Hindawi
International Journal of Photoenergy
Volume 2019, Article ID 2426538, 20 pages
https://doi.org/10.1155/2019/2426538

Research Article

Multiple DGs for Reducing Total Power Losses in Radial Distribution Systems Using Hybrid WOA-SSA Algorithm

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Received 15 December 2018; Revised 28 January 2019; Accepted 12 February 2019; Published 31 March 2019

Academic Editor: Huiqing Wen

Distributed generators (DGs) are currently extensively used to reduce power losses and voltage deviations in distribution networks. The optimal location and size of DGs achieve the best results. This study presents a novel hybridization of new metaheuristic optimizations in the last two years, namely, salp swarm algorithm (SSA) and whale optimization algorithm (WOA), for optimal placement and size of multi-DG units in radial distribution systems to minimize total real power losses (kW) and solve voltage deviation. This hybrid algorithm is implemented on IEEE 13- and 123-node radial distribution test systems. The OpenDSS engine is used to solve the power flow to find the power system parameters, such power losses, and the voltage profile through the MATLAB coding interface. Results describe the effectiveness of the proposed hybrid WOA-SSA algorithm compared with those of the IEEE standard case (without DG), repeated load flow method, and WOA and SSA algorithms applied independently. The analysis results via the proposed algorithm are more effective for reducing total active power losses and enhancing the voltage profile for various distribution networks and multi-DG units.

1. Introduction

A distributed generator (DG) is a small electricity-generating unit, and it is important in improving the power sector due to its small size, high efficiency, low operation cost, safety, and utilization of renewable energy resources. The increase in population and the progress in science have increased the need for electricity. Thus, the generated power must be increased to meet the demand, which has an important economic impact on countries. An increased load leads to an increase in losses due to poor voltage regulation. Capacitors in distribution systems play a key role in decreasing power losses. Capacitors are normally inserted to supply reactive power reparations in radial distribution systems. At present, DGs are widely applied because they use renewable resources and deliver active and reactive powers. The optimal placement of DG units in the distribution system is important and requires correct planning; otherwise, power losses will increase and voltage instability will occur. Therefore, the analysis and planning of DG units in power distribution systems are important areas of research.

In the current work, a novel hybrid approach is proposed by joining two new metaheuristic algorithms, namely, whale optimization algorithm (WOA) and salp swarm algorithm (SSA). The hybrid optimization algorithm called WOA-SSA aims at minimizing total RPLs (kW) and solve voltage deviation by installing multi-DG units simultaneously in two different radial distribution systems. Three-phase unbalanced IEEE 13- and 123-node systems are used in this work for testing. The IEEE 13-bus system involves six cases: one-, two-, three-, four-, five-, and six-DG units. The IEEE 123-bus system involves eight cases: one-, three-, four-, five-, six-, seven-,

eight-, and nine-DG units. The RPLs obtained from the proposed algorithm are compared with those obtained from the IEEE standard case (without DG) and those from WOA and SSA algorithms applied independently. MATLAB and a free power distribution system simulation tool, OpenDSS [1, 2], are used in the simulations.

The rest of the paper is organized as follows: Section 2 presents the related work. Section 3 proposes the mathematical formulation of the problem. Section 4 presents the proposed optimization algorithms. Section 5 presents the repeated load flow (RLF) method. Section 6 discusses the experiments and the simulation results. Section 7 elaborates the conclusions.

2. Related Work

Many metaheuristic approaches have been developed for placing DG units optimally in the network. El-Fergany [3] proposed a backtracking search optimization algorithm (BSA) to assign DGs along radial distribution networks (RDNs). The objective function is adopted with a weighting factor to reduce the real losses of the network and enhance the voltage profile for improving the operating performance. The proposed methodology is applied to 33- and 94-bus RDNs to examine its viability. Nguyen and Truong [4] proposed a reconfiguration methodology based on a cuckoo search algorithm (CSA) to minimize active power losses and maximize voltage magnitude. The CSA method is a new metaheuristic algorithm inspired from the obligate brood parasitism of some cuckoo species that lay their eggs in the nests of other host birds of other species for solving optimization problems. The effectiveness of the proposed CSA is tested on three different distribution network systems: 33-, 69-, and 119-node systems. Kansal et al. [5] proposed the optimal placement of DGs and capacitors for power compensation by maintaining the concept of distribution generation against centralized generation. The optimal location and size of DGs and capacitors are determined by minimizing the power distribution loss. The analytical approach is used to solve optimal placement problems. The proposed approach is tested on 33- and 69-bus test systems. Mahmoud et al. [6] proposed an efficient analytical method for optimally allocating DGs in electrical distribution systems to minimize power losses. The proposed analytical method can be used to obtain the optimal combination of different DG types in a distribution system for loss minimization. The analytical method for DG allocation is performed using two IEEE test systems, namely, a 33-bus system and a 69-bus system. Prabha and Jayabarathi [7] proposed a multiobjective technique for optimally determining the location and size of multi-DG units in a distribution network with different load models. The loss sensitivity factor (LSF) determines the optimal placement of DGs. Invasive weed optimization (IWO) is a population-based metaheuristic algorithm inspired by the behavior of weeds. This algorithm is used to find the optimal size of DGs. The proposed method is tested for different load models on IEEE 33- and 69-bus radial distribution systems. Prakash and Lakshminarayana [8] proposed a particle swarm optimization (PSO) algorithm to determine the optimal location and size of DGs. Complete analysis is carried out on IEEE 33- and 69-bus radial distribution systems. Each system is considered for two different cases, and comparative results obtained demonstrate the effectiveness of the proposed method in terms of placement and sizing of DG and minimization of power losses. Srinivasan and Visalakshi [9] presented an application of autonomous group particle swarm optimization (AGPSO) to solve power loss minimization in an RDN using the optimal allocation and sizing of DG units and capacitors with and without network reconfiguration to improve the efficiency of the RDN under seven cases (except the base case). The proposed technique is tested on a standard IEEE 69-bus RDN. Ceylan et al. [10] proposed an optimization model based on a recently developed heuristic search method, that is, gray wolf optimization (GWO), to coordinate various distribution controllers. Various case studies on IEEE 33- and 69-bus test systems modified by including tap changing transformers, capacitors, and photovoltaic solar panels are conducted. Mohan and Albert [11] proposed a hybrid GA-PSO algorithm to minimize losses and maintain acceptable voltage profiles in a radial distribution system simultaneously. The objective function is to optimally size and place DGs in appropriate buses in the system to reduce real power losses (RPLs) and operating cost and enhance voltage stability. The proposed algorithm is applied and demonstrated on IEEE 33- and 69-bus distribution systems. Jegadeesan and Venkatasubbu [12] proposed the hybridization of GA and artificial bee colony algorithm (ABC) for finding the optimal location and size of multiple DGs and capacitors in radial distribution systems. The main objective is to reduce the cost of the system by the optimal placement of multiple DGs and capacitors for decreasing RPLs. This hybrid algorithm is tested on IEEE 33- and 69-bus radial distribution systems. Javidtash et al. [13] proposed a novel combination of nondominated sorting GA and fuzzy method to minimize four objective functions, namely, cost, emission, power losses, and voltage deviation, on a typical 34-bus test microgrid. Grisales-Noreña et al. [14] proposed a population-based incremental learning (PBIL) algorithm to determine the optimal location of DGs and PSO to define the size those devices. The main objective is to reduce the computation time and active power losses and improve the nodal voltage profiles. The proposed algorithms are tested on IEEE 33- and 69-bus radial distribution systems. Khaled et al. [15] proposed a PSO to study the optimal power flow (OPF) of a power system integrated with a renewable DG. The hybrid DG wind and photovoltaic (PV) system is applied as a renewable DG on an IEEE 30-bus RDN. The main objective is to minimize the transmission losses. Swief et al. [16] proposed a cuckoo search optimization (CSO) technique for optimally determining the locations and sizes of photovoltaic (PV) and wind turbine (WT) DGs. The main objective is to maximize the reliability in the system. The proposed approach is tested on IEEE 69-bus test systems. El-Fergany [17] proposed a backtracking search algorithm (BSA) to study the effect of different load models on determining sizes and optimal

Table 1: Taxonomy of the reviewed optimal DG unit placement models.

Ref.	Proposed approach	Test system	Aim of the study
[3]	BSA	33 and 94 buses	Reduce the real losses and enhance the voltage profile
[4]	CSA	33, 69, and 119 nodes	Minimize active power losses and maximize voltage magnitude
[5]	Analytical and PSO	33 and 69 buses	Minimize the power distribution loss
[6]	Analytical	33 and 69 buses	Minimize power losses
[7]	LSF and IWO	33 and 69 buses	Minimize losses and operational cost and improve the voltage stability
[8]	PSO	33 and 69 buses	Minimize power losses
[9]	AGPSO	69 buses	Minimize power losses
[10]	GWO	33 and 69 buses	Minimize power losses
[11]	GA-PSO	33 and 69 buses	Minimize losses and maintain acceptable voltage profiles
[12]	GA-ABC	33 and 69 buses	Reduce the cost of the system and decrease RPLs
[13]	GA and Fuzzy	34 buses	Minimize cost, emission, power losses, and voltage deviation
[14]	PBIL and PSO	33 and 69 buses	Reduce active power losses and improve the nodal voltage profiles
[15]	PSO	30 buses	Minimize the transmission losses
[16]	CSO	69 buses	Maximize the reliability in the system
[17]	BSA	69 and 136 buses	Reduce power losses and improve network voltage profile
[18]	BSA and Fuzzy expert rules	33 and 94 nodes	Minimize the network power losses, consolidate the static voltage stability indices, and ameliorate the bus's voltage profile.

locations of the DGs. The main objective is to improve the network voltage profile and reduce power loss in RDNs. The proposed algorithm is tested on 136-bus and 69-bus radial distribution networks with four load models. El-Fergany [18] proposed a backtracking search algorithm multiobjective method and fuzzy expert rules for the optimal allocation of multitype DGs in radial distribution systems. The main aims were to minimize the network power losses, improve the bus's voltage profile, and consolidate the static voltage stability indices. The proposed method is tested on 94- and 33-node radial distribution systems with different scenarios. Table 1 presents a taxonomy of the reviewed optimal placement of DG unit models.

