is measured by the EENS which is the quantity of electrical energy that is expected not to be supplied when interruption events occur. The EENS can be stated in one of the following ways:

$$EENS = \sum_{i=1}^{N_c} P_i T_i L_i$$

where N_c represents the number of considered interruption events, P_i denotes the probability or frequency associated with event i , T_i is the interruption duration, and L_i represents the corresponding unsupplied load.

For normalization, the reliability component can be represented as:

$$f_{\text{EENS}} = \frac{EENS}{EENS_{\text{base}}}$$

where $EENS_{\text{base}}$ denotes the EENS value of the reference distribution network. The reliability component is thus embedded in the overall objective function in conjunction with the technical, economic, environmental, and voltage-performance terms. Therefore, optimization process takes into account several aspects of DG integration apart from power loss minimization.

3.4. Operational and DG Constraints

The optimization process is constrained by a set of operational and DG specific constraints to ensure that all candidate solutions generated by the GEO are electrically feasible and adhere to the operating characteristics of the selected DG type. The constraints mainly limit the magnitude of the bus voltages, the capacity of the DGs, the relationships between active-reactive powers and the uniqueness of the DG locations. These restrictions are used to exclude certain DG configurations that are technically infeasible, but still limit the distribution network to the specified constraints.

3.4.1 Bus Voltage Constraint

The voltage level at every bus is required to remain within the specified allowable limits, which can be formulated as follows:

$$V_i^{\min} \leq V_i \leq V_i^{\max}, \quad i = 1, 2, \dots, N_b$$

where V_i is the voltage magnitude at bus i , while $V_i^{\min}$ and $V_i^{\max}$ denote the corresponding minimum and maximum allowable voltage limits. This constraint ensures that DG integration does not result in unacceptable undervoltage or overvoltage conditions.

3.4.2 DG Capacity Constraint

The active-power output of each DG unit is restricted within its specified operating range:

$$P_{DG,i}^{\min} \leq P_{DG,i} \leq P_{DG,i}^{\max}$$

For DG types involving active-power generation, the active-power capacity is restricted to 0.1–2.0 MW. In addition, the total installed active DG capacity is restricted by:

$$\sum_{i=1}^{N_{DG}} P_{DG,i} \leq 3.0 \text{ MW}$$

For DG types capable of reactive-power exchange, the corresponding reactive-power limits and power-factor conditions are also maintained.

3.4.3 DG Operating Constraints

The active and reactive power characteristics are defined according to the selected DG operating type:

$$\text{Type-1: } Q_{DG,i} = 0$$

$$\text{Type-2: } P_{DG,i} = 0$$

$$\text{Type-3: } P_{DG,i} > 0, \quad Q_{DG,i} > 0$$

$$\text{Type-4: } P_{DG,i} > 0, \quad Q_{DG,i} < 0$$

The four DG operating modes are defined as follows: Type-1 represents active-power injection, Type-2 denotes reactive-power injection, Type-3 involves simultaneous active- and reactive-power injection,

whereas Type-4 corresponds to active-power injection accompanied by reactive-power absorption. In addition, duplicate DG locations are prohibited so that each DG unit is assigned to a distinct bus within an optimization solution.

3.5. Golden Eagle Optimizer (GEO) for DG Allocation

The GEO is a population-driven metaheuristic technique developed by emulating the hunting strategies exhibited by golden eagles (*Aquila chrysaetos*). The algorithm simulates the behavior of eagles finding good food based on the exploration and exploitation mechanisms. In this study, GEO is used to identify appropriate DG locations and capacities in the RDN while meeting the operational constraints given in section 3.4. The position of each eagle corresponds to a candidate DG allocation solution, in which the position specifies the selected bus locations and DG capacities.

3.6. Solution Representation and Population Initialization

Each eagle in the proposed DG allocation framework is a candidate solution for the DG allocation. Its position specifies the sites and sizes of the DG units located in the RDN. For N_{DG} DG units, the position of the k -th eagle is represented as:

$$X_k = [B_{k,1}, P_{k,1}, B_{k,2}, P_{k,2}, \dots, B_{k,N_{DG}}, P_{k,N_{DG}}]$$

where $B_{k,i}$ denotes the bus location and $P_{k,i}$ represents the active-power capacity of the i -th DG unit. The candidate locations are selected from buses 2–33 of the IEEE 33-bus system, excluding the slack bus. Each DG capacity is restricted to 0.1–2.0 MW:

$$0.1 \leq P_{k,i} \leq 2.0 \text{ MW}$$

while the total installed active DG capacity is limited by:

$$\sum_{i=1}^{N_{DG}} P_{k,i} \leq 3.0 \text{ MW}$$

The DG operating type is determined based on the considered type-1 to type-4 DG configuration and the characteristics of active and reactive power are determined as shown in Section 3.2. No duplicate DG locations allowed in a candidate solution.

The initial GEO population consists of 50 eagles generated within the defined search space:

$$X^0 = [X_1^0, X_2^0, \dots, X_{50}^0]$$

where X_k^0 represents the initial position of the k -th eagle. The solutions generated are tested for the specified DG constraints, and the values of their objective-function are computed. These fitness values are then employed to determine a set of promising candidate solutions used by the following GEO search mechanism.

