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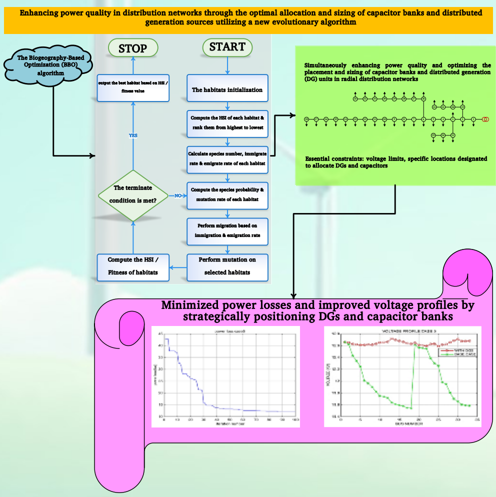
Enhancing Power Quality in Distribution Networks Through the Optimal Allocation and Sizing of Capacitor Banks and Distributed Generation Sources, Utilizing A New Evolutionary Algorithm

Leila Mohammadian

Highlights

- A new algorithm is proposed for simultaneous power quality improvement and optimal allocation/sizing of DGs and capacitor banks in radial distribution networks.
- The optimization goal is to minimize power losses and improve voltage profiles through proper DG and capacitor placement.
- Constraints include voltage limits, DG and capacitor sizes, and candidate bus locations.
- The method uses Biogeography-Based Optimization (BBO), which models solutions as islands exchanging features via immigration and emigration.
- Tested on the IEEE 33-bus radial distribution network, results were compared and validated against other references.

Graphical Abstract



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Enhancing Power Quality in Distribution Networks Through the Optimal Allocation and Sizing of Capacitor Banks and Distributed Generation Sources, Utilizing A New Evolutionary Algorithm

Leila Mohammadian *

Department of Electrical Engineering, Shabestar Branch, Islamic Azad University, Shabestar, Iran.

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* ***Corresponding author***
E-mail address
lemohammadian@iau.ir (L. Mohammadian)

A B S T R A C T

This study presents a comprehensive framework for enhancing power quality in radial distribution networks by simultaneously optimizing the placement and size of capacitor banks and distributed generation (DG) units. Employing the biogeography-based optimization (BBO) algorithm, this research addresses key objectives, including minimizing power losses and improving voltage profiles. The methodology incorporates critical operational constraints, such as voltage limits and permissible installation locations for DG units and capacitors. The proposed approach is validated using the IEEE 33-bus radial distribution system, where numerical results demonstrate a reduction in power losses by 88.28% with the simultaneous placement of DGs and capacitors (Mode 4), compared to the base case. Voltage profiles improved significantly, with the lowest voltage rising from 0.9117 pu in the base mode to 0.9835 pu. Additionally, Mode 5, involving variable power factors, achieved a 94.4% reduction in losses, further enhancing system efficiency. These results highlight the BBO algorithm's superior performance and computational efficiency in addressing complex distribution system challenges. This study is particularly relevant for optimizing renewable energy integration and future power system resilience.

1. Introduction

Recent advancements in the integration of distributed generation (DG) and capacitor placement have provided crucial insights into power distribution network optimization. In [1] explored the optimal placement of capacitors in distribution networks impacted by harmonic pollution, especially in the presence of wind energy-based DG sources. Their study emphasizes the importance of harmonics control in maintaining power quality and highlights the challenges posed by renewable energy integration into distribution systems. The findings provide a basis for designing harmonic-resilient networks with efficient capacitor placement strategies. In [2], reactive power optimization for DG units using stochastic modeling techniques is investigated to minimize power system losses. This work underscores the role of advanced mathematical approaches in addressing uncertainty in DG operations. By focusing on the probabilistic behavior of DG units, this study enhances system reliability and reduces energy losses, making it particularly relevant for modern power networks integrating renewable sources. [3] proposed a robust control strategy using nonlinear methods for maintaining load voltage stability in islanded wind energy conversion systems. Their research illustrates how effective control mechanisms can ensure stability under varying operational conditions. The study is significant for its focus on isolated systems, a critical area in renewable energy deployment, and highlights the challenges in managing voltage fluctuations caused by intermittent wind energy sources.

Electric power distribution networks typically operate at low voltage levels. These networks are connected to high-voltage transmission systems, which transport electricity over long distances before delivering it to consumers at a low voltage suitable for everyday use. However, distribution networks experience significant power losses due to the combination of low voltage and high current, particularly in comparison to transmission networks. This situation increases power costs and results in a bad voltage profile along the feeder [4,21]. The power losses in distribution networks are divided into two categories: active power loss and reactive power loss. Among these, active power loss is critical as it reduces transmission power efficiency and adversely affects the voltage profile. Consequently, minimizing active power losses in distribution networks is of greater importance than in transmission networks. Addressing this issue is predominantly the responsibility of the electrical distribution system [5]. Current statistics indicate that approximately 13% of generated power is lost at the distribution level. Because of the capacity limitations of radial lines, it is important to find alternative methods to meet future load demands with improved quality and reliability. To achieve this, strategies must be developed to release the existing line capacity to support additional loads [6]. A notable challenge is that most elements within distribution networks, such as motors and transformers, exhibit inductive properties, leading to a lagging power factor. This condition decreases system capacity, increases system losses, and causes voltage reductions at various points within the system [7]. Parallel capacitors are widely employed to address these challenges by reducing power losses, improving voltage profiles, enhancing power factors, and stabilizing the system's voltage [8,19].

Despite advancements in power distribution systems, optimizing the placement of capacitors and DGs remains an active research area. Previous studies have explored various optimization techniques, but there remain gaps in achieving comprehensive solutions that balance computational efficiency, cost-effectiveness, and network performance under practical constraints.

Several prior works have tackled this issue using diverse methodologies. For instance, [9] proposed a multi-objective optimization approach for distribution feeder reconfiguration alongside capacitor placement, employing a modified gravitational search algorithm to enhance reliability and voltage security. [10] introduced a fuzzy framework for optimizing radial systems, addressing balanced and unbalanced networks with high precision and fast convergence. [11] formulated an integrated demand response program (DRP) combining DGs and shunt capacitors to optimize energy loss, operational cost, and network reliability, leveraging a shuffled frog-leaping algorithm. [12] investigated dynamic distribution feeder reconfiguration (DDFR), incorporating DGs, PV panels, and energy storage to optimize energy loss and operational costs via a modified particle swarm optimization algorithm [18].

Hybrid approaches have also gained attention for addressing multi-objective challenges in distribution systems. In [13,22-23], practical planning of distribution networks includes the optimal selection of conductor sizes and strategic capacitor placement to handle increasing load demands. This study explores a hybrid approach combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), referred to as HGAPSO, to minimize power losses effectively. The method reduces overall costs associated with network planning and improves voltage profiles to achieve a semi-flat configuration under technical constraints such as voltage limits, conductor capacity, and reactive power injection [17]. This approach highlights the potential of combining optimization techniques to balance computational efficiency and system reliability.

Despite these efforts, challenges persist in efficiently integrating DG units and capacitor banks while considering real-world constraints such as voltage limits and operational costs. This study leverages the BBO algorithm to address these gaps by strategically placing DG units and capacitor banks to minimize power losses and improve voltage profiles in radial distribution networks.

This study builds upon the limitations of prior works and proposes the following contributions:

1. Development of a comprehensive optimization framework for capacitor and DG unit placement and sizing, leveraging advanced algorithms such as BBO.
2. Integration of renewable energy resources into distribution networks, addressing challenges related to voltage security and power quality, ensuring enhanced computational efficiency and practical applicability.
3. Presentation of practical scenarios, considering real-world network constraints, including voltage limits and permissible locations for DG units.

A graphical abstract summarizing the research workflow, key objectives, and contributions is provided in Figure 1.

2. The Theory of Biogeography

The BBO algorithm is a population-based optimization method inspired by the principles of biogeography. It was introduced by Dan Simon in 2008 and studies the distribution of species across different habitats over time. BBO mathematically models the migration and adaptation processes between habitats to solve complex optimization problems effectively. The algorithm draws on the natural dynamics of species migration and information exchange to enhance solutions iteratively.

