Research Article

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# Salp swarm and gray wolf optimizer for improving the efficiency of power supply network in radial distribution systems

https://doi.org/10.1515/jisys-2022-0221
received January 31, 2022; accepted July 29, 2022

**Abstract:** The efficiency of distribution networks is hugely affected by active and reactive power flows in distribution electric power systems. Currently, distributed generators (DGs) of energy are extensively applied to minimize power loss and improve voltage deviancies on power distribution systems. The best position and volume of DGs produce better power outcomes. This work prepares a new hybrid SSA–GWO metaheuristic optimization algorithm that combines the salp swarm algorithm (SSA) and the gray wolf optimizer (GWO) algorithm. The SSA–GWO algorithm ensures generating the best size and site of one and multi-DGs on the radial distribution network to decrease real power losses (RPL) (kW) on lines and resolve voltage deviancies. Our novel algorithm is executed on IEEE 123-bus radial distribution test systems. The results confirm the success of the suggested hybrid SSA–GWO algorithm compared with implementing the SSA and GWO individually. Through the proposed SSA–GWO algorithm, the study decreases the RPL and improves the voltage profile on distribution networks with multiple DGs units.

**Keywords:** distributed generators, radial distribution systems, real power losses, gray wolf optimizer, metaheuristic optimization, salp swarm algorithm, IEEE standard case

## 1 Introduction

As power demand increases, utility companies face several challenges, including power losses and low power, power factor, energy efficiency, continuity, short circuit scale, and stabilization. Moreover, around 13% of the produced energy in supply networks is lost in the form of power loss [1]. A greater current flows in the supply network than in the power transmission lines, causing a greater power loss. The efficient answer for power troubles performance is keeping low load point voltages. However, several solutions, for example, growing the ability of supplied load points with low voltages, are unusable. Another issue is that high-voltage lines of transportation on a radial network are restricted.

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The supply network can be improved by applying some optimization solutions. Moreover, using the distributed generation (DGs) units is the most successful approach to the problem of distribution systems. A DG is a tiny energy generator unity, and on account of its high performance, small size, depressed operating costs, and protection are critical in improving the power sector [2]. DGs are typically associated with sustainable energy sources, such as photovoltaic (PV) systems, solar systems, and wind turbines (WT). DGs come in three varieties: active power ($P$) can be supplied by the first form, the next can provide reactive energy ($Q$), and the last can provide both [3].

Many algorithms have been suggested for managing optimal placing and energy size problems in DG on the radial supply or distribution network (RDN). The best and most popular algorithms for solving the problem of optimization include Genetic algorithms (GA), Extreme Learning Machine (ELM), particle swarm optimization (PSO), and multi-objective processes are the approaches applied among the suggested methods [4–7]. In ref. [8], to discover the optimum location and scale of capacitors and multi-DGs in the radial distribution network, the authors suggested hybridizing the artificial bee colony algorithm and GA. The initial aim is to decrease the cost of the system by optimally positioning several capacitors and DGs to minimize actual power losses (RPLs).

In the work of ref. [9], an autonomous group particle swarm optimization method was described. The method is evaluated without and with network reconfiguration to improve RDN efficiency by using seven case studies (except the base case) to overcome power loss reduction in RDN through the best size and site of capacitors and DGs device. A standard IEEE 69-bus RDN is being tested for the suggested method. In the work of ref. [10], the authors suggest a new collection of non-dominated fuzzy sortation and GA techniques to decrease four-goal functions, namely, loss of power, deviation of voltage, cost, and emission, on a standard 34-node test micro-grid.

An algorithm of the kind described in ref. [11] was proposed to mitigate losses and preserve appropriate voltage profiles at the same time in a radial supply network. The aim is to optimal value and position DGs in the system in suitable buses to minimize real power losses (RPL) and running costs and increase voltage reliability. On IEEE 33-and 69-node delivery networks, the proposed algorithm is implemented and displayed. In the work of ref. [12], to resolve the problems of optimal positioning and sizing of SCs, and DGs, the Newton–Raphson method with a simple PSO algorithm was proposed. In ref. [13], the authors suggested an optimization sample to organize different distribution observers founded on a lately progressing heuristic search tool that is gray wolf optimization (GWO). Numerous case studies are being conducted on IEEE 69-and 33-node test systems modulated by PV panels, tap-changing transformers, and capacitors.

In the work of ref. [14], in order to solve the position trouble, a water cycle optimization algorithm (WCA) was applied. In the work of ref. [15], to optimally assess the positions and volume of WT and PV DGs, the authors suggested cuckoo search optimization. Increasing the accuracy and reliability of a system is a major aim. The solution proposed is being examined on IEEE 69-node examination systems. In the work of ref. [16], the authors used moth flame optimization (MFO) and two other optimization algorithms, PSO and Imperialist Competitive, to solve the voltage deviation issue.

In the work of ref. [17], in order to specify the size of DGs, the authors suggested PSO and a population-founded incremental education algorithm locate the best position of DGs. The major objectives are to enhance nodular voltage profiles and reduce RPL and computation time. IEEE 69 and 33-bus radial supply networks are considered for testing the suggested algorithms. In the work of ref. [18], a hybrid WOA-SSA algorithm was proposed based on the whale optimization algorithm (WOA) and salp swarm algorithm (SSA) as a way to reduce total RPL (kW), address voltage variance, optimum size, and scale of the multi-DGs unit in the radial supply network, reduce the total power kW, the energy cost, and increase the net savings. In refs. [19–24], the authors propose the MFO approach through the selection of the best size and location for capacitor banks in power radial supply systems.

