

Research Article

Optimal Siting and Capacity of Photovoltaic Distribution Generator in Radial Distribution Networks Using the Salp Swarm Algorithm and Geometric Mean Optimiser

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Article Info	Abstract
Article History	This research presents an optimisation framework for determining the optimal location and capacity of photovoltaic distribution generators (PVDGs) in radial distribution networks (RDNs) using two recent algorithms: the Salp Swarm Algorithm (SSA) and the Geometric Mean Optimiser (GMO). Unlike previous studies that treat distributed generation (DG) systems generically, this work offers a detailed modelling approach to PVDG power output and its direct impact on network performance. The framework is tested on both a standard IEEE 33-bus system and a practical Iraqi 66-bus system. Results show significant improvements in network performance after integrating optimal PVDG units, with power losses reduced by 61.334% and 61.571% using SSA and GMO, respectively, in the IEEE 33-bus system, and by 67.660% and 69.781% in the Iraqi 66-bus system. Additionally, the voltage stability index improved by 15.317% and 15.690% in the IEEE system and by 11.568% and 12.689% in the Iraqi system. The GMO algorithm demonstrated superior computational efficiency, converging faster and requiring fewer iterations than SSA. The accuracy and reliability of the results are further validated through comparison with previous work.
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1. Introduction

To address the increasing demand for electrical energy driven by growing loads in electricity distribution networks, decision-makers' interest and direction have shifted towards renewable energy, as it is environmentally friendly and helps reduce global warming [1-3]. Moreover, to the environmental benefit, renewable energy sources provide technical benefits such as decreasing active and reactive power losses, enhancing voltage profile level and stability, and increasing reliability and resilience of the system networks; also provides an economic benefit by decreasing operating and fuel costs, consequently, the economic benefit is reflected in favour of consumers [4-6]. Distribution generators, which are part of

renewable energy sources, are small units directly connected to the distribution network at precisely defined locations near load centres to ensure reliable delivery to consumers. The incorporation of distribution generators into the distribution network results in power flowing in multiple directions rather than in one [7, 8]. Therefore, the flow of power in multiple directions is one of the benefits of distributed generators to improve the performance of the distribution network. Distribution generators must be controlled, and the distribution network must not be penetrated in a large, random manner, as this negatively affects the distribution network [9, 10].

The performance of photovoltaic solar cell systems using hybrid optimisation algorithms for high-precision photovoltaic cell parameter estimation, such as the hybrid Gazelle–Nelder–Mead algorithm, enhanced slime mould algorithm, and improved tunicate swarm optimiser, is presented in Ekinici, et al. [11], Devarajah, et al. [12], Rosmizi, et al. [13]. These algorithms aim to increase the efficiency of solar systems, reduce errors in estimating operational parameters, accelerate convergence and improve overall model performance. A key feature is the introduction of innovative methodologies that combine exploration and exploitation.

The performance of distribution networks, as demonstrated in references [14-16], has been improved through the introduction of distributed generators, capacitor banks, and electric vehicles. This has led to enhanced voltage levels, reduced power losses, and increased network reliability using various methodologies. One of the most prominent features of these studies is the integration of renewable energy sources with realistic network optimisation tools, while accounting for the impact of electric vehicles.

Based on the previous analysis of distribution generation units, it is necessary to determine optimal siting and capacity to achieve optimal performance of the distribution network. Many previous studies have addressed the problem of determining optimisation strategies to enhance the performance of radial distribution networks; a group of researchers has proposed analytical methods to determine optimal placement and capacity of distribution generators [17-19]. On the other hand, optimisation algorithms have been proposed and widely utilised to solve the problems of optimal placement and sizing of distributed generators. These algorithms aim to improve voltage profiles, reduce electrical power losses, and increase network efficiency by optimising multiple power source locations and sizes. A key feature is the provision of practical solutions using advanced algorithms to achieve a balance between voltage stability and electrical losses [20-23].

In this paper, the results are compared with those of previous studies that addressed the optimal placement and sizing of distribution generators using active power loss as a single objective function. For example, Khasanov, et al. [24] proposed the Henry Gas Solubility Optimisation method to determine the optimal allocation strategy for solar distributed generator units in radial distribution networks, accounting for uncertainty. Their approach aims to improve voltage profiles, reduce power losses, and increase reliability under varying operating conditions. A key advantage of this method is the integration of multiple renewable energy sources with uncertainty analysis, which enhances the realism of the results. However, its drawbacks include the complexity of computational modelling and the difficulty of generalising results to larger networks without significant model modification.

Nagaballi and Kale [25] presented the Jaya algorithm, a modified teaching–learning–based optimisation method, and the grey wolf optimiser for the optimal distribution of generators in radial distribution networks. The paper aims to improve both technical and economic performance by reducing electrical losses, improving voltage profiles, and minimising operating costs through a multi-objective optimisation framework. A key advantage of this approach is the integration of economic analysis with technical network considerations, enabling more balanced and realistic solutions. However, the model exhibits high computational complexity, and its application to large-scale networks may require further simplification or computational resources.

Imran, et al. [26] proposed the Fireworks Algorithm to identify optimal locations for distributed generators in electrical distribution networks. The method aims to improve voltage profiles, reduce electrical losses, and enhance network efficiency by integrating network reconfiguration with distributed generator allocation. A key advantage of this approach is its comprehensive methodology, which simultaneously optimises the network's operational structure and generator placement. However, its drawbacks include limited applicability to specific network models and a lack of comprehensive analysis regarding the impacts of dynamic loads and renewable energy fluctuations.

Rao, et al. [27] presented harmony search algorithms to improve network efficiency, reduce losses, and enhance voltage profiles by modifying the network structure and optimising the distribution of distributed generators. A key advantage of this approach is the integration of network reconfiguration with distributed generator allocation, resulting in dual performance improvements. However, the study is limited by its focus on a small number of radial networks and its insufficient analysis of the impacts of load

fluctuations and renewable energy sources on system performance.

Similarly, Kowsalya [28] applied bacterial foraging optimisation to determine the optimal size and location of multiple distributed generators in electrical distribution systems, aiming to minimise power loss and improve voltage profiles while satisfying operating constraints. The results indicate that the proposed algorithm effectively avoids local optima and achieves a good balance between exploration and exploitation. However, its relatively high computation time compared with more recent algorithms may limit its applicability to large-scale networks.

El-Fergany [29] proposed the Backtracking Search Optimisation Algorithm (BSA) to improve distribution network performance by reducing electrical power losses and optimising voltage profiles through the optimal placement and sizing of multi-source generators. A key advantage of this approach is the efficient balance between exploration and exploitation, making it applicable to various generator types. However, the study is limited by its use of a small number of network scenarios and the lack of a comprehensive analysis of load fluctuations and renewable energy variability.

In contrast, Sultana and Roy [30] applied a multi-objective quasi-oppositional teaching-learning-based optimisation method, using the voltage stability index (VSI) as the sole objective function. Their research aims to identify optimal locations for distributed generators in radial networks while considering multiple objectives such as reducing power losses and improving voltage stability. The main advantages of this approach are its simplicity of implementation and flexibility in addressing multi-objective problems. However, its effectiveness depends on the initial parameter selection, and it may be prone to local optima in large or complex networks.

Furthermore, Sharma, et al. [31] proposed a quasi-oppositional, model-based optimisation algorithm with a quarantine mechanism to optimise the distribution of generators in radial distribution networks. The method aims to improve voltage profiles, reduce electrical losses, and enhance network efficiency using a nature-inspired optimisation framework. A key advantage of this approach is its innovative combination of exploration and exploitation, which improves solution accuracy. However, its complexity and limited generalizability to larger networks or varying dynamic operating conditions represent notable drawbacks.

Despite significant research efforts to identify optimal locations for PVDGs in radial distribution networks, challenges persist, including slow convergence and reliance on precise parameter tuning based on initial algorithm settings. This research gap highlights the need for more efficient optimisation

algorithms that can determine optimal locations for distributed PV in RDNs while achieving high-quality solutions with minimal iterations. This paper introduces modern algorithms that effectively balance exploration and exploitation. These algorithms are characterised by their accuracy, rapid convergence, and ability to handle the complexities of radial distribution networks.

Based on the reviewed literature, the main contributions of this paper are summarised as follows:

- The proposed optimisation techniques, SSA and GMO, are applied to determine the optimal placement and sizing of PVDGs in radial distribution networks (RDNs).
- The proposed algorithms enhance the technical and economic performance of RDNs by optimising PVDG integration.
- The algorithms are implemented using single-objective functions, including the Active Power Loss Index (APLI) and the Voltage Stability Index (VSI), as well as multiple objective functions (MOFs).
- The proposed methods are validated on a standard radial distribution network, specifically the IEEE 33-bus system.
- The proposed methods are also validated on a practical radial distribution network, namely the Iraqi 66-bus system.
- A comprehensive comparison and analysis with previous literature is conducted to verify the effectiveness of the proposed algorithms.

2. Problem Formulation

In this section, the objective is to minimise a multi-objective function (MOF) to achieve optimal integration of photovoltaic distribution generators (PVDGs). The MOF comprises the active power loss index (APLI), reactive power loss index (RPLI), voltage deviation index (VDI), the inverse of the voltage stability index (VSI), and the investment cost of PVDG units (ICDG).

2.1. Active Power Loss Index (APLI)

The first optimisation objective (OF_1) is obtained by minimising *APLI*, this objective function has been approved in previous studies [32-34] and is expressed mathematically as follows:

$$OF_1 = \min(APLI) \quad (1)$$

$$APLI = \frac{APL^{WithDG}}{APL^{WithoutDG} + APL^{WithDG}} \quad (2)$$

$$APL = \sum_{i=1}^{N_B} \sum_{\substack{j=2 \\ j \neq i, j > i}}^{N_B} \left(\frac{|V_i - V_j|}{|R_{ij} + X_{ij}|} \right)^2 \times R_{ij} \quad (3)$$

where, APL is the active power loss, N_B is the bus number of the radial distribution network, V_i is the voltage at i^{th} bus, V_j is the voltage at j^{th} bus, R_{ij} is the resistance between buses i^{th} and j^{th} , and X_{ij} is the reactance between buses i^{th} and j^{th} .