BBO differs from other evolutionary algorithms in several key aspects. It requires fewer parameter settings, operates with low computational complexity, and demonstrates efficient memory usage—even when tackling high-dimensional numerical problems. These characteristics make it an attractive tool for solving engineering challenges, although its application in real-world engineering problems has been relatively limited, signifying untapped potential in diverse optimization contexts [24-26].

In the BBO framework, potential solutions to a problem are represented as individual habitats, each characterized by a Habitat Suitability Index (HSI). The HSI serves as a measure of the quality of a solution, analogous to the fitness function used in other population-based algorithms. Habitats with high HSI values represent effective solutions, whereas low HSI values indicate less optimal solutions. The algorithm improves solutions over successive generations by simulating migration and mutation processes.

In BBO, each element is likened to an island or habitat, where the exchange of traits among these elements is illustrated through migration and intra-migration. Figure 2 illustrates the migration of species and the emergence of a new island.

Each element in a solution is identified as a Suitability Index Variable (SIV). Regions classified as suitable habitats for a species correspond to a high HSI. A high HSI indicates effective performance in the optimization process, whereas a low HSI signifies inadequate performance.

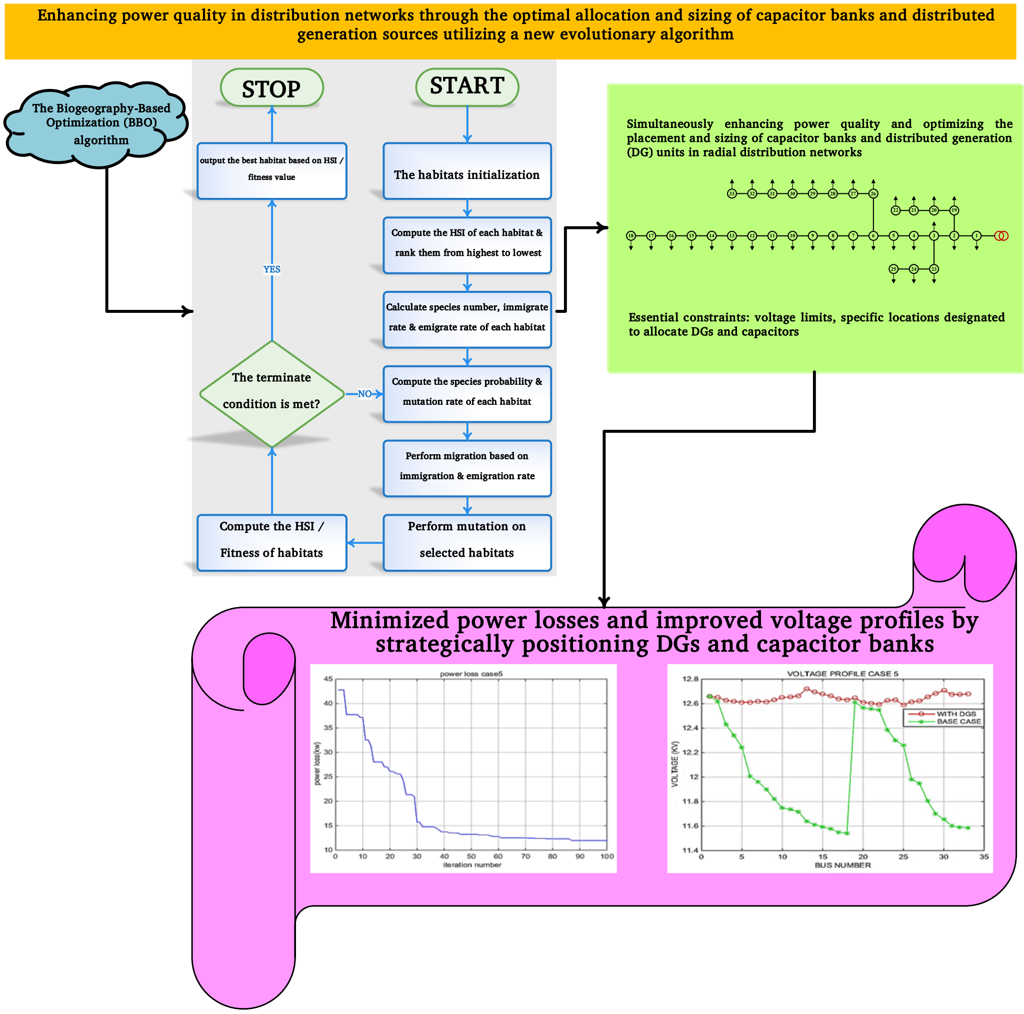

Figure 1. Graphical abstract.

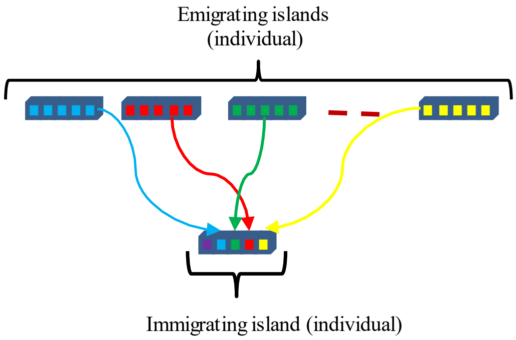

Figure 2. Migration of species and the formation of a new island.

Population growth serves as a strategy to address challenges within heuristic algorithms. In BBO, the subsequent generation is generated by migrating solution characteristics between islands and acquiring attributes from them. Additionally, mutation is introduced throughout the population in a manner akin to that found in genetic algorithms. Figure 3 illustrates the connection between the BBO algorithm and biogeography theory.

Migration Mechanism: Migration is a core concept in BBO, emulating the movement of species between habitats. Habitats with high HSI (strong solutions) can effectively share their desirable traits (solutions) with other habitats, enhancing the overall population quality. Each solution has an emigration (external migration rate) rate (μ) and an immigration (internal migration) rate (λ). Strong solutions typically have lower immigration rates and higher emigration rates, enabling them to share information without being disrupted by external influences. Conversely, weaker solutions have higher immigration rates, allowing them to acquire traits from stronger solutions.

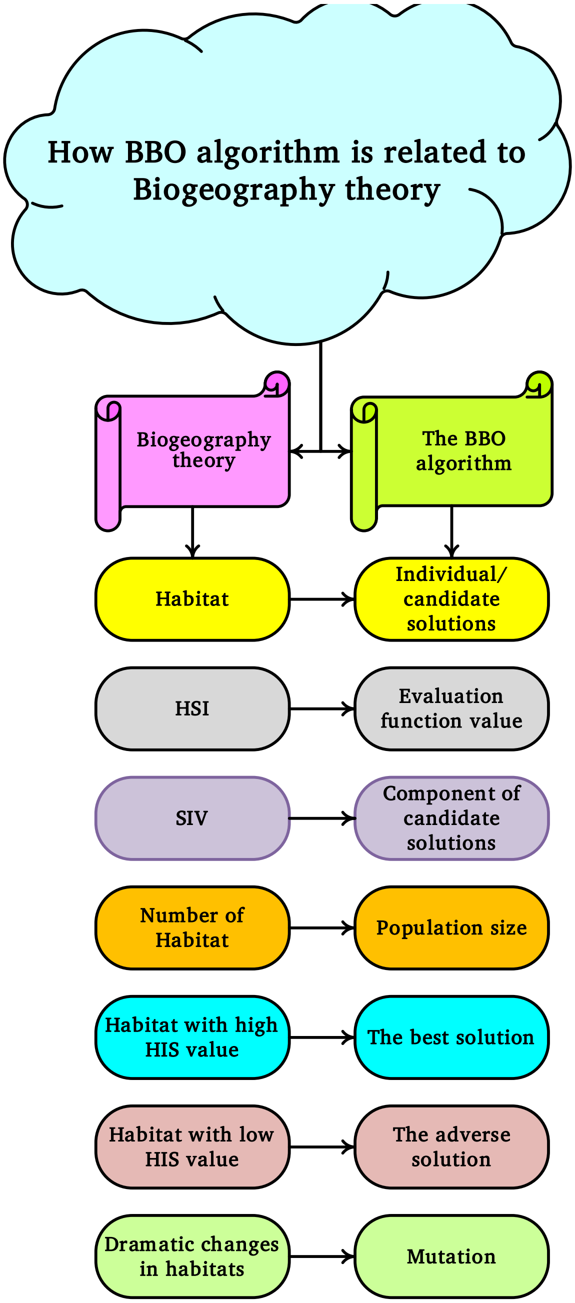

Figure 3. Relationship between the BBO algorithm with the Biogeography theory.