3. Mathematical Problem Formulation

3.1. Objective Function. The problem of optimal placement and size of DG units in the radial distribution system aims to improve a specific objective function such as minimizing RPLs and enhancing the voltage profile. The objective function in this article can be written as follows:

$$\text{Minimize } F(x,y) = \sum_{i=1}^{N_{\text{branch}}} P_{\text{loss}}^{i} + \sum_{j=1}^{N_{\text{bus}}} \left| V_j - 1 \right|, \tag{1}$$

where $F(x,y)$ is the aim of optimal placement and size of DGs, N_{branch} is the number of branches, N_{bus} is the number of buses, P_{loss}^{i} is the active power loss on branch i (kW), and V_j is the voltage magnitude of bus j (p.u.).

3.2. Constraints. The problem of optimal placement and size of DG units in the radial distribution system has the following constraints:

(i) The bus voltage magnitude is the first constraint. It must be kept within the given limits at each bus as follows:

$$0.95 \le \left| V_j \right| \le 1.05, \tag{2}$$

where V_j is the voltage magnitude at bus j (p.u.)

(ii) The capacity limits of DGs in the test system are obtained by

$$P^{\min} \le P_i \le P^{\max}, \tag{3}$$

where P_i is the real power capacity of the DG at bus i. $P^{\min}$ and $P^{\max}$ represent the minimum and maximum real power capacities of DGs, respectively

(iii) The optimal location of DGs must be greater than 1 and less than or equal to the number of buses in the test system. The first bus is a stack bus:

$$2 \le DG_{Li} \le B_{L\ \max}, \tag{4}$$

where DG_{Li} represents the location of the DG in bus i and $B_{L\ \max}$ represents the maximum location of the bus

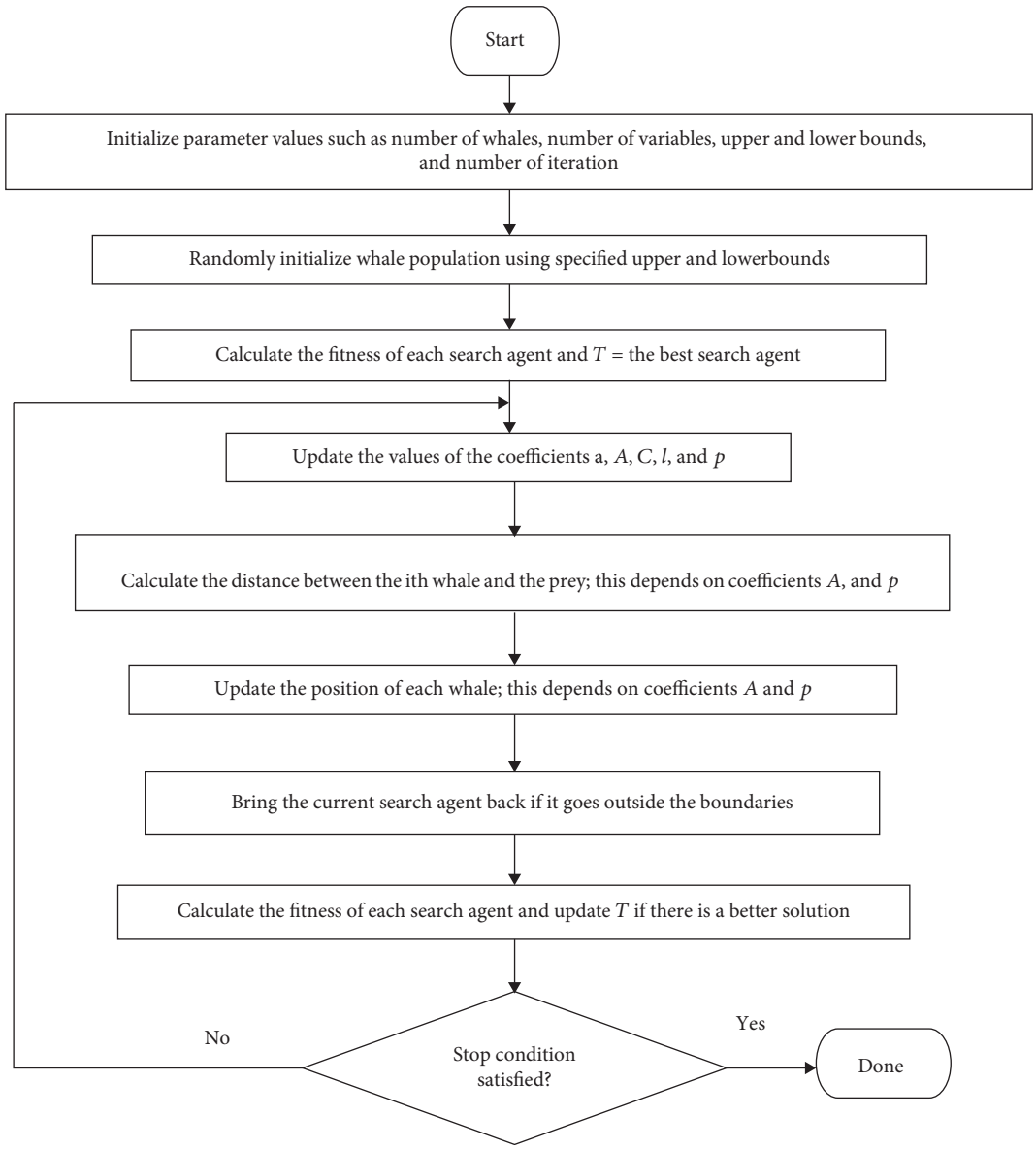

Figure 1: Flowchart of WOA.

4. Hybrid WOA-SSA Algorithm

4.1. WOA. WOA is a new metaheuristic algorithm that was refined in 2016 by Mirjalili and Lewis; the basic inspiration of this algorithm is the social behavior of humpback whales and the bubble-net hunting strategy [19]. Whales are considered the largest mammals in the world. A whale can be 30 m long and weigh 180 tons. Seven major kinds of whales exist, namely, Minke, killer, Sei, humpback, finback, right, and blue. Whales generally look similar to predators. Whales live in groups or alone. However, they are generally spotted in groups. Humpback whales have a special hunting method called the bubble-net feeding method [20]. Humpback whales choose to hunt small fishes or schools of krill near the surface. They create special bubbles over a circle or a "9"-shaped path to hunt. Humpback whales can locate their victims and surround them. The WOA algorithm supposes that the current best candidate solution is the goal prey or is near the optimal. After the best search agent is identified, the other search agents will try to update their positions to the best search agent. Figure 1 represents a flowchart of the WOA algorithm. This algorithm is tested with 6 structural design problems and 29 mathematical optimization problems; it has been proven more successful compared to conventional methods and modern metaheuristic algorithms [19]. Additionally, it is used by many researchers in different optimization areas. Mostafa et al. [21] proposed an approach for liver segmentation in MRI images based on WOA. Sayed et al. [22] proposed a novel optimization algorithm called chaotic whale optimization algorithm (CWOA) for feature selection based on the chaos theory and WOA. Hassan and Hassanien [23] proposed a novel automated approach for extracting the vasculature of retinal fundus images based on WOA. For more information around this algorithm, see Reference [19].

