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Optimized placement, sizing, and selection of distributed generation using the salp swarm algorithm

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Abstract
The salp swarm algorithm (SSA) was introduced as a method for efficiently selecting the optimal location, size, and type of distributed generation (DG) in a distribution system. SSA is a probabilistic algorithm that simulates the behavior of a population of agents, specifically by replicating the foraging behavior of salps in water. Salps often form cohesive groups called salp chains in deep waters. This behavior enables them to optimize locomotion through coordinated and swift movements while maximizing their foraging efficiency. This study investigated three types of DG: photovoltaic (PV), wind, and diesel. The methodology distinguishes between different types of DG, determines their optimal placement, and optimizes their sizing for maximum performance. Simulations are conducted on the IEEE 69-bus system. The results indicate that the proposed SSA approach successfully identifies the most suitable sites, sizes, and types of DG. A benchmark comparison is performed to assess the effectiveness of the proposed SSA method against the evolutionary programming (EP) approach. The results demonstrate that SSA outperforms EP in reducing power losses and improving the voltage profile.

Keywords
Salp swarm algorithm (SSA), Distributed generation (DG), Foraging behavior, IEEE 69-bus system, Evolutionary programming.

1.Introduction
The growing demand for electricity has placed significant stress on power systems, leading to higher power losses, voltage instability, and increased operational costs. Traditional centralized power generation models often lead to inefficiencies due to transmission constraints and distribution losses [1]. Distributed generation (DG) has emerged as a viable solution to alleviate these issues by integrating small-scale, decentralized power sources such as solar photovoltaics (PV) and wind turbines (WT) within distribution networks. DG units enhance grid resilience, reduce transmission losses, improve voltage profiles, and contribute to a more sustainable and efficient power system [2–4].

However, the integration of DG requires careful consideration of factors such as optimal placement, sizing, and type selection to maximize its benefits while maintaining system stability and reliability [5].

Despite its advantages, DG implementation presents challenges related to system stability, power quality, and economic feasibility. Poorly planned DG placement and sizing can cause voltage fluctuations, increased losses, and undesirable power flow effects [6]. Identifying the optimal location, size, and type of DG is crucial to maximizing efficiency while minimizing power losses and operational costs [7]. Many existing methods lack a robust, computationally efficient solution that guarantees system-wide improvements [8]. Therefore, a more advanced optimization approach is necessary to address these challenges effectively. This paper aims to develop an optimization framework based on the

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salp swarm algorithm (SSA) to determine the optimal placement, sizing, and type of DG units in a distribution network. SSA is easier to construct than most other evolutionary algorithms due to its uncomplicated design and minimum parameter tuning requirements [9]. This characteristic makes SSA a suitable choice for solving complex problems.
The primary objective of this study is to improve voltage stability, reduce power losses, and enhance overall system efficiency. The key contributions of this paper include:

- A novel application of the SSA for optimizing the placement, sizing, and selection of DG units to enhance power system performance.
- A comparative analysis of the proposed method against existing optimization techniques to establish its effectiveness.
- Performance evaluation of the SSA-based approach using standard test distribution networks.
- A demonstration of the effects of optimal DG integration on power loss reduction and voltage profile improvement.

The paper is structured as follows: Section 2 provides a comprehensive literature review of relevant studies. Section 3 details the methodology, including DG modeling, problem formulation, and the development of the SSA. Section 4 presents the results, followed by an in-depth discussion in Section 5. Finally, Section 6 concludes the study and offers recommendations for future research.

2.Literature review

Research indicates that improper placement and sizing of DG units can lead to increased system losses compared to systems without DG. Cortez et al. [10] presented a study that utilizes particle swarm optimization (PSO) to determine the most efficient positioning and sizing of hybrid solar-wind DG units in the IEEE 33-bus test system under three distinct scenarios. The findings indicate that system voltage improved and power losses were reduced when DG was installed at an optimal location and size. A similar trend is observed in [10], where optimal DG placement and sizing result in reduced power losses, improved voltage profiles, and enhanced system stability. The sizing and allocation of DGs were optimized by considering factors such as minimizing power losses, improving voltage profiles, and enhancing stability.

A stability index was introduced in [11], utilizing Thevenin impedance within a distribution network. Various artificial intelligence techniques, including PSO [12], Fractional Lévy flight bat algorithm [13], dwarf mongoose optimization [14], whale optimization algorithm [15], improved wild horse optimization algorithm [16], and adaptive grey wolf optimizer [17], have been applied to determine the optimal placement and sizing of DG units. Heuristic algorithmic approaches have demonstrated their effectiveness in solving this problem, even when addressing multiple objectives.

In the field of optimization, the SSA has recently emerged as a promising approach [18]. It mimics the collective behavior of salps as they search for food in water. The algorithm designates the leading salp in the chain as the leader, while the others act as followers. The SSA method has proven effective in solving multi-objective electric power load dispatch problems, outperforming other algorithms [19]. It maintains a balance between exploration and exploitation, making it suitable for numerical and engineering optimization problems. SSA has also been successfully applied to hybrid photovoltaic-thermoelectric generator (PV-TEG) systems to optimize power extraction, achieving high-quality GMPP solutions even with poor initial conditions due to its robust and reliable search processes [20]. Furthermore, SSA improves power flow efficiency by reducing fuel costs, power losses, and voltage fluctuations while ensuring voltage stability in electric power systems [21]. In this study, SSA is chosen for solving the DG allocation problem due to its demonstrated superiority in addressing various optimization challenges.

Most previous studies have focused on a single type of DG, with only a few exploring multiple DG types. Yehia et al. [22] introduced a hybrid fuzzy-metaheuristic approach to determine the optimal sizing and placement of various DG types. The study considered three scenarios: (1) a DG system with a power factor of unity, (2) a DG system supplying active and reactive power at a constant power factor of 0.866 p.u., and (3) multiple DG systems injecting active and reactive power at a variable power factor. Although the proposed algorithm improved system performance, the results did not specify the optimal DG type.

