Enhanced voltage stability in power distribution networks through optimal reconfiguration using hybrid metaheuristic algorithms

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ABSTRACT

An optimal network reconfiguration (ONR) is used in distribution power systems to improve voltage decreases within the permitted period and minimize real power losses. Consequently, attaining optimal reconfiguration in distribution systems is regarded as the primary objective of numerous researchers. Conventional heuristic techniques such as genetic algorithms (GA), ant colony optimization (ACO), and particle swarm optimization (PSO) can reduce active power losses and enhance network stability. These algorithms indicate a greater number of difficulties, including inadequate convergence characteristics, a reduction in power loss, and an increase in bus voltage. This research proposes effective optimization strategies utilizing the salp swarm algorithm (SSA) and whale optimization algorithm (WOA) to augment bus voltage, reduce distribution losses, and improve network dependability. The proposed algorithms are executed and evaluated on the IEEE 33-bus and 69-bus networks to determine the ideal network architecture. The efficacy of the examined methodologies is illustrated through MATLAB under steady-state conditions, showcasing benefits in the reduction of active power loss relative to current algorithms. The comparison indicates that the SSA algorithm exhibits superior performance in terms of power losses and bus voltage enhancement relative to the WOA method. due to its enhanced exploration and exploitation capabilities, which help avoid local optima and ensure a more effective search for optimal solutions. SSA's adaptive mechanism and cooperative behavior improve convergence speed and solution accuracy, making it more efficient for optimization in network reconfiguration.

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1. INTRODUCTION

A radial distribution system (RDS) consists of a network of radial feeders interconnected by various tie switches and tie lines [1]-[3]. Electric distribution utilities must endeavor to minimize power losses in the RDS. Two conventional effective strategies that can be utilized in the system are optimal reconfiguration and capacitor placement. Optimization techniques were employed in RDS to ascertain the optimal placement and dimensions of diverse devices, including capacitors, reconfiguration, and flexible AC transmission systems (FACTS) [4]-[6]. In recent years, various heuristic optimizations have been introduced for optimal network reconfiguration (ONR) and optimal capacitor placement (OCP) in distribution networks [7], [8]. The allocation of ONR and OCPs in distribution networks offers several technical benefits, such as reduced power loss expenses, diminished energy losses, and enhanced power quality amongst voltage and current harmonics [9], [10]. Optimization algorithms, analytical, numerical, and meta-heuristic have been applied to OCP and ONR challenges [11]-[14]. For instance, [15] proposed a distribution network reconfiguration model to reduce power losses and enhance quality using the ant lion optimizer (ALO), tested on IEEE 33-bus systems. Similarly, [16] introduced a discrete enhanced grey wolf optimizer (DIGWO) for simultaneous ONR and OCP, minimizing energy losses and costs in 69-bus systems.

The results of the proposed approach were compared to those of other contemporary algorithms. Faraby *et al.* [17] introduced a synthesis of optimization strategies for simultaneous distribution generation placement, optimal control problem, and optimal network reconfiguration to minimize losses and voltage drops while considering harmonic distortion from nonlinear loads. The proposed study is validated by the evaluation of the IEEE 33-bus test standard system across multiple MATLAB-based scenarios, thereafter corroborated by comparisons with the simulated annealing and firefly (SAF) algorithms. The findings indicate the efficacy of the PSO method in optimizing the objective function under specified limitations.

Sultana and Roy [18] suggested a computationally efficient method utilizing the krill herd (KH) algorithm to identify optimal OCP and ONR placements aimed at minimizing actual power losses in distribution networks. Moreover, the concept of opposition-based learning (OBL) is integrated with the proposed KH technique to enhance the convergence speed outcomes. The standard KH and the novel oppositional KH (OKH) approaches are assessed on 33-bus and 69-bus systems to illustrate their efficacy and superiority. This illustrates the efficacy of the proposed methodology for addressing ONR concerns. Hussain *et al.* [19] introduced various optimization strategies to determine the allocation of the ONR and OCP by selecting the optimal open switches and positioning OCPs in both solo and dual RDS designs. The employed strategies were evaluated on two prevalent networks (IEEE 33-bus and IEEE 69-bus). Subsequently, a comparison of the proposed strategies was conducted, revealing that the modified biogeography-based optimization (MBBO) method is the most effective and rapid strategy for attaining optimal locations. Zhao *et al.* [20] offered two methodologies: individual ONR and ONR succeeded by OCP, which have been employed to identify the optimal algorithm that delivers superior performance. Consequently, three algorithmic procedures were employed to achieve the optimal design in both the individual and dual methodologies. Furthermore, two prevalent IEEE case studies (33-bus and 69-bus) were employed to assess the optimal performance of the proposed techniques. The real power losses and the voltage of the buses were computed using the direct backward forward sweep method (DBFSM). The results indicate that the suggested dual technique effectively identifies the optimal solution for significant loss reduction and enhancement of the voltage profile through the MBBO algorithm. This study implements SSA and WOA for ONR in RDS, using MATLAB to validate their performance on IEEE 33- and 69-bus networks. Results demonstrate superior power loss reduction and voltage improvement compared to conventional methods.