In the work of ref. [25], an approach is presented for reducing system operating costs and active power loss while at the same time maintaining an acceptable voltage profile. The SVC's location was specified by the voltage collapse proximity indication method (VCPI), and TCSC's optimal location was specified by applying the power flow analysis method. Testing has been conducted according to IEEE 30 and IEEE 57 standards. In the work of ref. [26], the authors proposed the use of two meta-heuristic algorithms, namely

Harris Hawk–Particle Swarm Optimization (HHOPSO) and its hybrid version for solving voltage-constrained reactive power planning (VCRPP). This study aims to determine the optimal location of Var sources using a VCPI and make use of the IEEE 57 bus test system for testing. Using fuzzy logic and crow search algorithms (CSA), the authors proposed a novel method to determine capacitor placement positions [27]. This method is referred to as the oppositional CSA. In this study, the proposed method was applied to standard IEEE 30 and IEEE 57 bus networks, and it was compared to several other methods of planning variables that have been established. It was observed that the proposed method successfully reduced the active power loss and costs associated with system operation.

This study aims to present a new SSA–GWO hybrid algorithm based on two different meta-heuristic algorithms, GWO and SSA, respectively. The hybrid optimization SSA–GWO algorithm aims to reduce the full power loss (kW) and solve the voltage variance by installing a multi DGs unit. This article uses three-phase off-balance IEEE 123 bus simulation systems to test the proposed algorithm's performance.

The rest of this article is arranged as follows. In Section 2, we present a mathematical formulation of the problem. SSA–GWO optimization algorithms are described in Section 3. The results of the simulated experiments are presented in Section 4. In Section 5, the conclusions, findings, and recommendations for future research are provided.

# 2 Methods and materials

## 2.1 Distributed generators (DG)

DGs' best placement and scale on the radial delivery network are necessary for reducing energy loss and enhancing voltage profile. The SSA–GWO algorithm finds a better site and volume of DGs in all the buses except the slack bus to lessen energy loss and improve the voltage. Figure 1 shows a typical DG network.

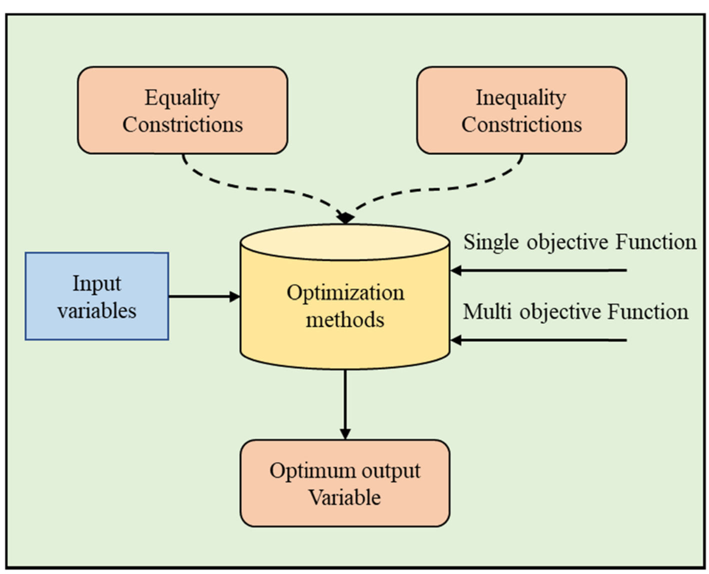


**Figure 1:** A typical DG network.

A one-line scheme of the two nodes of a delivery network is shown in Figure 2 [28]. In Figure 1, the two branches (bus $i$) are the send end bus and the receiving end bus (bus $i + 1$)). Equation (1) and (2) will calculate the active energy ($P_{i+1}$) and the reactive energy ($Q_{i+1}$).

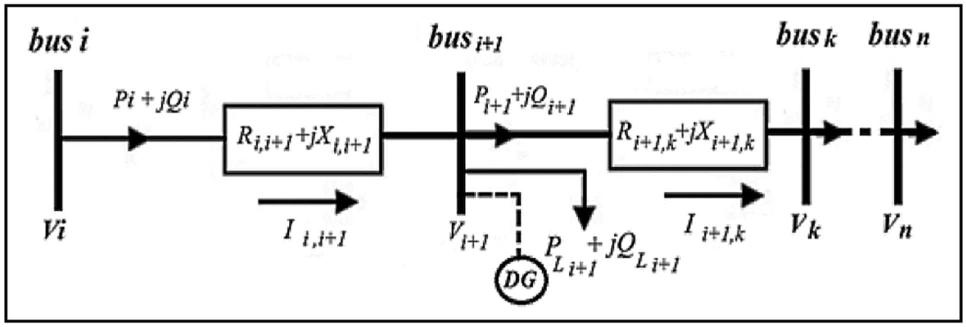


**Figure 2:** A line radial feeder diagram with DG placement.

$$P_{i+1} = [P_i - P_{\text{loss},i+1} - P_{Li+1}], \tag{1}$$

$$Q_{i+1} = [Q_i - Q_{\text{loss},i+1} - Q_{Li+1}]. \tag{2}$$

The active loss of power ($P_{\text{loss}\,i,i+1}$) and reactive loss of power ($Q_{\text{loss}\,i,i+1}$) in the midst of two nodes can be found by equations (3) and (4). The full energy loss $\text{TP}_{\text{loss}}$ of the radial supply system can be computed by equation (5).