The key challenge highlighted in the literature is the complexity of optimizing DG placement, sizing, and selection while ensuring system stability, reducing power losses, and improving the voltage profile. Incorrect DG placement can increase losses, and integrating DG affects power quality and stability.

Balancing multiple objectives requires advanced optimization algorithms, but their efficiency varies. Most studies focus on a single DG type, with limited research on multi-DG integration and optimal DG selection.

3.Methodology

The selection of the most suitable location, size, and type of DG are determined by minimizing power losses. Furthermore, the impact of DG implementation on the enhancement of the voltage profile is also assessed. A comparison is made between the performance of SSA and that achieved through the utilization of the evolutionary programming (EP) technique.

3.1Active power losses minimization

In this study, one of the primary requirements for achieving an efficient operation of the distribution network was the minimization of active power losses. The specified criterion is presented in Equation 1.

$$Plosses = \sum_{i=1}^{N} \sum_{j=i+1}^{N} R_{ij} \times I_{ij}^2 \quad (1)$$

Where: R_{ij} denotes the resistance of the branch at position *(i,j)*, I_{ij} represents the current flowing through the branch at position *(i,j)*, and N denotes the total number of nodes in the system.

3.2Voltage profiles

Voltage profile improvement in a distribution system involves adjusting the system's operating conditions to ensure that the voltages at various nodes or buses are within acceptable limits. A common objective function for voltage profile improvement is to minimize the sum of squared voltage deviations as per Equation 2:

$$V_{min} = \sum_{j=1}^{m} (V_j - V_{desired})^2 \quad (2)$$

Where V_j is the voltage at bus j and $V_{desired}$ is the desired voltage.

3.3Type of DG

DG is an essential component of modern power systems, providing a decentralized approach to electricity generation. This project focuses on three types of DG sources: PV with a power factor of 1, WT with a power factor of 0.95, and a diesel generator with a power factor of 0.93. This aims to optimize the integration of these diverse DG sources into the distribution system while taking into account their distinct power factors.

The variation in power factors among the DG sources poses challenges in maintaining a balanced and efficient power system. The project aims to analyze the impact of this mismatch on the distribution system's performance. Determining the optimal size and location for each DG type, considering their power factors, is a complex optimization problem. It involves minimizing power losses, improving voltage profiles, and ensuring reliable power supply. Addressing power factor variation in DG sources is crucial for achieving a balanced and sustainable distribution system. The paper's findings contribute to developing guidelines for efficiently integrating diverse DG sources, paving the way for a resilient and optimized power distribution infrastructure.

3.4Salp swarm algorithm (SSA)

Salps are members of the Salpidae family and have bodies that are barrel-shaped and transparent, resembling jellyfish in appearance. Like jellyfish, salps pump water through their bodies to propel themselves. While the study of salps is still in its early stages, they exhibit fascinating behaviors, such as swarming. In deep waters, salps form structures known as salp chains. The reason behind their collective behavior remains unclear, but it is suggested that it enhances locomotion efficiency by coordinating movement and foraging [19, 23]. Studying salps is challenging due to the difficulty of accessing their natural habitat and the complexities of maintaining them in laboratory conditions [19, 23]. The notion of the SSA is derived from the observed coordinated movement and feeding patterns demonstrated by salps in marine environments. Marine invertebrates, known as salps, propel themselves by contracting and relaxing their body, resulting in the formation of a water jet. Moreover, they exhibit a distinctive behavior characterized by the formation of chains and the synchronized swimming of groups. The SSA algorithm splits the population into two groups: leaders, who guide the swarm, and followers, who track the leaders either directly or indirectly [24].

The population of salp chains is divided into two distinct types: namely leaders and followers, in order to construct a mathematical model. The leader stands at the front of the chain, while the rest are considered followers. As the name suggests, the leader guides the group, while followers stay connected to each other and the leader, either directly or indirectly. Salp positions in swarm-based approaches are determined within an n-dimensional search space, where n represents the number of problem variables. A two-dimensional matrix, x, stores the positions of all salps. The primary goal of the swarm is to locate a food supply denoted as "F," which is presumed to be located within the search space [24]. Equation 3 for updating the leader's position is given as follows:

$$x_j^1 = \begin{cases} F_j + c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 \geq 0 \\ F_j - c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 < 0 \end{cases} \quad (3)$$

In this formula, x_j^1 denotes the position of the initial salp (the leader) in the j[th] dimension, whereas F_j indicates the location of the food source in that dimension. The values ub_j and lb_j represent the upper and lower limits for the jth dimension. Furthermore, the variables c1, c2, and c3 are stochastic values employed in the computation. Equation 3indicates that the leader just adjusts its location in relation to the food supply. Parameter c_1 is essential in SSA as it facilitates the equilibrium between exploration and exploitation. The definition is as shown in Equation 4:

$$c_1 = 2e^{-\left(\frac{4l}{T}\right)^2} \quad (4)$$

The parameters c_2 and c_3 are determined through a random generation process that produces values between 0 and 1. These numbers determine the trajectory of the subsequent location in the j_{th} dimension, indicating whether it proceeds towards positive or negative infinity, together with the magnitude of the step size. The position of the followers is determined using the following equation derived from Newton's law of motion (Equation 5).

$$x_j^i \frac{1}{2}at^2 + v_0 t, \quad (5)$$

where $i \geq 2$, x_j^i denotes the position of the i[th] follower salp in the j[th] dimension, t represents time, v_0 signifies the starting velocity, and a indicates the ratio of final velocity to beginning velocity. In optimization, time is measured in iterations. The difference between each iteration is equal to 1. Assuming $v_0 = 0$, Equation 6 can be represented as follows:

$$x_j^i = \frac{1}{2}\left(x_j^i + x_j^{i-1}\right) \quad (6)$$

where i ≥ 2 and x_j^i denotes the position of ith follower salp in jth dimension. The salp chains can be simulated using Equation 3 and 6.