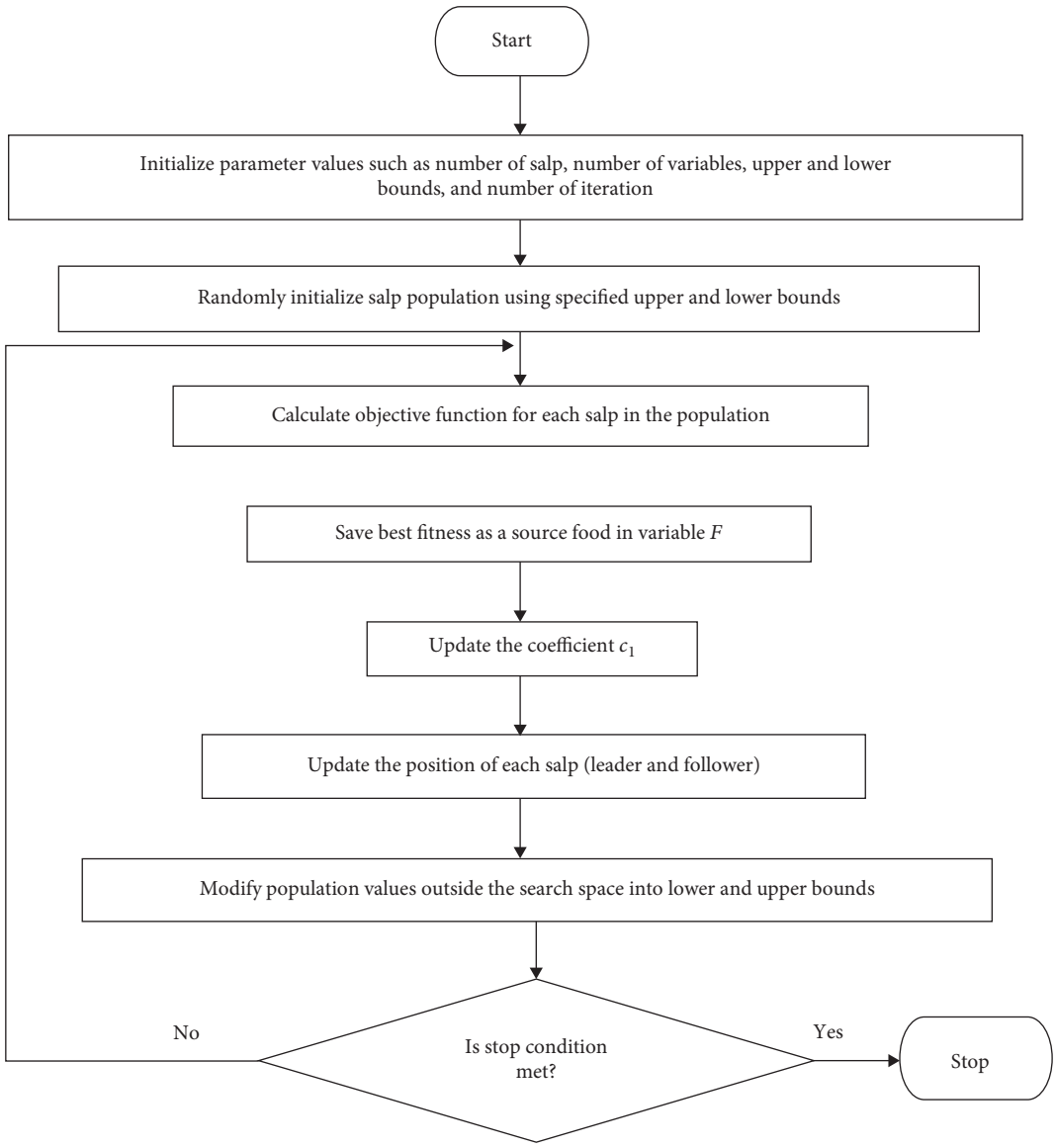

Figure 2: Flowchart of SSA.

4.2. SSA. SSA is a new metaheuristic algorithm that was refined in 2017 by Mirjalili et al.; the basic inspiration of this algorithm is the swarming behavior of salps in oceans when traveling and foraging [24]. In vast oceans, salps often create a salp chain swarm. The body shape of a salp is similar to a transparent barrel, and salps belong to the Salpidae family. Salp tissues are similar to those of a jellyfish. Their locomotion is also similar to that of a jellyfish, that is, water is pumped by the body to push and shift forward. The main cause of swarming behavior is unclear yet, but several researchers believe that swarming is done to obtain the best move using fast harmonic alterations and foraging. Few biological studies on this creature exist because the living environments are difficult to access, and salps are difficult to save in lab environments [24]. Figure 2 represents a flowchart of the SSA algorithm. This algorithm is tested to solve several challenging and computationally expensive engineering design problems (e.g., marine propeller design and airfoil design); it has been proven more successful compared to conventional methods and modern metaheuristic algorithms [24]. Additionally, it is used by many researchers in different optimization areas. El-Fergany [25] proposed an approach to define the best values of unknown parameters of the PEMFC model based on SSO. Sayed et al. [26] proposed a novel optimization algorithm called Chaotic Salp Swarm Algorithm (CSSA) for global optimization and feature selection based on the chaos theory and SSA. Ibrahim et al. [27] proposed a segmentation model for fish image segmentation and recognition based on the Simple Linear Iterative Clustering (SLIC) method for segmentation formulated with initial parameters optimized by the SSA. For more information around this algorithm, see Reference [24].

4.3. WOA-SSA for Solving the Optimal Location and Size of DG Units. SSA and WOA have not been used in the power

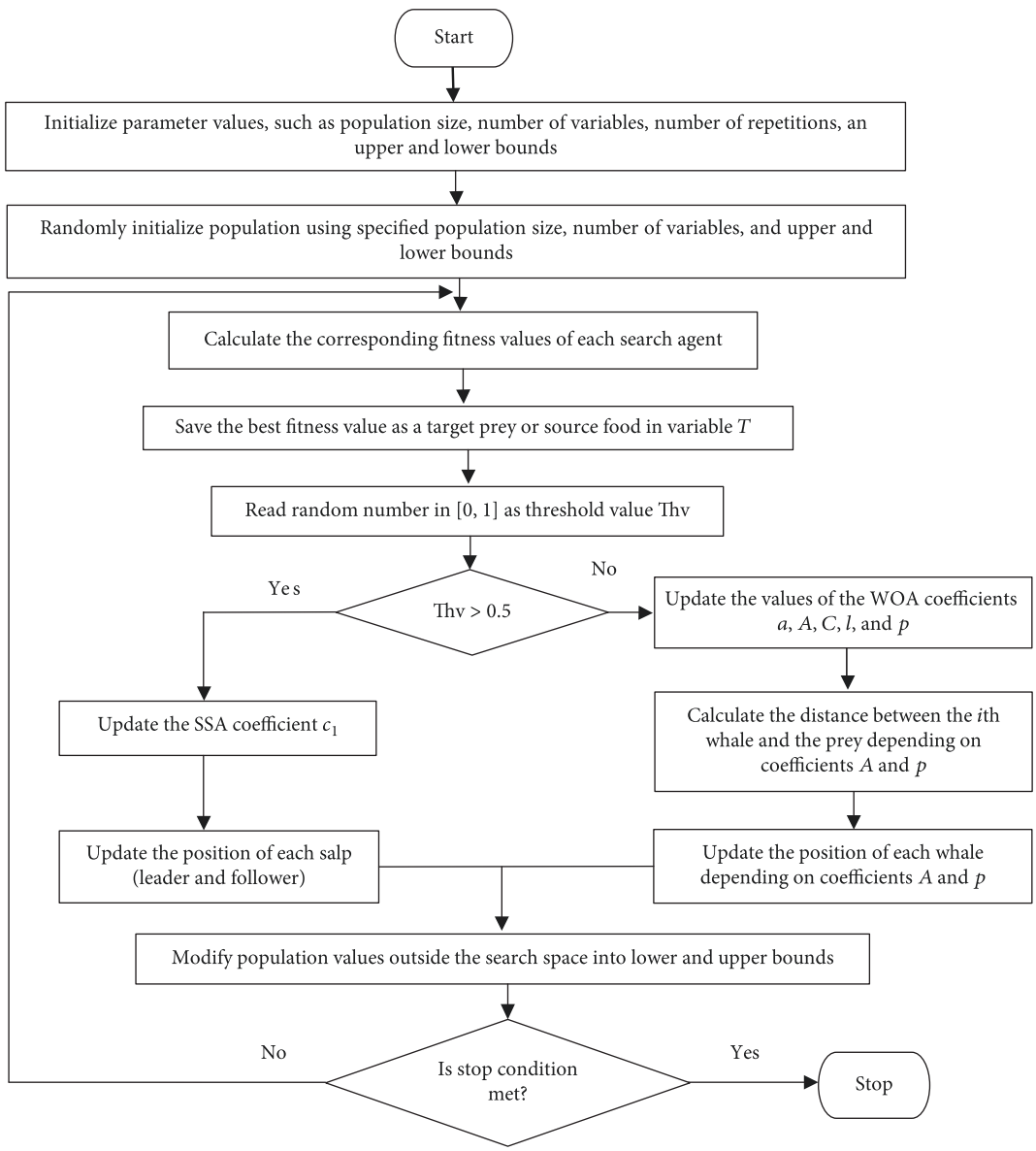

Figure 3: Flowchart of the proposed hybrid WOA-SSA.

optimization field. WOA-SSA is a hybridization of two algorithms, WOA and SSA, where the algorithms work simultaneously. A random number between 0 and 1 that represents the threshold value determines which algorithm to execute. If the value is less than 0.5, then WOA is executed; otherwise, SSA is executed. The proposed algorithm for improving the power distribution system needs some update to deal with the specific problem and to implement OpenDSS. Figure 3 presents a flowchart of the hybrid WOA-SSA algorithm. This hybrid optimization algorithm is implemented as follows:

(1) Initialize the set constants, such as population size n (number of salps or whales), number of variables d (dimension), maximum number of repetitions M_t, upper bound ub, and lower bound lb. Set the voltage magnitude limits, the possible DG locations, and the DG size limits

(2) Randomly create the location and size of the DG units depending on the population size, number of variables, and upper and lower bounds. Location represents discrete numbers, and size represents continuous numbers. The initial population is as follows:

$$X = \begin{bmatrix} X_{11} & \cdots & X_{1d} \\ X_{21} & \cdots & X_{2d} \\ \vdots & \ddots & \vdots \\ X_{n1} & \cdots & XS_{nd} \end{bmatrix}, \tag{5}$$

where X is the initial random population, X_{ij} is the position of the salps or whales in the ith population and jth variable, n is the population size, and d represents the number of variables

(3) Execute OpenDSS by using the specified load profile to run a load flow, perform power flow to calculate total active power losses (kW) and bus voltage magnitude (p.u.) using the solution candidates, and calculate the corresponding fitness values of each search agent of the test system using equation (1) as follows:

$$\mathrm{OX} = \begin{bmatrix} \mathrm{OX}_1 \\ \mathrm{OX}_2 \\ \vdots \\ \mathrm{OX}_n \end{bmatrix}, \tag{6}$$

where OX is the vector of fitness values, OX_i is the ith population fitness value, and n represents the search agent number

(4) Save the best search agent as the target prey or source food in variable T; T = the better search agent