3.7. GEO Search Mechanism

The GEO search method simulates the hunting strategy of golden eagles by moving in direction towards promising prey as well as complementary cruising. Once initialized, each eagle adjusts its position based on the prey's information received and the direction in which it is searching. The mechanism is designed to balance exploration of new DG configurations and exploitation of promising solutions by incorporating prey selection, memory, attack movement, cruise movement and position updating.

3.7.1 Prey Selection and Memory Mechanism

The optimal solutions found in the optimization process are put into the memory pool and considered as potential prey. For the k -th eagle, the selected prey position can be represented as:

$$X_{\text{prey}} = X_m$$

where X_m denotes a selected promising solution from the memory pool. This information guides the eagle toward better regions of the search space.

3.7.2 Attack Vector

The attack vector is the direction from the current position of the eagle to the chosen prey. It is determined by:

$$A_k = X_{\text{prey}} - X_k$$

where X_k is the current position of the k -th eagle. A larger directional component allows the eagle to move toward promising DG locations and capacities.

3.7.3 Cruise Vector

The cruise vector provides an additional search direction around the selected prey and helps maintain population diversity. It is generated perpendicular to the attack vector, satisfying:

$$A_k \cdot C_k = 0$$

where C_k represents the cruise vector. Attack and cruise directions are used together to avoid the tendency to focus too early on a single area.

3.7.4 Step and Position Update

The movement step is determined from the attack and cruise components and is used to update the eagle's position:

$$X_k^{t+1} = X_k^t + \Delta X_k^t$$

where X_k^t and X_k^{t+1} are the current and updated positions, respectively, and ΔX_k^t denotes the calculated movement step.

3.7.5 Exploration–Exploitation Control

The GEO search process modifies the movement behavior during each iteration, so as to balance exploration and exploitation. The early stages provide more opportunity for exploring the various DG locations and capacities, while later stages focus on exploiting around promising solutions. The dynamic search propensity can generally be represented as:

$$p(t) = f\left(\frac{t}{T}\right)$$

The variables t and T denote the current iteration and the predefined maximum number of iterations, respectively. This mechanism allows GEO to gradually refine the search to increasingly high-quality DG allocation solutions while allowing for diversity to prevent premature convergence.

3.8. Fitness Evaluation and Constraint Handling

The fitness evaluation stage determines the quality of each candidate DG allocation generated by the GEO algorithm. The respective DG locations and capacities are then considered for each eagle position and technical, economic, environmental and reliability parameters are calculated. The objective function described in Section 3.3 is used to combine these parameters for calculating the fitness value:

$$\text{Fitness}(X_k) = F_{\text{obj}}(X_k)$$

where X_k represents the k -th candidate solution and F_{obj} is the composite objective value.

Each candidate solution is then examined to see if it satisfies the constraints and limitations associated with the operation of the BES, such as bus-voltage limits, per-bus DG capacity limits, DG operating-type conditions, and limits on the number of duplicate DG locations. Only solutions that meet all of the given constraints are feasible. During fitness evaluation infeasible solutions are penalized to make the optimizer steer far away from infeasible configurations. The general penalized fitness function can be written as:

$$F_{\text{pen}} = F_{\text{obj}} + \lambda \sum_{r=1}^{N_c} \max(0, g_r(X_k))$$

where $g_r(X_k)$ represents the r -th constraint violation and λ is the penalty coefficient. The solution that is feasible and has the lowest fitness value is kept as the best solution and then used during the next iteration of GEO.

3.9. Overall Optimization Procedure

The entire optimization process is incorporated within an integral computational framework, which involves the representation of the solution to the DG problem, the evaluation of the objective-function, the operational constraints, and the GEO searching mechanism. First, the RDN is defined in IEEE 33-bus system, and the selected DG configuration is defined. Then, 50 eagles are created, each of which corresponds to a possible combination of DG locations and capacities. The fitness of each potential solution is tested using the composite objective function, while operating-type, position, voltage, and DG capacity limitations are verified simultaneously.

The GEO algorithm then uses the attack and cruise mechanisms to update the eagle positions, and to select promising solutions. The updated solutions are again evaluated, and the best feasible solution is retained.

Algorithm 1: GEO-Based Multi-Type DG Allocation

Input: IEEE 33-bus radial distribution network, DG type, number of DG units, DG capacity limits, population size $N_p = 50$, and maximum iterations $T = 100$.

Output: Optimal DG locations, DG capacities, and minimum composite objective value.

1. Initialize the IEEE 33-bus distribution network and DG parameters.
2. Define the selected DG type and number of DG units.
3. Generate an initial population of 50 eagles within the defined search space.
4. Evaluate the composite objective function and check all operational and DG constraints.
5. Store the best feasible solutions in the GEO memory pool.
6. Select the prey and calculate the corresponding attack and cruise vectors.
7. Update the eagle positions using the GEO movement mechanism.
8. Check the updated DG configurations against voltage, capacity, operating-type, and location constraints.
9. Re-evaluate the feasible solutions and update the best solution.
10. Repeat Steps 6–9 until $T = 100$ iterations are completed.
11. Repeat the optimization process for 20 independent runs.
12. Select the final DG allocation corresponding to the minimum composite objective value among the feasible solutions.