It's important to note that when an individual migrates to another island, the original island doesn't lose any traits in the procedure. Figure 4 shows the migration of species between habitats. The concepts of migration and intra-migration are mathematically modeled through a probabilistic framework. Furthermore, if the probability of a specific species, S, retaining its habitat at time t is considered as P_s, how this probability evolves from time t to time t + Δt will be described as follows:

$$P_s(t+\Delta t) = P_s(t)(1-\lambda_s\Delta t - \mu_s\Delta t) + P_{s-1}\lambda_{s-1}\Delta t + P_{s+1}\mu_{s+1}\Delta t \quad (1)$$

If the time (t) is small enough in Equation (1), then the following Equation (2) is obtained:

$$\dot{P_s} = \begin{cases} -(\lambda_s+\mu_s)P_s + \mu_{s+1}P_{s+1} S = 0 \\ -(\lambda_s+\mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_{s+1}P_{s+1} 1 \le S \le S_{max} \\ -(\lambda_s+\mu_s)P_s + \lambda_{s-1}P_{s-1} S = S_{max} \end{cases} \quad (2)$$

The migration rates and internal migration values are as follows in Equations (4) to (5):

$$\mu k = EK/n \quad (3)$$

$$\lambda k = I(1-k/n) \quad (4)$$

Let's define the variables: I represents the highest possible internal migration rate, E is the highest possible displacement rate, K represents the count of member species (k), and n represents the total number of species. To explore a specific scenario where E is equivalent to I, it will proceed as follows in Equation (5):

$$\lambda\kappa + \mu\kappa = E \quad (5)$$

3. Biogeography-based optimization

Figure 5 presents a flowchart that shows the BBO process. Following other evolutionary algorithms, the initial phase of BBO entails the generation of a random population known as 'habitat.' To assess the quality of individual solutions, known as potential solutions, as well as the appropriateness of the habitats and regions, two essential parameters are established: HSI and SIV. The BBO framework fundamentally consists of two operations: migration and mutation. In this context, consider a defined problem where a set of potential solutions is represented as vectors coupled with a method for quality assessment. High-quality solutions can be compared to islands with a high Island Suitability Index (ISI), while those of lower quality are akin to islands characterized by a low ISI. It is crucial to note that the ISI aligns with the concept of "fitness" in other population-based optimization algorithms. The primary operations of BBO—migration and mutation of solutions—are depicted in Figures 6 and 7, respectively. Initially, potential solutions are adjusted to improve their quality. In this stage, an immigration rate (λ) is defined to assess the necessity of modifying the island. An emigration rate (μ) is implemented to select the solution that will probably migrate. It is crucial to emphasize that the algorithm is designed to avoid overfitting solutions to maintain quality. Natural hazards present a variety of threats to geographical regions, often resulting in abrupt fluctuations in HSI values. Consequently, the habitat may diverge from its equilibrium HSI during the mutation. At this stage, a probability factor is calculated for each individual within the population, as delineated in Equation (2), to assess the need for mutation.

Mutation ensures diversity within the population, preventing premature convergence to suboptimal solutions. Natural disturbances, such as environmental changes, are modeled as abrupt alterations in habitat conditions, which trigger mutations. The mutation rate for a habitat is proportional to the deviation of its HSI from equilibrium or the probabilities associated with the number of species, and it can be expressed as Equation (6):

$$m(s) = m_{max}\left((1-Ps)/P_{max}\right) \quad (6)$$

which is a parameter defined by the user.

The BBO algorithm iteratively applies these mechanisms to identify optimal solutions. The overall process can be summarized as follows:

1. **Initialization:** Generate a random initial population (habitats) and compute their HSIs.
2. **Migration:** Exchange solution traits between habitats based on immigration and emigration rates, enhancing solution diversity and quality.
3. **Mutation:** Apply probabilistic alterations to solutions to introduce diversity and avoid local optima.
4. **Evaluation:** Recalculate the HSI of each habitat after migration and mutation, and rank the solutions from best to worst.
5. **Convergence Check:** Repeat the process until a termination criterion, such as the maximum number of iterations or a satisfactory solution quality, is met.

The algorithm's ability to balance exploration and exploitation makes it a compelling choice for multi-objective optimization problems in engineering.

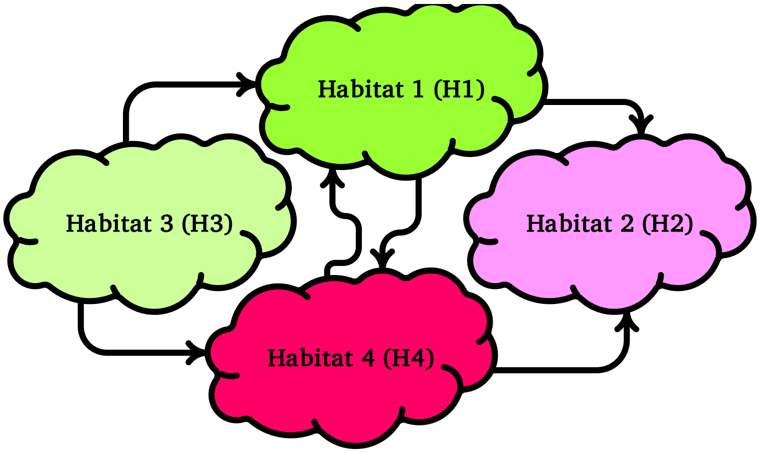

Figure 4. Species migration between habitats.

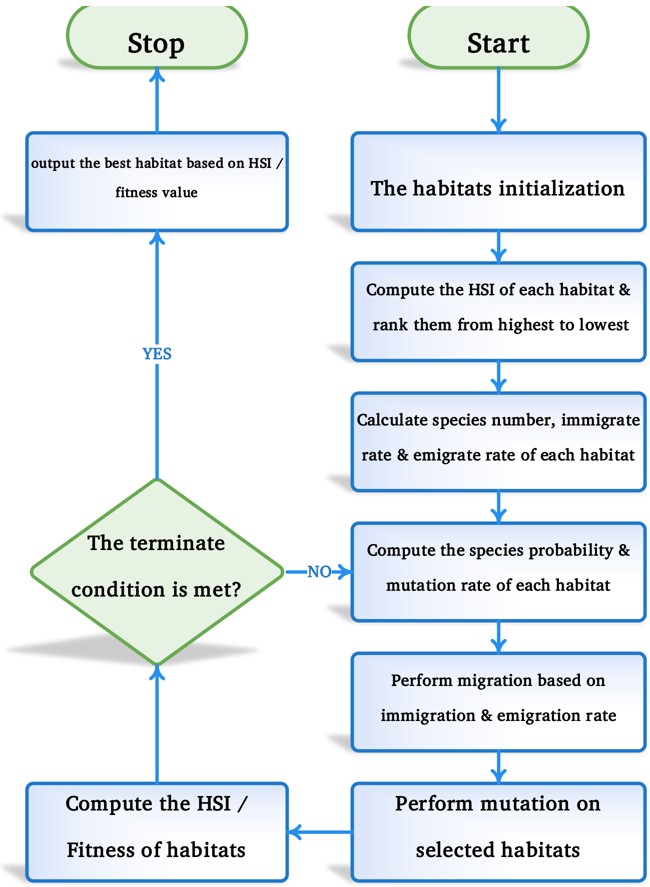

Figure 5. The flowchart of the BBO optimization method.