Figure 1 illustrates the flowchart of the SSA. According to *Figure 1*, the SSA parameters must be configured, encompassing the upper bound, lower bound, and maximum iterations, as required. The first salp population is thereafter generated with random places and velocities.

The quantity of variables is contingent upon the amount of DG types, either ten (for a singular kind of DG) or fifteen (for numerous types of DG). The variables evaluated for different forms of DG are L1, L2, L3, L4, L5, P1, P2, P3, P4, P5, pf1, pf2, pf3, pf4, and pf5. L1 - L5 denotes the location of DG, P1 - P5 indicates DG sizing, and pf1 - pf5 signifies three categories of DG. Furthermore, the fitness function is established to assess the performance of each salp. Then, the quality of each solution is assessed based on its ability to minimize power loss and improve the voltage profile in the system.

This involves applying the solutions to a model of the 69-bus system and evaluating the resulting power loss and voltage levels. The solution that has the best fitness value so far has been identified. After that, the parameter c1, which helps balance exploration and exploitation, is updated. Furthermore, the position of the leading salp (the one at the front of the chain), representing the current best solution, is updated. This typically involves movement towards the food source (the optimal solution). Then, the positions of the follower salps are updated based on their current positions and the position of the leading salp. This simulates the chain-like movement of salps in nature. Next, the upper and lower bounds are checked to ensure that the updated positions of the salps still fall within the allowed variable bounds. Lastly, the algorithm is terminated if the maximum number of iterations has been reached. Otherwise, it returns to step 2 for another round of fitness evaluation and position updates.

3.5Evolutionary programming (EP)

To evaluate the effectiveness of SSA, its outcomes are compared with those of a well-known technique, EP. EP is chosen for its capability to explore complex solution spaces and optimize DG placement and sizing [25]. It is a stochastic optimization approach similar to the genetic algorithm (GA), focusing on the behavioral relationship between parents and offspring. The number of variables and their range are set similarly to SSA. During initialization, constraints are applied to ensure that EP generates random numbers meeting predefined criteria, such as a specific power factor value and a minimum bus voltage of 0.90 p.u. Offspring are generated through mutation applied to random integers. *Figure 2* presents the flowchart of EP.

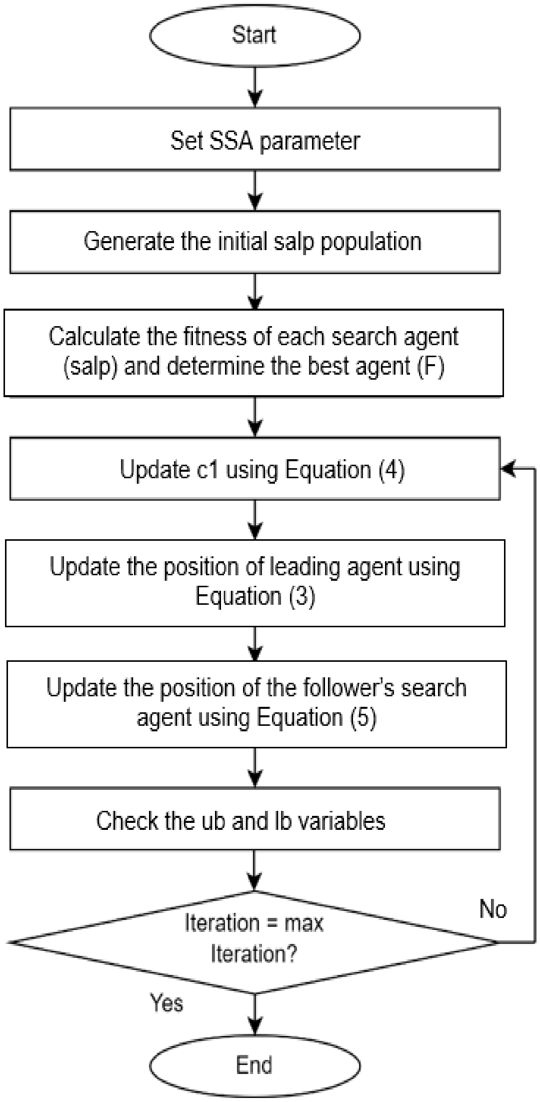

Figure 1 Flowchart of SSA

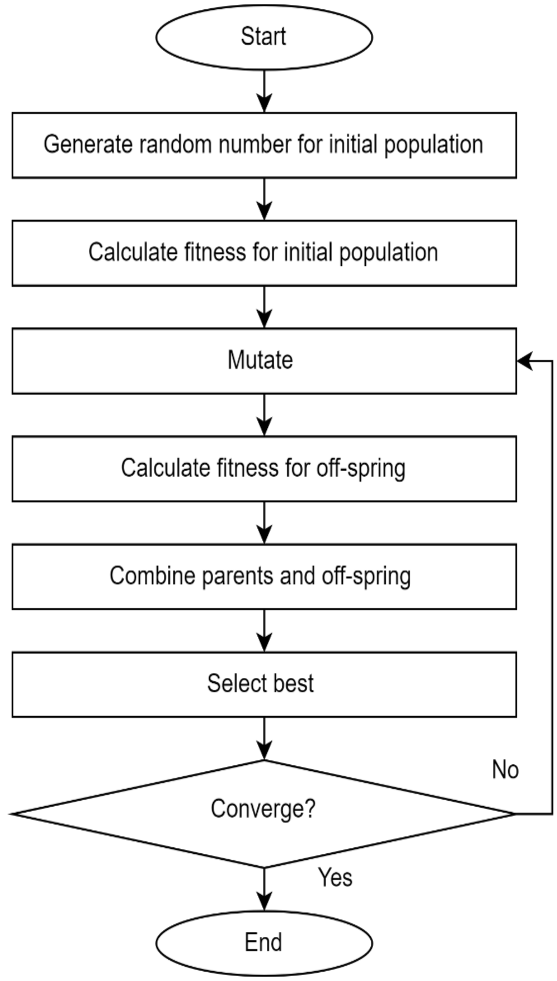

Figure 2 Flowchart of evolutionary programming

3.6 Test System

DG is generally implemented in a distribution system. Consequently, the evaluated approaches were tested using the IEEE 69-bus distribution test system, comprising 69 buses, seven laterals, and 68 branches. The system features a radial architecture and operates at a voltage level of 12.66 kV. The total active and reactive loads are 3.8 MW and 2.69 Mvar, respectively. Under standard conditions, the system loses 223.1 kW of active power. The voltage range is 0.95 to 1.05 per unit (p.u). *Figure 3* illustrates the IEEE-69-bus system.