$$P_{\text{loss}(i,i+1)} = I^2_{i,i+1} \times R_{i,i+1} = \left(\frac{p_i^2 + jQ_i^2}{|V_i^2|}\right) \times R_{i,i+1}, \tag{3}$$

$$Q_{\text{loss}(i,i+1)} = I^2_{i,i+1} \times X_{i,i+1} = \left(\frac{p_i^2 + jQ_i^2}{|V_i^2|}\right) \times X_{i,i+1}, \tag{4}$$

$$\text{TP}_{\text{loss}} = \sum_{i=0}^{n-1} P_{\text{loss}(i,i+1)}. \tag{5}$$

The objective function is utilized to lessen the full RPL and enhance the voltage. It can be written as the following:

$$\text{Minimize}f = \sum_{i=1}^{N_{\text{pranch}}} P^i_{\text{loss}} + \sum_{j=1}^{N_{\text{bus}}} |V_j - 1\,|. \tag{6}$$

DGs' best positioning and scale have some constraints such as bus voltage magnitude, DGs' capacity limits, and optimal DGs' optimal location as represented in equations (7)–(9), respectively.

$$0.95 \le |V_j| \le 1.05, \tag{7}$$

$$P_{\min} \le P_i \le P_{\max}, \tag{8}$$

$$2 \le \text{DG}_{\text{Li}} \le B_{L_{\max}}, \tag{9}$$

where $P^i_{\text{loss}}$ is the real loss of power (kW) in a branch $i$. $V_j$ is the magnitude of voltage on bus $j$ (p.u.). $P_i$ is the actual energy volume of the DG on the bus $i$. $P_{\min}$ and $P_{\max}$ are the min and max active power sizes of DGs, respectively. $\text{DG}_{\text{Li}}$ is the site of the DG on bus $i$, and $B_{L_{\max}}$ has the greatest site on the bus.

## 2.2 SSA

Mirjalili et al. [29] presented the SSA as a recent nature-inspired optimization in 2017. SSA is designed to build a population-based optimizer by simulating the swarm behavior observed in nature. Figure 3 shows a basic SSA algorithm.

So far, to the best of our knowledge, no study has been conducted on the effectiveness of the original SSA as an ELM trainer. The SSA algorithm shows a sufficient propensity for diversification and intensification, making it suitable for developing ELM training tasks. It is also critical to note that the advantages of

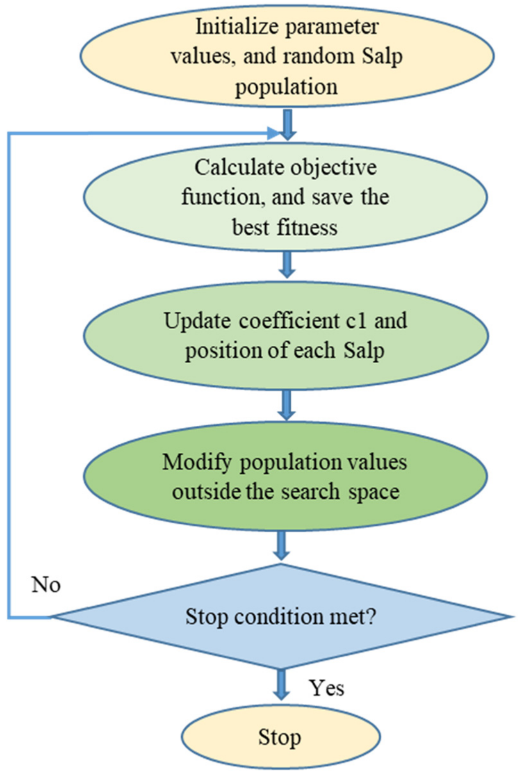


**Figure 3:** The basic SSA algorithm.

the SSA approach cannot be obtained by utilizing traditional optimization techniques, such as GSA, PSO, and GWO [30]. An SSA can be characterized by its capability, flexibility, simplicity, and ease of use in parallel and serial modes. In addition, it only has one parameter, which decreases the adaptively to keep diversification and intensification inclinations in balance.

### 2.3 Gray wolf optimizer (GWO)

Gray wolves in nature are socially and hierarchically structured, which the GWO algorithm emulates. Within a wolf pack, there may be different types of members based on the level of dominance, such as $\alpha$, $\beta$, $\delta$, and $\omega$. In terms of dominance and leadership power, the most dominant wolf is $\alpha$, and the level decreases from $\alpha$ to $\omega$ [31]. Figure 4 shows the hierarchy of dominance among gray wolves in a pack.

Implementation of this mechanism consists of classifying a population of potential solutions for a given optimization problem into four groups. A population of six solutions is being considered in this process. However, the first three most suitable solutions are considered $\alpha$, $\beta$, and $\delta$. All the remaining solutions are combined in the group of $\omega$ wolves.