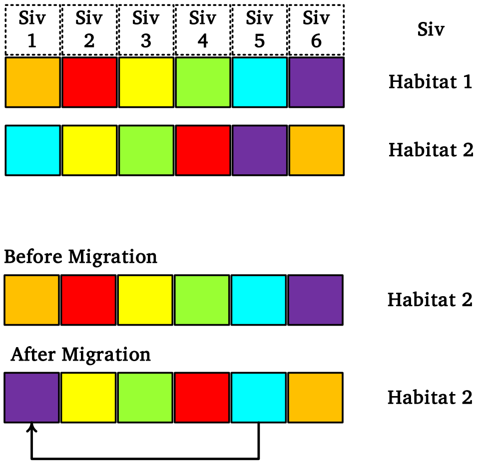

Figure 6. Migration process in BBO.

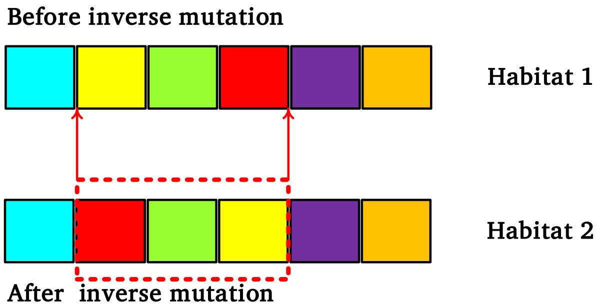

Figure 7. Mutation process in BBO.

4. Formulation of the problem

The optimization problem in this study aims to identify the optimal placement and sizing of DG units and capacitor banks within radial distribution systems. The objectives include minimizing active power losses, improving voltage profiles, and ensuring efficient resource utilization while adhering to predefined operational constraints. Some key considerations include:

- Achieving optimal load distribution to reduce system losses.
- Optimizing operational modes to enhance the overall power factor of the system.
- Refining generator parameters to improve efficiency.
- Reducing design costs while maximizing efficiency, among others.

Figure 8 illustrates the single-line diagram of the radial distribution system comprising 33 buses.

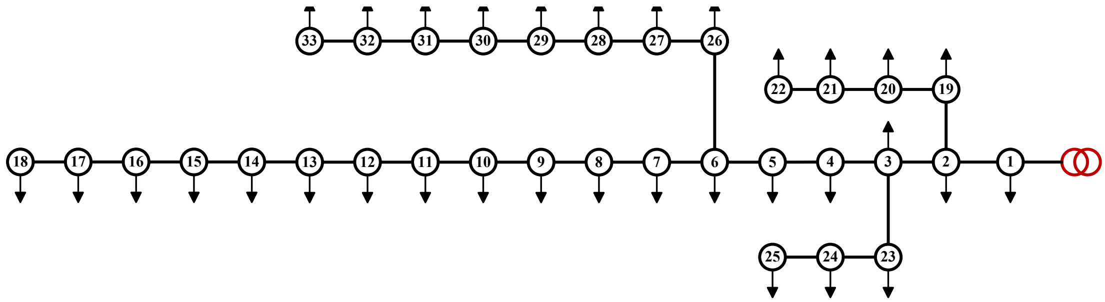

Figure 8. Single-line diagram of the radial distribution system of 33 buses [6].

Allocating and determining the optimal capacity of DGs is articulated as a nonlinear optimization problem. Each engineering system is represented by a collection of variables, manifesting features to be design or decision variables.

Variables $(x_i, i = 1,2, \ldots, n())$provide a set of design variables for the design vector $X = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$.

4.1. Objectives

The primary objectives are the minimization of real power losses and voltage profile improvement, ensuring the bus voltage magnitude is maintained within the permissible range, and enhancing voltage stability.

4.2. Design Variables

The optimization design variables include:
DG variables: DG location and DG active/reactive power output
Capacitor variables: Capacitor location and capacitor reactive power output.

4.3. Constraints

Voltage Constraints: Maintain voltage levels within acceptable operational limits for all buses:
Reactive Power Injection: Capacitor bank outputs must remain within their capacity:
Power Balance: Ensure system equilibrium between generation and demand.
Power Factor Constraints (for Variable Power Factor Modes): DGs must operate within the permissible power factor range:
Location Constraints: Only specified candidate buses are eligible for DGs and capacitors.

4.4. Optimization Modes

Five operational modes are analyzed:
1. **Mode 1:** Optimal placement of capacitors for reactive power compensation.
2. **Mode 2:** Allocating DGs with a unit power factor (active power injection).
3. **Mode 3:** Allocating DGs with a variable power factor (active and reactive power injection).
4. **Mode 4:** Simultaneous placement of capacitors and DGs with a unit power factor.
5. **Mode 5:** Simultaneous placement of capacitors and DGs with variable power factors.

4.4.1. First stage:

At this stage, the various parameters employed for optimization are quantified through the principles of biogeography. In this study, the initial population, represented as the number of habitats, is set at 100, with the number of iterations also established at 100. The selection index is designated as 10, while the maximum migration rate is set at $E=1$, the maximum value for the intra-migration rate is $I=1$, and the maximum mutation rate is $m_{max}=0.005$ is selected.

4.4.2. The second stage:

The initial population is generated through a random process. This study examines five distinct configurations, which encompass the optimal placement of capacitor banks, the optimal placement of DGs operating at a unit power factor, the optimal placement of DGs with variable power factor, the simultaneous optimal placement of capacitors and DGs with unit power factor; and the simultaneous optimal placement of capacitors and DGs with variable power factor.

Mode 1: Optimal placement of capacitor banks for reactive power compensation can enhance the voltage profile and the system power factor. The initial population is defined in the following manner as in Equation (7).

$$X = [x_i] = \left[L_1 L_2 \dots L_{N_{Cap}} Q_1 Q_2 \dots Q_{N_{Cap}}\right]_{1\times(2\times N_{Can})} \tag{7}$$

where N_{Cap} is the number of capacitors installed in $L_{N_{Cap}}$. Q is the reactive power provided by the capacitor bank. In this study, for example, for the number of capacitors, 3, according to the initial population number of 100, the dimensions of the initial population matrix are 6×100. The location of the capacitors is randomly selected between buses 2 and 33, and the reactive power value is randomly chosen between 0 and 1200 kVars.

Mode 2: Optimum placement of DGs with unit power factor: In this case, the DG unit only injects active power. The initial population is defined as follows in Equation (8).

$$X = [x_i] = \left[L_1 L_2 \dots L_{N_{DG}} P_1 P_2 \dots P_{N_{DG}}\right]_{1\times(2\times N_{DG})} \tag{8}$$

where N_{DG} is the number of DGs that are installed in $L_{N_{DG}}$. P is the active power produced by DGs. In this study, for instance, with three DGs, the dimensions of the initial population matrix are defined as 6×100, consistent with the size of the initial population. The locations of the DGs are randomly allocated between buses 2 and 33, while the active power values are randomly assigned within the range of 0 to 1000 kW for comparison with other references.

Mode 3: Optimum placement of DGs with variable power factor: In this mode, the placement of optimal DGs that can provide reactive power with variable power factor is done. The initial population is defined as follows in Equation (9).

$$X = [x_i] = \left[L_1 L_2 \dots L_{N_{DG}} P_1 P_2 \dots P_{N_{DG}} pf_1 pf_2 \dots pf_{N_{DG}}\right]_{1\times(3\times N_{DG})} \tag{9}$$

where N_{DG} is the number of DGs that are installed proportionally in $L_{N_{DG}}$ is the active power produced by DGs, and is the power factor of DGs. For the number of DG 3, according to the number of the initial population is 100, the dimensions of the initial population matrix are 100×9. The positions of the DGs are randomly determined within the interval between buses 2 and 33, while the active power values are randomly selected from a range of 0 to 1200 kW. Additionally, the power factor for each unit is randomly assigned within the range of -0.9 to 0.9.

