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Network reconfiguration and optimal distributed generations allocation with whale optimizer algorithm

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Original Research

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Abstract:

Power distribution networks have become more interested in Distributed Generations (DG) due to their potential for reducing power loss and improving system dependability. Discovering the optimal site, size, and reconfiguration strategy for a DG-based distribution network using a metaheuristic algorithm is the main goal of this study. The multi-objective and multi-constrained feature of the Whale Optimization Algorithm (WOA) makes it a useful optimization technique for network reconfiguration. In this paper, the forward-backward load flow technique is employed due to its easy implementation, quick and reliable convergence. The recommended approach is validated through two different test systems. Four different scenarios are considered. Improvements in power loss reduction and voltage profile illustrate the effectiveness of the proposed technique. The obtained results showed that DG allocation after network reconfiguration resulted in a greater reduction of power losses and refinement of the voltage profile of the network. Also, a comparison is employed with other optimization methods, it can be seen that the suggested method's performance is clearly superior, as shown by the numerical data. Losses were reduced by 67.8% and 63.21% on IEEE 33 and 69 bus systems, respectively, when using the suggested strategy. All the simulations are conducted through MATLAB.

Keywords: Distribution generation; Power loss reduction; Reconfiguration; Voltage profile improvement; Whale optimizer algorithm

1. Introduction

Electricity distribution is changing significantly as a result of increasing environmental awareness and persistent energy demand. Distributed generations (DGs) and optimal network reconfiguration are promising solutions to reduce energy consumption while promoting sustainable energy practices [1, 2]. DGs, such as solar photovoltaics, wind turbines, and micro-generators, offer decentralized and renewable power sources that can considerably impact the operational efficiency and environmental sustainability of distribution networks [3–5]. Solving a mathematical optimisation problem is necessary to ensure optimal allocation of DG [6]. The electricity system's capacity, efficiency, stability, and long-term viability will all be greatly enhanced by this. Benefits of optimisation approaches in energy management for DG allocation include decreased costs and emissions, increased system performance, greater utilisation of energy resources, and optimisation of allocation processes has been demonstrated to be beneficial [7, 8].

The optimisation approaches used to solve the DG allocation and reconfiguration challenges are summarised in Table 1. Three separate optimisation strategies—analytical, metaheuristic, and hybrid—have been employed to address these issues. Through extensive simulations, we show that our method outperforms traditional techniques in terms of convergence speed, active power loss reduction and voltage profile improvement.

Classical approaches to optimization, such as gradient-based methods and Linear Programming (LP), have been applied to address the DG allocation problem [15–17]. However, these methods often suffer from limitations, such as convergence to local optima and high computational overhead. Metaheuristic algorithms, which can efficiently explore enormous solution spaces and identify near-optimal solutions, have gained popularity as a means of overcoming these obstacles. Among various metaheuristic algorithms, the Whale Optimization Algorithm (WOA) has recently emerged as a powerful optimization technique. WOA efficiently finds the global optimum of an objective function by simulating the surrounding prey and bubble-net feeding methods used by humpback whales. Several optimization issues in the scientific and technical fields have been successfully solved using this approach.

Table 1. An overview of various optimization methods for DG allocation and reconfiguration.

Study	Year	Objective	Minimization functions	Maximization functions	Optimization technique	Discussion on reconfiguration
[9]	2023	Optimal allocation and optimum sizing of DG	Active power losses	Voltage Profile, Impedance	Genetic Algorithm and Grey Wolf Optimizer	Not considered
[10]	2023	Ideal sizing and allocation of DG	Cost, Energy losses, Voltage Deviation, Annual economic loss	Voltage Profile, System efficiency	Whale Optimization Algorithm	Not considered
[11]	2022	Optimal DG placement	Power Loss, Pollutant Emission, Voltage deviation, THD, Cost	Voltage Stability Index (VSI)	Firefly Algorithm	Not considered
[12]	2022	Optimal DG size and position	Power Loss	Reliability Assessment	Wild Horse Optimization Algorithm	Not considered
[13]	2016	Optimal DG placement and Reconfiguration	Power Loss	VSI	Cuckoo Search Algorithm	Considered
[14]	2015	Network Reconfiguration	Power Loss, voltage deviation index	–	Cuckoo Search Algorithm	Considered
This research	–	Optimal DG placement and Reconfiguration	Active Power Loss	Voltage Profile, System efficiency	Whale Optimization Algorithm	Considered

Optimizing DG placement and capacity, such as wind in a distribution system, has been a hot topic for authors studying the power system in recent years [9, 18–20]. Under the assumption that DGs can be dispatched, the authors presented several methods for dealing with stressed systems. For instance, in [21, 22], the authors used dispatchable DG to minimize power line losses while increasing the voltage stability margin. Authors in [23–25] formulated a three-objective optimization problem with the goals of improving voltage profile, minimizing power loss, and enhancing voltage stability. The authors considered optimal DG problems for single and multiple DG sizing in [26]. The active power flow in the distribution system was minimized using the Genetic Algorithm (GA) approach.
An approach to PV generator allocation was detailed in [27] that aimed to improve the voltage profile while reducing power loss. The research focused solely on well-balanced testing platforms. In contrast, the research in [28] looks at how the integration of solar systems into the current infrastructure is affected by the effects of hourly changes in load demand. The method being presented aims to minimize power loss so that the PV systems can be deployed efficiently across the system. The aforementioned methodology is only tested on the balanced test networks with the most popular meta-heuristic algorithm, PSO. In order to evaluate the hosting capability of DG sources within the system and guarantee resilience in the face of different adverse scenarios, the authors of [29] proposed a method. In order to minimize losses, a hybrid data-driven strategy was used to reconfigure the distribution system and allocate DG units optimally in [30]. With high penetration of non-linear loads, simultaneous allocation of DG units and shunt capacitors was carried out in [31]. Nevertheless, [30] and [31] took into account the fact that there are a variety of DG units and load models. The simultaneous allocation of multi-type DGs was described in a generic analytical statement in [32]. The goal of this research is to use the WOA for both DG allocation and network reconfiguration. With the combination of DG allocation and network reconfiguration within the WOA, this study provides a comprehensive approach to optimize distribution networks and foster the seamless integration of renewable energy sources. This study utilizes the inherent strengths of the WOA for exploration and exploitation, thus providing an effective and efficient alternative compared to traditional optimization approaches. The IEEE 33 and 69 bus systems are utilized to validate the proposed methodology. Based on the results of the study, DG allocation and network reconfiguration together improve voltage profile and diminish power losses. The main objectives of this research are as below:

- Consider optimal allocation problem and network reconfiguration in four different scenarios.
- Implement the WOA method to identify the best placement and capacity of DG units, and optimize the switching states of network elements.
- Perform extensive simulations on IEEE 33 and 69 bus test systems to assess the effectiveness of the suggested strategy.
- Compare the obtained results of this paper with further optimization algorithm to verify the superiority of the suggested technique.