## 3 Proposed SSA–GWO algorithm

An inhabitant based on the optimization approach suggested by Mirjalili et al. is the SSA [29]. By computing it with the Salp chain looking for ideal nourishment sources, the attitude of the SSA is more convincing. The eating source in the seeking space is called F and is the aim of this swarm. In the SSA, the wolfs are split into either leaders or followers according to the roles of the individuals in the chain (i.e., Salps). With a chief, the followers initiate and use the chain to guide them in their movements.

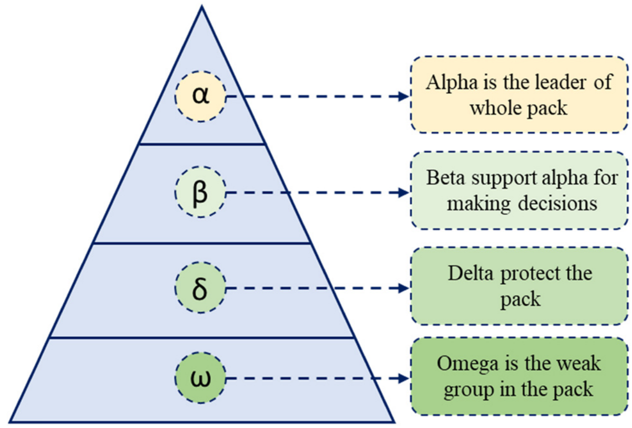


**Figure 4:** A hierarchy of dominance among gray wolves within a pack [26].

Gray wolf optimization is an intelligent swarm mechanism sophisticated by Mirjalili et al. [31], which is well known for its group hunting and the leadership hierarchy of wolf mimics. The gray wolf belongs to the family Canidae and prefers to live in a pack. They have a rigid hierarchy of social dominance; a male or female called Alpha is the king. A hybrid method to solve the issue of the best position and capability of DG units in the radial supply network is proposed in this article. SSA–GWO is a crossbreeding of two optimization algorithms, SSA and GWO, where algorithms operate concurrently. The flowchart in Figure 5 illustrates the hybrid SSA–GWO algorithm.

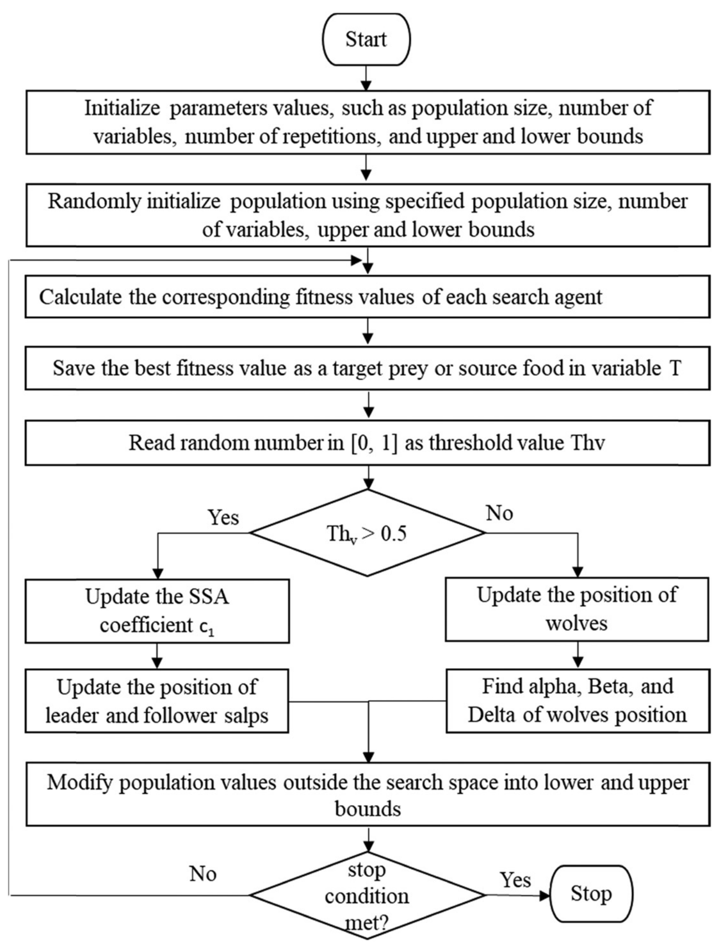


**Figure 5:** Flowchart for the suggested hybrid SSA–GWO algorithm.

## 4 Simulation and results

With the aid of a simulation system based on the IEEE 123-bus, a sample optimization procedure was implemented to determine DG devices' position and their volume (kW). The network maps of the nodes circuit are shown in Figure 6.