2. METHOD

2.1. Minimizing real power losses with ONR

The ONR technique minimizes real power losses while keeping voltages within safe limits, significantly improving RDS reliability. Compared to baseline scenarios, ONR reduces active power losses and boosts bus voltages. This study focuses on loss minimization as in (1), with the following objective function [20]:

$$\min F_1 = Min\, P_{T,loss} = \min \sum_{i=1}^{N_{br}} {I_i}^2 R_i \tag{1}$$

Where, $\mathrm{F_1}$: This represents the first objective function in an optimization problem. In this context, it is related to power loss minimization; $\mathrm{P_{T,loss}}$: This is the to power loss in the electrical distribution system, the goal is to minimize this quantity; $\sum_{i=1}^{Nbr} I_i^2\ R_i$: This is a summation over all branches (or lines) in the network, where I index each branch:

- $\mathrm{N_{br}}$ is the total number of branches in the system.
- I_i is the current flowing through branch i.
- R_i is the resistance of branch i.
- $I_i^2 R_i$ represents the power loss in branch i due to joule heating effect.

Where $P_{T,loss}$ represents the total losses of the active power in kW, N_{br} represents the no. of the branches, I_i represents the current flow in the branch i, and R_i is the branch's resistance. The second objective function is the voltage profile enhancement, where the voltage must be kept within safe limits. The voltage objective function is written as in (2) [21].

$$\max F_2 = V_C\ R\ e_v + C_i\ R\ e_i \tag{2}$$

Where, V_c represents the bus voltage limits, C_i is the limit of the branch current, $R\ e_v$ is the retribution factor of the bus voltage. This constant becomes zero when the voltage of the bus is within permissible limits, $R\ e_i$ is the retribution factor of the current branch, where if the branch of the current does not above the restrictions, it equals zero.

2.2. Constraints

The constraints that substantiate the superior performance of the RDS are categorized into technological and operational limitations. The subsequent parameters delineate the technical constraints for bus voltage and branch current as in (3) and (4) [21].

$$V_{min} \leq |V_c| \leq V_{max} \tag{3}$$

$$|I_i| \leq I_{i,max} \tag{4}$$

Where V_c represents the voltage's magnitude for the bus I, V_{max} and V_{min} are the maximum and minimum voltages, respectively, where the allowable values of these voltages of $V_{max} = 1.05\ p.u$ and $V_{min} = 0.95\ p.u$ and the maximum current is given by $I_{i,max}$ for the branch i. Furthermore, each branch current must not beyond its maximum value, and the supply of the power system must be inspected. In addition, the entire size of the capacitors Q_{CT} should be designed within the limits of less than the reactive power of the load for the RDS system, Q_{load} as shown in (5).

$$Q_{CT} \leq Q_{load} \tag{5}$$

On the other hand, the operational constraints can be represented by radial constraints, and the power balance constraint by calculating the bus's determinant for the incidence matrix [A] as confirmed in [20], [21]. Also, the power balance constraint can be written as follows: where *P_sp* is the supplied power, and *P_dem* is total power of the load as shown in (6).

$$P_{sp} = P_{dem} + P_{T,loss} \tag{6}$$

3. NETWORK RECONFIGURATION USING OPTIMIZATION ALGORITHMS

3.1. Whale optimization algorithm (WOA) optimization

The WOA is a heuristic methodology that emulates the hunting tactics of humpback whales [22]. This algorithm offers advantages such as the avoidance of local optima and rapid convergence [22], [23]. Initially, the search agents are dispatched to locate the optimal prey during the exploration phase, after which their placements are adjusted to align with the nearest superior search agent to the optimum. Consequently, the exploration phase might be articulated as in (7)-(10) [23].