The remainder of this paper is structured as follows: The objective function and restrictions of the optimization model are described in Section 2. Section 3 provides an in-depth description of the WOA and its adaptation to solve the DG allocation issue. Section 4 presents the validation methodology and performance analysis using IEEE standard test systems and discusses the implications of the results. Finally, section 5 summarizes the outcomes of this paper.

2. Problem formulation

Since the distribution network reconfiguration is an optimization problem, it includes objective functions and constraints, which are as follows:

2.1 Active power losses

One possible goal is to reduce active power losses to a minimum. This index is considered as follows [33]:

$$P_{loss} = \sum_{i=1}^{Nb} g_m[(V_m^s)^2 + (V_m^r)^2 - 2V_m^s V_m^r \cos\theta_m] \tag{1}$$

where V_m^s and V_m^r are the values of the voltage amplitude at the two ends of sending and receiving line m, respectively. g_m is conductivity of line m, θ_m is the phase difference between the two ends voltages of line m, and Nb is the number of lines.

2.2 Voltage profile

Voltage is one of the most vital indicators of power quality, which its profile improvement can be considered as one of the objective functions in the optimization problem. This objective function can be expressed mathematically as the following equations [9]:

$$VDI = \sqrt{\frac{1}{N_{bus}} \times \sum_{i=1}^{N_{bus}} (v_i - v_p)^2} \tag{2}$$

$$v_p = \frac{1}{N_{bus}} \times \sum_{i=1}^{N_{bus}} v_i \tag{3}$$

where VDI is the voltage deviation index, v_i is the voltage of ith bus, v_p is the average bus voltage and N_{bus} is the bus number. The magnitude of transmission network busbar voltage changes is bounded by a $\pm 5\%$ tolerance, which is represented in Eq. 4 [34, 35]. Maintaining the voltage within the specified range helps prevent voltage collapse, voltage instability, and other undesirable phenomena that can lead to system-wide failures. The tolerance will be used to evaluate the voltage profile of the system and achieve the goal of minimizing busbar voltage deviation.

$$0.95\,\text{p.u.} \leq V_j \leq 1.05\,\text{p.u.} \tag{4}$$

2.3 The backward forward sweep method

Since the backward-forward sweep (BFS) power flow is easy to implement, converges quickly and reliably, and requires low memory, it is frequently employed for load flow distribution systems. Using Kirchhoff's current law (KCL) and Kirchhoff's voltage law (KVL), the BFS method consists mostly of three fundamental iterative phases. The calculation of current at nodes, backward sweep, and forward sweep are the three stages that must be repeated in order to reach convergence. The BFS uses an easy-to-understand and flexible radial distribution system numbering procedure to identify each feeder, lateral, and sub-lateral branch. In the radial distribution system, which can be seen in Fig. 1, the buses p and q at the ends of the branch represent buses that conduct transmission and those that receive it.
The following procedures are to determine the BFS load flow:

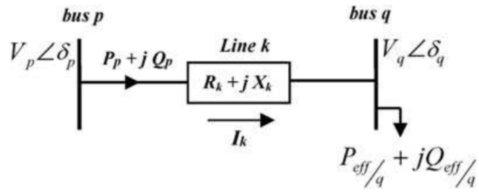

Figure 1. The model of two buses in a system.

- Initialization
  - Line and load information for the distribution system must be included.
  - Insert power and voltage at their foundational levels.
  - Determine the initial impedance.
  - line and load data must be calculated in per unit.
  - Use a unified bus voltage throughout the system (1 p.u.).
  - Consider convergence tolerance ε = 0.0001 and ΔV_{max} = 0.
- Assign numbers in the system
  The purpose is to assign a unique identifier to each segment of the distribution network, such as a feeder, lateral, or sub-lateral that links two buses. The distribution network's total number of sections, denoted as N_{Sec}^{Total}, is given below:

$$N_{Sec}^{Total} = N_{bus}^{Total} - 1 \tag{5}$$

  where, N_{bus}^{Total} represents the total number of buses. For instance, to determine how many segments connect node p and node q, we know that each segment will be labeled with a number that is one less than the bus number at the destination node, which can be written as:

$$N_{\frac{sec}{p}-q} = N_{\frac{sec}{q}} - 1 \tag{6}$$

  where, $N_{\frac{sec}{p}-q}$ shows the section number between buses p and q, $N_{\frac{bus}{q}}$ is the number of q. Each section within the distribution system should be assigned a number.

- Determine the current at the nodes
  The current injection at node i at iteration k, is given below:

$$I_i^{(k)} = (\frac{S_i}{V_i^{(k-1)}})^* - (Y_i)(V_i^{(k-1)}) \tag{7}$$

  In the above equation, $I_i^{(k)}$ shows the current injection at bus i, S_i represents the power injection at bus i, $V_i^{(k-1)}$ is the bus i voltage at iteration $k-1$, and Y_i shows the sum of all shunt components.

- Backward sweep
  Beginning at the end buses, move towards the branches connected to the substation at iteration k. Therefore, KCL is capable of identifying the currents in

every branch and determining the powers through these branches as follows:

$$I_L^{(k)} = -I_j^{(k)} - \sum_{m=1}^{M} (\frac{S_m}{V_j^{(k)}})^* \tag{8}$$

$$S_L^{(k)} = (V_j^k + Z_L * I_L^k)(I_L^k)^* \tag{9}$$

where, $I_L^{(k)}$ shows the current flow in branch L at iteration k, $I_j^{(k)}$ is the bus j current injected because of shunt components, M represents the number of branches, S_m is the complex power of branch m, $V_j^{(k)}$ is the bus j voltage, $S_L^{(k)}$ shows the branch power flow, and Z_L show the branch impedance L.