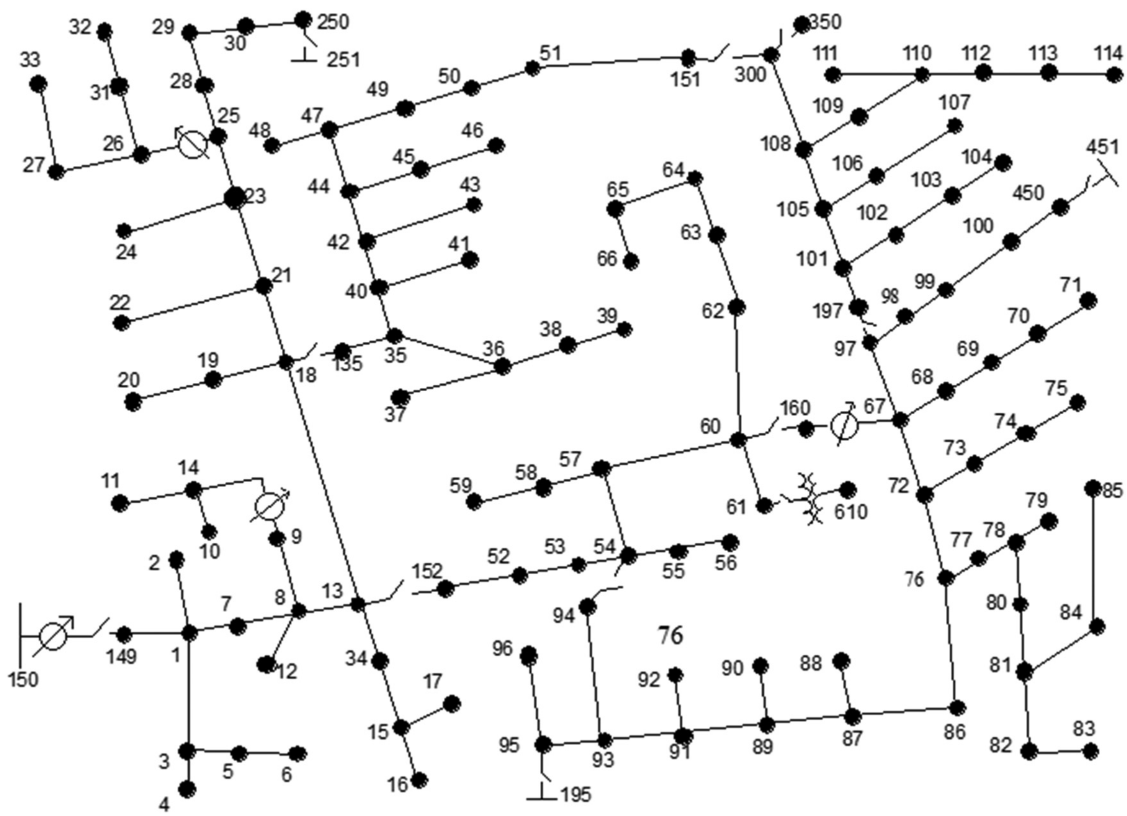


**Figure 6:** IEEE 123-bus node map [18,32].

Table 1 represents the constant power load applied in the IEEE 123-bus simulation trial systems [18]. In this research, the DG part is used to take a unity power operator. Thence, only real power is added to the IEEE simulation test device without reactive power in the various simulations. The length (km) of the IEEE 123-node simulation system is 12, inclusive of 126 lines, 123 buses, and the most prevalent elements found in existing systems, such as voltage regulators and shunt capacitor banks. All details of this simulation training, like bus data, line data, and load profile, have been listed in [32]. This simulation system has a combined simulated power load (kVAr) and actual power load (kW) of 1,920 kVAr and 3,490 kW, respectively. In equation (8), the $P_{\text{min}}$ and $P_{\text{max}}$ are DGs' min, and max active power sizes equal 0 and 5,000 kW, respectively.

Compared to the normal IEEE situation without a DG connection, the best results of SSA–GWO are compared, and GWO and SSA algorithms are implemented individually. Table 2 displays that the performance of the suggested multiple DG algorithm is higher than that of the SSA and GWO processes and the IEEE situation without DG units. The best outcome seen in Table 2 is gained using the suggested algorithm. A contrast of the real loss of power (kW) of the line, profile of voltage, and convergence of the IEEE 123-node simulation network is shown in Figures 4–6, respectively, after the addition of five DG units to the suggested SSA–GWO, GWO, and SSA algorithms.