(5) Select a random number in $[0, 1]$ as the threshold value (Thv); if the value is greater than 0.5, then go to 10

(6) Update WOA coefficients a, A, C, l, and p as follows:

$$a = 2 - t\left(\frac{2}{M_t}\right), \tag{7}$$

where a linearly decreases from 2 to 0 over the course of iterations, t is the current iteration, and M_t is the maximum iteration

The vectors A and C are calculated as follows:

$$\begin{aligned} A &= 2ar - a, \\ C &= 2r, \end{aligned} \tag{8}$$

where a linearly decreases from 2 to 0 over the course of iterations, and r is a random vector in $[0, 1]$

(7) Calculate the distance between the ith whale and the prey depending on coefficients A and p as follows:

$$\begin{aligned} D &= |C \cdot X_{\mathrm{rand}} - X_i(t)|, \quad \text{if } p < 0.5 \text{ and } |A| \geq 1, \\ D &= |C \cdot T(t) - X_i(t)|, \quad \text{if } p < 0.5 \text{ and } |A| < 1, \\ D &= |T(t) - X_i(t)|, \quad \text{if } p \geq 0.5, \end{aligned} \tag{9}$$

where D is the distance between the ith whale and the prey, C is the coefficient vector, X_{rand} is a random whale, X_i is the whale in position i, T is the target prey, t is the current iteration, and p is a random number in $[0, 1]$

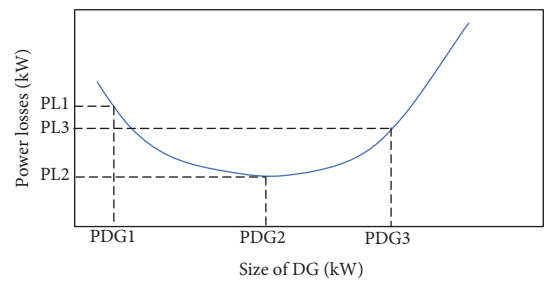

Figure 4: Relationship between increased DG size and total power losses.

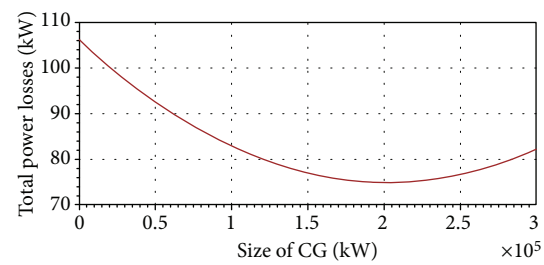

Figure 5: Power loss curve at bus number 675 for a 13-bus test system.

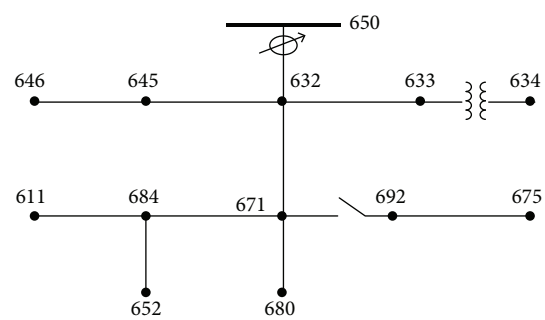

Figure 6: IEEE 13-bus map.

(8) Update the position of each whale depending on coefficients A and p as follows, then go to 12:

$$\begin{aligned} X(t+1) &= X_{\mathrm{rand}} - A \cdot D, \quad \text{if } p < 0.5 \text{ and } |A| \geq 1, \\ X(t+1) &= T(t) - A \cdot D, \quad \text{if } p < 0.5 \text{ and } |A| < 1, \\ X(t+1) &= D \cdot e^{bl} \cdot \cos(2\pi l) + T(t), \quad \text{if } p \geq 0.5 \end{aligned} \tag{10}$$

where X_{rand} is a random whale, D is the distance between the ith whale and the prey, t is the current iteration, p is a random number in $[0, 1]$, b is the constant for defining the shape of the logarithmic spiral $(b = 1)$, and l is a random number $[-1, 1]$

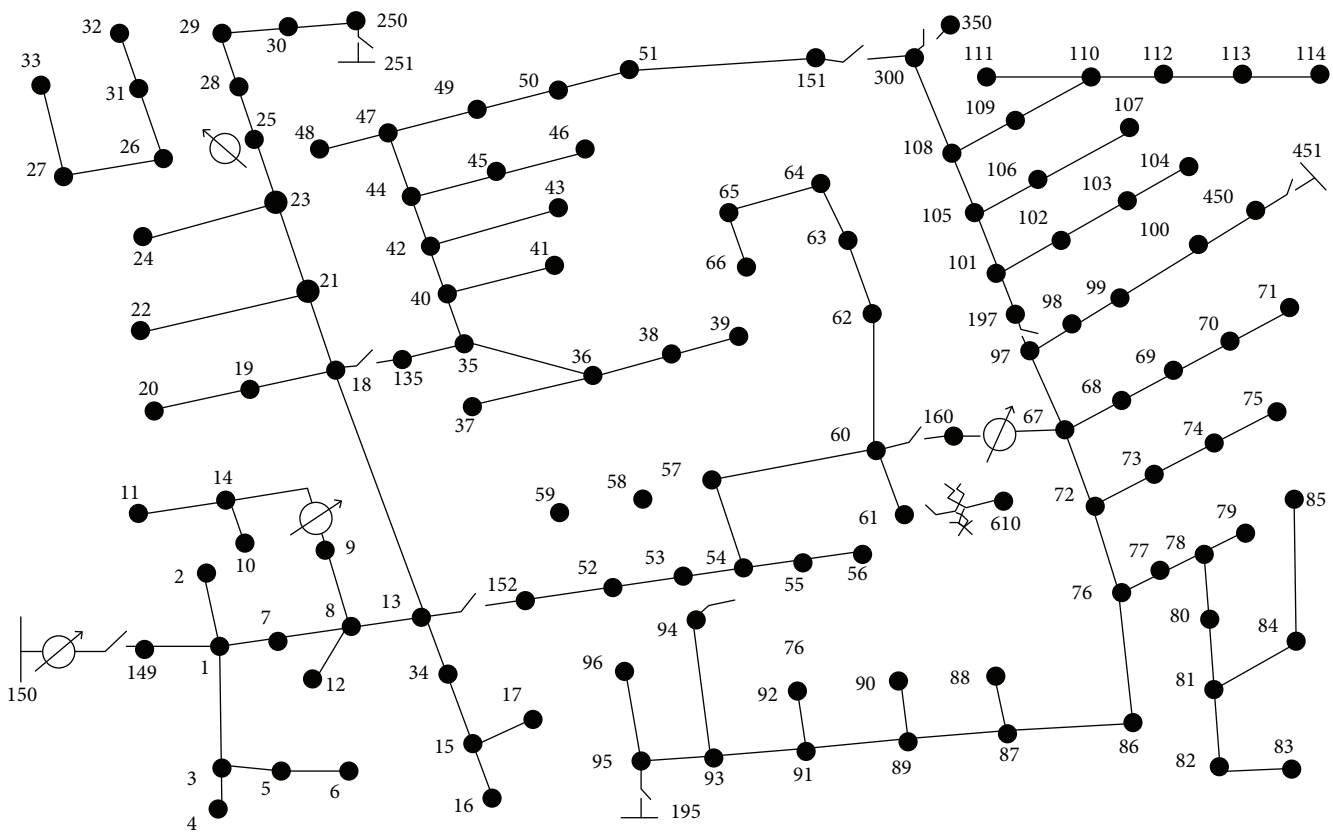

Figure 7: IEEE 123-bus map.

(9) Update SSA coefficient c_1 as follows:

$$c_1 = 2.\mathrm{e}^{-(4t/M_t)^2}, \tag{11}$$

where t represents the current iteration and M_t is the maximum number of iterations

(10) Update the position of each salp using equation (12) for the leader and equation (13) for the follower:

$$x_j^1 = \begin{cases} F_j + c_1\left(\left(\mathrm{ub}_j - \mathrm{lb}_j\right)c_2 + \mathrm{lb}_j\right), & c_3 \geq 0, \\ F_j - c_1\left(\left(\mathrm{ub}_j - \mathrm{lb}_j\right)c_2 + \mathrm{lb}_j\right), & c_3 < 0, \end{cases} \tag{12}$$

$$x_j^i = \frac{1}{2}\left(x_j^i + x_j^{i-1}\right), \tag{13}$$

where x_j^1 represents the position of the leader in the jth dimension; F_j is the position of the food source; c_2 and c_3 are random numbers between $[0, 1]$; and lb_j and ub_j represent the lower and upper bounds, respectively

(11) Modify the solution candidate's values outside the search agent into lower and upper bounds

(12) Repeat steps 3–11 until the stopping condition is met

Table 2: Active and reactive constant loads on an IEEE 13-bus test system.

Bus no.	Phases	Active load (kW)	Reactive load (kVar)	Load type
671	a, b, c	1155	660	Delta
634	a	160	110	Wye
634	b	120	90	Wye
634	c	120	90	Wye
645	b	170	125	Wye
646	b, c	230	132	Delta
692	a, b, c	170	151	Delta
675	a	485	190	Wye
675	b	68	60	Wye
675	c	290	212	Wye
611	c	170	80	Wye
652	a	128	86	Wye
670	a	17	10	Wye
670	b	66	38	Wye
670	c	117	68	Wye
Total		**3466**	**2102**	

(13) Print the optimal results, such as total active power losses (kW), location and size of the DG, and the minimum and maximum magnitudes of the bus voltage (p.u.)

Table 3: Active and reactive constant loads on an IEEE 123-bus test system.