Results

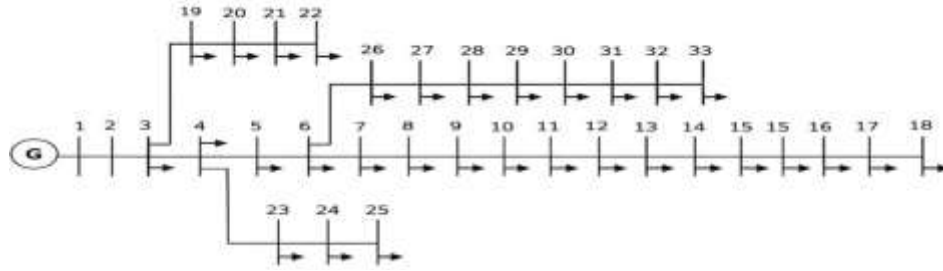
This section describes the results of the tested performance of proposed GEO based multi-type DG allocation framework on the IEEE 33 bus RDS. Technical, economic, environmental and reliability indicators are used to assess the results for different types of DG and penetration levels. Power losses, voltage stability, annual total owning cost, CO₂ emissions and EENS are analysed.

4.1. Test System and Simulation Setup

Fig. 2 demonstrates that the proposed GEO-based multi-type DG allocation system is tested on the IEEE 33-

bus RDS. The system is engineered to operate at a 12.66 kV base voltage and 100 MVA base power, with a total power consumption estimated at 3.7 MW and 2.3 MVAR. There are 32 branches and 33 busses in the network, with Bus 1 serving as the substation. Software such as MATLAB R2021a is used to conduct the optimization and power-flow investigations.

Fig. 2: IEEE 33-bus radial distribution system used for DG allocation and performance evaluation.



4.2. Technical Performance of Different DG Configurations

4.2.1. Active and Reactive Power Loss Performance

The technical performance of the IEEE 33-bus distribution system is displayed in Table 2 for four different configurations: basic case, one-DG, two-DG, and three-DG. All of these configurations are tested under four different operating modes with DGs working at a power factor of 0.9. Within the outcomes are VSI, minimum and maximum bus voltages, % decrease in losses, active and reactive power losses, and so on. The base case has an active power loss of 0.211MW. DG integration gives a decrease in losses with all configurations, the best decrease in losses is observed in Type-3. Lower active power loss of 0.0251 MW, reactive power loss of 0.0196 MVar, and VSI of 0.946909 were achieved with improved voltage performance by configuring three DG Type-3 at busses 13, 30, and 3.

Table 2. Technical Performance of Different DG Configurations at 0.9 Power Factor for the IEEE 33-Bus System

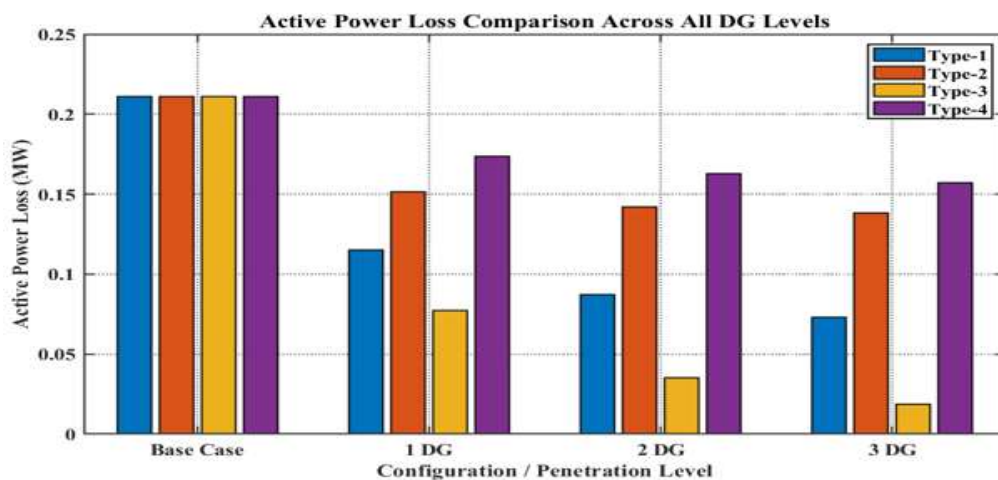
0.9 PF	Optimal DG Bus Number	Injected Active power (MW)	Injected Reactive Power (MVar)	Active Power loss	Reactive Power loss	% Loss Reduction	Min Voltage, Bus Number	Max Voltage, Bus Number	VSI
Base Case				0.211	0.143		0.9038, Bus 18		0.666763
Type 1									
1 DG	7	2.0000	0	0.1152	0.0824	45.40	0.9364, Bus 18	1.0000, Bus 1	0.768668
2 DG	13 30	0.8494 1.1177	0	0.0872	0.0597	58.66	0.9672, Bus 33	1.0000, Bus 1	0.875087
3 DG	3 30 13	1.3287 0.9850 0.7851	0	0.0785	0.0550	62.81	0.9671, Bus 33	1.0000, Bus 1	0.874759
Type 2									
1 DG	30	0	1.2577	0.1514	0.1038	28.26	0.9165, Bus 18	1.0000, Bus 1	0.705144
2 DG	26 30	0	0.8288 0.8792	0.1454	0.0999	31.07	0.9208, Bus 18	1.0000, Bus 1	0.718540
3 DG	30 13 24	0	1.0328 0.3974 0.5402	0.1383	0.0942	34.47	0.9320, Bus 18	1.0000, Bus 1	0.754269
Type 3									
1 DG	28	2.0000	0.9686	0.0772	0.0597	63.39	0.9432, Bus 18	1.0000, Bus 1	0.791289
2 DG	13 30	0.8271 1.3678	0.4006 0.6624	0.0353	0.0252	83.29	0.9803, Bus 25	1.0000, Bus 1	0.923056
3 DG	13 30 3	0.8297 1.1729 1.5318	0.4018 0.5681 0.7419	0.0251	0.0196	88.08	0.9865, Bus 25	1.0030, Bus 13	0.946909