The APLI is defined using a normalisation formula that incorporates operating conditions before and after the integration of the PVDG within a single expression. This approach ensures that index values remain within a consistent range, facilitating the interpretation of results and improving numerical stability during optimisation. Moreover, it provides a balanced representation of the achieved improvement by considering both pre- and post-optimisation states, rather than relying on a single reference condition. Additionally, this normalisation helps standardise the ranges of different objective functions within a multi-objective framework, preventing the dominance of any single indicator and promoting a more balanced optimisation outcome.

2.2. Reactive Power Loss Index ($RPLI$)

The second optimisation objective (OF_2) is obtained by minimising $RPLI$, this objective function has been approved in Pon Ragothama Priya, et al. [34], Settoul, et al. [35], which is expressed mathematically by the following equations:

$$OF_2 = \min(RPLI) \quad (4)$$

$$RPLI = \frac{RPL^{WithDG}}{RPL^{WithoutDG} + RPL^{WithDG}} \quad (5)$$

$$RPL = \sum_{i=1}^{N_B} \sum_{\substack{j=2 \\ j \neq i, j > i}}^{N_B} \left(\frac{|V_i - V_j|}{|R_{ij} + X_{ij}|} \right)^2 \times X_{ij} \quad (6)$$

where RPL is the reactive power loss, N_B is the bus number of the radial distribution network, V_i is the voltage at i^{th} bus, V_j is the voltage at j^{th} bus, R_{ij} is the resistance between buses i^{th} and j^{th} , and X_{ij} is the reactance between buses i^{th} and j^{th} .

Similarly, a normalised definition of the $RPLI$ was adopted, combining the operating conditions with and without PVDG units. This definition ensures that the index values remain within a limited range, improving the reliability of the results and mitigating unwanted numerical influences. This approach also

enables a fair comparison across different operating scenarios and distribution networks with varying characteristics. From an MOF perspective, this definition contributes to more stable convergence of the algorithms used while maintaining a balance among different performance indicators.

2.3. Voltage Deviation Index (VDI)

The third optimisation objective (OF_3) is obtained by minimising VDI , this objective function has been approved in Pon Ragothama Priya, et al. [34], Selim, et al. [36], which is expressed mathematically by the following equations:

$$OF_3 = \min(VDI) \quad (7)$$

$$VDI = \left| \frac{\sum_{i=1}^{N_B} V_i}{N_B} - 1 \right| \quad (8)$$

where, N_B is the bus number of the radial distribution network, V_i is the voltage at i^{th} bus.

2.4. Voltage Stability Index (VSI)

The fourth optimisation objective (OF_4) is obtained by minimising the inverse of the VSI ; a positive value far from zero indicates a stable operating state, while a decreasing value indicates that the system is approaching the voltage breakdown limit. This objective function has been approved in Selim, et al. [36], Adepoju, et al. [37], Gao, et al. [38], which is expressed mathematically by the following equations:

$$OF_4 = \min\left(\frac{1}{VSI}\right) \quad (9)$$

$$VSI = \frac{1}{N_B} \sum_{i=1}^{N_B} \sum_{\substack{j=2 \\ j \neq i, j > i}}^{N_B} \left[|V_i|^4 - 4(P_j R_{ij} - Q_j X_{ij})^2 - 4(P_j X_{ij} - Q_j R_{ij})^2 \times |V_i|^2 \right] \quad (10)$$

where, N_B is the bus number of the radial distribution network, V_i is the voltage at i^{th} bus, P_j is the active power at j^{th} bus, Q_j is the reactive power at j^{th} bus, R_{ij} is the resistance between buses i^{th} and j^{th} , and X_{ij} is the reactance between buses i^{th} and j^{th} .

2.5. Investment Cost of PVDG (ICDG)

The fifth optimisation objective (OF_5) is obtained by minimising $ICDG$, this objective function has been adopted in Adetunji, et al. [39], Belbachir, et al. [40], which is expressed mathematically by the following equations:

$$OF_5 = \min(ICDG) \quad (11)$$

$$ICDG = \frac{1}{S_B} \sum_{i=1}^{N_{DG}} C_{DG,i} \times P_{DG,i} \quad (12)$$

$$C_{DG} = C_{Capital} + C_{O \text{ and } M} \quad (13)$$

where, S_B is the base MVA, N_{DG} is the number of PVDG installed in the radial distribution network, $C_{DG,i}$ is the cost of PVDG at i^{th} bus, $P_{DG,i}$ is the active power of PVDG at i^{th} bus, $C_{Capital}$ is the capital cost of PVDG, $C_{O \text{ and } M}$ is the operation and maintenance cost of PVDG.

The capital cost is 4,000 \$/kW, which includes the photovoltaic solar power unit, inverter, portage costs, and installation engineering [40]. With any increase in investment cost, the optimal size of PVDG units decreases to achieve the lowest MOF value, and the opposite occurs when cost decreases. In contrast, the optimal distribution locations remain relatively stable because network optimisation is more dependent on the units' spatial locations.

A *MOF* represents the sum of the objective functions that have been stated individually and can be represented mathematically by the following equation:

$$MOF = \frac{1}{N_{OF}} (OF_1 + OF_2 + OF_3 + OF_4 + OF_5) \quad (14)$$

where, N_{OF} is the number of objective functions, and is equal to 5 in this paper.

To construct the *MOF*, all five indicators used in the paper were combined into a simple average with equal weights. To ensure a balanced contribution from each indicator to the optimisation process and to prevent bias arising from scale differences and the physical nature of each indicator, all values were pre-normalised so that they fell within the range [0, 1] before being combined. This approach ensures the MOF is balanced and reliable and allows the use of a simple average weight without specifying additional weights for each indicator.

2.6. Equality and Inequality Constraints

To implement an MOF, a set of equality and inequality constraints must be satisfied, and the active and reactive power must be balanced, such as equality constraints, which are expressed mathematically by the following equations:

$$P_{slack} + \sum_{i=1}^{N_{DG}} P_{DG,i} = \sum_{i=1}^{N_B} P_i^D + APL \quad (15)$$

$$Q_{slack} = \sum_{i=1}^{N_B} Q_i^D + RPL \quad (16)$$

where, P_{slack} is the active power generation from the slack bus (bus 1), Q_{slack} is the reactive power generation from the slack bus (bus 1), N_{DG} is the number of PVDG installed in the radial distribution network, $P_{DG,i}$ is the active power of PVDG at i^{th} bus, N_B is the bus number of the radial distribution network, P_i^D is the total active power demand of the radial distribution network, Q_i^D is the total reactive power demand of the radial distribution network.

Distributed generators (DGs) can be classified into four main types based on the nature of the power they inject into the grid, as widely discussed in the literature [10, 18, 29]:

- Type 1: Injects only active power and operates at a unit power factor without generating reactive power.

A common example of this type is the photovoltaic (PV) systems.

- Type 2: Injects only reactive power and operates at a zero-power factor without generating active power.

Examples include synchronous compensators and VAR compensators.

- Type 3: Injects active power while absorbing reactive power from the grid. A common example of this type is the induction generators used in wind farms.

- Type 4: Injects both active and reactive power into the grid. Examples include synchronous generators and cogeneration units.

Based on this classification, this paper focuses exclusively on Type 1 distribution generators, where PVDGs are modelled as injecting only active power, without contributing to reactive power, a common assumption adopted in many previous studies.

While the voltage limits and PVDG unit limits, such as inequality constraints, are expressed mathematically by the following equations:

$$V_i^{min} \leq V_i \leq V_i^{max} \quad (17)$$

$$P_{DG,i}^{min} \leq P_{DG,i} \leq P_{DG,i}^{max} \quad (18)$$

$$\sum_{i=1}^{N_{DG}} P_{DG,i} \leq \sum_{i=1}^{N_B} P_i^D + APL \quad (19)$$

$$2 \leq DG_{Location} \leq N_B \quad (20)$$

where, V_i is the voltage at i^{th} bus, V_i^{min} is the minimum voltage at i^{th} bus, V_i^{max} is the maximum voltage

at i^{th} bus, $P_{DG,i}$ is the active power of PVDG at i^{th} bus, $P_{DG,i}^{\min}$ is the minimum active power of PVDG at i^{th} bus, $P_{DG,i}^{\max}$ is the maximum active power of PVDG at i^{th} bus, N_{DG} is the number of PVDG installed in the radial distribution network, N_B is the bus number of the radial distribution network, P_i^D is the total active power demand of the radial distribution network, DG_{Location} is the location of PVDG in the radial distribution network.

3. Optimisation Algorithms

In this section, modern optimisation algorithms are adopted to determine the optimal locations and capacities of photovoltaic distribution generators (PVDGs) in radial distribution networks (RDNs). The optimisation methods used include the Salp Swarm Algorithm (SSA) and the Geometric Mean Optimiser (GMO). The overall optimisation framework is implemented according to the flowchart shown in Figure 1, where all algorithms follow the same general execution sequence. The detailed working mechanisms of SSA and GMO are explained separately in Sections 3.1 and 3.2, respectively, as indicated by the red rectangle in Figure 1.

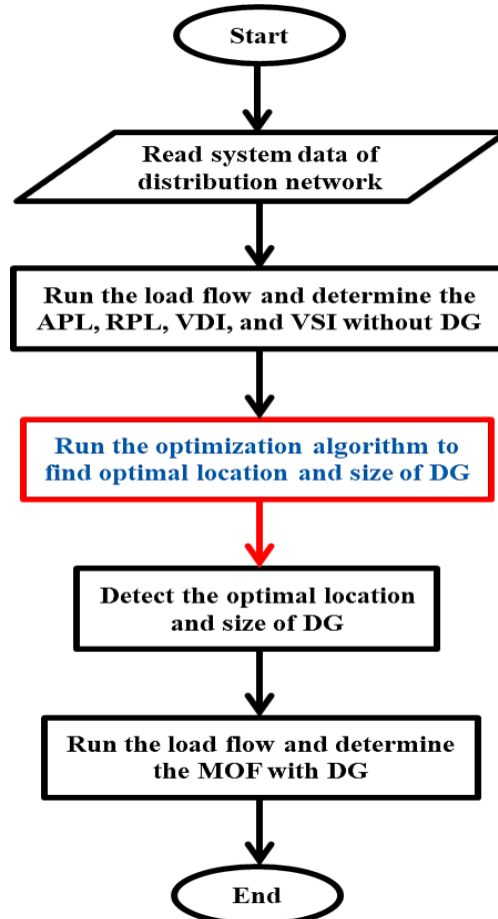


Figure 1. Flowchart of the proposed optimisation algorithms (SSA and GMO)

Furthermore, load flow analysis is performed using the Backward/Forward Sweep (BFS) method [41, 42], due to its high suitability for radial distribution networks and its numerical efficiency. Table 1 lists the parameters of the proposed optimisation algorithms and the operational constraints used for load-flow analysis of both the IEEE 33-bus system and the Iraqi 66-bus distribution system.