Mode 4: Optimal simultaneous placement of capacitor banks and DGs with a unit power factor: In this scenario, the locations of the capacitors and DGs are selected independently, assuming that the DGs are solely capable of supplying active power. The initial population is defined as follows in Equation (10):

$$X = [x_i] = \begin{bmatrix} L_1^{DG} L_2^{DG} .. L_{N_{DG}}^{DG} P_1 P_2 .. P_{N_{DG}} \\ .. L_1^{Cap} L_2^{Cap} .. L_{N_{Cap}}^{Cap} Q_1 Q_2 .. Q_{N_{Cap}} \end{bmatrix}_{1\times(2\times N_{DG}+2\times N_{Cap})} \tag{10}$$

where N_{DG} and N_{Cap} are the number of DGs and capacitors that are installed in the bus $L_{N_{DG}}^{DG}$ and $L_{N_{Cap}}^{Cap}$, respectively. DGs generate active power, while capacitor banks supply the reactive power. For the number of DG 3 and the number of capacitor 3, according to the initial population number of 100, the dimensions of the initial population matrix are 12×100. Of course, the number of capacitors and DGs can be chosen differently. The location of DGs and capacitors is randomly selected between buses 2 and 33, the active power value is randomly chosen between 0 and 500, and the reactive power value is randomly selected between 0 and 1200 kVars using Equation (11).

$$X = \begin{bmatrix} L_1^{DG} L_2^{DG} .. L_{N_{DG}}^{DG} P_1 P_2 .. P_{N_{DG}} pf_1 pf_2 . \\ . pf_{N_{DG}} L_1^{Cap} L_2^{Cap} .. L_{N_{Cap}}^{Cap} Q_1 Q_2 .. Q_{N_{Cap}} \end{bmatrix}_{1\times(3\times N_{DG}+2\times N_{Cap})} \tag{11}$$

where N_{DG} and N_{Cap} are the number of DGs and capacitors that are installed in the bus $L_{N_{DG}}^{DG}$and $L_{N_{Cap}}^{Cap}$, respectively. DGs generate active power, while capacitor banks supply the reactive power. For the number of DGs, 3, and the number of capacitors, 3, according to the number of the initial population, 100, the dimensions of the initial population matrix are 15×100. Of course, the number of capacitors and DGs can be chosen differently. The location of DGs and capacitors is randomly selected between buses 2 and 33, the amount of active power is randomly chosen between 0 and 1200 kW, and the amount of reactive power is selected between 0 and 1200 kW. The power factor of each unit is randomly chosen between 1 and -1.

4.5. The third step: calculating the values of the objective function

At this stage, first, the values of the objective function, i.e., losses, are calculated from Equation (12) using power flow for each vector of the initial population solution. Then, the order of the rows of the initial matrix is changed based on the values of the objective function in ascending order. Therefore, the first line is the best solution, having the least losses. The last line is the worst solution and has the highest losses.

$$P_{loss} = \sum_{i=1}^{n} R_i |I_i|^2 \tag{12}$$

where $P_{loss}$is the total loss of the distribution system, R_i the ohmic resistance of the branches, $|I_i|$ The magnitude of current passing through branches, and n is the number of branches in the distribution system.

4.6. Fourth step: applying the migration operator

In this step, we need to apply the migration operator. For this, we must first determine the number of species for each solution vector. In this way, the highest number of species is considered the best answer, i.e., the first line. No species is considered for the worst answer, i.e., the last line. This means that the number of species in the first row is 99, and in the last one is 0. Then, the values for each solution are calculated using the number of species and the relations of migration rate and intra-migration rate. To apply the migration operator, we calculate the criterion value for the internal migration rate from Equation (13):

$$\lambda_{scale} = \lambda_{lower} + (\lambda_{upper} - \lambda_{lower}) \times (\lambda(k) - \lambda_{min})/(\lambda_{max} - \lambda_{min}) \tag{13}$$

In this regard, λ_{lower} and λ_{upper} are the lower limit and the upper limit for the intra-migration rate, respectively, and λ_{min} and λ_{max} are the minimum and maximum values for the intra-migration rate, respectively. λ_{lower} and λ_{upper} are considered 0 and 1, respectively, in this study. The values of λ_{min} and λ_{max} are 0 and 1. Therefore, like the in-nomadic rate for a solution vector with k species, the criterion value for the in-nomadic rate is $\lambda(k)$. To apply the migration operator, first, the selection process is performed, and a number (10, in this study) that has a lower objective function value is removed from the solution vectors. Then, the migration operator is applied to the residuals of the solution as follows:

First, a random number between 0 and 1 for each variable in a solution vector is generated, that is, for each SIV in a solution vector. If this number is smaller than the criterion value of the inner migration rate for that vector, we perform migration on that variable. Because the solution vectors that have lower objective function values also have a small internal migration rate, the probability that migration is applied to them is low, and they are less changed at this stage, conversely, the solution vectors that have more objective function values and have a larger intra-migration rate, and therefore the probability that the migration operation is applied to them is high, and they are changed more at this stage. After a variable in one vector is selected for the migration operation, the migration rate values of the other vectors are used to find a replacement variable from another vector. This vector is randomly chosen among other vectors so that the probability of selecting a vector is equal to the rate of change of that vector. In this way, considering that the solution vectors with lower objective function values have a larger migration rate, the probability that these vectors are selected is higher. After choosing the vector, the equivalent value of SIV chosen in the previous step is removed from this vector and replaced. After applying the migration operator, considering that the values of the vectors have changed, we recalculate the values of the objective function for each solution vector and change the order of the rows of the matrix based on the values of the new objective function in ascending order.

5. Results and Analysis

5.1. Simulation setup

The proposed BBO algorithm is applied to a 33-bus IEEE benchmark system, which operates at a voltage level of 12.66 kV and comprises 32 buses and four feeders. The parameters utilized for the BBO include a population size of 200, a habitat modification probability of 1, migration probability bounds in the gene range of [0,1], a step size for numerical integration probability of 1, a rate and maximum value of 1 for each island, and a mutation probability of 0.5. This study presents simulation analyses for three distinct scenarios. Case 1 performs the optimal placement and capacitor banks capacity determination; Case 2 addresses the optimal placement and capacity determination of DGs; and the final case investigates the simultaneous optimal placement and capacity determination of both capacitor banks and DGs. All harmonic sources are assumed to be in phase, with their corresponding data provided in Table 1 [20]. Figure 8 depicts the final radial configuration of the system following compensation, while Figure 9 illustrates the convergence characteristics of both the BBO and GA in terms of the loss objective function. The analysis demonstrates that capacitors and DGs can significantly reduce active power losses and enhance the voltage profile and Total Harmonic Distortion (THD) at each bus within the system, as evidenced by Figures 10 and 11.

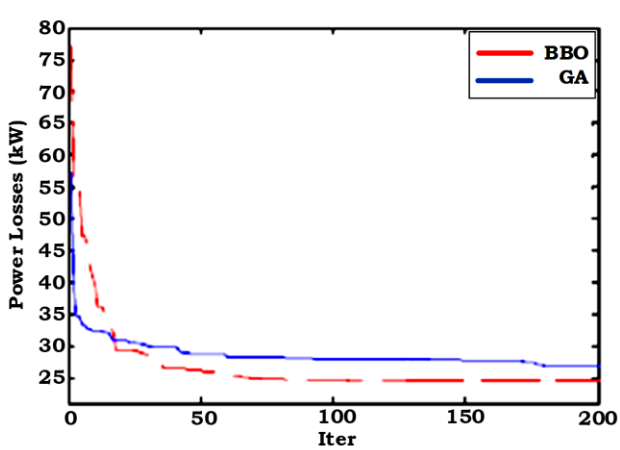

Figure 9. Convergence characteristic of BBO and GA.