Type 4									
1 DG	6	1.4225	0.6890	0.1735	0.1179	17.78	0.9185, Bus 18	1.0000, Bus 1	0.71763 2
2 DG	6 14	1.0235 0.4046	0.4957 0.1959	0.1627	0.1118	22.88	0.9298, Bus 18	1.0000, Bus 1	0.74755 6
3 DG	6 24 14	0.0840 0.6545 0.3987	0.3894 0.3170 0.1931	0.1573	0.1081	25.46	0.9294, Bus 18	1.0000, Bus 1	0.74619 4

4.2.2. Active Power Loss Comparison

The active power losses of the IEEE 33-bus system with the basic scenario and with different penetration levels are shown in Fig. 3. The active power loss recorded by the system without integration of DG is 0.211 MW. With one DG unit, the losses decrease to 0.1152 MW for Type-1, 0.1514 MW for Type-2, 0.0772 MW for Type-3, and 0.1735 MW for Type-4. For two DG units, the corresponding losses are 0.0872, 0.1454, 0.0353, and 0.1627 MW. With three DG units, the losses further decrease to 0.0785, 0.1383, 0.0251, and 0.1573 MW for Types 1–4, respectively. The results indicate that the active power losses tend to decrease as the number of DG units increases with Type-3 configuration having the minimum losses in all the cases.

Fig 3: Comparison of active power losses for different DG operating types and penetration levels.



4.3. Voltage Profile and Stability Performance

4.3.1. Bus Voltage Performance

Table 3 shows the economic, environmental, and reliability performance of IEEE 33-bus system with varying types and penetration levels of DGs. The base case shows an annual total cost of Rs. 22.3546 Cr/year, CO₂ emissions of 22,354.63 t/year, and EENS of 38.48 MWh/year. DG integration decreases these indicators and the amount depends on the type and number of DG. For three DG units, "Type-1, Type-2, Type-3, and Type-4" achieve cost reductions of 56.21%, 1.42%, 67.76%, and 42.48%, respectively. The three-DG type-3 configuration at buses 13, 30 and 3 gives the lowest annual cost of Rs. 7.2111 Cr/year, CO₂ emissions of 6,058.94 t/year, and EENS of 24.96 MWh/year, corresponding to reductions of 67.76%, 72.91%, and 35.15%, respectively.

Table 3. Economic, environmental, and reliability performance of different DG configurations for the IEEE 33-bus system.

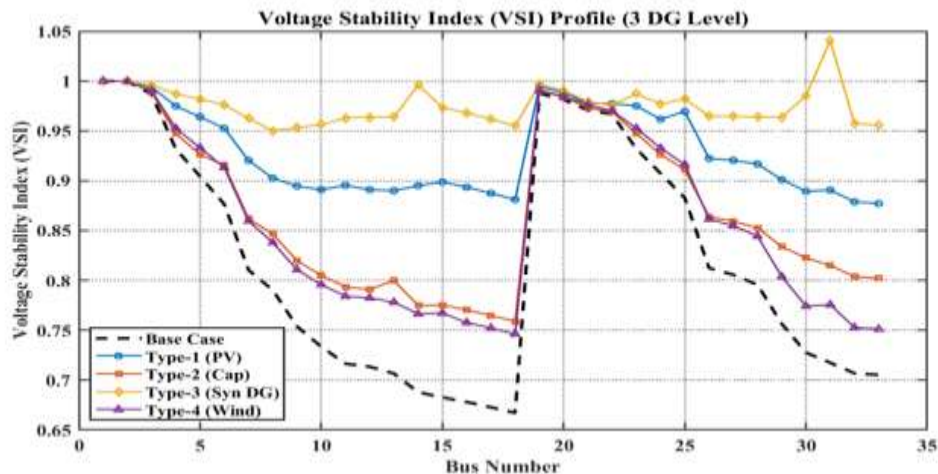
DG Configuration	No. of DGs	Optimal DG Buses	Total Cost (Rs. Cr/yr)	Cost Reduction (%)	CO ₂ Emissions (t/yr)	CO ₂ Reduction (%)	EENS (MWh/yr)	EENS Reduction (%)
Base Case	0	—	22.3546	—	22354.63	—	38.48	—
Type-1	1	7	11.7878	47.27	10421.18	53.38	29.16	24.22
Type-2	1	30	22.0629	1.30	22015.16	1.52	38.48	0.00
Type-3	1	28	11.8754	46.87	11081.01	50.43	29.16	24.22
Type-4	1	6	15.1192	32.37	14163.47	36.63	31.85	17.23
Type-1	2	30, 13	11.7429	47.47	10391.83	53.53	29.26	23.96
Type-2	2	30, 26	22.0236	1.48	21964.76	1.74	38.48	0.00
Type-3	2	13, 30	10.8235	51.58	9962.71	55.43	28.38	26.24
Type-4	2	14, 26	15.5077	30.63	14613.00	34.63	32.27	16.14