Bus no.	Phases	Active load (kW)	Reactive load (kVAr)	Load type	Bus no.	Phases	Active load (kW)	Reactive load (kVAr)	Load type
1	a	30	20	Wye	62	c	25	20	Wye
2	b	12	10	Wye	63	a	27	20	Wye
4	c	26	20	Wye	64	b	50	35	Wye
5	c	13	10	Wye	65	a	23	25	Delta
6	c	25	20	Wye	65	b	24	25	Delta
7	a	14	10	Wye	65	c	52	50	Delta
9	a	24	20	Wye	66	c	52	35	Wye
10	a	13	10	Wye	68	a	12	10	Wye
11	a	26	20	Wye	69	a	25	20	Wye
12	b	14	10	Wye	70	a	13	10	Wye
16	c	26	20	Wye	71	a	26	20	Wye
17	c	12	10	Wye	73	c	27	20	Wye
19	a	26	20	Wye	74	c	28	20	Wye
20	a	26	20	Wye	75	c	28	20	Wye
22	b	25	20	Wye	76	a	62	80	Delta
24	c	26	20	Wye	76	b	46	50	Delta
28	a	28	20	Wye	76	c	45	50	Delta
29	a	28	20	Wye	77	b	26	20	Wye
30	c	24	20	Wye	79	a	27	20	Wye
31	c	13	10	Wye	80	b	30	20	Wye
32	c	14	10	Wye	82	a	29	20	Wye
33	a	26	20	Wye	83	c	12	10	Wye
34	c	25	20	Wye	84	c	13	10	Wye
35	a	28	20	Delta	85	c	25	20	Wye
37	a	28	20	Wye	86	b	13	10	Wye
38	b	12	10	Wye	87	b	27	20	Wye
39	b	13	10	Wye	88	a	29	20	Wye
41	c	12	10	Wye	90	b	29	20	Wye
42	a	13	10	Wye	92	c	24	20	Wye
43	b	25	20	Wye	94	a	26	20	Wye
45	a	15	10	Wye	95	b	14	10	Wye
46	a	14	10	Wye	96	b	13	10	Wye
47	a, b, c	64	75	Wye	98	a	26	20	Wye
48	a, b, c	137	150	Wye	99	b	30	20	Wye
49	a	23	25	Wye	100	c	28	20	Wye
49	b	45	50	Wye	102	c	12	10	Wye
49	c	23	20	Wye	103	c	27	20	Wye
50	c	29	20	Wye	104	c	26	20	Wye
51	a	15	10	Wye	106	b	25	20	Wye
52	a	25	20	Wye	107	b	25	20	Wye
53	a	26	20	Wye	109	a	29	20	Wye
55	a	13	10	Wye	111	a	15	10	Wye
56	b	13	10	Wye	112	a	11	10	Wye
58	b	13	10	Wye	113	a	25	20	Wye
59	b	15	10	Wye	114	a	13	10	Wye
60	a	14	10	Wye					
Total							**3490**	**1920**	

Table 4: Performance of WOA-SSA compared with those of the standard case without a DG unit, RLF method, WOA, and SSA on an IEEE 13-bus RDN with a single DG.

Particulars	Base case without DG	Algorithms			
		RLF	WOA	SSA	WOA-SSA
Optimal location	—	675	675	675	675
Optimal DG size (kW)	—	1913.217	1908.062	1905.825	1913.074
Total power losses (kW)	110.948	74.933	74.943	74.947	**74.934**
% power loss reduction	—	32.5%	32.5%	32.5%	**32.5%**
Minimum voltage (p.u.), bus	0.97288, 611	0.99338, 611	0.99331, 611	0.99329, 611	**0.99338, 611**
Maximum voltage (p.u.), bus	1.04, 675	1.0379, 632	1.0379, 632	1.0379, 632	**1.0379, 632**
Mean voltage (p.u.)	1.0037	1.011	1.011	1.011	**1.011**
Standard deviation voltage (p.u.)	0.020686	0.013075	0.013051	**0.013041**	0.013075
Computational time (S)	—	88689	**428**	484	450

5. Repeated Load Flow (RLF) Method

DG units greatly influence the power distribution system. Specifically, the addition of any size of DG in any location will increase or decrease total power losses in the distribution network. The RLF method is used to calculate the optimal location and size of DGs for obtaining the minimum total power loss in the distribution network. Although this algorithm produces exact results, it requires a large amount of load flow calculation; therefore, the method is inefficient and "exhaustive." The total power losses in the distribution system are decreased when the DG size is increased until a certain extent, and then losses start to arise, as shown in Figure 4. The size and location of DGs with the minimum total power loss in the distribution system are the optimal.

As shown in Figure 4, PDG2 represents the optimal DG size. Using this method, the optimal location and size of DGs for the 13-bus test system are 675 and 1913.217 kW, respectively, and those are 67 and 1978.595 kW for the 123-bus test system. Figure 5 shows the trend of power loss with the variation of DG size of the 13-bus test system, at bus number 675. The steps of this algorithm are presented as follows:

Step 1. Set the maximum DG size (kW, PDGmax = 5000), the maximum possible DG locations (Lmax), the current total power losses (TPl = large number), the current location (Cl = 2), the current DG size (DGp = 0), and the voltage magnitude limits.

Step 2. Execute OpenDSS to calculate the total active power losses (kW) and the bus voltage magnitude (p.u.) by using the specified load profile.

Step 3. If the voltage magnitude is without limits, then go to Step 6.

Step 4. If the total active power losses > TPl, then go to Step 6.

Step 5. TPl = total active power losses.

Step 6. If DGp > PDGmax, then go to Step 8.

Step 7. DGp = DGp + 0.001.

Step 8. If Cl > Lmax, then go to Step 10.

Step 9. If Cl = Cl + 1, then go to Step 2.

Step 10. Print the optimal DG size (DGp) and location (Cl) and total power losses.

6. Experiments and Simulation Results

The proposed optimization model for the location and size (kW) of multi-DG units has been implemented on IEEE 13- and 123-bus test systems. The node maps of the circuits are shown in Figures 6 and 7 [28, 29]. A fixed-power (FP) load is used in the simulation for different test systems. Tables 2 and 3 represent the FP load values on the IEEE 13- and 123-node test systems, respectively [28, 29]. The population is set to 30 in the simulation for different test systems, and the numbers of iterations are 1000 and 100 in the simulation on the IEEE 13- and 123-node test systems, respectively. The best results for all simulations in this study are achieved in 10 iterations. All DG units in this study have a unity power factor. Therefore, only the active power (kW) is injected in the different simulations in the IEEE test system without reactive power (kVAr).

6.1. IEEE 13-Bus Test System. This small test system is highly loaded, including 13 buses, 12 lines, and most of the features used in a real network, such as shunt capacitor banks, voltage regulators, overhead, unbalanced loads, and underground lines. The simulation constant load profile of the IEEE 13-bus test system is presented in Table 2. All information about this case study such as line data, bus data, and load profile has been explained in [28]. The total active power load (kW) and reactive power load (kVAr) of this test system are 3466 kW and 2102 kVAr, respectively. The optimal results of WOA-SSA are

Table 5: Performance of WOA-SSA compared with those of the standard case, WOA, and SSA on an IEEE 13-bus RDN with multiple DGs.

DG no.	Particulars	Base case without DG	Algorithms WOA	SSA	WOA-SSA
2	Candidate buses	—	645, 675	645, 675	611, 675
	Optimal DG size (kW)	—	438.9 2090.454	1794.687 2007.456	361.804 2024.676
	Total DG size (kW)	—	2529.354	3802.143	2386.48
	Total power losses (kW)	110.948	74.871	74.85	**74.838**
	% power loss reduction	—	32.5%	32.5%	**32.6%**
	Minimum voltage (p.u.), bus	0.97288, 611	0.99202, 634	0.99293, 634	**0.99294, 634**
	Maximum voltage (p.u.), bus	1.04, 675	1.0394, 632	1.0387, 632	**1.0385, 632**
	Mean voltage (p.u.)	1.0037	1.0115	1.0113	**1.0113**
	Standard deviation voltage (p.u.)	0.020686	0.014066	**0.013567**	0.013665
	Computational time (S)	—	450	506	**440**
3	Candidate buses	—	680, 611, 675	645, 646, 675	611, 645, 675
	Optimal DG size (kW)	—	4705.369 1434.894 2039.296	2877.887 2928.977 1982.26	1673.064 665.587 2022.381
	Total DG size (kW)	—	8179.559	7789.124	4361.032
	Total power losses (kW)	110.948	74.838	74.852	**74.832**
	% power loss reduction	—	32.6%	32.5%	**32.6%**
	Minimum voltage (p.u.), bus	0.97288, 611	0.99257, 634	0.9922, 634	**0.99276, 634**
	Maximum voltage (p.u.), bus	1.04, 675	1.039, 632	1.0389, 632	**1.0389, 632**
	Mean voltage (p.u.)	1.0037	1.0114	1.0113	**1.0112**
	Standard deviation voltage (p.u.)	0.020686	0.013757	**0.013427**	0.013658
	Computational time (S)	—	**475**	550	539
4	Candidate buses	—	646, 692, 611, 675	652, 611, 645, 675	645, 646, 634, 675
	Optimal DG size (kW)	—	32.418 8.923 2879.988 2013.935	631.618 664.226 646.792 2004.942	2786.184 3093.839 1591.05 1921.799
	Total DG size (kW)	—	4935.264	3947.578	9392.872
	Total power losses (kW)	110.948	74.937	74.834	**72.762**
	% power losses reduction	—	32.5%	32.6%	**34.4%**
	Minimum voltage (p.u.), bus	0.97288, 611	0.99285, 634	**0.99295, 634**	0.99008, 634
	Maximum voltage (p.u.), bus	1.04, 675	1.0388, 632	1.0387, 632	**1.0341, 632**
	Mean voltage (p.u.)	1.0037	1.0113	1.0113	**1.0099**
	Standard deviation voltage (p.u.)	0.020686	0.013609	0.013558	**0.012129**
	Computational time (S)	—	542	550	**540**
5	Candidate buses	—	632, 684, 611, 634, 675	634, 633, 632, 611, 675	611, 684, 634, 692, 675
	Optimal DG size (kW)	—	3124.516 4176.683 2663.978 1.041 2036.525	4020.34 3095.887 1498.569 3793.034 2007.206	1252.741 720.198 1922.402 265.501 2042.348

Table 5: Continued.