**Table 1:** Constant reactive and real loads on IEEE 123 node test device [18]

| Bus no. | Phases | Active load (kW) | Reactive load (kVAr) | Load type | Bus no. | Phases | Active load (kW) | Reactive load (kVAr) | Load type |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 30 | 20 | W | 62 | 3 | 25 | 20 | W |
| 2 | 2 | 12 | 10 | W | 63 | 1 | 27 | 20 | W |
| 4 | 3 | 26 | 20 | W | 64 | 2 | 50 | 35 | W |
| 5 | 3 | 13 | 10 | W | 65 | 1 | 23 | 25 | D |
| 6 | 3 | 25 | 20 | W | 65 | 2 | 24 | 25 | D |
| 7 | 1 | 14 | 10 | W | 65 | 3 | 52 | 50 | D |
| 9 | 1 | 24 | 20 | W | 66 | 3 | 52 | 35 | W |
| 10 | 1 | 13 | 10 | W | 68 | 1 | 12 | 10 | W |
| 11 | 1 | 26 | 20 | W | 69 | 1 | 25 | 20 | W |
| 12 | 2 | 14 | 10 | W | 70 | 1 | 13 | 10 | W |
| 16 | 3 | 26 | 20 | W | 71 | 1 | 26 | 20 | W |
| 17 | 3 | 12 | 10 | W | 73 | 3 | 27 | 20 | W |
| 19 | 1 | 26 | 20 | W | 74 | 3 | 28 | 20 | W |
| 20 | 1 | 26 | 20 | W | 75 | 3 | 28 | 20 | W |
| 22 | 2 | 25 | 20 | W | 76 | 1 | 62 | 80 | D |
| 24 | 3 | 26 | 20 | W | 76 | 2 | 46 | 50 | D |
| 28 | 1 | 28 | 20 | W | 76 | 3 | 45 | 50 | D |
| 29 | 1 | 28 | 20 | W | 77 | 2 | 26 | 20 | W |
| 30 | 3 | 24 | 20 | W | 79 | 1 | 27 | 20 | W |
| 31 | 3 | 13 | 10 | W | 80 | 2 | 30 | 20 | W |
| 32 | 3 | 14 | 10 | W | 82 | 1 | 29 | 20 | W |
| 33 | 1 | 26 | 20 | W | 83 | 3 | 12 | 10 | W |
| 34 | 3 | 25 | 20 | W | 84 | 3 | 13 | 10 | W |
| 35 | 1 | 28 | 20 | D | 85 | 3 | 25 | 20 | W |
| 37 | 1 | 28 | 20 | W | 86 | 2 | 13 | 10 | W |
| 38 | 2 | 12 | 10 | W | 87 | 2 | 27 | 20 | W |
| 39 | 2 | 13 | 10 | W | 88 | 1 | 29 | 20 | W |
| 41 | 3 | 12 | 10 | W | 90 | 2 | 29 | 20 | W |
| 42 | 1 | 13 | 10 | W | 92 | 3 | 24 | 20 | W |
| 43 | 2 | 25 | 20 | W | 94 | 1 | 26 | 20 | W |
| 45 | 1 | 15 | 10 | W | 95 | 2 | 14 | 10 | W |
| 46 | 1 | 14 | 10 | W | 96 | 2 | 13 | 10 | W |
| 47 | 1,2,3 | 64 | 75 | W | 98 | 1 | 26 | 20 | W |
| 48 | 1,2,3 | 137 | 150 | W | 99 | 2 | 30 | 20 | W |
| 49 | 1 | 23 | 25 | W | 100 | 3 | 28 | 20 | W |
| 49 | 2 | 45 | 50 | W | 102 | 3 | 12 | 10 | W |
| 49 | 3 | 23 | 20 | W | 103 | 3 | 27 | 20 | W |
| 50 | 3 | 29 | 20 | W | 104 | 3 | 26 | 20 | W |
| 51 | 1 | 15 | 10 | W | 106 | 2 | 25 | 20 | W |
| 52 | 1 | 25 | 20 | W | 107 | 2 | 25 | 20 | W |
| 53 | 1 | 26 | 20 | W | 109 | 1 | 29 | 20 | W |
| 55 | 1 | 13 | 10 | W | 111 | 1 | 15 | 10 | W |
| 56 | 2 | 13 | 10 | W | 112 | 1 | 11 | 10 | W |
| 58 | 2 | 13 | 10 | W | 113 | 1 | 25 | 20 | W |
| 59 | 2 | 15 | 10 | W | 114 | 1 | 13 | 10 | W |
| 60 | 1 | 14 | 10 | W | | | | | |
| Total | | | | | | | **3,490** | **1,920** | |

The total actual energy casualties are diminished by 26.506% in an IEEE 123 bus simulation network. Figure 7 shows the contrast of substantial loss of power on the IEEE 123-bus test network after implementing SSA, GWO, and SSA–GWO algorithms with five DGs.

Figure 8 shows the number of actual losses of power on transmission lines with 5 DGs on the circuit used for testing. This figure shows that the energy losses in the proposed algorithm are less than the energy