Type-1	3	3, 30, 13	9.7879	56.21	8176.68	63.43	27.49	28.56
Type-2	3	30, 13, 24	22.0363	1.42	21947.35	1.82	38.48	0.00
Type-3	3	13, 30, 3	7.2111	67.76	6058.94	72.91	24.96	35.15
Type-4	3	13, 6, 24	12.8621	42.48	11611.65	48.06	29.80	22.55

4.3.2. Voltage Stability Index (VSI) Comparison

The VSI profiles for the base case and the four types of DG operation are shown in Fig. 4 for the three-DG level. The VSI reduces significantly down the feeder to about 0.6668 at the lowest VSI bus. The VSI profiles are enhanced throughout the network with the integration of DG. Type-2 and Type-4 show moderate improvement and Type-1 shows higher VSI values for multiple buses. Type-3 presents the best VSI profile for most buses, with the lowest VSI of 0.9469, while Type-1, 2, and 4 present the lowest VSI of 0.8748, 0.7543, and 0.7462, respectively. The Type-3 configuration also can achieve a VSI of greater than 1.0 in some buses, up to about 1.04 for the profile plotted. The findings demonstrate that including Type-3 DG improves the voltage stability performance.

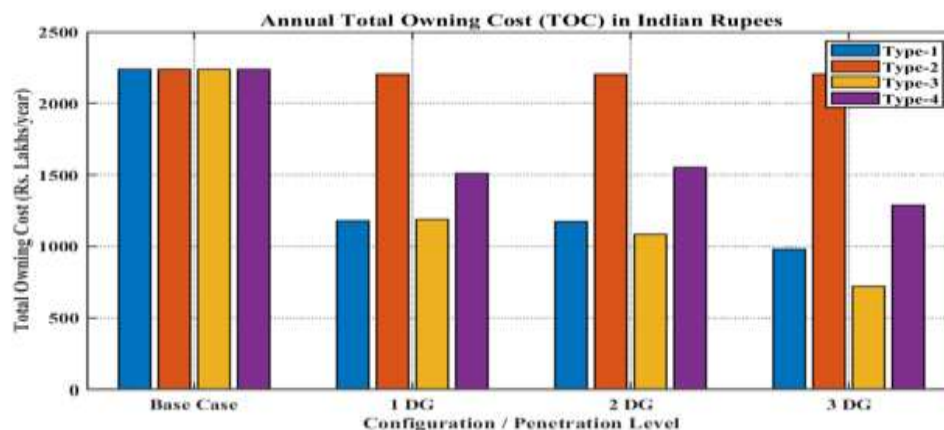
Fig 4: Voltage Stability Index (VSI) profiles for different DG operating types at the three-DG level.



4.4. Economic Performance

Fig. 5 shows the Total Owning Cost (TOC) for the various penetration levels for DG and the base case. The basic price for TOC is Rs. 22.3546 Cr/year. When the number of DG is 1, the TOC is reduced to Rs. 11.7878 Cr/year for Type-1, Rs. 22.0629 Cr/year for Type-2, Rs. 11.8754 Cr/year for Type-3, and Rs. 15.1192 Cr/year for Type-4. The cost of maintenance of 2 DG units is Rs. 11.7429, 22.0236, 10.8235, and 15.5077 Cr/year, respectively. The lowest TOC, that is Rs. occurs in Type-3 using 3 DG units. 7.2111 Cr/year, followed by Type-1 at Rs. 9.7879 Cr/year. The results show that the annual ownership costs can be significantly lowered by increasing the DG penetration, especially with the configuration that offers both active and reactive power support.

Fig 5: Annual Total Owning Cost (TOC) for different DG operating types and penetration levels.



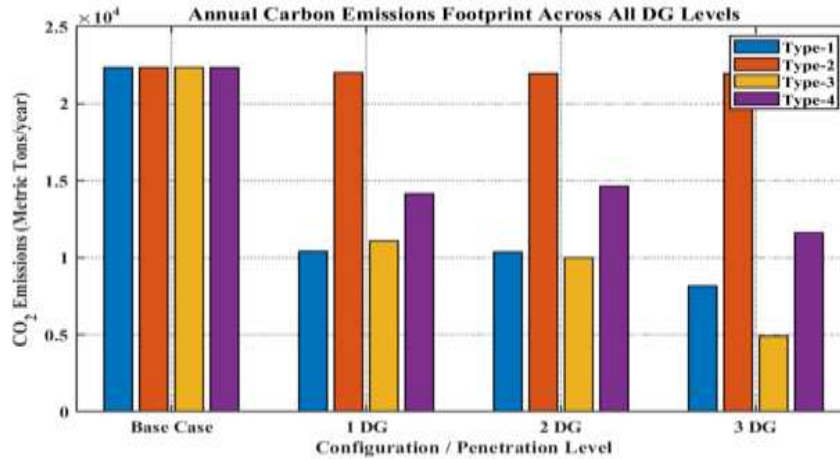
4.5. Environmental Performance

4.5.1. Annual CO₂ Emission Comparison

The annual CO₂ emission for the base case and the various penetration levels of DG is compared in Fig. 6. The base case records the highest emissions of 22,354.63 tons/year. With one DG unit, emissions decrease