Table 1. Parameters of SSA or GMO to find the allocation of PVDG

Parameters of SSA or GMO	IEEE 33 Bus	Iraqi 66 Bus
No. of population or agent	50	50
Max. iteration	50	50
DG location (LB)	2	2
DG location (UB)	33	66
DG size (LB)	300	500
DG size (UB)	1500	3000
Max. voltage	1.05	1.05
Min. voltage	0.95	0.95

3.1. Salp Swarm Algorithm (SSA)

The SSA uses the swarm method and, to search for food, relies on the properties of the salp chain. The mathematical representation of the SSA is classified into two groups of the population. The leader is located at the front of the population group in the salp chain. At the same time, the rest of the population follows the leader [36, 43]. The leader's salp location is updated mathematically by the following equation:

$$x_j^1 = \begin{cases} F_j + c_1 ((ub_j - lb_j)c_2 + lb_j) & c_3 \geq 0.5 \\ F_j - c_1 ((ub_j - lb_j)c_2 + lb_j) & c_3 < 0.5 \end{cases} \quad (21)$$

where, x_j^1 is the location of the salp leader in j^{th} dimension, F_j is the location of the food in j^{th} dimension, ub_j is the upper bound indicator in j^{th} dimension, lb_j is the lower bound indicator in j^{th} dimension, c_2 and c_3 are random coefficient numbers lie between 0 and 1.

The coefficient c_1 is a very important parameter to achieving a balance between exploration and exploitation, which is expressed mathematically by the following equation:

$$c_1 = 2 \exp^{-\left(\frac{4 \times iter}{maxiter}\right)^2} \quad (22)$$

While the followers of salps locations are updated mathematically by the following equation:

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}) \quad (23)$$

where, $i \geq 2$ and x_j^i refers to the location of i^{th} follower salp in j^{th} dimension.

Figure 2 illustrates the flowchart for detecting the optimal siting and capacity of PVDG in radial distribution networks using SSA, and Figure 3 shows the pseudo-code algorithm for the optimal allocation of PV-DG.

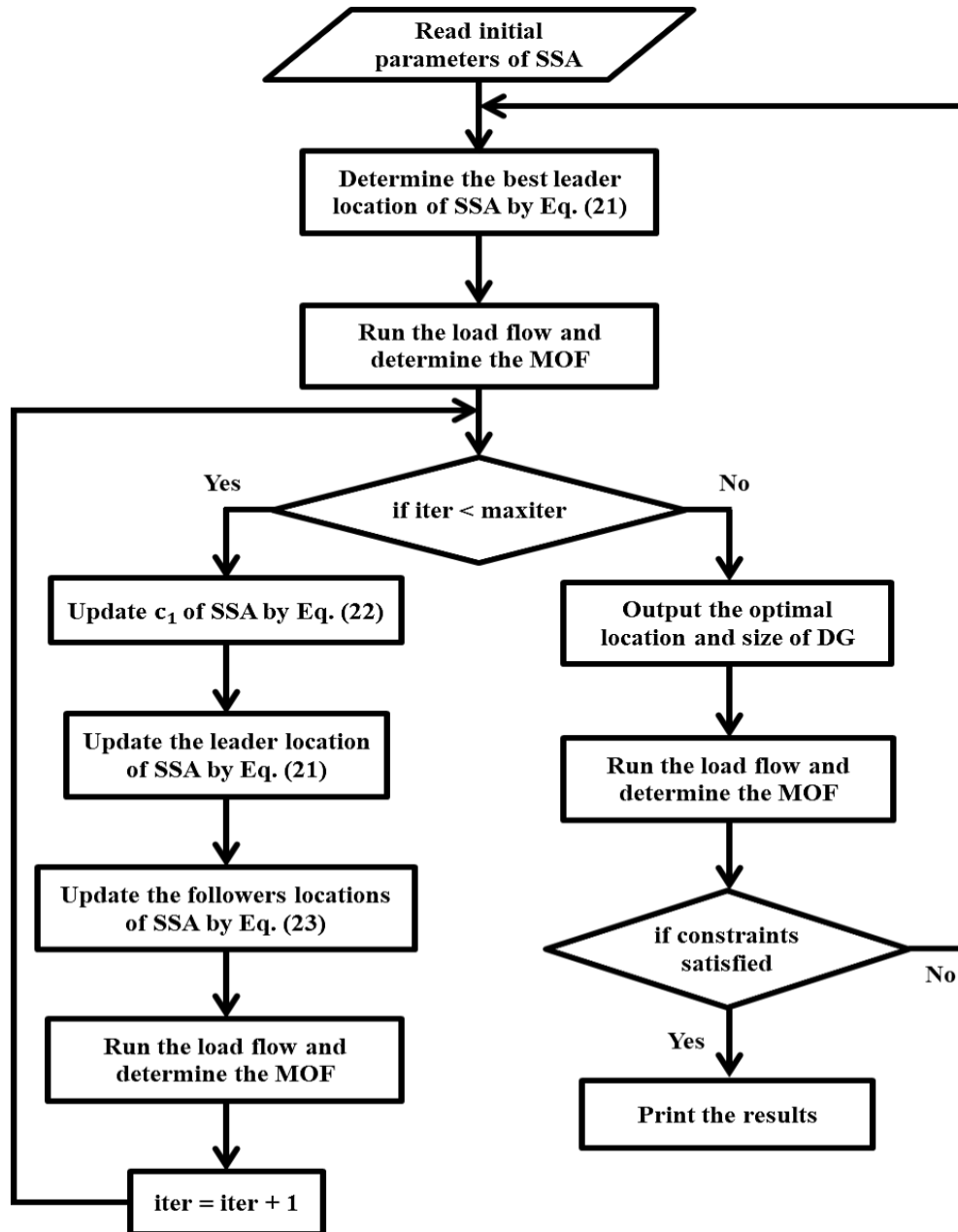


Figure 2. Flowchart of the proposed SSA to find the optimal allocation of PV-DG

3.2. Geometric Mean Optimiser (GMO)

The GMO is a new optimisation technique that mathematically simulates the qualitative characteristics of the geometric mean operator. This operator can evaluate the objective function and diversity of search agents in the search space simultaneously. In GMO, the weight of each agent is calculated based on its geometric meaning, taking into account the measured objective values it opposes.

Therefore, the optimisation problem can be solved in relation to the agent's situation to guide other agents [44, 45]. Applying the GMO mathematically can be done using the following steps:

```

Initialize SSA parameters  $N$ ,  $maxiter$ , ...etc
Generate initial salp positions randomly within bounds
 $iter = 1$ 
Determine the initial leader position using Eq. (21)
Run load flow and evaluate the objective function (MOF)
while  $iter \leq maxiter$  do
    Update control parameter  $c_1$  using Eq. (22)
    Update leader position using Eq. (21)
    for  $i = 2:N$  do
        Update follower position using Eq. (23)
    end for
    for  $i = 1:N$  do
        Run load flow for salp  $i$ 
        Evaluate MOF( $i$ )
    end for
    if constraints are satisfied then
        Identify the salp with minimum MOF
        Update leader position with the best feasible solution
    end if
     $iter = iter + 1$ 
end while
Output the optimal DG location and size
Print the final results

```

Figure 3. The pseudo-code algorithm of SSA for optimal PV-DG allocation

Compute the fuzzy Membership Function (MF) for all agents by the following equation:

$$MF_j^{iter} = \frac{1}{1 + \exp\left(-\frac{4}{\sigma^{iter}\sqrt{e}} \times (Z_{best,j}^{iter} - \mu^{iter})\right)}; j = 1, 2, \dots, N \quad (24)$$

where, MF_j^{iter} is the MF value of the j^{th} personal best agent at the current iteration, $Z_{best,j}^{iter}$ is the objective function value of the j^{th} personal best agent at the current iteration, σ^{iter} and μ^{iter} are the standard deviation and mean deviation of the objective function values of all agents at the current iteration.

Compute the Dual Fitness Index (DFI) for a search agent by the following equation:

$$DFI_i^{iter} = MF_1^{iter} \times \dots \times MF_{i-1}^{iter} * MF_{i+1}^{iter} \times \dots \times MF_N^{iter} = \prod_{\substack{j=1 \\ j \neq i}}^N MF_j^{iter} \quad (25)$$

where, DFI_i^{iter} is the DFI of the i^{th} agent at the current iteration, N is the number of agents in the population.

Compute the locations of guide agents by the following equation:

$$Y_i^{iter} = \frac{\sum_{j \in N_{best}, j \neq i} DFI_j^{iter} \times X_j^{best}}{\sum_{j \in N_{best}} DFI_j^{iter} + \varepsilon} \quad (26)$$

where Y_i^{iter} is the location vector of the unique global guide agent computed for the agent i^{th} at the current iteration, DFI_j^{iter} is the DFI of the j^{th} agent at the current iteration, X_j^{best} is the best location vector of the j^{th} search agent, ε is a very small positive number to prevent singularity.