**Table 2:** Performance of SSA–GWO compared with IEEE standard case, SSA, and GWO algorithms on IEEE 123-node with DGs

| DG no. | Particulars | 123-bus without DG | Algorithms | | |
|---|---|---|---|---|---|
| | | | SSA | GWO | SSA–GWO |
| 1 | Optimal location | — | 67 | 67 | 67 |
| | Total power losses (kW) | 95.434 | 70.246 | 70.984 | 70.162 |
| | Optimal DG size (kW) | — | 2017.729 | 2021.233 | 1978.521 |
| | % Power losses reduction | — | 26.416% | 25.620% | **26.481%** |
| | Minimum voltage (p.u.), bus | 0.98401 (65) | 0.97824 (65) | 0.97173 (65) | 0.97858 (65) |
| | Mean voltage (p.u.) | 1.0207 | 1.0173 | 1.0186 | **1.0152** |
| | Maximum voltage (p.u.), bus | 1.0481 (83) | 1.0477 (83) | 1.0477 (83) | 1.0403 (83) |
| 3 | % Power losses reduction | — | 25.626% | 25.922% | **26.206%** |
| | Optimal location | — | 149 56 97 | 90 28 160 | 151 67 56 |
| | Total power losses (kW) | 95.434 | 70.978 | 70.696 | 70.425 |
| | Minimum voltage (p.u.), bus | 0.98401 (65) | 0.98948 (65) | 0.98791 (65) | 0.97858 (65) |
| | Maximum voltage (p.u.), bus | 1.0481 (83) | 1.0476 (83) | 1.0463 (83) | 1.0403 (83) |
| | Mean voltage (p.u.) | 1.0207 | 1.0209 | 1.0209 | **1.0152** |
| | Optimal DG size (kW) | — | 755.84 | 4890.122 | 1345.624 |
| | | | 1558.834 | 3822.095 | 2642.309 |
| | | | 1667 | 1826.522 | 1994.325 |
| 5 | Mean voltage (p.u.) | 1.0207 | 1.0171 | 1.0158 | **1.0117** |
| | Minimum voltage (p.u.), bus | 0.98401 (65) | 0.98545 (65) | 0.97585 (65) | 0.97991 65 |
| | % Power losses reduction | — | 25.678% | 26% | **26.506%** |
| | Total power losses (kW) | 95.434 | 70.928 | 70.621 | 70.138 |
| | Maximum voltage (p.u.), bus | 1.0481 (83) | 1.0468 (83) | 1.0454 (83) | 1.0412 83 |
| | Optimal location | — | 81 26 56 66 48 | 81 48 149 23 67 | 7898612967 |
| | Optimal DG size (kW) | — | 46.577 | 1486.329 | 1550.443 |
| | | | 570.353 | 2005.140 | 3560.75 |
| | | | 4572.243 | 2088.604 | 1532.325 |
| | | | 217.167 | 1325.345 | 4062.252 |
| | | | 2010.437 | 1275.563 | 1889.452 |

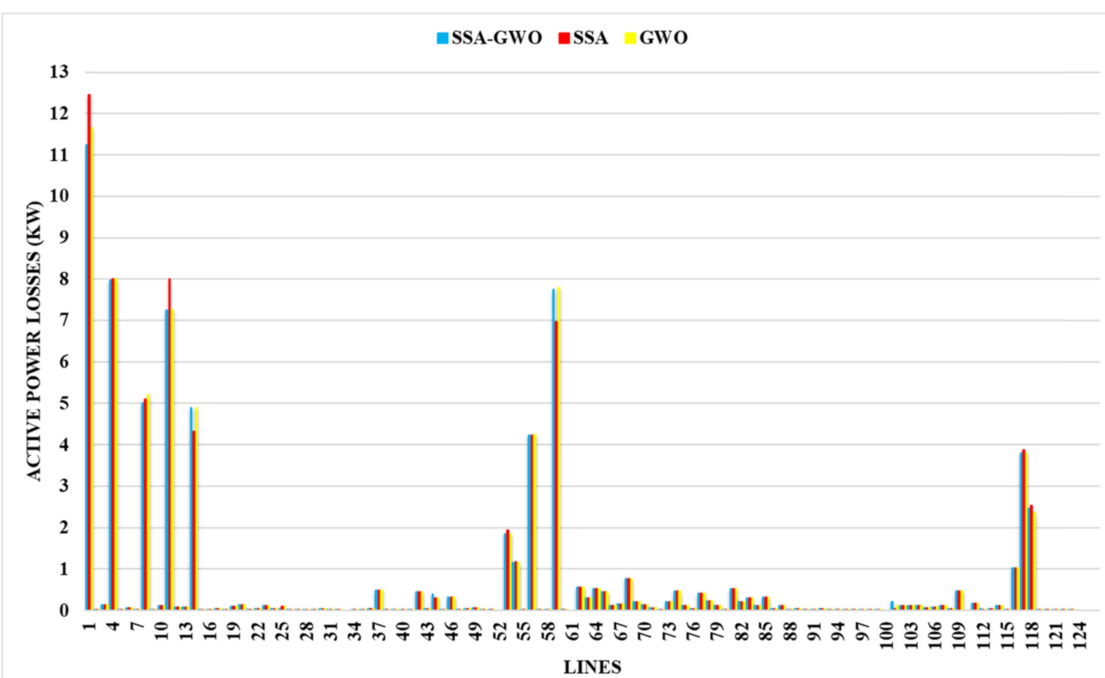


**Figure 7:** The contrast of actual loss of power on the IEEE 123-bus test network with SSA, GWO, and SSA–GWO and five DGs.