- Forward sweep
  KVL operates in a forward sweep by updating nodal voltages from the branches in the first section to those in the last, starting with iteration k. At iteration k, the voltage at receiving end q of a branch L connected to sending end p is given below:

$$V_q^{(k)} = V_p^{(k)} - Z_L * I_L^k \tag{10}$$

  where, $V_p^{(k)}$ and $V_q^{(k)}$ show the sending and receiving voltages, respectively.

- Inspect the voltage discrepancies
  The voltage mismatches for all nodes are determined after the previous steps have been computed. For instance, the voltage mismatch at bus i and iteration k can be determined as follows:

$$\Delta V_i^{(k)} = ||V_i^{(k)}| - |V_i^{(k-1)}|| \tag{11}$$

  The voltage convergence must be checked after calculating the voltage mismatches:

  – If $\Delta V_i^{(k)} > \Delta V_{max}$, then ΔV_{max} is equal to $\Delta V_i^{(k)}$.
  – If $\Delta V_{max} \leq \varepsilon$, move to step 8, otherwise increase the iteration number and proceed to step 3.

- Analyze stopping criterion
  If the maximum number of iterations has been reached or the voltage mismatch convergence has been achieved, the program will terminate.

- Calculate power loss
  By plugging the node voltages and branch currents derived from the BFS algorithm into equation 1, we can determine the overall power losses of the distribution system.

2.4 Bus voltage constraint

The voltage fluctuations in distribution systems are very limited and the standards usually allow only minor changes around the nominal value. Therefore, the voltage of the buses should always be within a permissible range, which is expressed as below:

$$v_i^{min} \leq v_i \leq v_i^{max}, \quad i = 1, 2, \ldots, N_{bus} \tag{12}$$

where v_I is the voltage of ith bus, v_i^{min} and v_i^{max} are the minimum and maximum permissible voltages of ith bus, respectively.

2-1-Line current constraint

Each branch's current must be maintained at or below its full capacity to avoid the lines from being overloaded. This is expressed by the following relation:

$$|I_i| \leq |I_i^{max}|, \quad i = 1, 2, \ldots, N_{Line} \tag{13}$$

where $|I_i|$ is the absolute value of current in ith line, $|I_i^{max}|$ are the maximum permissible current of ith line and N_{Line} is the number of lines.

2.5 System radial configuration and isolation constraints

The most significant limitation on the network reconfiguration problem is the requirement that all buses be contained within a radial distribution system layout. In this paper, the system configuration is verified using the method proposed in [36, 37].

3. Whale optimization algorithm

The WOA is a meta heuristic optimization technique inspired by the social behavior and hunting strategies of humpback whales. This research article presents a comprehensive review of the WOA, exploring its key concepts, algorithmic components, and underlying principles. The paper discusses the evolution of WOA, its adaptations, and variants developed to address various optimization challenges. The primary goal of the WOA is to efficiently search for the global optimum of a given objective function in diverse problem domains. The algorithm mimics the cooperative foraging behavior of humpback whales, involving the three main phases: exploration, exploitation, and encircling prey. These phases allow WOA to balance exploration of the solution space to discover promising areas and exploitation to converge towards the optimal solution [38].

3.1 Encircling of prey

Finding and enclosing prey is a common hunting tactic for humpback whales. Since we don't know where the ideal design is in the space of possible designs before we start, WOA works on the assumption that the best possible solution is either the target or very near to it. The remaining search agents will update their positions to naturally gravitate toward the best search agent once it has been discovered. The following equations model this behavior:

$$\vec{D} = |\vec{C}.\vec{X}_p(t) - \vec{X}(t)| \tag{14}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \tag{15}$$

where t is the iteration, $\vec{A}$ and $\vec{C}$ show coefficient vectors, $\vec{X}_p(t)$ indicates current optimal solution position, and $\vec{X}(t)$ is the position vector.
The vectors $\vec{A}$ and $\vec{C}$ are given below:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{16}$$

$$\vec{C} = 2.\vec{r}_2 \tag{17}$$

In the above equations $\vec{a}$ is linearly decreased from 2 to 0 as iterations progressed and r_1, r_2 are random vectors in [0, 1].

3.2 Bubble net hunting mechanism

Two methods are developed to determine the bubble net hunting mechanism:

3.2.1 Shrinking encircling prey

To create this behavior, decrease the value of $\vec{a}$ in 16. Note that the variation range of $\vec{A}$ is also decreased by $\vec{a}$. In other words, as a is gradually reduced from 2 to 0, $\vec{A}$ is a random value in the interval [-a ,a]. By choosing values for $\vec{A}$ at random in [-1,1], anywhere between the starting position and the optimal agent's position can be found as the new location of a search agent.

3.2.2 Spiral updating position

This strategy initially considers the separation between the whale situated at (X ,Y) and prey located at (X^*,Y^*). As a result, a spiral equation has been developed between the location of the whale and its prey in order to replicate the helix-shaped movements of humpback whales, which is as given below:

$$\vec{X}(t+1) = \vec{D}'.e^{bl}.\cos(2\pi l) + \vec{X}^*(t) \tag{18}$$

where $\vec{D}' = |\vec{X}^* - \vec{X}(t)|$ shows the distance of the ith whale to the prey, b is a parameter used to specify the logarithmic spiral's shape, and l is an arbitrary number in [-1,1].
Keep in mind that humpback whales hunt by swimming in a converging spiral pattern around their prey. To represent this simultaneous behavior, during optimization, whales' positions are supposed to be updated with a probability of 50% using either method. The form is given below:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A}.\vec{D} & if \quad p < 0.5 \\ \vec{D}'.e^{bl}.\cos(2\pi l) + \vec{X}^*(t) & if \quad p \geq 0.5 \end{cases} \tag{19}$$

where p is an arbitrary integer between 0 and 1.