to 10,421.18 tons/year for Type-1, 22,015.16 tons/year for Type-2, 11,081.01 tons/year for Type-3, and 14,163.47 tons/year for Type-4. For two DG units, the corresponding emissions are 10,391.83, 21,964.76, 9,962.71, and 14,613.00 tons/year, respectively. With three DG units, Type-3 achieves the lowest emissions of 6,058.94 tons/year, followed by Type-1 at 8,176.68 tons/year. Overall, there is relatively little reduction in the total, with Type-2 being purely reactive-power support without active-power generation, while with active-power injection, the reduction in annual CO₂ emissions is larger. The three-DG Type-3 configuration has the highest reported environmental improvement of 72.91%.

Fig 6: Annual CO₂ emissions for different DG operating types and penetration levels.

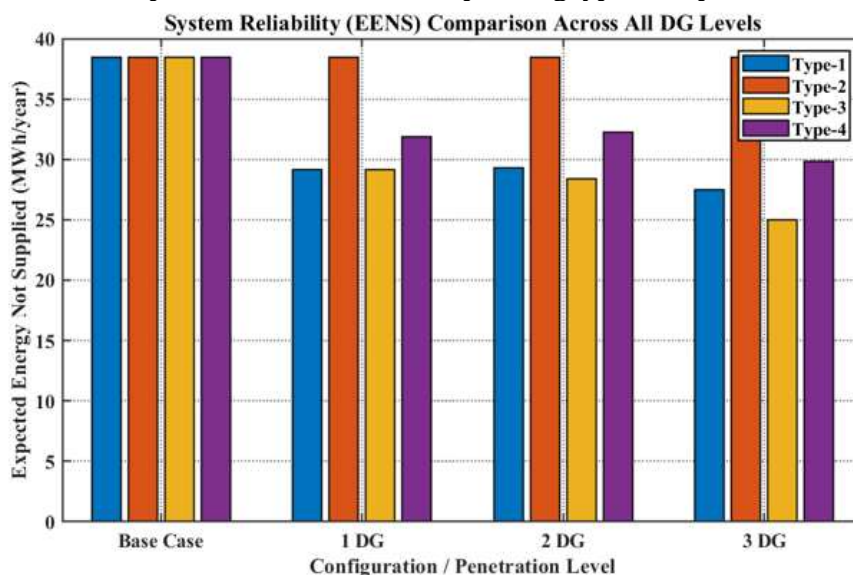


4.6. Reliability Performance

4.6.1. Expected Energy Not Supplied (EENS) Comparison

Fig. 7 shows the plot of EENS for base case and various DG penetrations. The base case EENS is 38.48 MWh/year. Using one DG unit reduces EENS to 29.16 MWh/year for Type-1, to 38.48 MWh/year for Type-2, to 29.16 MWh/year for Type-3 and to 31.85 MWh/year for Type-4. For two DG units, the corresponding values are 29.26, 38.48, 28.38, and 32.27 MWh/year. With three DG units, EENS further decreases to 27.49, 38.48, 24.96, and 29.80 MWh/year for Types 1–4, respectively. The 3-DG Type-3 configuration is therefore the configuration with the lowest EENS, which is 35.15% lower than the base case.

Fig 7: EENS comparison for different DG operating types and penetration levels.



Conclusion and Future Scope

In this study, a GEO-based framework for optimal multi-type multi-DG allocation in the IEEE 33-bus radial distribution network (RDN) has been presented. Four operating types for the DG, namely Type-1, Type-2, Type-3, and Type-4, were taken into account and the different running configurations of one DG, two DG, and three DG were evaluated. Optimize the DG locations and capacities to meet the voltage, capacity, operating-type and network constraints. The results revealed that the integration of DG can have a significant impact on technical, economic, environmental, and reliability performance. The evaluated configurations: 2-DG, 3-DG, and 3-DG showed the lowest reported active power loss of 0.0251 MW, which was lower than the base case (0.211 MW), and the minimum bus voltage was enhanced from 0.9038 p.u. to

0.9865 p.u. This configuration decreased the total cost of ownership for the year by Rs. 22.3546 Cr/year to Rs. 7.2111 Cr/year, CO₂ emissions from 22,354.63 to 6,058.94 tons/year, and EENS from 38.48 to 24.96 MWh/year. The results have shown that incorporating DG operating characteristics together with location and capacity gives a more comprehensive view of the performance of a distribution network. Further studies may be conducted on larger practical networks, load uncertainty, variability of renewable generation, network reconfiguration, protection requirements, and communication constraints, but it is important to note that this study uses the IEEE 33-bus benchmark.