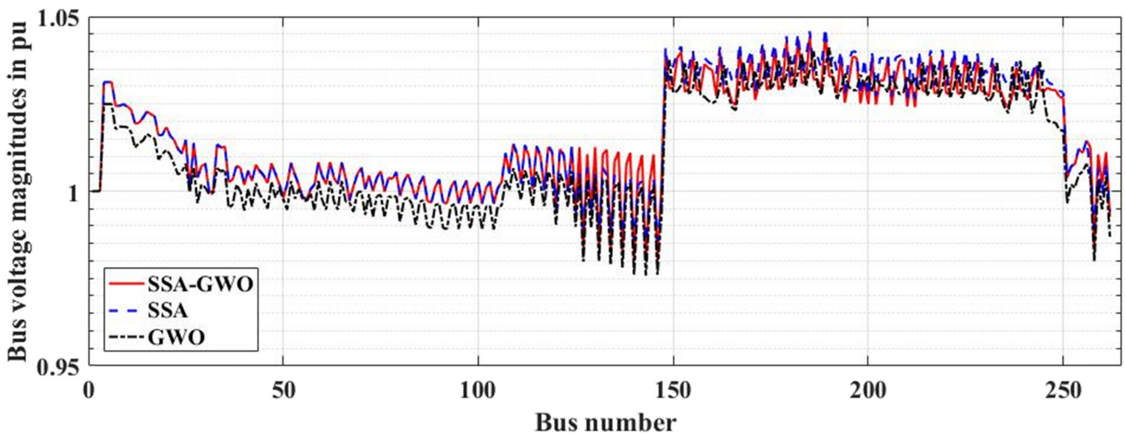


**Figure 8:** The voltage profile with SSA, GWO, and SSA–GWO on the IEEE 123-bus simulation system with five DGs.

losses in other algorithms (SSA and GWO). Figure 5 shows the amount of voltage profile on the bus in the circuit used for testing with 5 DGs, as we note that the voltage stability is better in the proposed algorithm than in the rest of the algorithms.

Figure 9 compares the convergence after implementing SSA, GWO, and SSA–GWO algorithms on the IEEE 123-bus simulation system with five DGs.

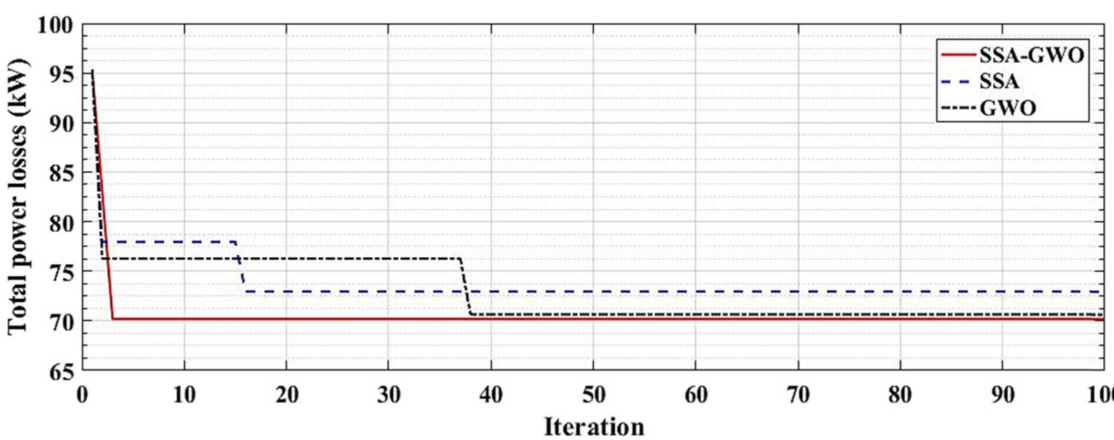


**Figure 9:** The convergence with SSA, GWO, and SSA–GWO and five DGs on the IEEE 123-bus simulation system.

Figure 9 shows the results from all the simulated algorithms in this study after running 100 iterations. This study found that the best results were achieved within the first 10 iterations for all simulations. This study takes into consideration DG units with a power factor. The IEEE test system runs various simulations without reactive power (kVAr) and only active power (kW).

## 5 Conclusion

Different studies show that using distributed generation (DGs) units is the most successful approach to the problem of distribution systems. The DG power supply network can be improved by applying some optimization solutions. In this work, a novel SSA–GWO is suggested to solve multiple DGs' best placement and capacity in the power radial distribution network. The proposed algorithm hybridizes two metaheuristic optimizations, the SSA and GWO algorithm. Subsequently, SSA–GWO is applied as a hybrid optimization algorithm to reduce total actual loss of power (kW) and solve voltage deviation by installation simultaneously in three-phase off-balance multi-DGs units from the IEEE 123-node simulation network. Hybrid (SSA–GWO) succeeds in searching for a better position and volume of DGs units than SSA and GWO implemented individually. Missing data or errors limitation should be considered when optimization performs with the proposed method. The case study acquired better outcomes after five DGs were applied to the IEEE 123-bus simulation system. In the simulation setting, the population is set to 30, and the number of iterations in the IEEE 123-node is set to 100. This study found that the best results were achieved within the first 10 iterations for all simulations. As a future study, we consider investigating new combinations of algorithms to solve multiple DGs' best placement and capacity in power radial distribution networks.

**Acknowledgements:** It would be our pleasure to extend our sincere declaration to the Department of Computer Science at Mustansiriyah University in Baghdad, Iraq. This research would not have been possible without their support. Special thanks go to the Center of Intelligent and Autonomous Systems, Faculty of Computer Science and Information Technology, University Tun Hussein Onn Malaysia (UTHM), for their participation in this research.

**Funding information:** The communication of this research has been made possible with the support of the UTHM Publisher's Office and Universiti Tun Hussein Onn Malaysia through the Publication Fund E15216.

**Conflict of interest:** There is no conflict of interest to disclose by the authors. It is certified by the authors that the work submitted is original, and it has not been submitted to any other journal for review. The authors have reviewed the manuscript and agree with its content, and there is no conflict of interest to disclose.

**Data availability statement:** This research uses an online data set that is appropriately cited within the article and can be found online.

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