3.3 Search for prey

The same manner, depending on the difference of the $\vec{A}$ vector can be used to explore for prey. Actually, humpback whales conduct their searches at random with respect to one another. Forcing the search agent to disperse significantly from the reference whale, the $\vec{A}$ vector can be employed with random values outside the range [-1,1]. In the exploration phase, as opposed to the exploitation phase, when the best search agent is used to update a search agent's position, a randomly selected search agent is utilized to do so. Using this mechanism and $|\vec{A}| > 1$, the WOA algorithm can conduct a global search and emphasize exploration. The mathematical form is given below:

$$\vec{D} = |\vec{C}.\vec{X}_{rand} - \vec{X}| \tag{20}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \tag{21}$$

where$\vec{X_{rand}}$ represents a randomly chosen whale from the present population. The steps involved in putting WOA into action are in Fig. 2.

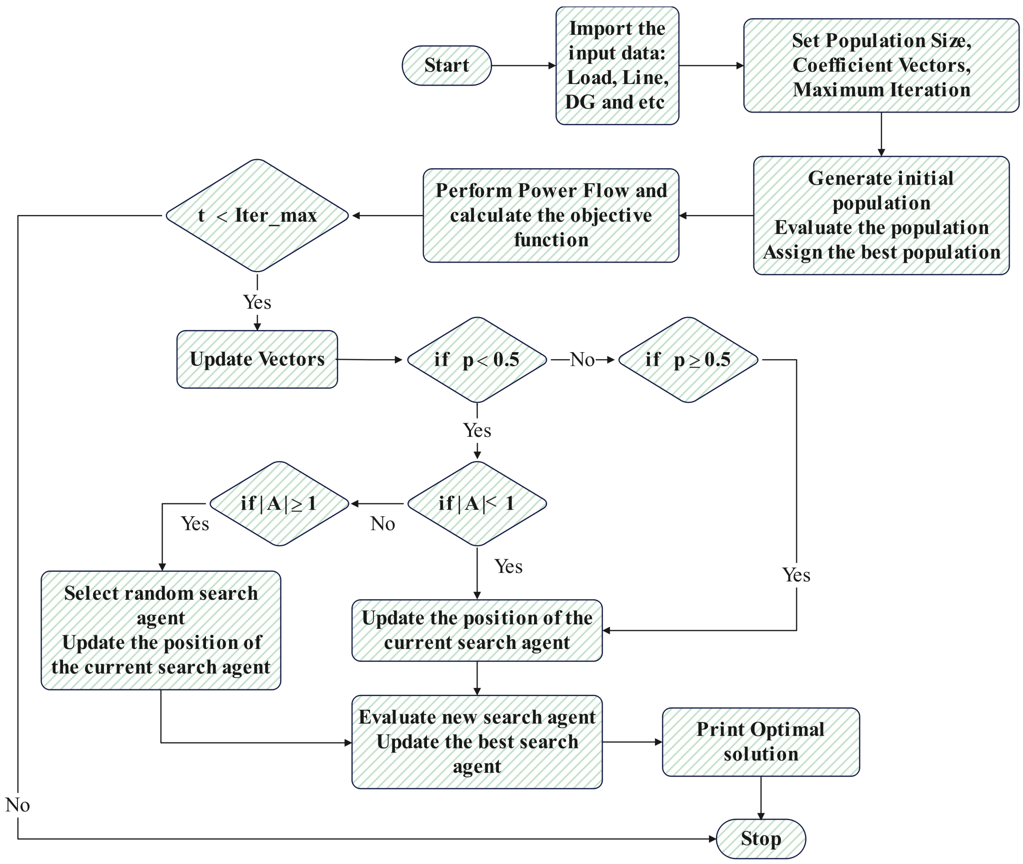

Figure 2. The flow chart of WOA approach.

4. Simulation and results

The efficiency of the suggested method is demonstrated by applying it to IEEE 33 and 69 bus networks. In this paper, numerical calculations are performed in four separate scenarios. The first case is related to normal network conditions, the second case is when DG is installed in the network separately, in the third case, network reconfiguration is applied separately, and in the fourth case, DG placement and sizing after network reconfiguration are considered. In all scenarios, number of population and maximum iteration are considered 10 and 10, respectively.

4.1 System 1

The data of this 33-bus network is available in [39, 40]. Fig. 3 is a schematic representation of the IEEE 33-bus network. This network has a nominal voltage of 12.66 kV and the active and reactive loads installed in this network is equal to 3715 kW and 2300 kVar, respectively. The total active power loss is equal to 202.6 kW. The system has 37 branches, 32 sectionalizing switches and 5 tie switches. The switches 37, 36, 35, 34 and are open before the reconfiguration of the system.

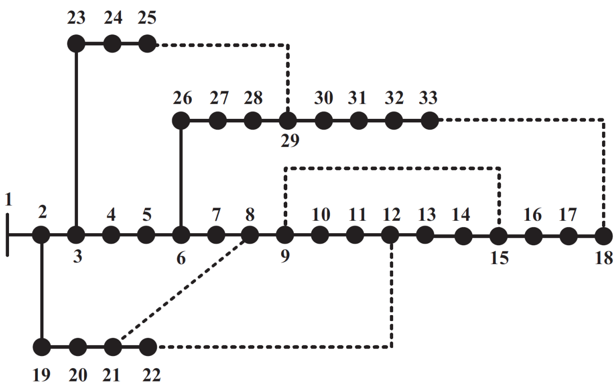

Figure 3. The IEEE 33-bus distribution system.

4.1.1 Case I (Normal network conditions)

Table 2 displays the outcomes of applying the proposed technique in all cases. As mentioned before, in the first case, network reconfiguration and DG placement are not considered. In this case, the network is in the normal condition and the switches 37, 36, 35, 34 and 33 are open. The network loss in this case is 202.6 kW.

4.1.2 Case II (DG placement and sizing using WOA)

According to Table 2, it can be seen that after DG placement, the active power losses reduced from 202.6 kW to 81.09 kW (59.9 % reduction) which indicates the effective and useful role of reconfiguration. It can be seen from the simulation that bus 31 is the optimal location for DG placement and its optimal capacity is 1566 kW. Fig. 4 shows the effect of applying the proposed technique in this case on network voltage profile. It is obvious in Fig. 4, the network voltage profile has significantly enhanced after DG placement. For instance, in bus 18, the voltage was 0.913 p.u. before the DG placement, while after implementing DG it reaches 0.944 p.u. That is nearly 3.3 % increase in bus voltage 18. Also, the voltage value of bus 18 is the voltage minimum in this case. The convergence curve of WOA for this case can be seen in Fig. 5. It can be seen that the WOA converges to the optimal global solution after 9 iterations.