DG no.	Particulars	Base case without DG	Algorithms WOA	SSA	WOA-SSA
	Total DG size (kW)	—	12002.743	14415.036	6203.19
	Total power losses (kW)	110.948	74.845	74.839	**74.834**
	% power losses reduction	—	32.5%	32.6%	**32.6%**
	Minimum voltage (p.u.), bus	0.97288, 611	0.99259, 634	**0.99291, 634**	0.99252, 634
	Maximum voltage (p.u.), bus	1.04, 675	1.039, 632	**1.0387, 632**	1.039, 632
	Mean voltage (p.u.)	1.0037	1.0114	**1.0113**	1.0114
	Standard deviation voltage (p.u.)	0.020686	0.013745	**0.013574**	0.013781
	Computational time (S)	—	626	658	**614**
6	Candidate buses	—	652, 680, 645, 633, 671, 675	646, 680, 632, 671, 684, 675	645, 652, 633, 684, 671, 675
	Optimal DG size (kW)	—	1760.35 982.198 2423.365 3418.675 3279.92 1991.147	3087.157 1820.051 887.208 1812.839 1620.26 2025.412	1704.998 2942.587 3221.933 818.585 188.281 2032.203
	Total DG size (kW)	—	13855.655	11252.927	10908.587
	Total power losses (kW)	110.948	74.872	74.869	**74.864**
	% power loss reduction	—	32.5%	32.5%	**32.5%**
	Minimum voltage (p.u.), bus	0.97288, 611	0.99306, 634	0.99269, 634	**0.99261, 634**
	Maximum voltage (p.u.), bus	1.04, 675	**1.0386, 632**	1.0389, 632	1.039, 632
	Mean voltage (p.u.)	1.0037	**1.0113**	1.0114	1.0114
	Standard deviation voltage (p.u.)	0.020686	**0.013496**	0.01369	0.013731
	Computational time (S)	—	677	692	**659**

compared with those of the standard IEEE case without DG installation, RLF method, and WOA and SSA algorithms applied independently for a single DG unit, as shown in Table 4.

The numerical results in the table below reflect a similarity between the proposed algorithm and the RLF method, but WOA-SSA is faster. Table 5 indicates that the efficiency of the proposed algorithm with multi-DG units is better than those of the standard IEEE case and WOA and SSA algorithms applied independently.

Table 5 shows that the results of the proposed algorithm are better than those of other algorithms. The best case is when four-DG units are used. Figures 8, 9, and 10, respectively, represent a comparison of the active power losses (kW) on lines, the voltage profile, and the convergence on the IEEE 13-bus test system after adding four-DG units by the proposed WOA-SSA, SSA, and WOA algorithms. The comparison of the WOA-SSA, SSA, and WOA running times on six cases of the IEEE 13-bus test system is shown in Figure 11.

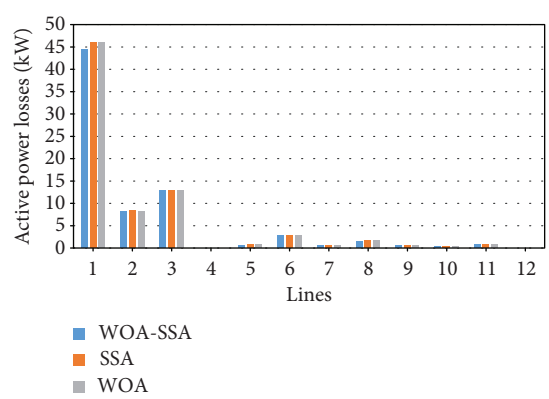

Figure 8: Comparison of the active power losses (kW) on lines of the IEEE 13-bus simulation system after adding four DG units by the proposed WOA-SSA, SSA, and WOA algorithms.

6.2. IEEE 123-Bus Test System. The length (km) of this test system is 12, including 123 buses, 126 lines, and the most common components found in actual networks, such

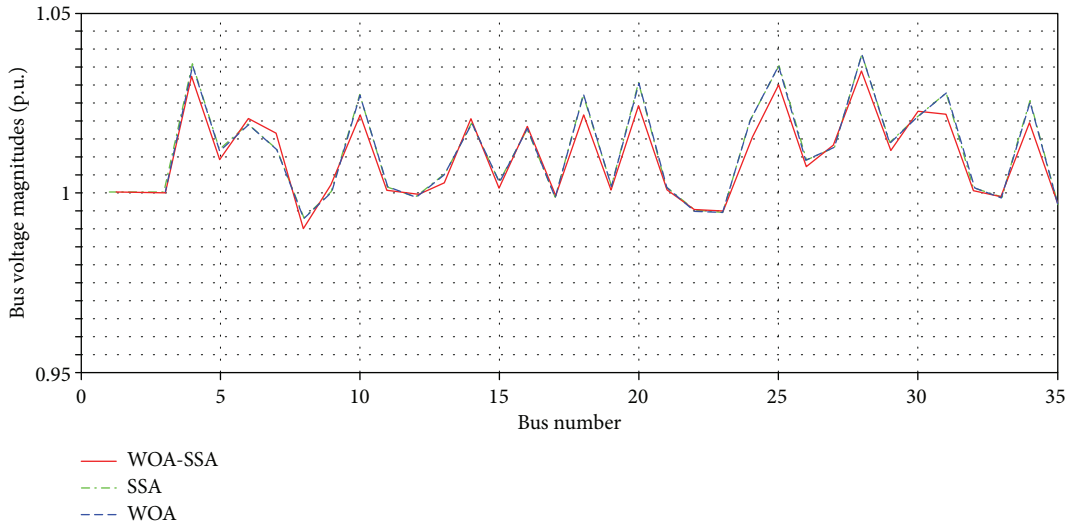

Figure 9: Comparison of the voltage profile of the IEEE 13-bus simulation system after adding four DG units by the proposed WOA-SSA, SSA, and WOA algorithms.

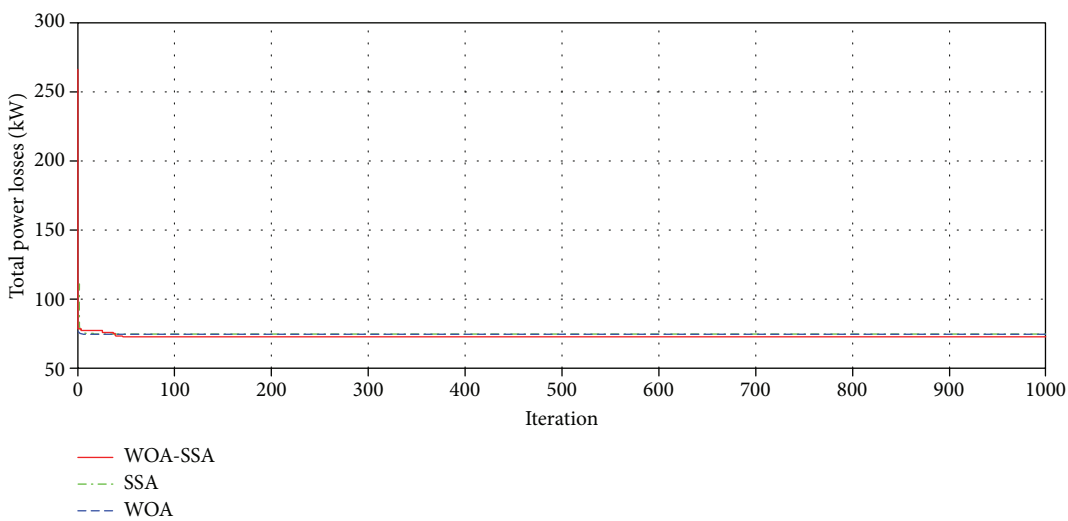

Figure 10: Comparison of the convergence of the IEEE 13-bus test system after adding four DG units by the proposed WOA-SSA, SSA, and WOA algorithms.

shunt capacitor banks and voltage regulators. The system contains several close and open switches that enable researchers to test the reconfiguration strategies in this test system. The simulation constant load profile of the IEEE 123-bus test system is presented in Table 3. All information about this case study such as line data, load profile, and bus data has been explained in [29]. The total active power load (kW) and reactive power load (kVAr) of this test system are 3490 kW and 1920 kVAr, respectively. The optimal results of WOA-SSA are compared with those of the standard IEEE case without DG installation, RLF method, and WOA and SSA algorithms applied independently for a single DG unit, as shown in Table 6.