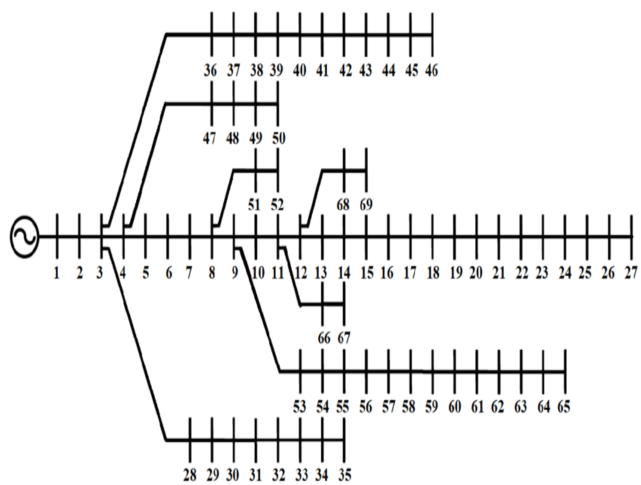

Figure 3 IEEE 69-bus distribution test system

4.Results

To evaluate the effectiveness of the proposed method for optimizing the sizing of five DG units using SSA, the results were divided into four cases and compared with EP. The following four case studies were considered:

Case 1: PV as DG with a power factor of 1
Case 2: WT as DG with a power factor of 0.95
Case 3: Diesel generator as DG with a power factor of 0.93
Case 4: Multiple types of DGs

The proposed SSA algorithm was implemented in MATLAB R2021b on a system equipped with an Intel Core i5-5287U CPU running at 2.90 GHz. Both SSA and EP simulations were conducted under identical settings, including the maximum iteration count and the number of search agents. The number of iterations and search agents was set to 200 and 20, respectively.

4.1Case 1: photovoltaic as DG

In this case study, a unity power factor is assigned to the PV as DG. *Table 1* presents the optimal DG results obtained using SSA and compares them with those from the EP method. As shown in *Table 1*, SSA achieved the most favorable outcome, with a power loss of 0.0642 megawatts (MW) and a minimum voltage of 0.9899 p.u. In contrast, EP resulted in a power loss of 0.0924 MW and a minimum voltage of 0.9527 p.u. *Figure 4* illustrates the convergence curve of SSA, which converged at the 140th iteration.

In the *Table 1*, PDG (MW) and QDG megavolt-amperes reactive (MVar) represent the real and reactive power outputs of distributed generation (DG) units, respectively. In this study, all QDG values are zero, indicating that the DG units operate at a unity power factor, meaning they generate only real power (PDG) without contributing reactive power (QDG = 0). *Table 1* presents a comparison of SSA and EP in terms of DG placement and performance. The location column indicates the bus number in the IEEE 69-bus system where the DG unit is installed. The PDG (MW) column provides the real power output at each DG location, while the QDG (MVar) column shows the reactive power output, which remains zero due to the unity power factor. The power loss (MW) column represents the total power loss in the system after DG placement, and the Vmin (p.u.) column records the minimum voltage observed in the system. From the observations, SSA outperforms EP, achieving a lower power loss (0.0642 MW) and a higher minimum voltage (0.9899 p.u.) compared to EP, which results in a power loss of 0.0924 MW and a minimum voltage of 0.9527 p.u. Additionally, SSA distributes DG units more effectively across different locations, leading to improved system performance. The results demonstrate the superiority of SSA over EP in optimizing DG placement and sizing, thereby reducing power losses and enhancing voltage stability within the distribution network.

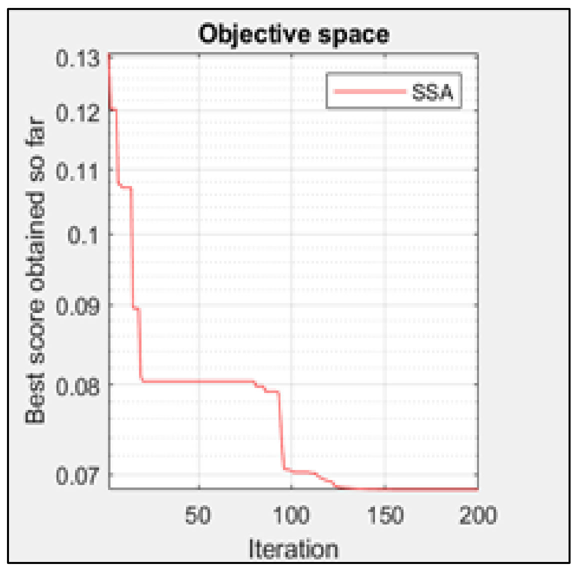

Figure 4 Convergence curve of SSA for case 1

Table 1 Result for SSA and EP for case 1

	Location	PDG (MW)	QDG (MVar)	Power loss (MW)	Vmin (p.u)
SSA	50	0.5917	0	0.0642	0.9899
	18	0.4035	0		
	66	0.4013	0		
	64	0.3106	0		
	61	1.3593	0		
EP	12	0.1842	0	0.0924	0.9527
	65	0.3244	0		
	29	0.1419	0		
	11	0.7307	0		
	61	0.5060	0		

4.2Case 2: WT as DG

For Case 2, the analysis considers the placement of five WT units, each operating at a power factor of 0.95. The findings for this case are summarized in *Table 2*. Based on the tabulated data, the SSA approach achieves the lowest power loss of 0.068 MW, along with a corresponding minimum voltage of 0.979 p.u. The optimal DG placement is identified at buses 2, 11, 50, 17, and 61. The best sizing values for the DG units are 1.9368, 0.3035, 0.5618, 0.3149, and 1.3056 MW, respectively. The convergence curve for Case 2, obtained using SSA, is illustrated in *Figure 5*. The overall analysis indicates that SSA outperforms EP in optimizing DG placement and sizing. SSA achieves a lower power loss of 0.068 MW and a higher minimum voltage of 0.979 p.u., compared to EP, which results in 0.0794 MW power loss and 0.964 p.u. minimum voltage. Additionally, SSA distributes DG units more effectively, leading to better system stability and efficiency.