4.1.3 Case III (Network reconfiguration using WOA)

In this case, network reconfiguration is determined using WOA. According to Table 2, after reconfiguration, the opened switches are 14 – 36 – 6 – 11 – 25. The active power losses reduced from 135.14 kVar to 126.46 kVar. The reactive power losses reduced from 202.6 kW to 164.44 kW. It is obvious that optimizing the switching states of network elements minimizes power losses in the network, which results in enhancing system efficiency. In Fig. 4 we can observe the voltage profile for case III, and in Fig. 5 we can observe the convergence curve of the WOA. By comparing the findings shown in Fig. 4, it becomes evident that the reconfigured system voltage profile is significantly better. In this case, the voltage minimum is 0.934 p.u., which is for bus 33. According to Fig. 5, after 7 iterations, the WOA finds the best global solution.

4.1.4 Case IV (DG placement after network reconfiguration usinWOA)

In case IV, network reconfiguration is considered before DG placement and sizing. According to Table 2, in this case the opened switches are 14 – 36 – 6 – 11 – 25 and the active power losses reduced to 65.06 kW which shows a 67.8 % decrease compared to the first case. Also, the reactive power losses reduced to 57.97 kVar which shows a 57.1 % decrease compared to the first case. In this case, the bus 29 is the optimal location for DG placement and its optimal capacity is 1864 kW. Compared to the second scenario, the installation capacity is increased. This proves that the suggested approach functions properly.
Fig. 4 shows the network voltage profile following the suggested method's implementation. The improved distribution system is evident in Fig. 4, which shows that the network voltage profile has been significantly improved following the reconfiguration of the network and the placement of DG. For example, in comparison to the first scenario, the voltage on bus 18 increases by approximately 3.3%, going from

Table 2. Results of applying the proposed method in all cases.

Case number	Open switches	Active power loss (kW)	Reactive power loss (kVar)	DG location	DG capacity
Case I	33 – 34 – 35 – 36 – 37	202.67	135.14	-	-
Case II	33 – 34 – 35 – 36 – 37	81.09	60.36	Bus 31	1566 kW
Case III	14 – 36 – 6 – 11 – 25	164.44	126.46	-	-
Case IV	14 – 36 – 6 – 11 – 25	65.06	57.97 Bus	29	1864 kW

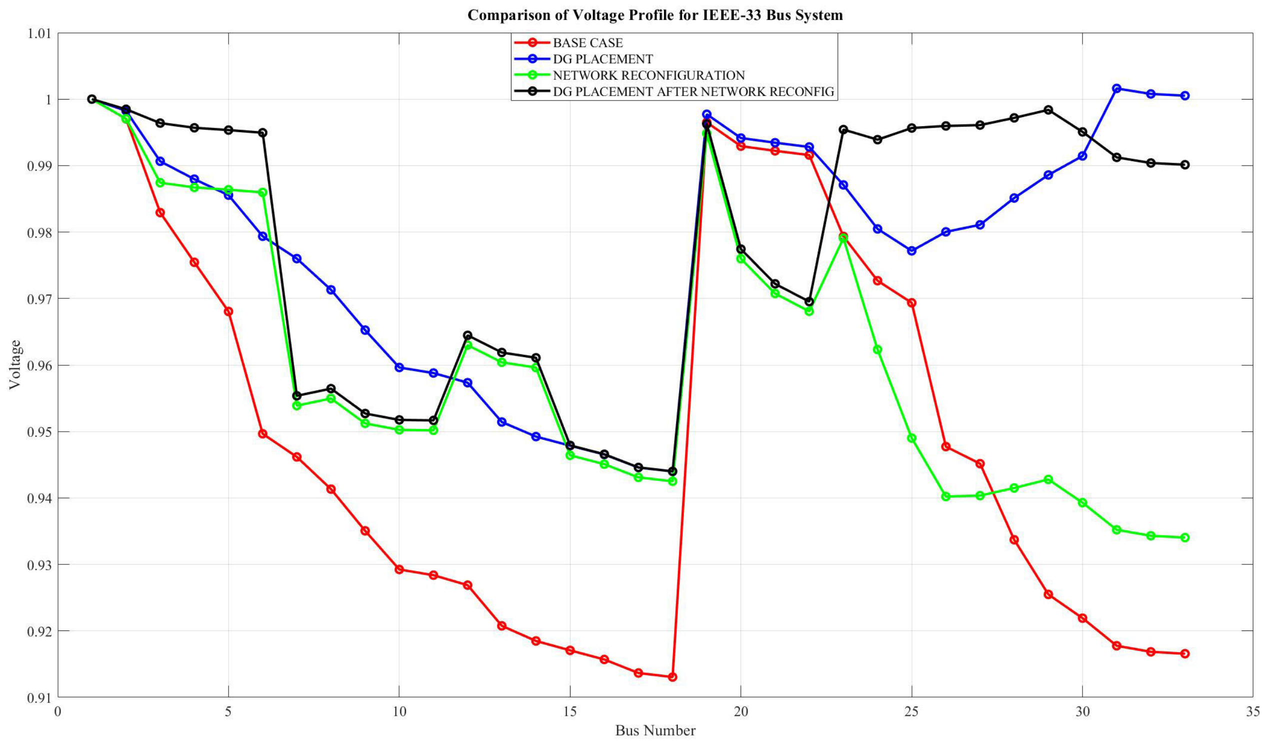

Figure 4. The network voltage profile using WOA in all scenarios.