References

1. Alharbi, Abdullah M., and Ahmed A. Zaki Diab. 2026. "Optimal Distributed Generation Allocation Considering Renewable and Load Uncertainties." *Scientific Reports* 16: 22139. doi:10.1038/s41598-026-48972-8.
2. Sundar, R., D. Ashokaraju, T. Dharmaraj, T. Thangaraj, P. Sabarish, P. Rajakumar, and Eric Sylvester Mwanandiye. 2026. "Distributed Generation and Shunt Capacitor Allocation in Radial Distribution Power Networks Using a Hybrid Optimization Approach." *Scientific Reports* 16: 6299. doi:10.1038/s41598-026-37713-6.
3. Sahay, Sumeet, Saubhagya Ranjan Biswal, Gauri Shankar, Amitkumar V. Jha, Bhargav Appasani, Avireni Srinivasulu, et al. 2025. "Optimized Placement of Distributed Generators, Capacitors, and EV Charging Stations in Reconfigured Radial Distribution Networks Using Enhanced Artificial Hummingbird Algorithm." *Scientific Reports* 15: 11144. doi:10.1038/s41598-025-89089-8.
4. Bouchikhi, Nasreddine, Fethi Boussadia, Riyadh Bouddou, Ayodeji Olalekan Salau, Saad Mekhilef, Chaima Gouder, et al. 2025. "Optimal Distributed Generation Placement and Sizing Using Modified Grey Wolf Optimization and ETAP for Power System Performance Enhancement and Protection Adaptation." *Scientific Reports* 15: 13919. doi:10.1038/s41598-025-98012-0.
5. Saxena, Nitin, Maleeha Pandit, and Laxmi Srivastava. 2024. "Multi-Objective DG Placement in Radial Distribution Systems Using the Ibl Logic Algorithm." *Frontiers in Energy Research* 12: 1453715. doi:10.3389/fenrg.2024.1453715.
6. Wang, Shifeng, Zhixiang Li, and Mohammad Javad Golkar. 2024. "Optimum Placement of Distributed Generation Resources, Capacitors and Charging Stations with a Developed Competitive Algorithm." *Heliyon* 10 (4): e26194. doi:10.1016/j.heliyon.2024.e26194.
7. Tanwar, Surender Singh, Ganesh Prasad Prajapat, Ravindra Rathod, Sanjay Kumar Bansal, and Sukhlal Sisodia. 2024. "AHP Based Technical, Economic and Environmental Impact Analysis with Optimal DG Placement in Radial Distribution Network." *International Journal of Applied Power Engineering* 13 (3): 530–538. doi:10.11591/ijape.v13.i3.pp530-538.
8. Huy, Truong Hoang Bao, Dieu Ngoc Vo, Khoa Hoang Truong, and Thanh Van Tran. 2023. "Optimal Distributed Generation Placement in Radial Distribution Networks Using Enhanced Search Group Algorithm." *IEEE Access* 11: 103288–103305. doi:10.1109/ACCESS.2023.3316725.
9. Khan, Muhammad Haris, Abasin Ulaslyar, Abraiz Khattak, Haris Sheh Zad, and Mohammad Alsharef. 2022. "Optimal Sizing and Allocation of Distributed Generation in the Radial Power Distribution System Using Honey Badger Algorithm." *Energies* 15 (16): 5891. doi:10.3390/en15165891.
10. Selim, Ali, Salah Kamel, Amal A. Mohamed, and Ehab E. Elattar. 2021. "Optimal Allocation of Multiple Types of Distributed Generations in Radial Distribution Systems Using a Hybrid Technique." *Sustainability* 13 (12): 6644. doi:10.3390/su13126644.
11. Babu, Ponnamm Venkata K., K. Swarnasri, and Wei Meng. 2020. "Optimal Integration of Different Types of DGs in Radial Distribution System by Using Harris Hawk Optimization Algorithm." *Cogent Engineering* 7 (1): 1823156. doi:10.1080/23311916.2020.1823156.
12. Halve, Shrunkhala Shyamkant, Rajesh Arya, and Atul Koshti. 2022. "Metaphor-Less RAO-3 and Sine Cosine Algorithm for Optimal Sizing of Distributed Generations of Multiple Types in Radial Distribution System." *ELECTRICA* 23 (2): 177–191. doi:10.5152/electrica.2022.22019.
13. Wanjekeche, Tom, Andreas A. Ndupuka, and Lupembe Nicksen Mukeni. 2023. "Strategic Sizing and Placement of Distributed Generation in Radial Distributed Networks Using Multiobjective PSO." *Journal of Energy* 2023: 6678491. doi:10.1155/2023/6678491.
14. Anjum, Zeeshan Memon, Dalila Mat Said, Mohammad Yusri Hassan, Zohaib Hussain Leghari, and Gul Sahar. 2022. "Parallel Operated Hybrid Arithmetic-Salp Swarm Optimizer for Optimal Allocation of Multiple Distributed Generation Units in Distribution Networks." *PLOS ONE* 17 (4): e0264958. doi:10.1371/journal.pone.0264958.
15. Mohammadi-Balani, Abdolkarim, Mahmoud Dehghan Nayeri, Adel Azar, and Mohammadreza Taghizadeh-Yazdi. 2021. "Golden Eagle Optimizer: A Nature-Inspired Metaheuristic Algorithm." *Computers & Industrial Engineering* 152: 107050. doi:10.1016/j.cie.2020.107050.
16. Pham, Thai Dinh, Thang Trung Nguyen, and Le Chi Kien. 2022. "Optimal Placement of Photovoltaic Distributed Generation Units in Radial Unbalanced Distribution Systems Using MATLAB and OpenDSS-Based Cosimulation and a Proposed Metaheuristic Algorithm." *International Transactions on Electrical Energy Systems* 2022: 1446479. doi:10.1155/2022/1446479.