Table 2 Result for SSA and EP for case 2

	Location	PDG(MW)	QDG (MVar)	Power Loss (MW)	Vmin (p.u)
SSA	2	1.9368	0.9380	0.068	0.9790
	11	0.3035	0.1470		
	50	0.5618	0.2721		
	17	0.3149	0.1525		
	61	1.3056	0.6323		
EP	12	0.1842	0.0892	0.0794	0.9640
	65	0.3244	0.1571		
	29	0.1419	0.06087		
	11	0.7307	0.3539		
	61	0.5060	0.2451		

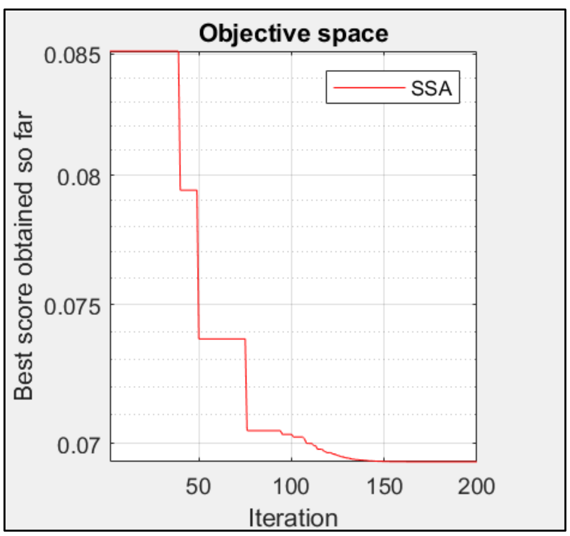

Figure 5 Convergence curve of SSA for case 2

4.3Case 3: diesel generator as DG

In Case 3, the diesel generator is designated as DG. Typically, the power factor of a diesel generator falls between the range of 0.90 to 0.95 [26]. Thus, this study examines a diesel generator with a power factor of 0.93 on average. *Table 3* presents the ideal parameters achieved using the proposed method for the diesel generator. The system has a minimal power loss of 0.0665 kW and a minimum voltage of 0.9788 p.u. The most suitable position for DG is determined to be at buses 16, 49, 63, 61, and 47 with corresponding DG size values of 0.382, 0.775, 0.437, 0.788, and 0.695 MW. The convergence graph for Case 3 is depicted in *Figure 6*. For Case 3, SSA demonstrates superior performance compared to EP, achieving a lower power loss of 0.0665 MW and a higher minimum voltage of 0.9788 p.u., whereas EP results in 0.0779 MW power loss and 0.9662 p.u. minimum voltage. SSA also provides a more effective DG distribution, ensuring better system efficiency and voltage stability.

4.4Case 4: Multiple types of DGs

In case 4, DGs are randomly picked from diverse categories. *Table 4* summarizes the findings of case 4, which examines the ideal placement, type, and size of DG units, taking into account various DG types (PV, WT, and Diesel). Two optimization strategies, the SSA and EP, were utilized for comparison analysis. The primary criteria evaluated are the reduction of power loss and the preservation of voltage levels within acceptable thresholds. The optimal DG locations discovered by SSA were buses 23, 48, 33, and 61. The relative DG sizes were 0.0882 MW, 0.983 MW, 0.0218 MW, and 1.715 MW. SSA designated WT for buses 23 and 61, whereas buses 48 and 33 were assigned PV systems. The cumulative power loss recorded was 0.0677 MW. The lowest voltage (Vmin) was 0.9812 p.u., signifying the system's voltage stability. The optimal DG locations indicated by EP were buses 39, 62, 44, 58, and 13. The relative DG sizes were 0.4252 MW, 1.4289 MW, 0.2604 MW, 0.1817 MW, and 0.5489 MW. EP designated WT at buses 39 and 58, whilst PV systems were assigned to buses 62, 44, and 13. The cumulative power loss recorded was 0.075 MW. The minimum voltage was 0.9789 p.u.

Table 3 Result of SSA and EP for Case 3

	Location	PDG(MW)	QDG(MVar)	Power loss (MW)	Vmin (p.u)
SSA	16	0.3817	0.1849	0.0665	0.9788
	49	0.7746	0.3751		
	63	0.4374	0.2119		
	61	0.7879	0.3816		
	47	0.6954	0.3368		
EP	12	0.1842	0.0726	0.0779	0.9662
	65	0.3244	0.128		
	29	0.1419	0.0558		
	11	0.7307	0.2886		
	61	0.506	0.1998		

Table 4 Result of SSA and EP for Case 4

	Location	PDG(MW)	QDG(MVar)	DG Type	Power Loss (MW)	Vmin (p.u)
SSA	23	0.0882	0.0268	Wind	0.0677	0.9812
	48	0.983	0	PV		
	33	0.0218	0	PV		
	61	1.715	0.1189	Wind		
	22	0.2683	0	PV		
EP	39	0.4252	0.1111	Wind	0.075	0.9789
	62	1.4289	0	PV		
	44	0.2604	0	PV		
	58	0.1817	0.979	Wind		
	13	0.5489	0	PV		