$$\vec{D} = \left|\vec{C}\vec{x}^*(t) - \vec{x}(t)\right| \tag{7}$$

$$\vec{x}(t+1) = \vec{x}^*(t) - \vec{A}.\vec{D} \tag{8}$$

$$\vec{A} = 2\vec{a}\,.\vec{r} - \vec{a} \tag{9}$$

$$\vec{C} = 2\vec{r} \tag{10}$$

The key parameters include: $\vec{x}^*(t)$ (best agent location), $A⨁C$ (coefficient vectors), t (current iteration), $\vec{x}^*(t)$ (position vector), $\vec{a}$ (linear decrease 2→0), and $\vec{r}$ (random vector [0,1]). as in (11) and (12). The exploitation phase uses bubble-net foraging via two mechanisms, as shown in Figure 1: shrinking encircling and spiral updating.

$$\vec{x}(t+1) = \vec{x}^*(t) - \vec{A}.\vec{D} \tag{11}$$

$$\vec{x}(t+1) = \overrightarrow{D'}\, e^{bl} \cos(2\pi l) + \vec{x}^*(t) \tag{12}$$

The above item can be defined: $\overrightarrow{D'}$ denotes the spacing between both the search agent and the prey, $\overrightarrow{D'} = |\vec{x}^*(t) - \vec{x}(t)|$, b is a constant generally equal to (1), and l is the random number in [0,1].

A bubble-net feed, whales dive deep below schools of fish and use bubbles blown from their blowholes to stun and trap fish closer to the surface. One whale generally leads the effort, followed by the rest of the group. The leader will usually be responsible for blowing the bubbles, and the other members will surround the fish, following them to the surface by swimming in spiral patterns to keep the fish trapped. Humpback whales are known as “gulpers”, which means they feed by leaving their mouths open, swallowing everything in their path before closing their mouths, pushing water out through their baleen plates, and swallowing the critters (usually fish and small crustaceans) they caught. During bubble net feeding, the whales swimming toward the surface will have their mouths open and gulp fish from the school they have corralled.

Two mathematical models have been proposed to mimic the whale performance while attacking their prays: The shrinking encircling mechanism and Spiral updating position. To update the whales’ position around the best solution in the search space, the shrinking encircling mechanism mimics this process. To model the shrinking, encircling, and spiral swimming behaviors, a probability of 50% is assumed to select between these two behaviors throughout the course of optimization. Each whale selects the operation to be performed randomly based on its location with respect to the optimal solution so far.

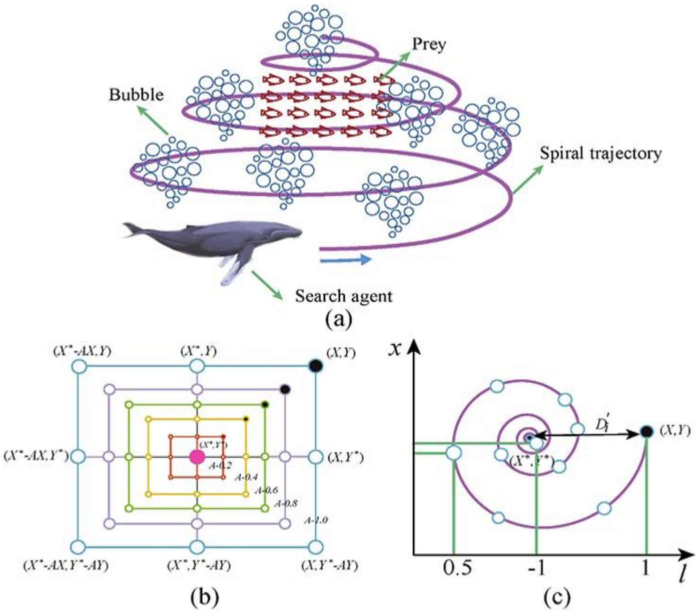

Figure 1. A bubble net search strategy: (a) humpback whales' bubble-net eating, (b) mechanism of the shrinking encircling, and (c) updating of the spiral location

3.2. Salp swarm algorithm for enhanced mobility and foraging

The SSA method was created based on the navigation and feeding behavior of salps in water, as illustrated in Figure 2. However, salps were studied for their swarming behavior in deep seas, resulting in what is referred to as the salp chain. The primary impetus for salp chain activity is to enhance mobility through rapid synchronized movements and foraging, as in (13). The subsequent equation is proposed to revise the leader's position [23].

$$X_d{}^1 = \begin{cases} F_d + C_1\big((ub_d - lb_d)C_1 + lb_d\big), C_3 \geq 0 \\ F_d - C_1\big((ub_d - lb_d)C_2 + lb_d\big), C_3 < 0 \end{cases} \tag{13}$$