Then, the Gaussian mutation strategy is incorporated to increase the diversity of the guide agents. The following equation expresses this mutation strategy:

$$Y_{i,mut}^{iter} = Y_i^{iter} + w * randn \times (Std_{max}^{iter} - Std^{iter}) \quad (27)$$

where, $Y_{i,mut}^{iter}$ represent the mutated version of Y_i^{iter} , which is used to guide the search agents at the current iteration. Y_i^{iter} denotes the location vector of the unique global guide agent computed for the i^{th} agent at the current iteration. $randn$ represents a random number drawn from a standard normal distribution. Std_{max}^{iter} denotes the maximum standard deviation value of the best agents at the current iteration, while. Std^{iter} represents the standard deviation vector computed for the best agents at the same iteration. The parameter w is used to reduce the mutated step size and is expressed by the following equation:

$$w = 1 - \frac{iter}{maxiter} \quad (28)$$

At the update, the velocity and location of agents are expressed by the following equations:

$$V_i^{iter+1} = w \times V_i^{iter} + \varphi \times (Y_{i,mut}^{iter} - X_i^{iter}); \varphi = 1 + (2 \times rand - 1) \times w \quad (29)$$

$$X_i^{iter+1} = X_i^{iter} + V_i^{iter+1} \quad (30)$$

where, V_i^{iter+1} is the velocity of i^{th} agent at $(iter + 1)$ iteration, V_i^{iter} is the velocity of i^{th} agent at the current iteration, X_i^{iter+1} is the location of i^{th} agent at $(iter + 1)$ iteration, X_i^{iter} is the location of i^{th} agent at the current iteration, $Y_{i,mut}^{iter}$ represent the mutated of Y_i^{iter} used for guide search agents at current iteration, φ is a measuring parameter number, $rand$ is a random coefficient number that lies between 0,1.

The main reason for the effectiveness of the GMO is its ability to simulate the collective behaviour of biological groups when searching for optimal solutions, thereby avoiding local optima and achieving more accurate results. Figure 4 illustrates the flowchart for determining the optimal siting and capacity of

PVDGs in radial distribution networks using the GMO, while Figure 5 presents the pseudo-code of the GMO algorithm for optimal PV-DG allocation.

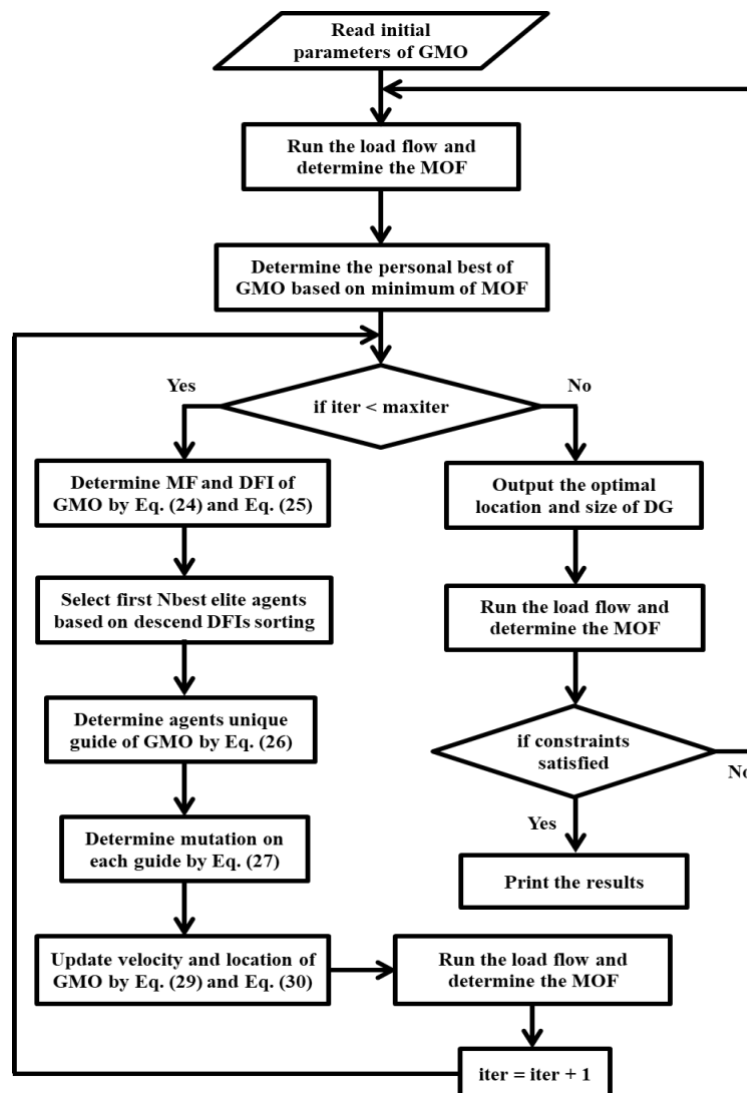


Figure 4. Flowchart of the proposed GMO to find the optimal allocation of PV-DG

4. Study and Simulation Results

In this section of the paper, the proposed optimisation techniques have been applied to the standard IEEE 33-BUS network and the practical BAQ-EAST-TAHREER 66-BUS network. The results were obtained from several runs of 20, and the specifications of the personal computer are: Intel(R) Core(TM) i5-7200U CPU @ 2.50 GHz, Installed RAM: 4.00 GB.

4.1. Test 1: IEEE 33 BUSES

IEEE 33 BUS consists of 32 lines, the base voltage is 12.66 kV, the base MVA is 100 MVA, and the one line diagram is shown in Figure 6, node 1 (green node) is the slack bus and all other buses (red nodes) are load buses; the total active power load is 3715 kW while the total reactive power load is 2300 kVAr

[46]. The total active power loss (APL) is 210.99 kW, the total reactive power loss (RPL) is 143.03 kVAr, the voltage deviation index (VDI) is 0.0547, and the voltage stability index (VSI) is 0.8043, which represent the power flow results of IEEE 33 BUS at the base case. To demonstrate the effectiveness of the proposed optimisation algorithms, two cases were carried out: a single-objective function and comparisons with previous papers, and a third case applied to multi-objective functions.

```

Initialize GMO parameters  $N$ ,  $maxiter$ , ...etc
Generate initial agents' positions and velocities
iter = 1
Run load flow and evaluate MOF for all agents
Determine  $p\_best$  of each agent based on the minimum MOF
while iter  $\leq$   $maxiter$  do
    Determine MF and DFI for all agents using Eq. (24) and Eq. (25)
    Sort agents in descending order based on DFI
    Select the first  $N\_best$  elite agents
    Determine the unique guide of each agent using Eq. (26)
    Apply geometric mutation on each guide using Eq. (27)
    Update velocity of agents using Eq. (29)
    Update position of agents using Eq. (30)
    for  $i = 1:N$  do
        Run load flow for all agents
        Evaluate MOF for all solutions
    end for
    if constraints are satisfied then
        Update personal bests and global best solution
    end if
    iter = iter + 1
end while
Output the optimal DG location and size
Print the final results

```

Figure 5. The pseudo-code algorithm of GMO for Optimal PV-DG Allocation

Case 1: Single Objective Function (APL)

To determine the optimal placement and capacity of PVDGs using APL as the single objective function, the simulation results for the optimisation techniques (SSA and GMO) are presented in Table 2. The results show that APL is reduced from 210.99 kW to 74.12 kW and 73.51 kW using SSA and GMO, respectively. The GMO outperforms SSA. This superiority is also evident from the convergence behaviour illustrated in Figure 7a, where GMO converges more rapidly to the best solution (minimum APL) than SSA. In addition, Figure 7b presents the boxplots of the proposed techniques, further demonstrating the superior performance of the GMO over the SSA. The statistical performance metrics for this case, including the average (mean), standard deviation (SD), execution time (runtime), and best solution, are summarised in Table 3.