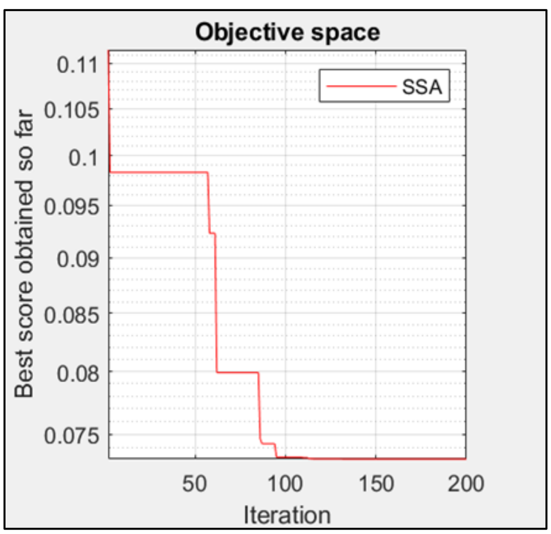

Figure 6 Convergence curve of SSA for case 3

5.Discussion

Based on the results presented in *Table 1*, it can be concluded that SSA is a superior method compared to EP for solving optimal location and sizing of PV. *Figure 4* demonstrates the effectiveness of the algorithm in Significantly reducing power loss over 200 iterations. Initially, the best score starts at approximately 0.13, showing a steep drop in the first 50 iterations to around 0.08, indicating rapid exploration and identification of promising solutions early in the optimization process. Beyond this point, the rate of improvement slows down, with more incremental changes observed until the algorithm converges at a best score of about 0.07 after around 140 iterations. This convergence suggests that the SSA has effectively fine-tuned the placement and sizing of PV systems, achieving minimal power loss. The results confirm that the SSA is a suitable and robust approach for tackling the complex optimization problem of integrating PV systems into power grids, ensuring efficient energy distribution with minimized losses. From the results tabulated in *Table 2*, it can be seen that the optimal placement and sizing of DG for case 2 determined via SSA outperforms the findings provided by EP in terms of reducing power loss and improving voltage. The convergence graph for Case 2 in *Figure 5*, which optimizes the location and sizing of WT using the SSA, shows a steady improvement in minimizing power loss. The score drops quickly from around 0.085 to 0.075 in the first 50 iterations, indicating the algorithm's effectiveness in finding good solutions early. The score continues to improve gradually, stabilizing at around 0.07 after 100 iterations. When compared to the optimization for PV systems, the WT results show a similar convergence trend, with both cases reaching a final score of about 0.07. The SSA algorithm reaches convergence after 154 iterations. This consistency suggests that the SSA is equally effective in optimizing both WT and PV systems, achieving similar levels of power loss reduction in both scenarios. In Case 3, the power loss achieved by the use of SSA is considerably lower compared to EP, resulting in a power loss of 0.0779 MW as indicated in *Table 3*. In addition, the SSA also achieves a greater voltage enhancement, with a minimum voltage of 0.9788 per unit, as compared to EP. According to the convergence curve depicted in *Figure 7*, the SSA algorithm achieved convergence after 95 iterations. The convergence graph for Case 3, shows a steady reduction in power loss, starting from 0.11 and dropping to around 0.075 after 100 iterations. This mirrors the trend seen in the PV and WT cases, where the SSA effectively identifies optimal solutions early on and gradually refines them. Despite initially having a slightly higher power loss, all three cases converge to a similar final value between 0.07 and 0.075 MW, demonstrating the robustness and effectiveness of SSA across different DG types in minimizing power loss and improving system performance.

The findings from Case 4, concerning the ideal placement, type, and size of DG units, provide significant insights into the efficacy of various optimization methodologies. The two optimization strategies employed (SSA and EP) were evaluated for their efficacy in minimizing power losses and sustaining voltage levels within permissible thresholds. Both SSA and EP designated distinct groups of buses for DG installation. The SSA-based approach proposed placement at buses 23, 48, 33, and 61, whereas EP's optimal solution focused on buses 39, 62, 44, 58, and 13. These disparities illustrate the intrinsic characteristics of the optimization strategies. SSA often converges on solutions that emphasize the optimal combination of DG types and placements to minimize power loss, while EP investigates a wider array of alternatives, possibly leading to more diverse DG placement solutions.
The DG type assignments varied across the two methodologies. The SSA allocated WT to buses 23 and 61; however, the EP positioned WT at buses 39 and 58. This mismatch highlights the significance of the optimization algorithm in identifying the optimal sites for each DG type, predicated on power loss mitigation and voltage stability. The SSA technique allocated PV systems to buses 48 and 33, but the EP method positioned PV systems at buses 62, 44, and 13. These disparities indicate that EP may favor a more equitable distribution of DG installations, whereas SSA seeks to maximize locations that yield the greatest enhancement in system performance. The dimensions of the DG units deployed in the network differed between the two optimization approaches. The DG sizes for SSA were comparatively smaller, with a maximum capacity of 1.715 MW at bus 61, while the EP results indicated a greater cumulative power loss associated with bigger DG sizes at multiple buses. The total power loss using SSA was measured at 0.0677 MW, while EP recorded a slightly higher power loss of 0.075 MW. This difference suggests that SSA more effectively reduces power loss through optimal DG placement and sizing. The lower power loss achieved by SSA can be attributed to its ability to strategically identify locations with the highest potential for loss reduction, utilizing a targeted optimization approach.