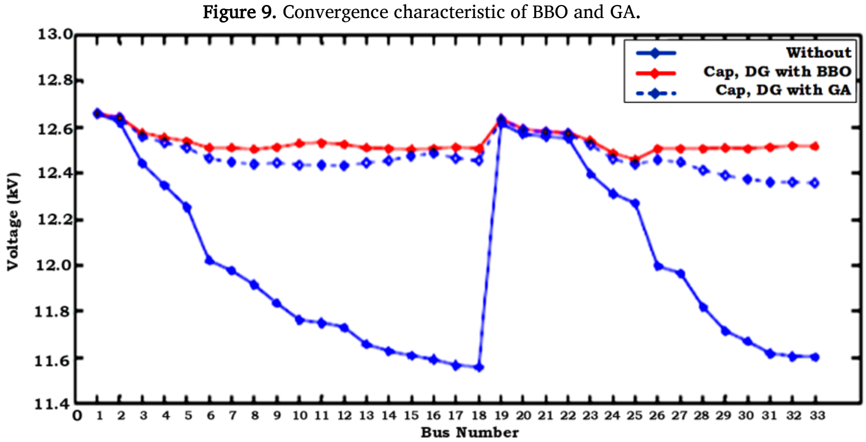

Figure 10. Voltage profile before and after installation of the capacitor and DG at each system bus.

The described method has been implemented along with the load distribution program of distribution systems using MATLAB software for the five mentioned modes. In this section, the obtained results are presented and analyzed. Then, they are compared with the results of some other sources.

5.2. The results obtained for the first case: Optimal placement of capacitor banks to provide reactive power

There are three capacitors in this mode, and their reactive power is between 0 and 1200 kVars. The obtained results are presented in Table 2 and compared with the base state [6].

Although the loss reduction percent of the simulation performed in this article is slightly lower than in [6], the results show that this loss reduction was achieved by installing capacitors with a total reactive power of 1972.8 kVars, while in [6], reducing the mentioned losses requires the installation of capacitors with a total reactive power of 2900 kW. Figure 12 presents convergence characteristics in terms of the number of iterations. This algorithm has a suitable convergence response.

Table 1. Harmonic information.

Harmonic order	5	7	11	13	17	19
W	0.03	0.02	0.01	0.004	0.003	0.001

Table 2. Results obtained for Mode 1.

	Location and reactive power of capacitors (kVars)		Power loss (kW)	Loss reduction %	The lowest voltage and its bus
Base mode	-		211.87	-	0.9117 bus 18
Result of the simulation	13 24 30	359.7 545.9 1067.2	139.57	34.1	0.9361 bus 18
Reference [6]			130.03	35.8	

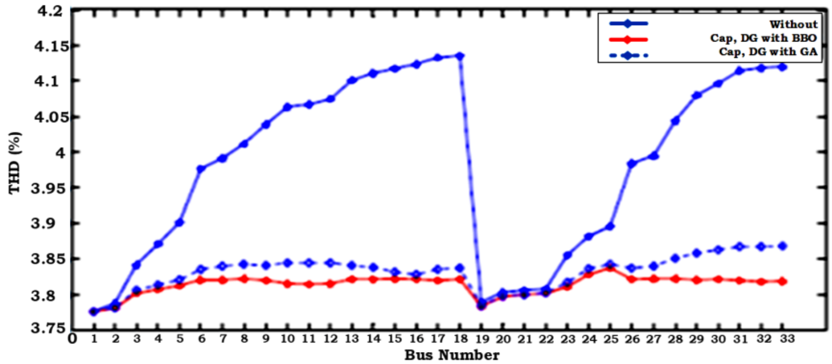

Figure 11. THD before and after installing capacitors and DG at each system bus.

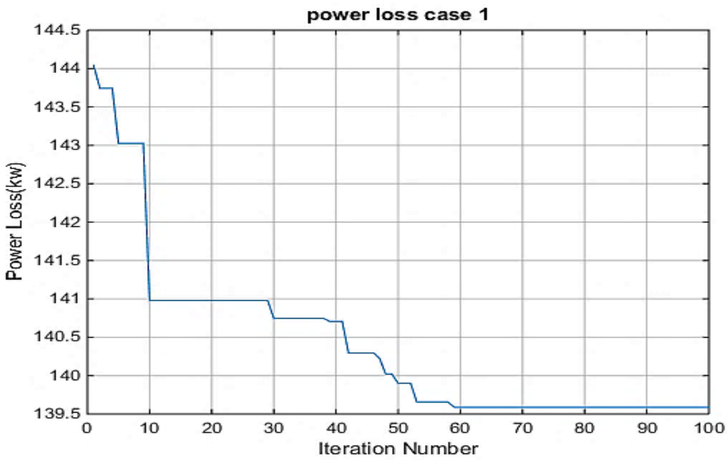

Figure 12. Characterization of the convergence of the first mode according to the number of iterations.

The voltage values of the buses in the basic state and after the capacitor are shown in Figure 13. It can be seen that the capacitors have improved the voltage profile of the distribution system.

So, in the first case, by placing and determining the optimal capacity of the capacitor banks, the reactive power passing through the branches of the distribution system is reduced, and this causes the real power loss of the system to be significantly reduced and the voltage profile improved.

5.3. The results obtained for the second case: Optimal placement of DGs with a single power factor

The number of DGs, in this case, is three, and their active production power is between 0 and 1000 kW. The obtained results are presented in Table 3 and compared with the base state and [15].

The convergence characteristic in terms of the number of iterations is presented in Figure 14. Bus voltage values in the basic state and after the addition of distributed generation units are shown in Figure 15. It can be seen that DGs affect voltages very well and have improved the voltage profile of the distribution system.

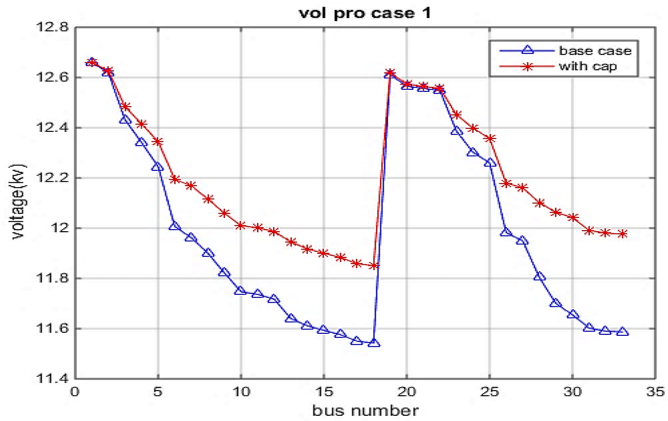

Figure 13. Bus voltage values in the basic state and after the capacitor for the first state.

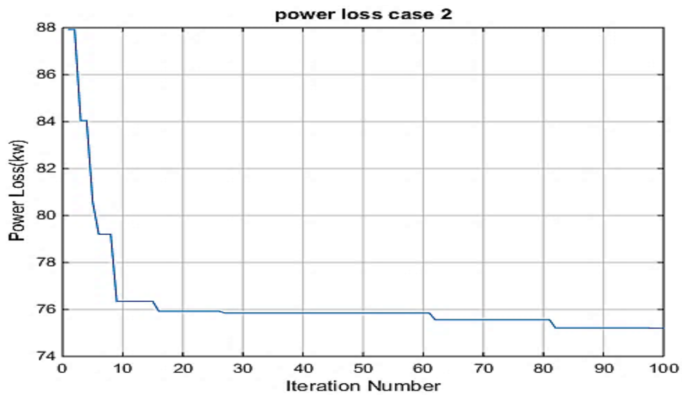

Figure 14. Convergence characteristic of the second mode according to the number of iterations.

Table 3. Results obtained for Mode 2.

	Location and active power of DGs (kW)		Power loss (kW)	Loss reduction percentage	The lowest voltage and corresponding bus
Base mode	-		211.87	-	0.9117 Bus18
Result of the simulation	12 24 30	940.6 977.6 944.6	75.27	64.4	0.9652 bus 18
Reference [15]	13 24 30	900 900 900	74.27	64.83	

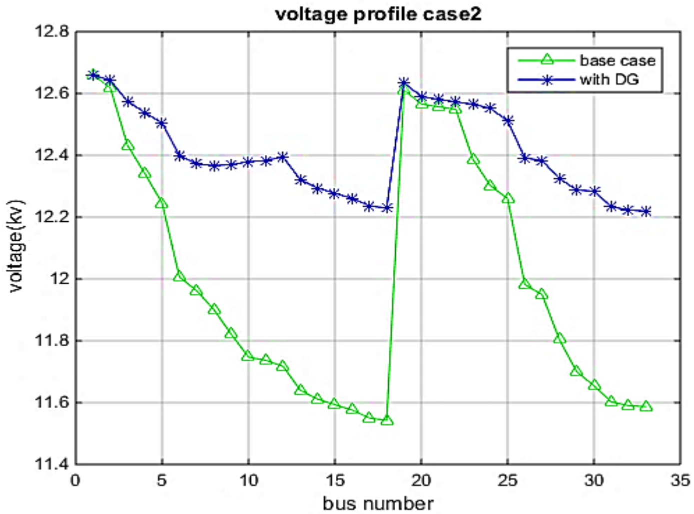

Figure 15. Bus voltage values in the basic state and after adding DGs for Mode 2.