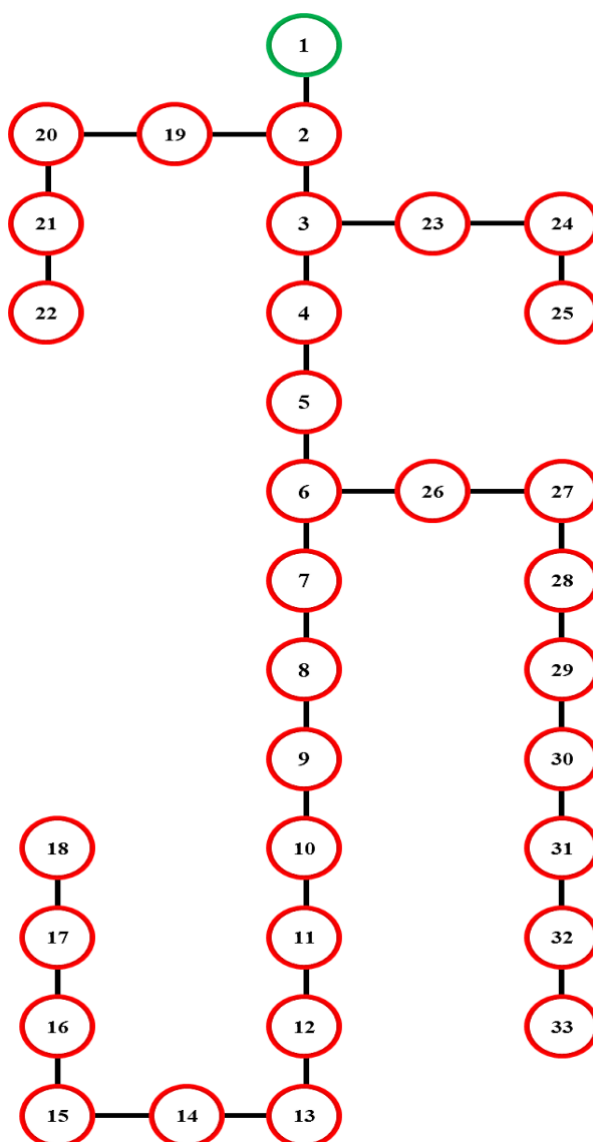


Figure 6. One line diagram of IEEE 33 BUSES

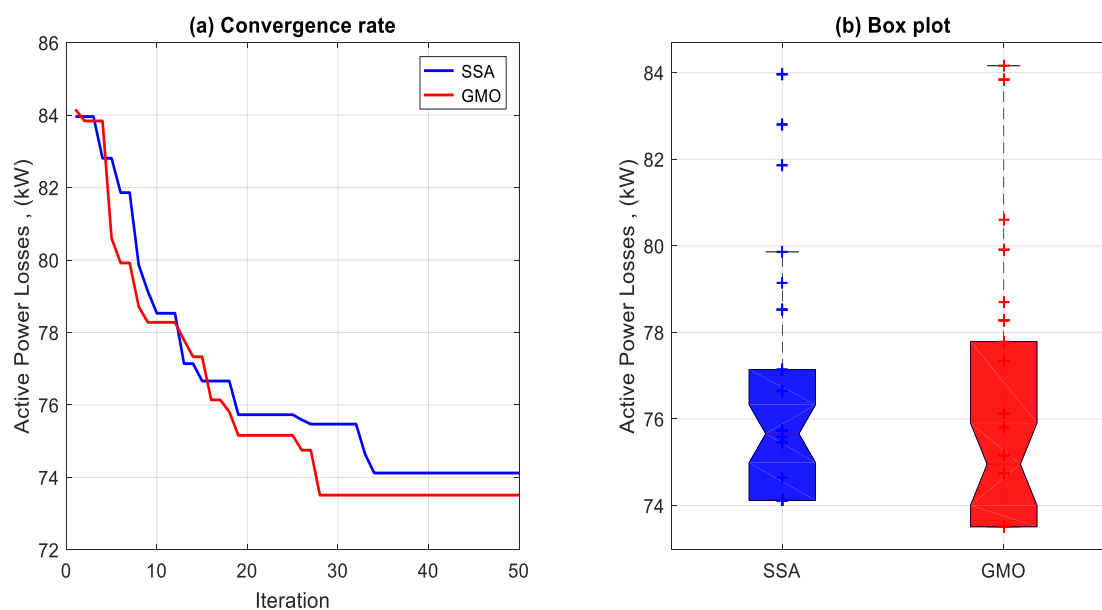


Figure 7. SSA and GMO for APL (IEEE 33 BUS), (a) Convergence rate, (b) Box plot

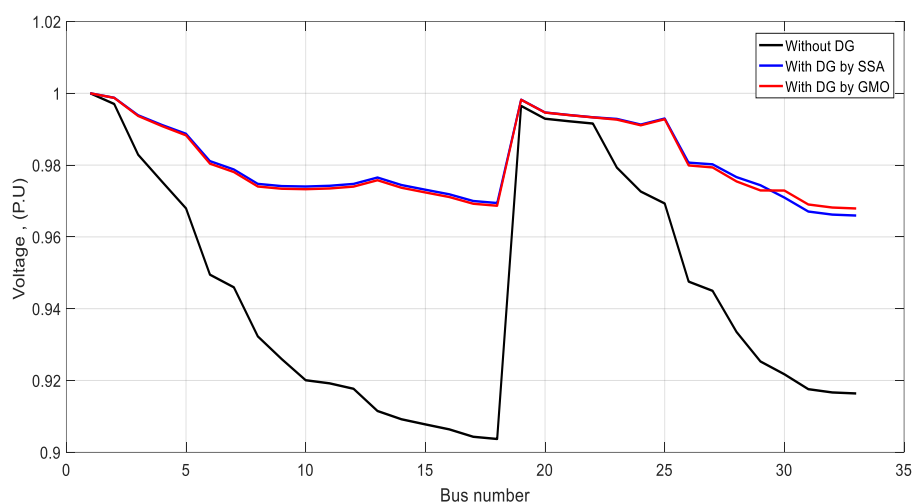
Table 2. Results of PVDG with minimised APL (IEEE 33 BUS)

Method	DG location	DG size (kW)	APL (kW)
SSA	13, 25, 29	822.6, 884.3, 1121.7	74.12
GMO	13, 25, 30	821.3, 883.5, 1069.4	73.51

Table 3. The statistical performance for case 1 with minimised APL (IEEE 33 BUS)

Method	Mean	SD	Best	Runtime
SSA	75.53	0.94	74.12	11.704
GMO	74.28	0.82	73.51	10.152

Furthermore, the overall performance of the RDN is enhanced by minimising the APL. The voltage profile is significantly improved, as illustrated in Figure 8, where all bus voltages remain above the minimum voltage limit of 0.95 p.u. after incorporating the PVDGs. In addition, to demonstrate the effectiveness of the proposed algorithms, the results obtained are compared with those reported in previous studies, as shown in Table 4.

**Figure 8.** The voltage profile of case 1 (IEEE 33 BUS)**Table 4.** Comparison results of PVDG with minimised APL (IEEE 33 BUS)

Method	DG location	DG size (kW)	APL (kW)
HGSO [24]	12, 24, 27	919.25, 504.82, 1237	83.98
JAYA [25]	12, 25, 29	1110, 795, 921	76.66
MTLBO [25]	15, 23, 32	885, 1066, 847	80.22
GWO [25]	12, 25, 30	955, 889, 1037	74.1
FWA [26]	14, 18, 32	589.7, 189.5, 1014.6	88.68
HSA [27]	17, 18, 33	572.4, 107, 1046.2	96.76
BFOA [28]	14, 18, 32	652.1, 198.4, 1067.2	89.9
BSOA [29]	13, 28, 31	632, 487, 550	89.05
Propose SSA	13, 25, 29	822.6, 884.3, 1121.7	74.12
Propose GMO	13, 25, 30	821.3, 883.5, 1069.4	73.51

Case 2: Single Objective Function (VSI)

The simulation results for the optimisation techniques (SSA and GMO) for determining the optimal siting and capacity of PVDGs, using the voltage stability index (VSI) as the single objective function, are presented in Table 5. In the base case, the VSI is 0.8043; it increases to 0.9779 and 0.9792 with SSA and GMO, respectively. The GMO achieves a higher VSI value than the SSA. Figure 9a illustrates the convergence characteristics of the optimisation algorithms, showing that the GMO converges closer to the optimal solution (maximum VSI) than the SSA. In addition, Figure 9b presents the boxplots of the proposed techniques, further demonstrating the superior performance of the GMO over the SSA. The statistical performance metrics for this case, including the average (mean), standard deviation (SD), execution time (runtime), and best solution, are summarised in Table 6.

Table 5. Results of PVDG with maximising VSI (IEEE 33 BUS)

Method	DG location	DG size (kW)	VSI (P.U)	1/ VSI (P.U)
SSA	12, 16, 32	1015.6, 1211.3, 1008.8	0.9779	1.0225
GMO	10, 15, 31	1065.2, 961.4, 1156.8	0.9792	1.0212

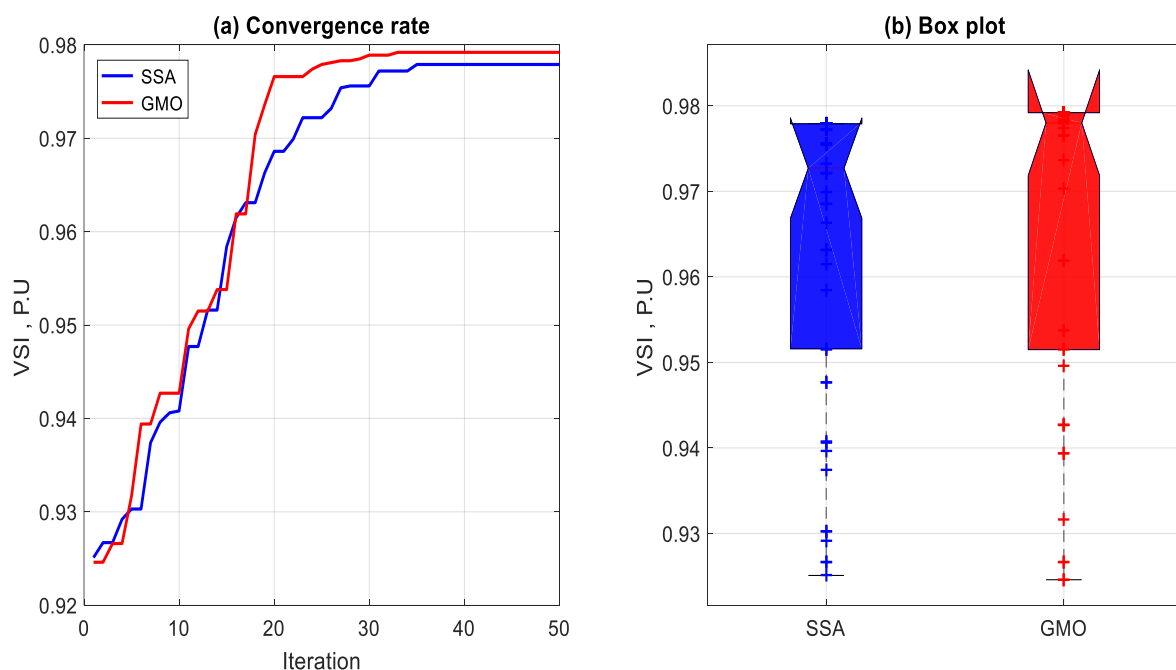


Figure 9. SSA and GMO for VSI (IEEE 33 BUS), (a) Convergence rate, (b) Box plot

Table 6. The statistical performance for case 2 with maximising VSI (IEEE 33 BUS)

Method	Mean	SD	Best	Runtime
SSA	0.9584	0.0214	0.9779	11.682
GMO	0.9698	0.0107	0.9792	10.237

Moreover, the overall performance of the RDN is enhanced by maximising the VSI. The voltage profile is significantly improved, as illustrated in Figure 10, where all bus voltages remain above the minimum limit of 0.95 p.u. after integrating the PVDGs. In addition, to demonstrate the effectiveness of the proposed algorithms, the results obtained are compared with those reported in previous studies, as shown in Table 7.