Both optimization procedures yielded voltage levels within acceptable parameters, with SSA attaining a Vmin of 0.9812 p.u. and EP achieving a Vmin of 0.9789 p.u. The voltage levels are around the nominal voltage of 1.0 p.u., indicating that both solutions preserved sufficient voltage stability. The minor discrepancy in voltage stability between the two strategies indicates that the SSA-based solution may have more efficiently reconciled power loss reduction with voltage regulation. Both technologies effectively maintain voltage stability throughout the system, which is essential for dependable operation in practical power systems. The comparison between SSA and EP highlights the strengths and limitations of each algorithm, providing a clear understanding of their respective merits and drawbacks. SSA exhibited enhanced efficacy in power loss mitigation, with the lowest aggregate power loss (0.0677 MW) and a superior minimum voltage (0.9812 p.u.). This indicates that SSA may be more effective in identifying the ideal arrangement for minimizing power loss and regulating voltage. Conversely, EP provided a more varied array of solutions, featuring distinct DG locations and sizes, suggesting its capacity to investigate a wider search field. Nevertheless, EP's elevated power loss (0.075 MW) and marginally reduced voltage stability indicate a greater susceptibility to suboptimal solutions relative to SSA in this scenario.
In practical applications, the outcomes of both optimization algorithms yield valuable insights for the best placement of DG units in distribution networks. The findings demonstrate that both SSA and EP may

efficiently diminish power losses and uphold voltage stability; however, SSA may provide a more optimum solution with reduced losses and superior voltage regulation. The various DG placements and types designated by each approach highlight the significance of choosing the appropriate optimization method according to the unique objectives and limitations of the power system. Furthermore, although both methodologies employed a straightforward distribution test system, subsequent research may explore the application of these methods to more intricate and realistic networks to assess their scalability and performance across varied operational situations.

In summary, the findings indicate that SSA is a more effective approach for reducing power loss and ensuring voltage stability in the analyzed network, although EP offers a wider array of potential options, which may be advantageous in more intricate systems or varying operational conditions.

Figure 7 and *Table 5* demonstrate the comparative efficacy of the SSA and EP in reducing power loss (Ploss) across four scenarios: PV, WT, diesel generator, and multiple types of DG systems. The current system has a power loss of 0.2246 MW, indicating its inefficiency. Optimization yielded substantial reductions in all instances. SSA demonstrates exceptional performance, achieving power loss reductions of 71.42%, 69.72%, 70.39%, and 69.87% in Cases 1, 2, 3, and 4, respectively, bringing the power loss down to 0.0642 MW, 0.068 MW, 0.0665 MW, and 0.0677 MW. In contrast, EP also enhances performance but with slightly lower reductions, achieving 58.86%, 64.63%, 65.30%, and 66.61% in the corresponding cases. *Figure 7* graphically supports this trend, showing that SSA consistently outperforms EP across all DG systems (PV, WT, diesel generator, and multiple DG types) by yielding the lowest power loss values. Although EP improves the existing system, its power loss reduction is marginally lower than that of SSA. The findings confirm that SSA is a superior optimization technique, delivering greater percentage reductions in power loss, significant energy savings, improved system efficiency, and enhanced reliability—establishing it as an optimal method for loss reduction in modern power systems.

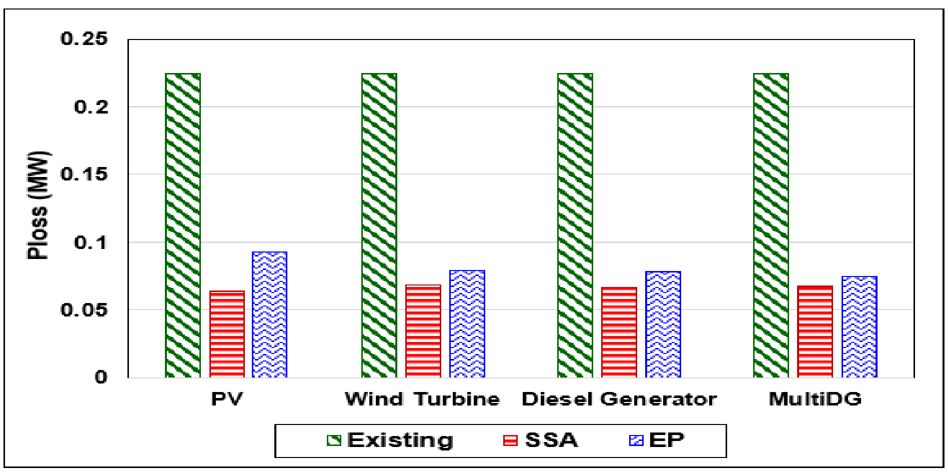

Figure 7 Comparison of power loss for all cases

Table 5 Percentage of power loss reduction for all cases

Cases	Item	SSA	EP
Existing	Ploss (MW)	0.2246 MW	
Case 1	% Ploss reduction	71.42%	58.86%
Case 2	% Ploss reduction	69.72%	64.63%
Case 3	% Ploss reduction	70.39%	65.30%
Case 4	% Ploss reduction	69.87%	66.61%

Figure 8 illustrates the minimum voltage levels attained across several DG scenarios within a grid system. The scenarios examined encompass the current system, a system with PV integration, a system with WT integration, a system with diesel generator integration, and a system incorporating a

mixture of these (multiple DG types). The minimum voltage is a crucial characteristic that directly affects the stability and reliability of the grid. The current system demonstrates the lowest minimum voltage, suggesting possible voltage stability concerns. This indicates that the current infrastructure may be insufficient to accommodate the rising electricity demand. The incorporation of solar PV results in a marginal enhancement of the minimum voltage relative to the current system. This is probably attributable to the decentralized structure of PV generation, which mitigates voltage decreases at the load locations. Similar to PV integration, the incorporation of WT also results in a slight improvement in the minimum voltage. This is ascribed to the augmented power generation capability and the potential for reactive power assistance from WT. The incorporation of diesel generators results in a notable enhancement in the minimum voltage. This is mainly attributable to the synchronous characteristics of diesel generators, enabling them to deliver reactive power support and uphold voltage stability. The multiple DG types scenario, which integrates PV, WT, and diesel generation, achieves the highest minimum voltage values. This suggests that a varied combination of generation sources can significantly improve voltage stability and overall system reliability. *Figure 8* highlights the need for strategic DG planning and integration for enhancing voltage stability and reliability in smart grids. The selection of DG technology, along with its ideal placement and dimensions, is essential for attaining these goals. The results also illustrate the potential advantages of DG integration for improving voltage stability and reliability in smart grids. Through meticulous planning and the integration of DG resources, it is feasible to establish more resilient and sustainable power systems.