17. Malik, Muhammad Zeeshan, Mahesh Kumar, Amir Mahmood Soomro, Mazhar Hussain Baloch, Muhammad Farhan, Mehr Gul, and Ghulam Sarwar Kaloi. 2020. "Strategic Planning of Renewable Distributed Generation in Radial Distribution System Using Advanced MOPSO Method." *Energy Reports* 6: 2872–2886. doi:10.1016/j.egyr.2020.10.002.
18. Janamala, Varaprasad, U. Kamal Kumar, and Thandava Krishna Sai Pandraju. 2021. "Future Search Algorithm for Optimal Integration of Distributed Generation and Electric Vehicle Fleets in Radial Distribution Networks Considering Techno-Environmental Aspects." *SN Applied Sciences* 3: 464. doi:10.1007/s42452-021-04466-y.
19. Werkie, Yalew Gebru, and Habtemariam Aberie Kefale. 2022. "Optimal Allocation of Multiple Distributed Generation Units in Power Distribution Networks for Voltage Profile Improvement and Power Losses Minimization." *Cogent Engineering* 9 (1): 2091668. doi:10.1080/23311916.2022.2091668.
20. Adegoke, Samson Ademola, Yanxia Sun, Adesola Sunday Adegoke, and Damilola Ojeniyi. 2024. "Optimal Placement of Distributed Generation to Minimize Power Loss and Improve Voltage Stability." *Heliyon* 10 (21): e39298. doi:10.1016/j.heliyon.2024.e39298.
21. Hantash, Neda, Tamer Khatib, and Maher Khammash. 2020. "An Improved Particle Swarm Optimization Algorithm for Optimal Allocation of Distributed Generation Units in Radial Power Systems." *Applied Computational Intelligence and Soft Computing* 2020: 8824988. doi:10.1155/2020/8824988.
22. Bhadoriya, Jitendra Singh, and Atma Ram Gupta. "A novel transient search optimization for optimal allocation of multiple distributed generator in the radial electrical distribution network." *International Journal of Emerging Electric Power Systems* 23, no. 1 (2022): 23-45.
23. Ahmed, Ali, Muhammad Faisal Nadeem, Arooj Tariq Kiani, Nasim Ullah, Muhammad Adnan Khan, and Amir Mosavi. "An improved hybrid approach for the simultaneous allocation of distributed generators and time varying loads in distribution systems." *Energy Reports* 9 (2023): 1549-1560.
24. Raza, Ali, Muhammad Zahid, Jinfu Chen, Saeed Mian Qaisar, Tehseen Ilahi, Asad Waqar, and Ahmad Alzahrani. "A novel integration technique for optimal location & sizing of DG units with reconfiguration in radial distribution networks considering reliability." *IEEE Access* 11 (2023): 123610-123624.
25. Salimon, Sunday Adeleke, Ifeoluwa Olajide Fajinmi, Olubunmi Onadayo Onatoyinbo, and Oyeniyi Akeem Alimi. "Allocation of single and multiple multi-type distributed generators in radial distribution network using mountain gazelle optimizer." *Technologies* 13, no. 7 (2025): 265.
26. Roy, Kingshuk, Sanjay K. Bansal, and Ramesh C. Bansal. "Performance enhancement of radial distribution system with optimal DG allocation." *International Journal of Modelling and Simulation* 45, no. 1 (2025): 245-263.
27. Dash, Subrat Kumar, and Sivkumar Mishra. "Continuous–Discrete Student Psychology-Based Optimization Algorithm for Optimal Planning of Distributed Generators and Distribution Static Compensators in Power Distribution Network." *Electrica* 24, no. 2 (2024): 284.
28. Zangmo, Rinchen, Suresh Kumar Sudabattula, Sachin Mishra, Nagaraju Dharavat, Naresh Kumar Golla, Naveen Kumar Sharma, and Vinay Kumar Jadoun. "Optimal placement of renewable distributed generators and electric vehicles using multi-population evolution whale optimization algorithm." *Scientific reports* 14, no. 1 (2024): 28447.
29. Murali, VenkataKirthiga, and Divya Bharathi Raj. "Optimizing Electric Vehicle Charging Stations and Distributed Generators in Smart Grids: A Multi-Objective Meta-Heuristic Approach." *IEEE Latin America Transactions* 23, no. 11 (2025): 1022-1035.
30. Qian, Jie, Min Wei, Ping Wang, Fei Wang, and Jianbo Dai. "Optimal distributed generation allocation in radial distribution networks using a modified seagull optimization algorithm with elite reserve strategy." *Energy Conversion and Management: X* (2025): 101228.
31. Roy, Arindam, and Vimlesh Verma. "Coordinated Allocation of Multi-Type DERs and EVCs in Distribution Networks Using a Multi-Stage GSA Framework." *Mathematics* 14, no. 5 (2026): 894.
32. Rajakumar, P., P. M. Balasubramaniam, and V. Ravi. "Hybrid sensitivity-driven enhanced modified ant lion optimizer framework for multi-distributed generation allocation in radial distribution networks." *Energy Reports* 15 (2026): 109144.
33. Khoudry, Elmahdi. "Optimal Placement and Sizing of Multiple Distributed Generators in Distribution Networks Using an Adapted Equilibrium Optimizer." *IEEE Access* (2026).