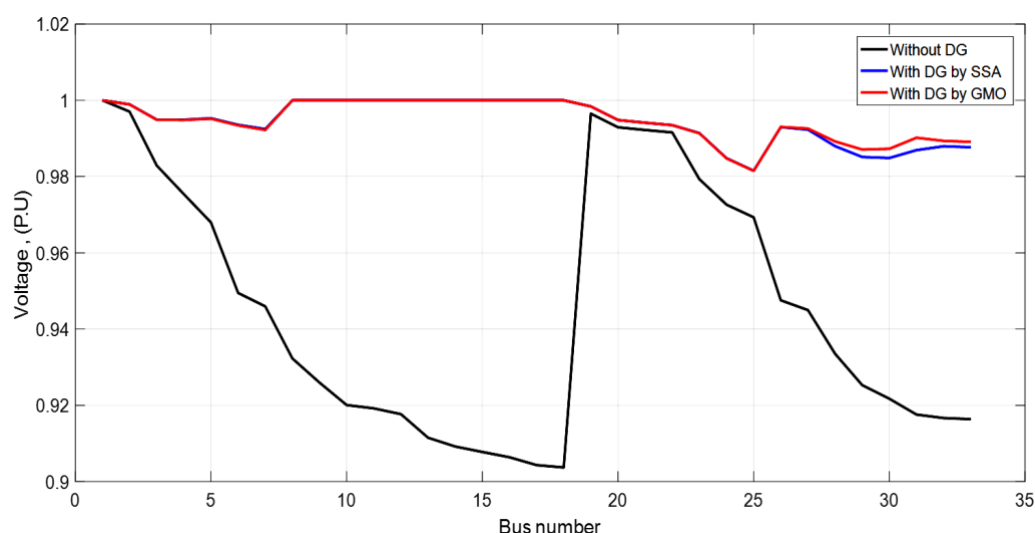


Figure 10. The voltage profile of case 2 (IEEE 33 BUS)

Table 7. Comparison results of PVDG with maximising VSI (IEEE 33 BUS)

Method	DG location	DG size (kW)	VSI (P.U)	1/ VSI (P.U)
TLBO [30]	8, 12, 31	1199.3, 1199.6, 1199.2	0.9604	1.0412
QTLBO [30]	6, 11, 29	1199.8, 1200, 1198.3	0.9618	1.0397
SIMBO-Q [31]	18, 24, 32	1427, 1076.1, 1462.3	0.9666	1.0346
QOSIMBO-Q [31]	12, 24, 33	1500, 1500, 1500	0.9772	1.0233
Propose SSA	12, 16, 32	1015.6, 1211.3, 1008.8	0.9779	1.0225
Propose GMO	10, 15, 31	1065.2, 961.4, 1156.8	0.9792	1.0212

Case 3: Multi-Objective Functions (MOF)

In this case, multiple objective functions (MOFs), including the active power loss index (APLI), reactive power loss index (RPLI), voltage deviation index (VDI), the inverse of the voltage stability index (VSI), and the investment cost of PVDG (ICDG), are considered to determine the optimal siting and sizing of PVDGs for the radial distribution system (RDS). The overall performance of the IEEE 33-bus system is improved after integrating PVDGs into the network. The optimisation techniques (SSA and GMO) demonstrate their effectiveness and superiority compared to the base case results. Additionally, the MOF values obtained with the GMO converge faster and more smoothly than those obtained with SSA, as shown

in Figure 11a. Figure 11b presents boxplots of the optimisation techniques, clearly showing the dominance of the GMO over the SSA. The statistical performance metrics for this case, including the average (mean), standard deviation (SD), execution time (runtime), and best solution, are summarised in Table 9.

Table 8. Results of PVDG with MOF (IEEE 33 BUS)

	SSA	GMO
	17	7
DG location	23	16
	30	31
DG size (kW)	634.4	1084.1
	1042.7	519.5
	1294.1	946.6
APL (kW)	81.58	81.08
RPL (kVAr)	58.71	56.97
VDI (P.U)	0.0188	0.0180
VSI (P.U)	0.9275	0.9305
APLI (P.U)	0.2788	0.2776
RPLI (P.U)	0.2910	0.2848
ICDG (\$)	0.1194	0.1025
MOF	0.3572	0.3515

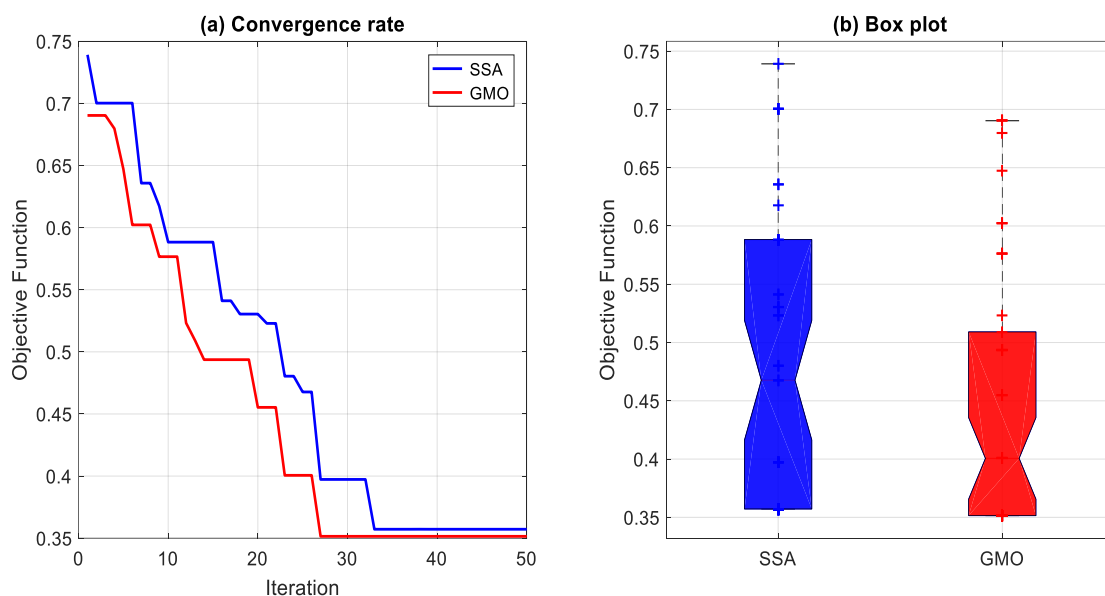


Figure 11. SSA and GMO for MOF (IEEE 33 BUS), (a) Convergence rate, (b) Box plot

Table 9. Statistical performance for case 3 with minimising MOF (IEEE 33 BUS)

Method	Mean	SD	Best	Runtime
SSA	0.4027	0.0319	0.3572	11.818
GMO	0.3752	0.0174	0.3515	10.309

On the other hand, to demonstrate the effectiveness of the proposed optimisation algorithms in determining the optimal placement and capacity of PVDGs for the IEEE 33-bus system, Figure 12 shows the improvement in VSI, while Figure 13 illustrates the reduction in APL.

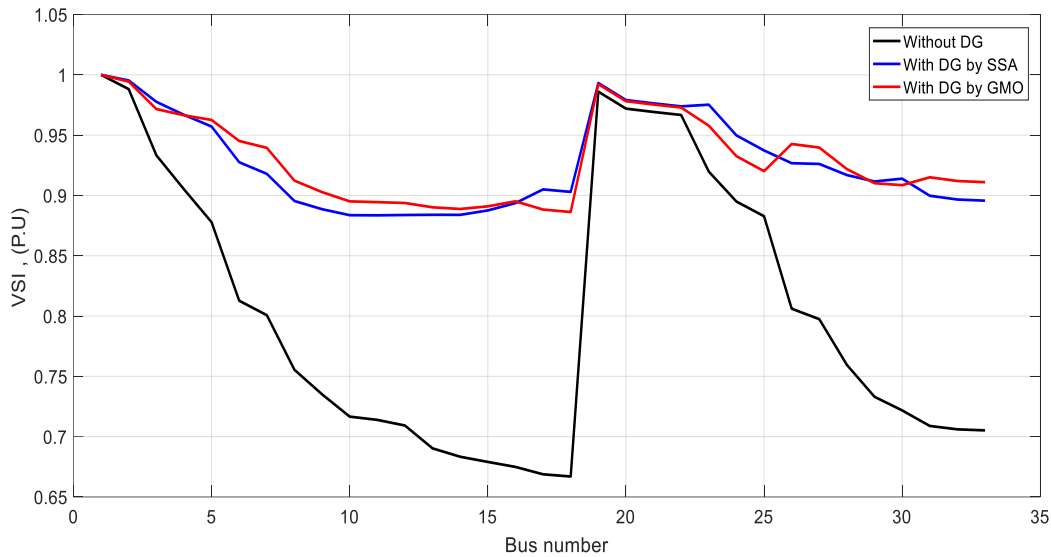


Figure 12. VSI of case 3 (IEEE 33 BUS)

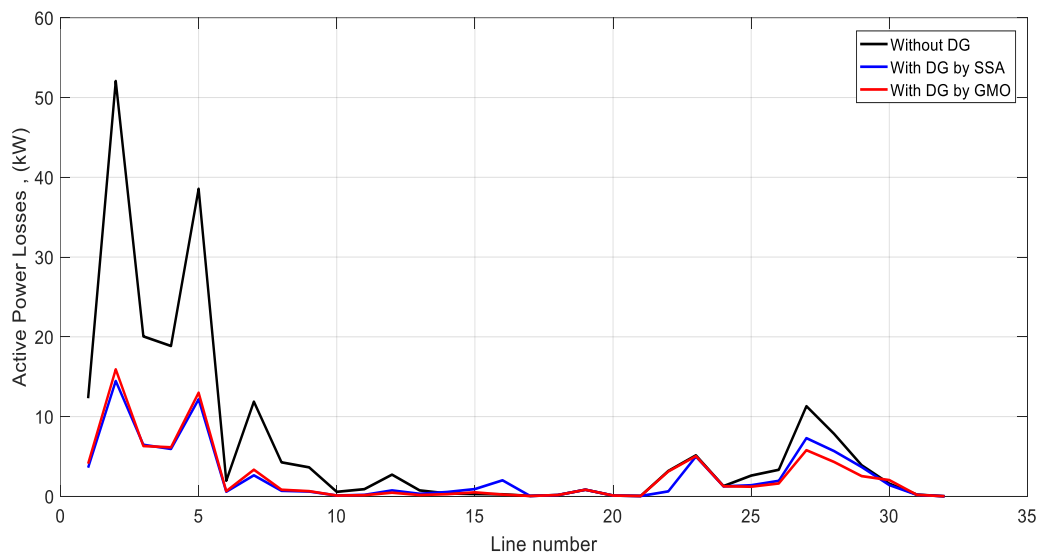


Figure 13. APL of case 3 (IEEE 33 BUS)

4.2. Practical 1: BAQ-EAST-TAHREER 66 BUSES

The BAQ-EAST-TAHREER 66-bus system consists of 65 lines. The base voltage is 11 kV, and the base power is 100 MVA. Line data are provided in Table 10, and the single-line diagram is shown in Figure 14. Node 1 (green) is the slack bus, the red nodes represent load buses, and the blue nodes denote connection buses (load buses not connected to distribution transformers). The total active power load is 8651 kW, while the total reactive power load is 5354 kVAr. In the base case, the total active power loss (APL) is 429.11 kW, the total reactive power loss (RPL) is 486.44 kVAr, the voltage deviation index (VDI) is 0.0592,

and the voltage stability index (VSI) is 0.7849.