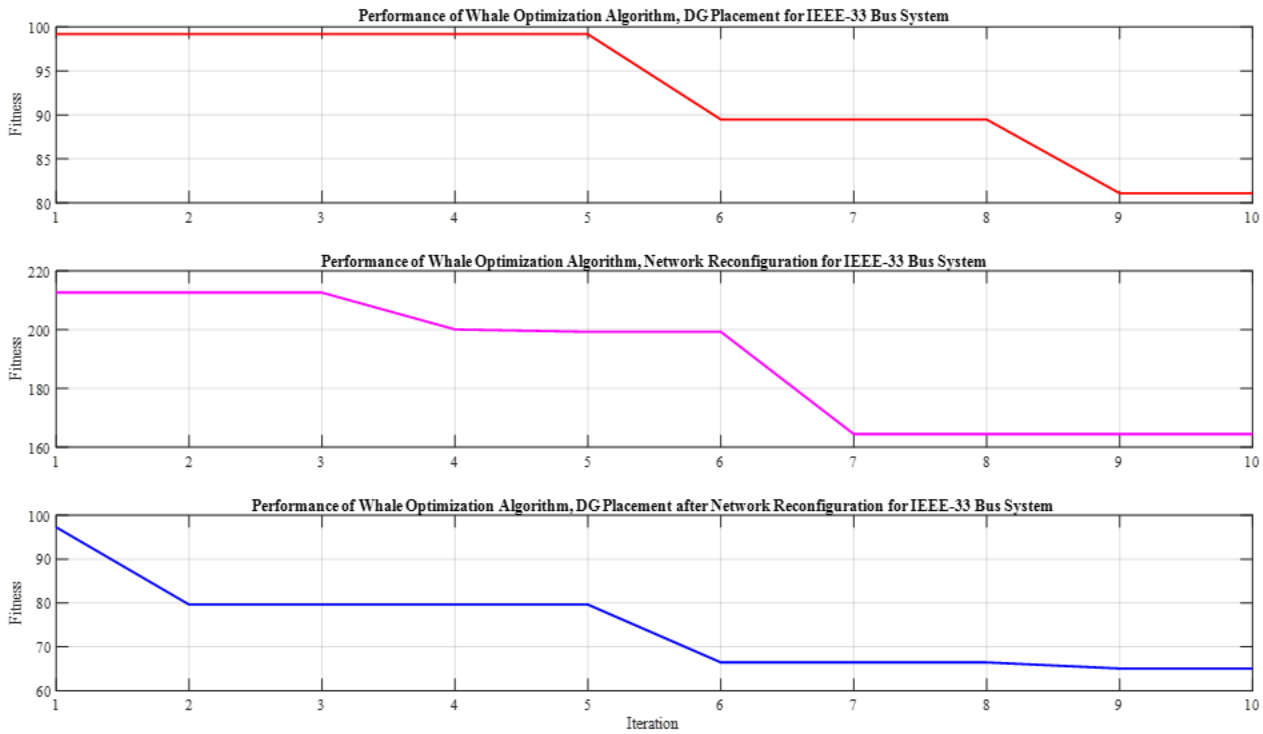

Figure 5. The convergence curve of the WOA in all scenarios.

0.913 p.u. to 0.944 p.u. This bus has the lowest voltage, just like in Case II. The WOA's convergence curve for case IV is shown in Fig. 4. After 6 iterations, the WOA converges to the best global solution.
Table 3 illustrates the obtained results by further optimization algorithm using IEEE 33-bus system. According to Table 3, the proposed strategy reduces power losses by a more significant amount than the solutions found using improved analytical (IA) method [41], Sensitivity Approaches (SA) [42], Particle Swarm Optimization (PSO) [43], Artificial Bee Colony algorithm (ABC) [44] and Harmony Search Algorithm (HSA) [45]. It was determined that WOA reduced loss by 67.8%. But there was a 45.18% decrease for IA, 45.16% for SA, 45.21% for PSO, 48.18% for ABC, and 45.23% for HSA, respectively. This indicates the WOA is more effective and results in a significant loss reduction compared to the other optimization algorithm. In the mentioned references, the authors proposed to increase the number of the DGs, which requires significant investment. However, the outcomes in this article were considerably enhanced through DG allocation and network reconfiguration using WOA technique.

4.2 System 2

The 69-bus network has a total of 69 nodes, 73 branches and 5 tie switches. Total connected loads are 3.802 MW and 2.696 MVAr [10, 13]. Fig. 6 is a schematic representation of the IEEE 69 bus network. Switches 69, 70, 71, 72, and 73 are open during normal operation.

4.2.1 Case I (Normal network conditions)

The outcomes of implementing the suggested method in each scenario are displayed in Table 4. As mentioned before, in the first case, network reconfiguration and DG placement are not considered. In this case, the network is in the normal condition and the switches 69, 70, 71, 72 and 73 are open. The active power loss is 224.9606 kW and the reactive power loss is 102.147 kVar.

4.2.2 Case II (DG placement and sizing using WOA)

According to Table 4, it can be seen that after DG placement, the active power losses diminished from 224.9606 kW to 140.138 kW (37.71 % reduction) which indicates the effective and useful role of reconfiguration. It can be seen from the simulation that bus 54 is the optimal location for DG and its capacity is 3370 kW. Fig. 7 shows the impact

Table 3. A comparison to the obtained results of IEEE 33-bus by further optimization algorithm.

Comparison to further optimization algorithm	Active power loss (kW)	Loss reduction (%)	DG capacity (MW)	DG location
IA [41]	111.10	45.18	2.60	Bus 6
1SA [42]	111.14	45.16	2.49	Bus 6
PSO [43]	111.03	45.21	2.59	Bus 6
ABC [44]	105.02	48.18	2.57	Bus 6
HSA [45]	111.00	45.23	2.59	Bus 6

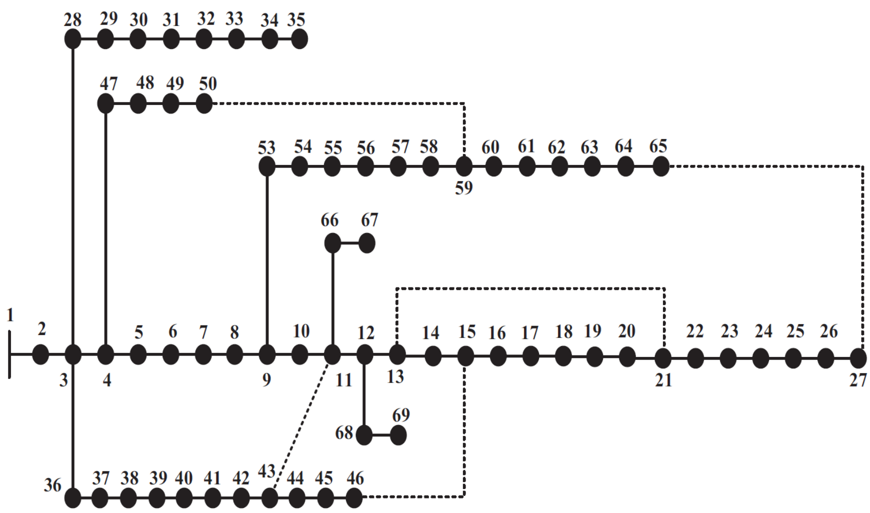

Figure 6. The IEEE 69-bus distribution system.