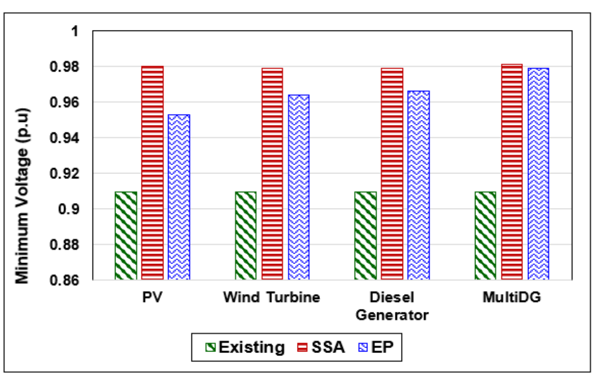

Figure 8 Comparison of minimum voltage for all cases

Figure 9 illustrates the voltage profiles of a power supply across several conditions. For the initial load flow analysis, the voltage profile of the system is assessed without any DG implemented. It probably indicates voltage reductions across the system, particularly near the end of the feeder (higher bus numbers), which is customary due to line impedances and load requirements. The voltage profile after the integration of multiple types of DG via the SSA for optimization demonstrates considerable enhancement in voltage levels relative to the initial load flow analysis. The voltage profile is more uniform and nearer to the nominal voltage (1.0 p.u.), signifying improved voltage regulation. The voltage profile following DG integration via the EP method resembles that of the SSA, demonstrating a significant enhancement in voltage levels relative to the initial load flow. The profile is predominantly level and sustains a voltage close to the nominal value. The incorporation of DG via both SSA and EP positively influences the voltage profile. The voltage levels have markedly enhanced, particularly in regions with elevated load demand (near the terminus of the feeder). This illustrates the efficacy of DG in enhancing voltage regulation and mitigating voltage dips. Both SSA and EP algorithms demonstrate efficacy in optimizing the placement and sizing of DG for voltage enhancement. The voltage profiles derived from both algorithms are analogous, indicating that both optimization methods can yield comparable outcomes. The higher voltage profiles signify improved voltage stability within the system. Ensuring voltage remains within acceptable parameters is essential for the dependable functioning of electrical apparatus and the general stability of the power system.

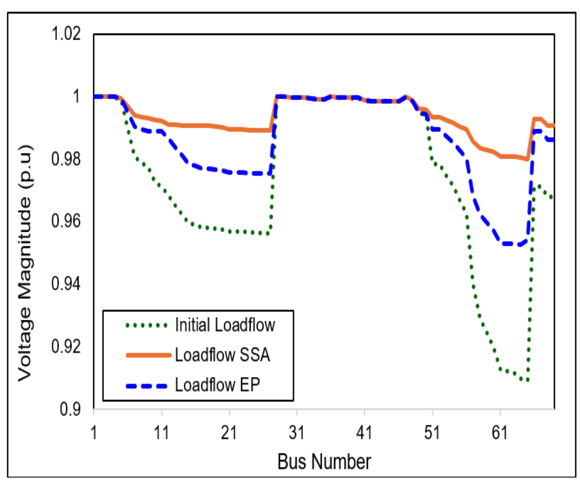

Figure 9 Voltage profile for Initial and Case 4

Limitations

This study has several limitations. DG is represented as a negative load, implying that the generated power directly offsets the network's demand. The power factor of the DG is determined by the type of generator used, without accounting for potential fluctuations under varying operational conditions. Additionally, the simulation is confined to steady-state conditions, excluding transient events and dynamic system behavior during disturbances or faults. Furthermore, the study utilizes the widely adopted IEEE 69-bus test system, considering only a single load variation. A complete list of abbreviations is listed in *Appendix I*.

6.Conclusion and future work

The SSA is a highly efficient method for optimizing DG selection in distribution systems. By simulating salps' foraging behavior, SSA effectively determines the optimal locations, sizes, and types of DG. This study analyzed three types of DG—PV, WT, and diesel—within the IEEE 69-bus system. The results demonstrate that SSA outperforms EP in reducing power loss and improving voltage profiles, highlighting its effectiveness in enhancing distribution system performance and efficiency. This underscores SSA's potential for sustainable energy integration and management.

Based on the study's findings, practitioners and researchers are encouraged to adopt SSA for DG optimization in distribution systems. SSA's ability to efficiently identify optimal DG placement, sizing, and selection offers significant promise for improving system performance. Given SSA's superior performance over EP, future research could explore its applicability in larger-scale distribution networks and diverse operating conditions. Additionally, refining and enhancing SSA could further enhance its potential for sustainable energy integration and management. Economic feasibility assessments of different DG integration scenarios are essential to identify the most cost-effective approach, while environmental impact evaluations are crucial to ensure a sustainable and eco-friendly microgrid.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Data availability

None.

Author's contribution statement

Zuhaila Mat Yasin: Conceptualization, Design, Data collection, Supervision, Investigation, Writing – original draft. **Siti Zaliha Mohammad Noor**: Conceptualization and Investigation. **Elia Erwani Hassan**: Investigation, Data collection, Writing – review and editing. **Tareq M. Shami**: Design technique, Analysis, Interpretation of results, Writing – review and editing.

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Appendix I

S. No.	Abbreviation	Description
1	DG	Distributed Generation
2	EP	Evolutionary Programming
3	GA	Genetic Algorithm
4	MVar	megavolt-Amperes Reactive
5	PSO	Particle Swarm Optimization
6	PV	Photovoltaic
7	PV-TEG	Photovoltaic-Thermoelectric Generator
8	SSA	Salp Swarm Algorithm
9	WT	Wind Turbine