Table 10. Line data of BAQ-EAST-TAHREER 66 BUSES

Line NO.	From Bus	To Bus	R(Ohm)	X(Ohm)	Line NO.	From Bus	To Bus	R(Ohm)	X(Ohm)
1	1	2	0.0934	0.0753	34	33	35	0.0433	0.0532
2	2	3	0.0365	0.0449	35	34	36	0.0151	0.0184
3	3	4	0.0919	0.1131	36	36	37	0.0365	0.0449
4	4	5	0.0146	0.0180	37	37	38	0.0131	0.0161
5	4	6	0.0123	0.0151	38	34	39	0.0562	0.0691
6	6	7	0.0161	0.0198	39	39	40	0.0187	0.0231
7	7	8	0.0177	0.0218	40	40	41	0.0121	0.0148
8	4	9	0.1545	0.1854	41	40	42	0.0122	0.0149
9	9	10	0.0067	0.0083	42	42	43	0.0175	0.0215
10	10	11	0.0193	0.0238	43	43	44	0.0079	0.0098
11	11	12	0.0198	0.0243	44	43	45	0.0067	0.0083
12	12	13	0.0445	0.0547	45	45	46	0.0093	0.0114
13	13	14	0.0336	0.0413	46	46	47	0.0084	0.0104
14	14	15	0.0091	0.0111	47	46	48	0.0068	0.0084
15	15	16	0.0075	0.0092	48	48	49	0.0171	0.0211
16	16	17	0.0554	0.0681	49	49	50	0.0446	0.0548
17	16	18	0.0563	0.0692	50	49	51	0.0307	0.0377
18	15	19	0.0559	0.0688	51	51	52	0.0061	0.0076
19	19	20	0.0152	0.0187	52	52	53	0.0162	0.0199
20	20	21	0.0061	0.0074	53	53	54	0.0927	0.1140
21	21	22	0.0119	0.0146	54	29	55	0.0365	0.0449
22	22	23	0.0139	0.0171	55	55	56	0.0161	0.0197
23	23	24	0.0183	0.0225	56	56	57	0.0201	0.0246
24	24	25	0.0181	0.0223	57	56	58	0.0149	0.0183
25	25	26	0.0103	0.0127	58	58	59	0.0369	0.0454
26	25	27	0.0135	0.0166	59	59	60	0.0171	0.0211
27	19	28	0.0324	0.0398	60	59	61	0.0293	0.0361
28	18	29	0.0291	0.0357	61	61	62	0.0127	0.0157
29	18	30	0.0071	0.0087	62	62	63	0.0424	0.0522
30	30	31	0.0178	0.0219	63	63	64	0.0287	0.0353
31	31	32	0.0464	0.0571	64	63	65	0.0449	0.0553
32	29	33	0.0424	0.0522	65	63	66	0.0193	0.0237
33	33	34	0.0319	0.0393					

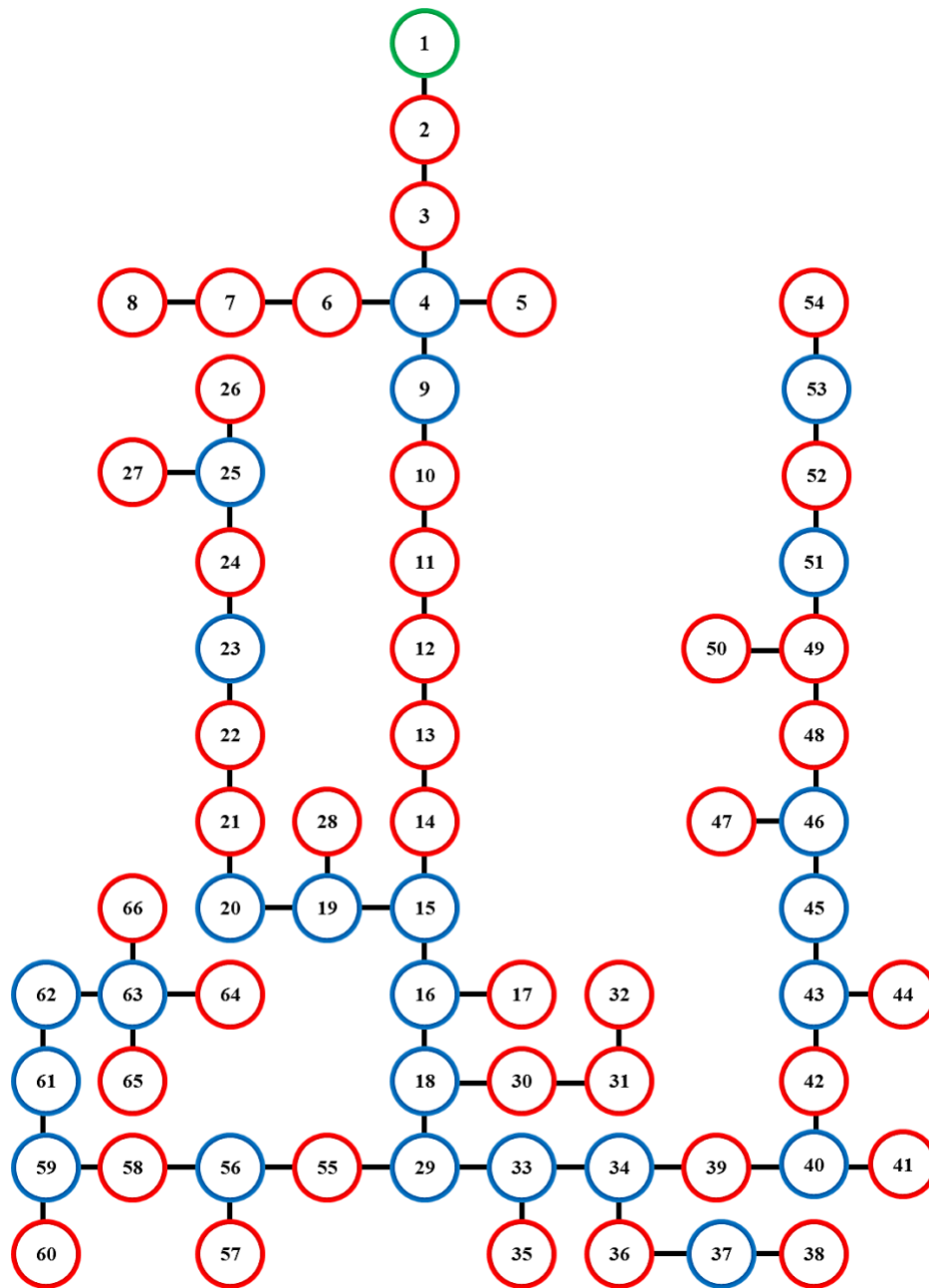


Figure 14. One line diagram of IRAQI 66 BUSES

To validate the efficiency and effectiveness of the proposed techniques, SSA and GMO are applied to the Iraqi 66-bus system to determine the optimal location and capacity of PVDGs based on the MOF. The results are presented in Table 11, showing clear improvements in system performance after adding PVDGs.

Moreover, when comparing the proposed algorithms, the GMO technique is observed to be superior to the SSA technique. As shown in Figure 15a, the GMO converges to the optimal solution faster and with fewer iterations than SSA. Similarly, Figure 15b presents the boxplots, which clearly demonstrate the dominance of the GMO over the SSA. The statistical performance metrics for the Iraqi 66-bus system,

including the average (mean), standard deviation (SD), execution time (runtime), and best solution, are summarised in Table 12.

Table 11. Results of PVDG with minimising MOF (IRAQI 66 BUS)

	SSA	GMO
DG location	16	12
	40	42
	57	55
DG size (kW)	2658.7	2463.6
	1822.2	2298.7
	1181.7	1754.2
APL (kW)	138.77	129.67
RPL (kVAr)	156.60	147.04
VDI (P.U)	0.0328	0.0303
VSI (P.U)	0.8757	0.8845
APLI (P.U)	0.2443	0.2320
RPLI (P.U)	0.2435	0.2321
ICDG (\$)	0.2276	0.2619
MOF	0.3780	0.3773

Consequently, the performance of the Iraqi 66-bus system improves after integrating PVDGs. The improvements in voltage profile and VSI are shown in Figures 16 and 17, respectively, while the reductions in APL and RPL are presented in Figures 18 and 19, respectively.