In the second case, by locating and determining the optimal capacity of the DG system with a unit power factor, the active power passing through the branches of the distribution system is reduced. This causes the real power loss of the system to be significantly reduced. At the same time, the voltage profile of the distribution system improves. By locating and determining the optimal capacity of a distributed generation system with variable power factor, both active and reactive power passing through the branches of the distribution system are reduced, causing the real power loss of the system to be reduced more than in the previous two cases, and the system voltage profile improvement is more than the base state.

5.4. The results obtained for the third case: Optimal placement of DGs with variable power factor

For this case, the number of DGs is 3. Their active power output is between 0 and 1200 kW, and the power factor is between 0.9 and -0.9. The results are presented in Table 4 and compared with the base case and [3]. As can be seen, the results obtained from the simulation have a better loss reduction compared to [6].

The convergence characteristic in terms of the number of iterations is presented in Figure 16. The voltage values of the buses in the basic state and after the addition of DGs are shown in Figure 17. It can be seen that DGs, in this case, affect the voltages strongly and have improved the voltage profile of the distribution system.

So, in Mode 3, by placing and determining the optimal capacity of capacitor banks and the distributed generation system with a single power factor, the capacitor banks reduce the reactive power passing through the branches of the distribution system. The DG system with a single power factor reduces the active power passing through the branches of the distribution system, causing the real power loss of the system to decrease more than the previous three conditions, and the voltage profile of the distribution system is also improved more than the basic condition.

Table 4. The results obtained for Mode 3.

	Location and active power of DGs (kW)			Power loss (kW)	Loss reduction percentage	The lowest voltage and corresponding bus
Base mode	-		Power factor	211.87	-	0.9117 bus 18
Result of the simulation	6 14 30	510 655 877	0.8887 0.8976 0.7483	21.24	90	0.982 bus 25
Reference [6]	17 30 12 32 29	300 500 500 300 293	0.89 0.55 0.89 0.89 0.39	39.99	80.3	

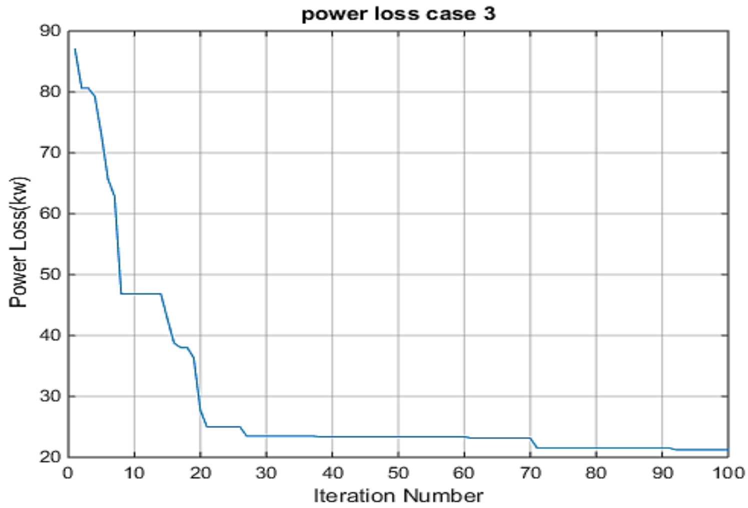

Figure 16. The convergence characteristic of Mode 3.

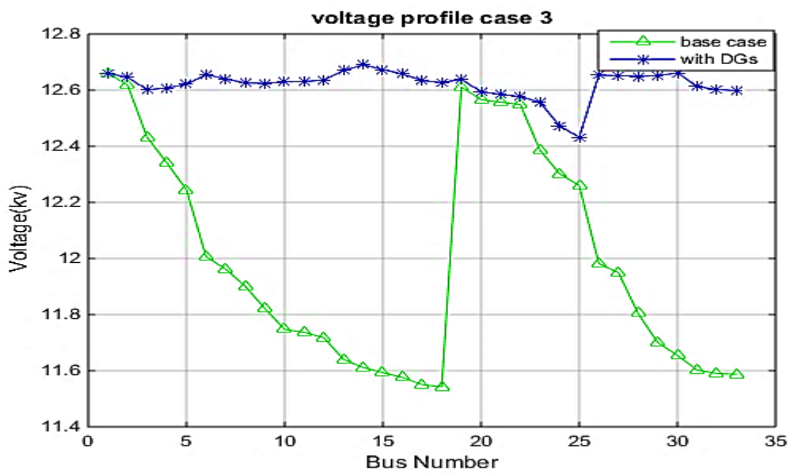

Figure 17. Bus voltage values in the basic state and after adding DGs for Mode 3.

Table 5. Results obtained for Mode 4.

	Location and active power of DGs (kW) and location and reactive power of the capacitor (kVAR)				Power loss (kW)	Loss reduction percentage	The lowest voltage and corresponding bus
Base mode	-				211.87	-	0.9117 bus 18
Result of the simulation	6	473	12	474	24.82	88.28	0.9835 bus 18
	15	498	24	513			
	32	493	30	965			
Reference [3]					24.45	87.9	

5.5. The results obtained for the fourth case: Simultaneous optimal placement of the capacitor bank and DGs with a single power factor

For this mode, the number of DGs is three, and the number of capacitors is also 3. The active power of DGs is between 0 and 500 kW. The power factor is between 0.9 and -0.9. The injected reactive power of capacitors is considered between 0 and 1200 kW. The results are presented in Table 5 and compared with the base state and [3]. The obtained results are close to the results of [3], but in this reference, 2581 kW of a capacitor and 1892 kW of DG have been used to reduce losses. The obtained results used 1951 kW of a capacitor and 1464 kW of DG for the same amount of loss reduction.

The convergence characteristic in terms of the number of iterations is presented in Figure 18. Bus voltage values in the basic state and after adding capacitors and DGs are shown in Figure 19 It can be seen that DGs and capacitors, in this case, affect the voltages strongly and have improved the voltage profile of the distribution system.

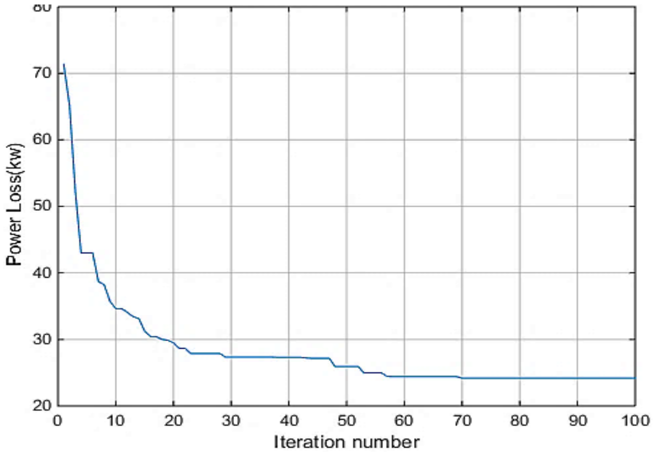

Figure 18. Convergence characteristic of Mode 4 according to the number of iterations.