The results from the proposed algorithm are similar to the results from the RLF method but with a better execution time and are better than those of the WOA and SSA

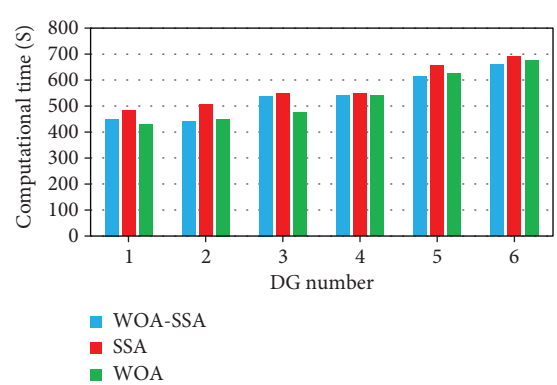

Figure 11: Comparison of the WOA-SSA, SSA, and WOA running times on six cases of the IEEE 13-bus test system.

Table 6: Performance of WOA-SSA compared with those of the standard case without a DG unit, RLF method, WOA, and SSA on an IEEE 123-bus RDN with a single DG.

Particulars	Base case without DG	Algorithms			
		RLF	WOA	SSA	WOA-SSA
Optimal location	—	67	67	67	67
Optimal DG size (kW)	—	1978.595	2020.456	2017.729	1979
Total power losses (kW)	95.434	70.17	70.598	70.246	**70.17**
% power loss reduction	—	26.5%	26%	26.4%	**26.5%**
Minimum voltage (p.u.), bus	0.98401, 65	0.97884, 65	0.97173, 65	0.97824, 65	**0.97884, 65**
Maximum voltage (p.u.), bus	1.0481, 83	1.047, 83	1.0477, 83	1.0477, 83	**1.047, 83**
Mean voltage (p.u.)	1.0207	1.0171	1.0186	1.0173	**1.0171**
Standard deviation voltage (p.u.)	0.018416	0.016418	0.018971	0.016546	**0.01642**
Computational time (S)	—	90156	230	256	**161**

Table 7: Performance of WOA-SSA compared with those of the WOA and SSA algorithms and the IEEE case without DG on an IEEE 123-bus RDN with multiple DGs.

DG no.	Particulars	Base case without DG	Algorithms WOA	SSA	WOA-SSA
3	Candidate buses	—	90, 28, 160	149, 56, 97	152, 45, 67
	Optimal DG size (kW)	—	5000 3822.095 1826.522	755.84 1558.834 1667	1745.644 2642.309 1995.555
	Total DG size (kW)	—	10648.617	3981.674	6383.508
	Total power losses (kW)	95.434	70.696	70.978	**70.292**
	% power loss reduction	—	25.9%	25.6%	**26.4%**
	Minimum voltage (p.u.), Bus	0.98401, 65	0.98791, 65	**0.98948, 65**	0.97858, 65
	Maximum voltage (p.u.), Bus	1.0481, 83	1.0463, 83	1.0476, 83	**1.0403, 83**
	Mean voltage (p.u.)	1.0207	1.0209	1.0209	**1.0152**
	Standard deviation voltage (p.u.)	0.018416	**0.014141**	0.015043	0.014254
	Computational time (S)	—	231	**224**	228
4	Candidate buses	—	52, 51, 25, 54	52, 42, 250, 54	13, 51, 36, 57
	Optimal DG size (kW)	—	4491.045 2109.597 2126.813 2034.666	1657.875 2089.409 3275.819 2146.397	488.383 1160.717 2568.928 2479.022
	Total DG size (kW)	—	10762.121	9169.5	6697.05
	Total losses (kW)	95.434	74.238	73.969	**73.091**
	% loss reduction	—	22.2%	22.5%	**23.4%**
	Minimum voltage (p.u.), bus	0.98401, 65	**0.98234, 65**	0.98097, 65	0.97407, 65
	Maximum voltage (p.u.), bus	1.0481, 83	1.0446, 83	1.0436, 83	**1.0458, 83**
	Mean voltage (p.u.)	1.0207	1.0135	1.013	**1.0123**
	Standard deviation voltage (p.u.)	0.018416	0.019012	0.01825	**0.017625**
	Computational time (S)	—	278	284	**274**
5	Candidate buses	—	81, 48, 149, 23, 67	55, 26, 56, 40, 57	78, 98, 61, 29, 67
	Optimal DG size (kW)	—	2686.689 2003.240 2039.694 1336.645 1770.532	38.473 589.953 4572.243 397.187 2016.337	1599.443 3560.55 1557.516 4062.252 1899.762
	Total DG size (kW)	—	9836.8	7614.193	12679.523
	Total power losses (kW)	95.434	70.635	72.928	**70.184**
	% power loss reduction	—	26%	23.6%	**26.5%**
	Minimum voltage (p.u.), bus	0.98401, 65	0.97585, 65	**0.98545, 65**	0.97991, 65
	Maximum voltage (p.u.), bus	1.0481, 83	1.0412, 83	**1.0468, 83**	1.0453, 83

Table 7: Continued.

DG no.	Particulars	Base case without DG	Algorithms WOA	SSA	WOA-SSA
	Mean voltage (p.u.)	1.0207	**1.0117**	1.0171	1.0159
	Standard deviation voltage (p.u.)	0.018416	0.016813	0.016408	**0.015152**
	Computational time (S)	—	237	255	**232**
6	Candidate buses	—	26, 28, 13, 10, 51, 53	8, 9, 35, 42, 250, 53	150, 35, 54, 13, 54, 54
	Optimal DG size (kW)	—	2457.965 2806.089 1605.001 1912.286 2838.475 2261.193	4565.555 258.574 1393.951 3839.614 1837.754 2789.804	4447.936 322.867 1040.216 191.239 2731.592 2236.8
	Total DG size (kW)	—	13881.009	14685.252	10970.65
	Total losses (kW)	95.434	74.061	73.937	**73.419**
	% loss reduction	—	22.4%	22.5%	**23.1%**
	Minimum voltage (p.u.), bus	0.98401, 65	0.98132, 65	0.97656, 65	**0.98629, 65**
	Maximum voltage (p.u.), bus	1.0481, 83	1.0432, 83	**1.042, 83**	1.045, 83
	Mean voltage (p.u.)	1.0207	1.0131	**1.0119**	1.0169
	Standard deviation voltage (p.u.)	0.018416	0.018087	0.016947	**0.015978**
	Computational time (S)	—	301	302	**273**
7	Candidate buses	—	36, 97, 75, 104, 53, 34, 72	36, 25, 50, 27, 57, 8, 67	53, 56, 42, 64, 51, 62, 67
	Optimal DG size (kW)	—	2391.085 5000 2797.53 3450.195 5000 4439.535 1888.471	1 1 5000 1748.772 1 5000 1877.048	1966.79 2039.543 2147.753 3201.916 3603.024 1561.412 1926.957
	Total DG size (kW)	—	24966.816	13628.82	16447.395
	Total power losses (kW)	95.434	71.376	70.597	**70.273**
	% power loss reduction	—	25.2%	26%	**26.4%**
	Minimum voltage (p.u.), bus	0.98401, 65	0.97374, 65	0.97372, 65	**0.97935, 65**
	Maximum voltage (p.u.), bus	1.0481, 83	1.0479, 83	**1.0448, 83**	1.0458, 83
	Mean voltage (p.u.)	1.0207	**1.0124**	1.0131	1.0169
	Standard deviation voltage (p.u.)	0.018416	0.017836	0.018325	**0.016181**
	Computational time (S)	—	238	264	**233**
8	Candidate buses	—	36, 26, 27, 30, 29, 22, 37, 13	48, 21, 7, 51, 23, 7, 47, 57	52, 8, 20, 29, 150, 30, 1, 52
	Optimal DG size (kW)	—	2845.921 3590.8 3277.099 1528.684 1221.43 2044.885 2279.321 2862.69	3731.289 2207.028 4943.676 1137.604 2771.666 2076.816 1761.434 2869.06	1217.977 1733.92 2376.75 181.628 2300.277 3794.711 3728.088 2376.548

Table 7: Continued.

DG no.	Particulars	Base case without DG	Algorithms WOA	SSA	WOA-SSA
	Total DG size (kW)	—	19650.83	21498.573	17709.899
	Total losses (kW)	95.434	74.856	74.363	**74.071**
	% loss reduction	—	21.6%	22.1%	**22.4%**
	Minimum voltage (p.u.), bus	0.98401, 65	**0.99074, 65**	0.96968, 65	0.9891, 65
	Maximum voltage (p.u.), bus	1.0481, 83	1.0465, 83	**1.0443, 83**	1.0485, 83
	Mean voltage (p.u.)	1.0207	1.0159	**1.0139**	1.0175
	Standard deviation voltage (p.u.)	0.018416	**0.015319**	0.018916	0.016697
	Computational time (S)	—	285	**274**	275
9	Candidate buses	—	23, 250, 49, 35, 18, 2, 17, 37, 52	29, 25, 54, 40, 250, 52, 149, 151, 57	17, 55, 2, 27, 44, 49, 44, 250, 57
	Optimal DG size (kW)	—	1041.278 3539.659 1006.816 1515.389 427.404 467.085 434.462 479.55 2200.006	4370.94 4105.06 4354.954 5000 2044.157 4093.852 3826.531 638.685 2427.329	2445.393 1150.91 68.636 2389.231 3098.096 2860.186 122.912 2677.014 2278.389
	Total DG size (kW)	—	11111.649	30861.508	17090.767
	Total losses (kW)	95.434	74.86	72.805	**72.576**
	% loss reduction	—	21.6%	23.7%	**24%**
	Minimum voltage (p.u.), bus	0.98401, 65	**0.98417, 65**	0.98069, 65	0.98257, 65
	Maximum voltage (p.u.), bus	1.0481, 83	1.0465, 83	1.0455, 83	**1.0436, 83**
	Mean voltage (p.u.)	1.0207	**1.0128**	1.0178	1.0164
	Standard deviation voltage (p.u.)	0.018416	0.018169	0.016801	**0.015684**
	Computational time (S)	—	278	279	**276**

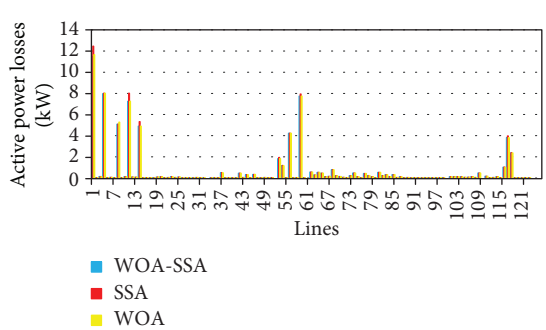

Figure 12: Comparison of the active power losses (kW) on lines of the IEEE 123-bus simulation system after adding five DG units by the proposed WOA-SSA, SSA, and WOA algorithms.

algorithms. Table 7 illustrates that the efficiency of the proposed algorithm with multi-DG units is better than those of the WOA and SSA algorithms and IEEE case without DG.