Table 4. Results of applying the proposed method in all cases for IEEE 69-bus.

Case number	Open switches	Active power loss (kW)	Reactive power loss (kVar)	DG location	DG capacity
Case I	69 – 70 – 71 – 72 – 73	224.96	102.14	-	-
Case II	69 – 70 – 71 – 72 – 73	140.138	58.49	Bus 54	3370 kW
Case III	13 – 70 – 58 – 10 – 61	104.3281	102.5826	-	-
Case IV	13 – 70 – 58 – 10 – 61	82.7595	85.1341	Bus 64	446 kW

of applying the proposed method in this case on network voltage profile. It is obvious in Fig. 7, the network voltage profile has significantly enhanced after DG placement. For instance, in bus 65, the voltage was 0.909 p.u. before the DG placement, while after implementing DG it reaches 0.9464 p.u. That is nearly 4.11 % increase in bus voltage 65. It should be noted that the voltage of bus 65 has not reached the minimum set voltage which is 0.95 p.u. It can be observed in Fig. 7 that the voltage value of bus 27 is the voltage minimum in this case. The convergence curve of WOA for this case can be seen in Fig. 8. From what we can tell, the WOA converges to the optimal global solution after 9 iterations.

4.2.3 Case III (Network reconfiguration using WOA)

Here, WOA is used to figure out how to reconfigure the network. Table 4 shows that following reconfiguration, the selected switches are 13 – 70 – 58 – 10 – 61. From 102.147 kVar to 102.5826 kVar, the reactive power losses rose slightly. Also, the decrease in active power losses was 53.62 %, going from 224.9606 kW to 104.3281 kW. Improving system efficiency is a natural consequence of minimizing power losses in the network, which can be achieved by optimizing the switching states of network nodes. Comparing the results obtained in Fig. 7, after reconfiguring the system, the voltage profile is clearly improved. In this case, the voltage minimum is 0.9495 p.u., which is for bus 61. According to Fig. 8, after 2 iterations, the WOA finds the best global solution.

4.2.4 Case IV (Network reconfiguration and DG placement and sizing using WOA)

In case IV, network reconfiguration is considered before DG placement and sizing. According to Table 4, in this case the opened switches are 13 – 70 – 58 – 10 – 61 and the active and reactive power losses reduced to 82.7595 kW and 82.1341 kVar, which shows a 63.21 % and 19.59 % decrease compared to the first case, respectively. In this case, bus 64 is the optimal location for DG and its optimal capacity is 446 kW. Compared to the second scenario, the installation capacity is decreased. However, the power loss reduction was significant in this case.

According to Fig. 7, significant enhancement of the network voltage profile is clearly visible after network reconfiguration and DG placement, which leads to a more efficient distribution system. For instance, the voltage of bus 65 rises from 0.909 p.u. to 0.9858 p.u. compared to the first case, representing an increase of about 8.45 %. Here, bus 61 has a voltage minimum of 0.9495 p.u. The voltage of the busbars was better kept within the prescribed range by DG allocation and network reconfiguration. For optimal power transmission and distribution efficiency and to keep losses to a minimum, it is crucial to keep the voltage within the specified range. It also aids in controlling the voltage of the electrical system, and prevents over voltages or under voltages. Fig. 8 shows the convergence curve of the WOA for case IV. It is evident that the WOA converges to the optimal global solution after 3 iterations. The WOA coverages to global optimum very fast, which showed to be effective in network reconfiguration and identifying optimal location and size of the DG.

Results from an additional optimization procedure applied to the IEEE 69-bus system are shown in Table 5. Table 5 shows that the proposed strategy achieves lower loss reduction than the solutions achieved by IA [41], SA [42], PSO [43], and HSA [45]. The loss reduction with WOA was calculated 63.21 %. However, IA, SA, PSO, and HSA had 63.84 %, 63.02 %, 63.00 %, and 61.33 % reduction,