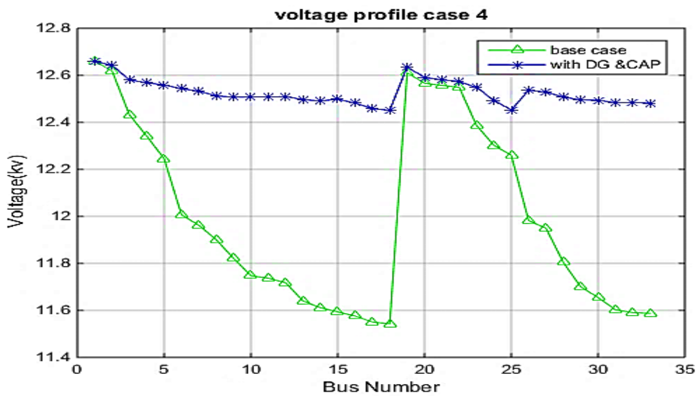

Figure 19. Bus voltage values in the basic state and after adding DGs and capacitors for Mode 4.

Table 6. Results obtained for Mode 5.

	Location and active power of DGs (kW) and their power factor, and location and reactive power of the capacitor (kVar)					Power loss (kW)	Loss reduction percentage	The lowest voltage and corresponding bus
Base mode	-					211.87	-	0.9117 bus 18
Result of the simulation	13	753	0.9	7	176	11.85	94.4	0.9923 Bus 18
	24	1112	0.94	19	232			
	30	1065	0.82	33	199			
Reference [13]	13	795	0.91	8	150	11.71	94.47	
	24	1069	0.9	18	150			
	30	1029	0.81	30	300			

So, in Mode 4, by placing and determining the optimal capacity of capacitor banks and a DG with variable power factor, capacitor banks reduce the reactive power passing through the branches of the distribution system. The distributed generation system with variable power factor reduces both active and reactive power crossing of the branches of the distribution system, and this causes the real power loss of the system to be reduced more than in the previous cases, and the voltage profile of the distribution system is also improved more than the base case.

5.6. The results obtained for the fifth case: Simultaneous optimal placement of the capacitor bank and DGs with variable power factor

For this mode, the number of DGs is three, and the number of capacitors is also 3. The active power of DGs is between 0 and 1200 kW. The power factor is between 1 and -1. The injected reactive power of capacitors is considered between 0 and 1200 kW. The results are presented in Table 6 and compared with the base state and [16]. The convergence characteristic in terms of the number of iterations is presented in Figure 20. Bus voltage values in the basic state and after adding capacitors and distributed generation units are shown in Figure 21. It can be seen that DGs and capacitors, in this case, affect the voltages strongly and have improved the voltage profile of the distribution system.

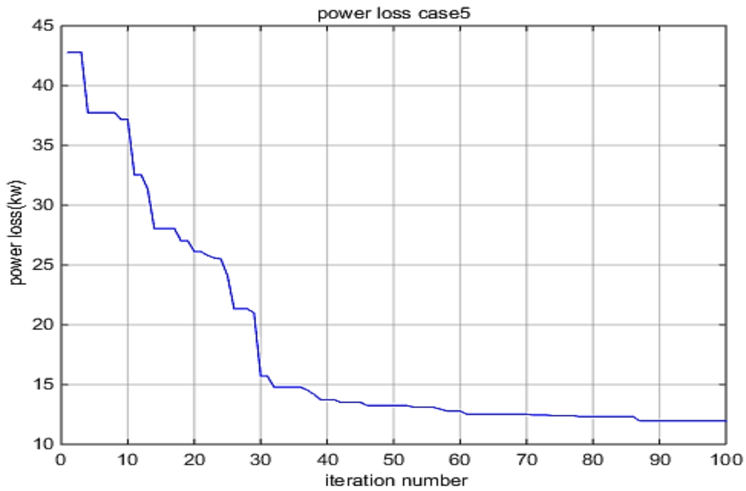

Figure 20. Convergence characteristic of Mode 5.

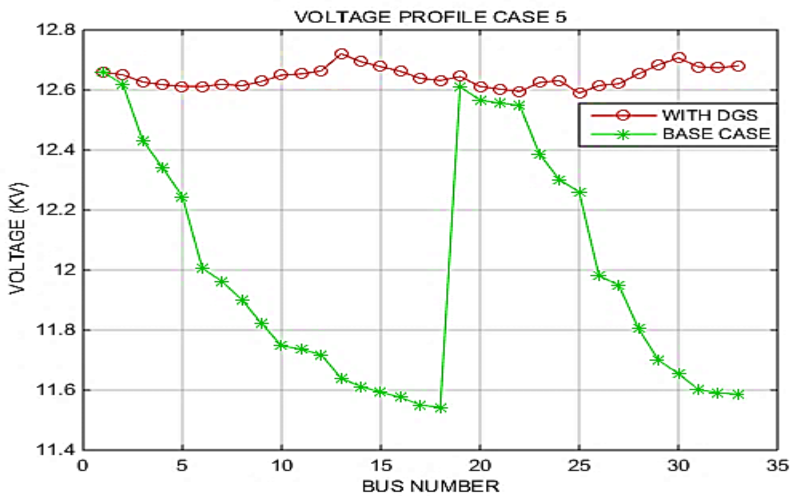

Figure 21. Bus voltage values in the basic state and after adding DGs and capacitors for Mode 5.

5.7. Optimization results

1. Mode 1- Capacitor Placement: Optimally allocating three capacitors, total power loss decreased from 211.87 kW to 139.57 kW, achieving a 34.1% reduction. The lowest bus voltage increased from 0.9117 pu to 0.9361 pu.
2. Mode 2 - DG Placement (Unit Power Factor): Optimally placing three DGs reduced power losses to 75.27 kW, achieving a 64.4% reduction. Voltage profile improvements raised the lowest bus voltage to 0.9652 pu.
3. Mode 3 - DG Placement (Variable Power Factor): Incorporating variable power factors resulted in losses as low as 21.24 kW, with a 90% reduction. Bus voltages improved significantly, with the lowest increasing to 0.982 pu.
4. Mode 4- Combined Placement with Unit Power Factor: Simultaneously allocating three DGs and three capacitors reduced power losses to 24.82 kW (an 88.28% reduction). The lowest voltage reached 0.9835 pu.
5. Mode 5 - Combined Placement with Variable Power Factor: This mode yielded the best results. Power losses were minimized to 11.85 kW (a 94.4% reduction). Voltage profiles improved significantly, with the lowest bus voltage rising to 0.9923 pu.

The results highlight the effectiveness of the proposed BBO-based optimization approach. In all five modes, significant reductions in power losses and enhancements in voltage profiles were achieved. The allocation of DGs with variable power factors demonstrated superior performance, particularly in Mode 5, where a combination of capacitors and DGs produced the most efficient results. These findings underscore the potential of BBO for addressing complex, multi-objective optimization problems in distribution systems.

6. Conclusion

This study proposed a biogeography-based optimization framework for the optimal placement and sizing of DG units and capacitor banks in radial distribution systems. As a result, power loss was minimized and the voltage profile improved simultaneously. The methodology demonstrated significant performance improvements across all 5 operational modes. Mode 5, combining capacitors and DGs with variable power factors, emerged as the most effective approach, reducing losses by 94.4% and improving the lowest bus voltage to 0.9923 pu.

Future research may explore the involvement of economic factors, such as installation and operational costs, and expand the model to accommodate higher-order harmonics and stochastic load variations.

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Declaration of competing interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All ethical standards, including avoidance of plagiarism, informed consent, research misconduct, data fabrication or falsification, duplicate publication or submission, and redundancy, have been fully observed by the author.

Bibliography

Leila Mohammadian was born in Tabriz, Iran, in 1984. She received her B.S., M.S., and Ph.D. degrees in Electrical Engineering from the Department of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran, in 2007, 2011, and 2015, respectively. She has been with the Department of Electrical Engineering, Shab.C., Islamic Azad University, Shabestar, Iran, since 2011. She has been an Assistant Professor since 2015. She is the author of more than 60 journal and conference papers. Her current research interests include the analysis and control of power electronic converters and their applications, power quality enhancement and FACTS devices, application of control systems and theory in power engineering, and power system dynamics, renewable energy sources, and energy storage systems.
Email: le.mohammadian@iau.ac.ir
ORCID: 0000-0001-5202-1397
Contribution Statement: Conceptualization, Methodology, Project administration, Resources, Supervision, Writing-review & editing.