The best results shown in Table 7 are obtained using the proposed algorithm. Figures 12, 13, and 14, respectively, illustrate a comparison of the active power losses (kW) on lines, the voltage profile, and the convergence on the IEEE 123-bus test system after adding five-DG units by the proposed WOA-SSA, SSA, and WOA algorithms. Figure 15 shows the comparison of WOA-SSA, SSA, and WOA running times on eight cases of the IEEE 123-bus test system.

7. Conclusion

Two metaheuristic algorithms, namely, WOA and SSA, are combined to develop a novel hybrid algorithm called

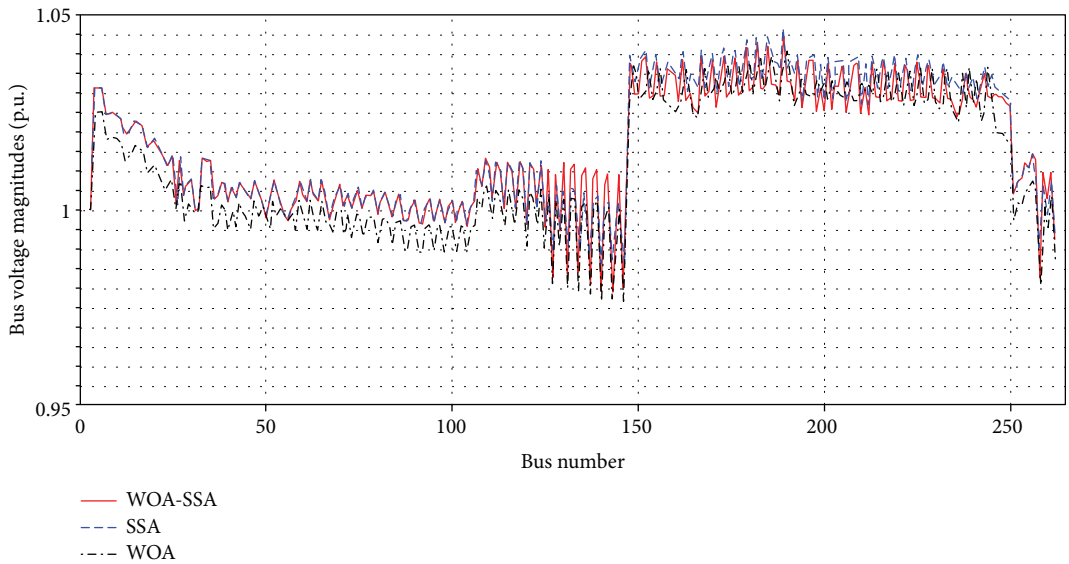

Figure 13: Comparison of the voltage profile of the IEEE 123-bus simulation system after adding five DG units by the proposed WOA-SSA, SSA, and WOA algorithms.

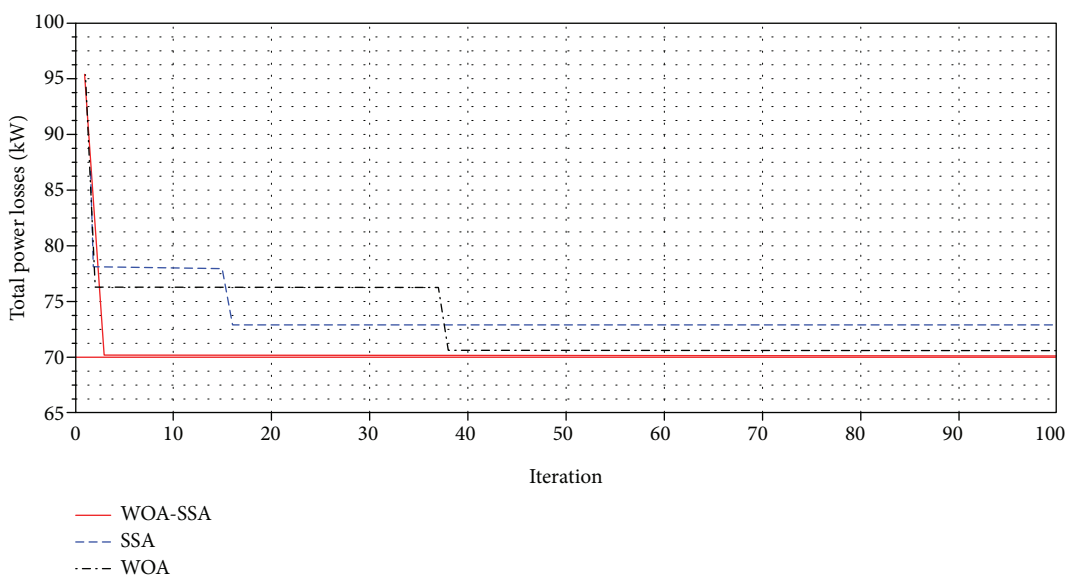

Figure 14: Comparison of the convergence of the IEEE 123-bus test system after adding five DG units by the proposed WOA-SSA, SSA, and WOA algorithms.

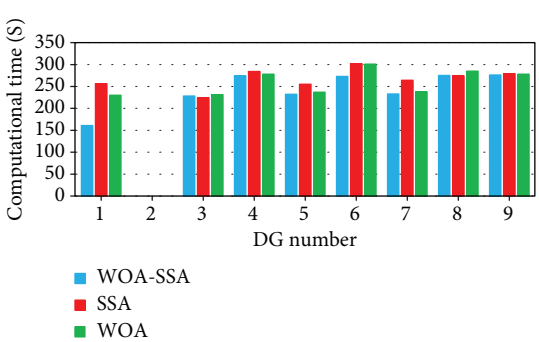

Figure 15: Comparison of the WOA-SSA, SSA, and WOA running times on eight cases of the IEEE 123-bus test system.

WOA-SSA for reducing power losses in radial distribution systems. The proposed algorithm is applied to minimize total RPLs (kW) and solve voltage deviation by installing multi-DG units simultaneously in three-phase unbalanced IEEE 13- and 123-node radial distribution systems. The proposed algorithm succeeds in finding the best location and size of DG units compared with WOA and SSA implemented independently. This algorithm also succeeds in finding the exact solution in a single DG compared with the RLF method. The analysis of the numeric results show that the total RPLs (kW) are close to one another in different test systems and cases. In the IEEE 13-bus test system, the best results are

obtained when four-DG units are used. A single-DG unit can be used when aiming for minimum penetration, whereas six-DG units can be used for maximum penetration. In the IEEE 123-bus test system, the best results are obtained when a one-DG unit is utilized. This case can be used when aiming for minimum penetration, whereas eight-DG units can be adopted for maximum penetration. The best results are obtained when a five-DG unit is utilized for multiple DGs. The practical results show how successful this algorithm is in finding the best location and size for the placement of various numbers of DG units, as well as better execution times compared with other algorithms. Economically, the total real power losses were decreased by 34.4% and 26.5% in the simulation on the IEEE 13- and 123-node test systems, respectively.

Abbreviations

DGs:	Distributed generators
SSA:	Salp swarm algorithm
WOA:	Whale optimization algorithm
kW:	Kilowatt
RPL:	Real power losses
RDNs:	Radial distribution networks
CSA:	Cuckoo search algorithm
PSO:	Particle swarm optimization
GA:	Genetic algorithm
OpenDSS:	Free power distribution system simulation tool
N_{branch}:	Number of branches
N_{bus}:	Number of buses
P^{i}_{loss}:	Active power loss at the ith branch
V_j:	Voltage magnitude at the jth bus
P_i:	Real power capacity of DG at the ith bus
$P^{\min}$ and $P^{\max}$:	Minimum and maximum real power capacities of DGs
DG_{Li}:	Location of the DG at the ith bus
$B_{L\ \max}$:	Maximum location of the bus
t:	Current iteration
a:	Linearly decreases from 2 to 0 over the course of iterations
M_t:	Maximum iteration
D:	Distance between the whale and the prey
F_j:	Position of food source at the jth dimension
lb_j and ub_j:	Lower and upper bounds at the jth dimension
p.u.:	Per unit
RLF:	Repeated load flow method
FP:	Fixed power
kVAr:	Kilo volt ampere reactive
BSA:	Backtracking search optimization algorithm
LSF:	Loss sensitivity factor
IWO:	Invasive weed optimization
AGPSO:	Autonomous group particle swarm optimization
GWO:	Gray wolf optimization
ABC:	Artificial bee colony algorithm.

Data Availability

The load profile data used to support the findings of this study are included within the article. Other data such as line data and bus data have been explained in References [20, 21].

Conflicts of Interest

The authors declare no conflict of interest.

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