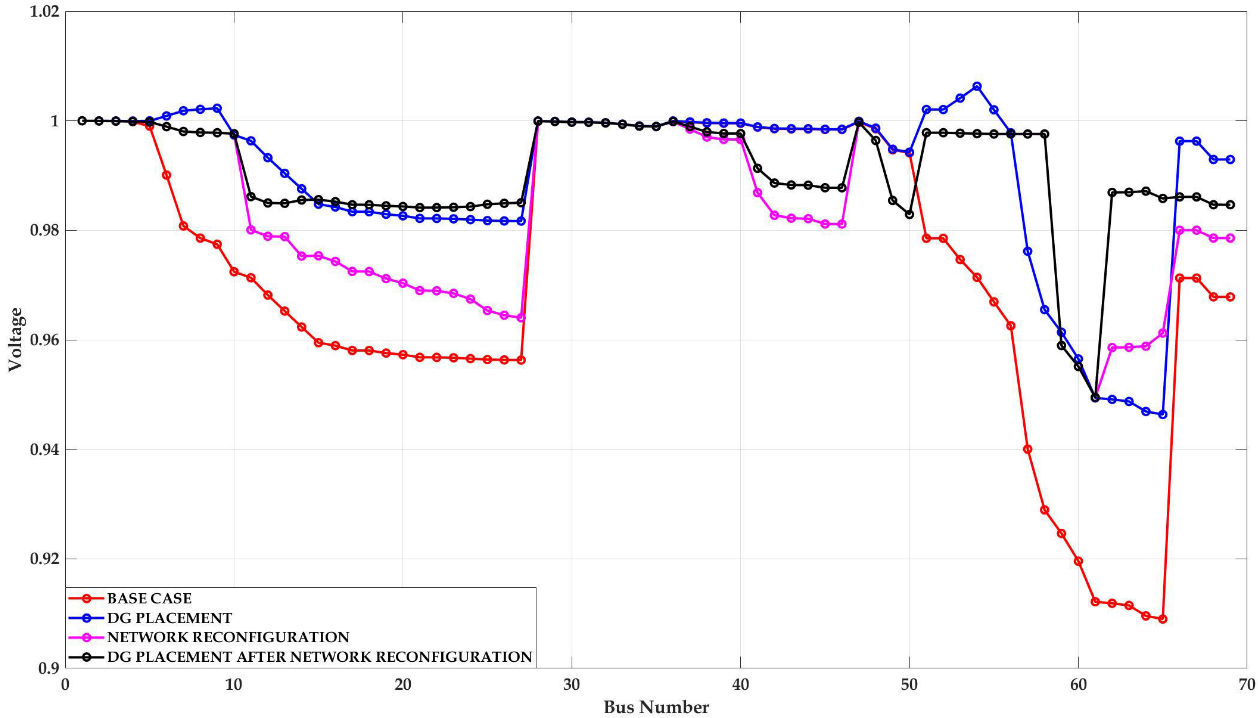

Figure 7. The network voltage profile using WOA in all scenarios.

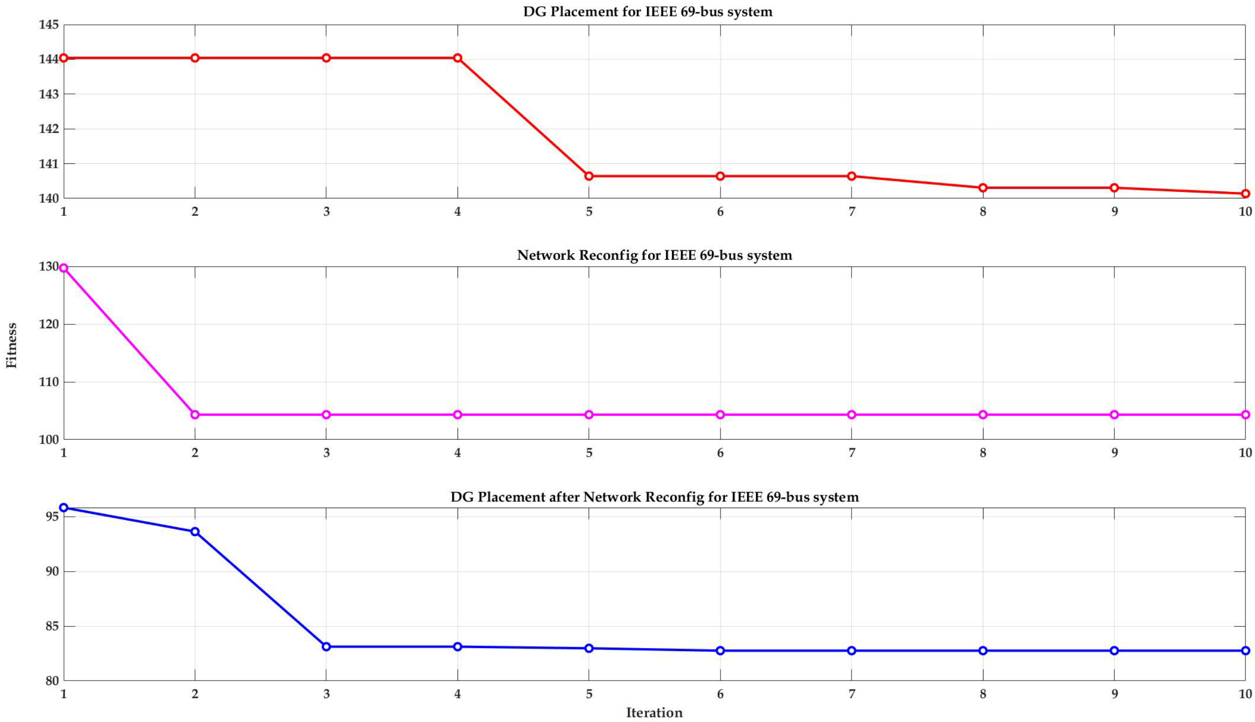

Figure 8. The convergence curve of the WOA in all scenarios.

Table 5. A comparison to the obtained results of IEEE 69-bus by further optimization algorithm.

Comparison to further optimization algorithm	Active power loss (kW)	Loss reduction (%)	DG capacity (MW)	DG location
IA [41]	81.33	63.84	1.90	Bus 61
SA [42]	83.19	63.02	1.83	Bus 61
PSO [43]	83.22	63.00	1.87	Bus 61
HSA [45]	86.97	61.33	1.79	Bus 63

respectively. This shows that the WOA is superior to the alternative optimization approaches and significantly reduces losses. Reconfiguring the network and allocating DG minimize power losses, which is an economical alternative approach compared to the mentioned methods.

5. Conclusion

In order to reduce power loss and improve the operational efficiency of power distribution systems, this research study suggests the Whale Optimization Algorithm (WOA) to handle the issues of DG allocation and distribution network reconfiguration. Standard test systems, IEEE 33 and 69 bus networks, are used for validation and performance analysis in four separate cases. The first case was normal condition network, which DG allocation and network reconfiguration were not considered; the second and third cases were DG allocation and network reconfiguration individually, respectively; and the last case was considering DG allocation after network reconfiguration. The obtained results revealed significant power loss reduction, improved voltage profiles, and efficient utilization of DGs, ultimately contributing to enhanced operational efficiency and sustainability of power distribution systems. DG allocation and network reconfiguration individually could improve voltage profile and diminish active and reactive power losses of the network. However, DG allocation after network reconfiguration resulted in a greater reduction of power losses and a refinement of the voltage profile of the network. In this condition, consumers experience fewer disruptions and voltage-related issues, leading to improved equipment performance and reduced downtime. Compared to other methods in the literature like Particle Swarm Optimization (PSO), Artificial Bee Colony algorithm (ABC), and Harmony Search Algorithm (HSA), the suggested method's performance is clearly superior, as shown by the numerical data. Moreover, it was observed that the WOA could coverage to global optimum very fast. As the algorithm approaches the global optimum quickly, fewer iterations or evaluations of the objective function are required.

Authors contributions
All authors have contributed equally to prepare the paper.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflict of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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