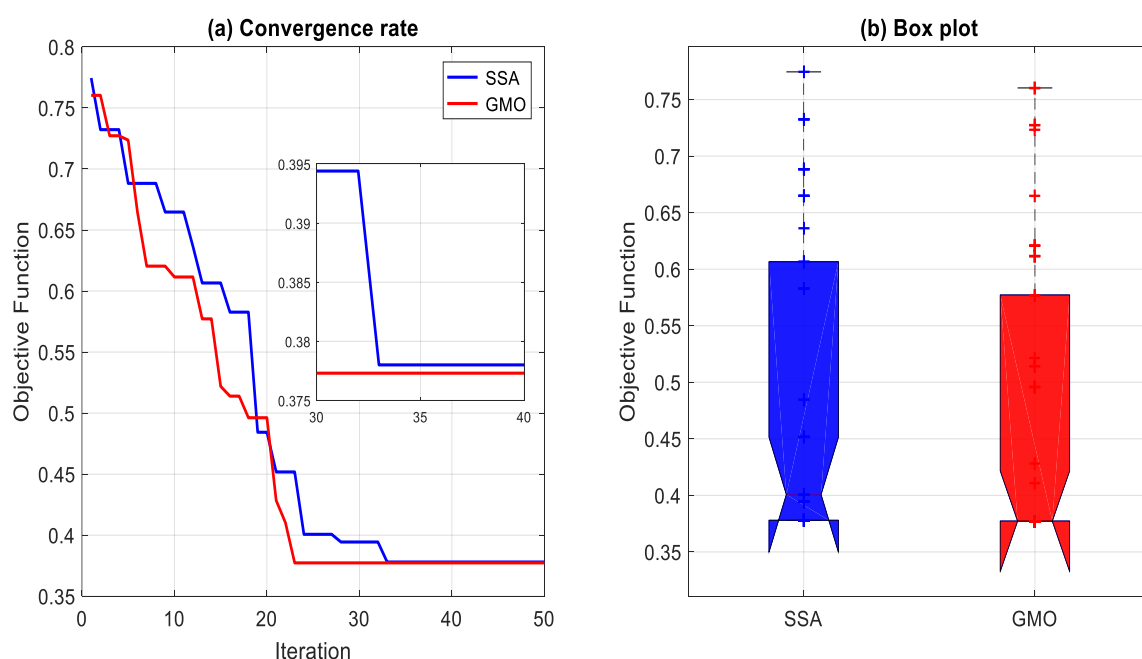
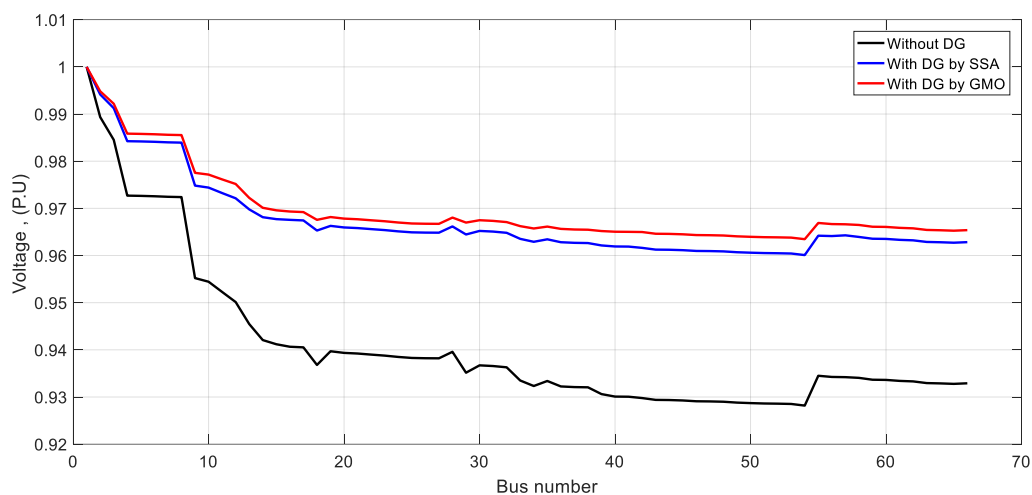
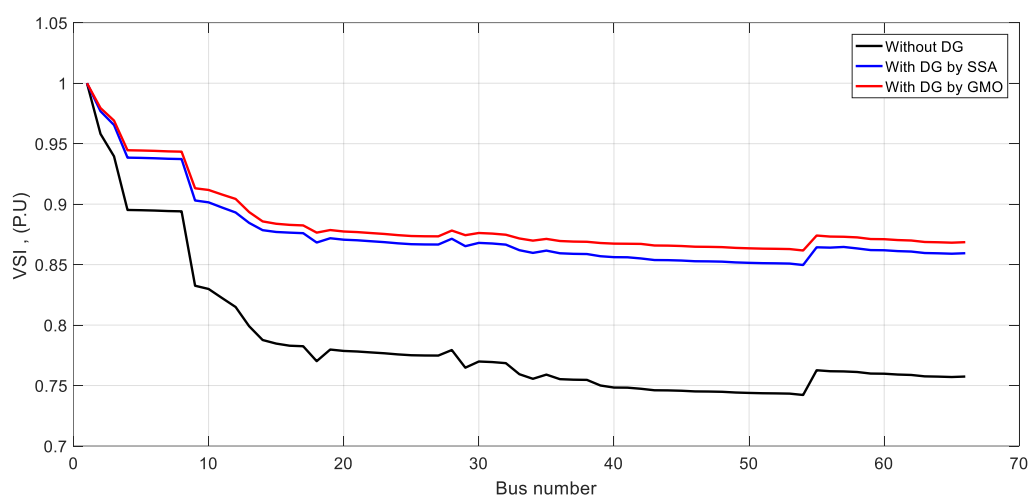
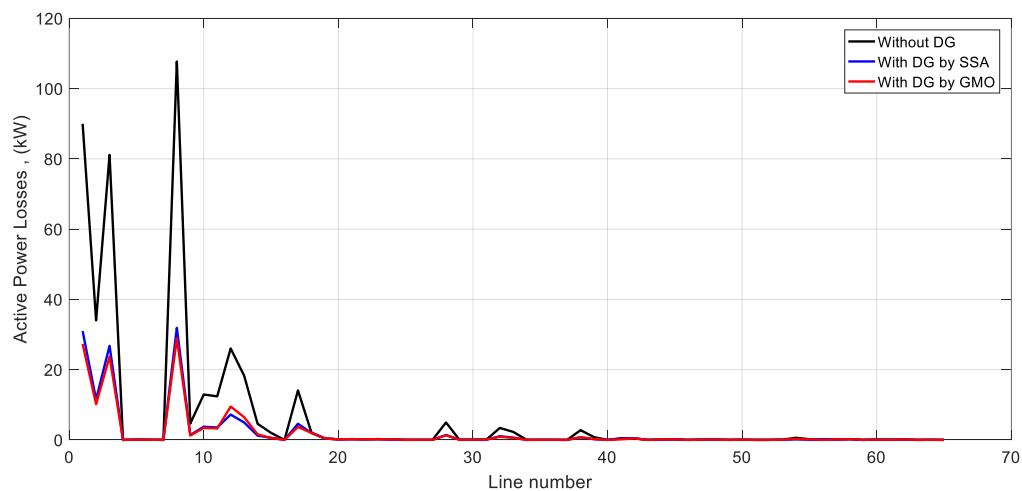


Figure 15. SSA and GMO for MOF (IRAQI 66 BUS), (a) Convergence rate, (b) Box plot

Table 12. The statistical performance of minimising MOF (IRAQI 66 BUS)

Method	Mean	SD	Best	Runtime
SSA	0.4281	0.0472	0.3780	14.577
GMO	0.4088	0.0258	0.3773	12.951

**Figure 16.** The voltage profile of MOF (IRAQI 66 BUS)**Figure 17.** VSI of MOF (IRAQI 66 BUS)**Figure 18.** APL of MOF (IRAQI 66 BUS)

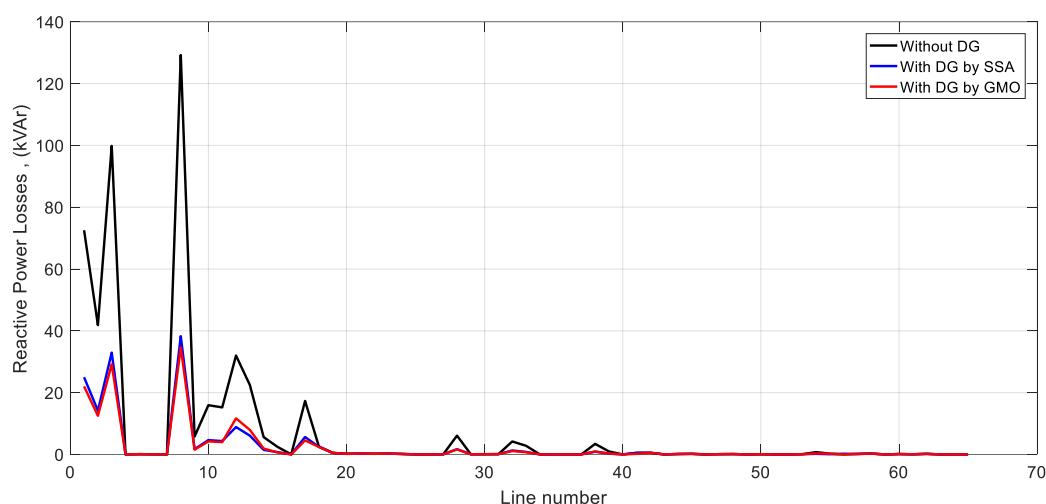


Figure 19. RPL of MOF (IRAQI 66 BUS)

5. Conclusion

Distribution networks face multiple challenges, including active and reactive power losses, deterioration of the voltage profile, and voltage instability. To address these issues, this paper proposes integrating photovoltaic distribution generators (PVDGs) into distribution networks using modern optimisation algorithms, namely the Salp Swarm Algorithm (SSA) and the Geometric Mean Optimiser (GMO), to determine the optimal placement and sizing of PVDGs.

To validate the scalability and accuracy of the proposed optimisation techniques, simulations were performed on both the standard IEEE 33-bus network and the practical Iraqi 66-bus network. The results demonstrate that the proposed methods significantly improve the overall performance of distribution networks relative to the base case and outperform previously reported approaches. In addition, this study incorporates both technical and economic objective functions, which further enhances the practical relevance of the proposed approach.

The simulation outcomes indicate notable improvements in system performance for both standard and practical radial distribution networks after integrating PVDGs. Moreover, the GMO algorithm consistently outperforms the SSA in terms of convergence speed and solution quality.

For future work, the proposed optimisation framework can be extended to determine optimal siting and sizing of wind turbines (WTs) with optimal power-factor settings, as well as to support peer-to-peer (P2P) electric vehicle (EV) applications in radial distribution networks.

Data Availability Statement: The data supporting the findings of this study are included within the article. Additional simulation data are available from the corresponding author upon reasonable request.

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Declaration of Competing Interest: The authors declare that they have no known competing interests.

Research Involving Human/Animal Participants: This article does not involve any studies conducted by the authors on animals or human participants.

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