The parameters of (13) are defined as follows: $X_d{}^1$ denotes the initial location of the salp in the d^{th} dimension, Fd represents the food source's location, $ub_d + lb_d$ are the upper and lower bounds of the d^{th}

dimension, and $C2$ and $C3$ [0,1] are the random coefficients. Moreover, the constant C_1 is written using (14) [24]-[26].

$$C_1 = 2 \times e^{-\left(\frac{l}{L}\right)^2} \tag{14}$$

Where L denotes all iterations of the algorithm, and l denotes the current iteration of the algorithm. The follower's location can be given as (15).

$$X_d{}^n = \frac{1}{2}\left(X_d{}^n + X_d{}^{n-1}\right) \tag{15}$$

Where $n \geq 2$, $X_d{}^n$ is the location of n^{th} follower salp.

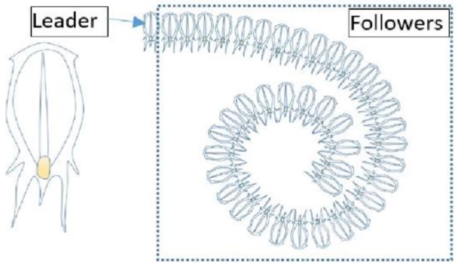

Figure 2. Structure of the salp swarm optimization: (a) signal leader salp and (b) slap followers

3.3. Assumptions made in the study

Assumptions made in the study: i) Stable network conditions: The study assumes a steady-state power system without sudden changes in load or generation; ii) Ideal parameter selection: The parameters used for SSA and WOA are assumed to be optimal without considering real-time tuning; iii) Accurate power system model: The system model used in the study is considered ideal, without accounting for external disturbances or measurement inaccuracies; and iv) Fair comparison environment: Both algorithms are tested under identical conditions, assuming that environmental factors do not favor one over the other.

3.4. Justification for selecting WOA and SSA

The study employs WOA and SSA due to their proven success in complex power system optimization. WOA mimics humpback whales' bubble-net hunting, balancing exploration and exploitation. SSA replicates salp chain behavior, maintaining stable optimization through dynamic exploration-exploitation balance. Both algorithms outperform classical and metaheuristic methods in accuracy and speed, excelling in nonlinear, multimodal, and constrained power distribution problems. Their fast convergence, low computational demand, and independence from initial values or derivatives make them robust for real-time and large-scale applications, ideal for the proposed framework.

4. RESULTS AND DISCUSSION

In the RDSN, the load flow (LF) analysis needs to be performed in the optimization process to obtain the losses and voltage deviation of the DS. The backward-forward (BF) technique replaced the Newton Raphson, Gauss Seidel or any other traditional LF schemes that evolved in the literature to realize the objective function proposed as the BF technique dominates previous techniques. The comparison of WOA and SSA was programmed in MATLAB 2021a to check the effectiveness of both the WOA and SSA algorithm. The proposed code implementations for both algorithms are executed on a portable computer using a Core i7-10750H CPU at 2.60 GHz with 16 GB of RAM. The WOA and SSA optimization techniques were implemented on the IEEE 33 and 69 bus distribution systems to validate the efficacy of these algorithms.

4.1. WOA and SSA algorithm application

Figure 3 illustrates the single line diagram of the IEEE 33 bus distribution system utilized in this context. The distribution system operates at 12.66 kV and 100 MVA, whereas the load values are 3715 kW and 2300 kVAR, as depicted in [27]. Furthermore, in the WOA algorithm, the quantity of search agents ranges from 10 to 20, with a maximum of 100 iterations. The SSA algorithm employs a population size of ten, a maximum of 100 iterations, and five tie switches. Additionally, for both algorithms, the open tie switches are [28]-[32].

Figure 4 illustrates the voltage profile utilizing WOA optimization prior to ONR (baseline scenario) and subsequent to the implementation of ONR on the IEEE 33-bus test network. The bus voltage was enhanced via the WOA, achieving a value of 0.938 p.u. Conversely, the optimal solution for ONR was achieved using the proposed SSA optimization, resulting in a significant voltage enhancement with a bus voltage of 0.95 p.u., as illustrated in Figure 5.

Table 1 compares the proposed SSA and WOA with MPSO, ACO, FA, and GSA under identical conditions, evaluating bus voltages, power losses, and tie-switch sequences. Results show SSA outperforms others, reducing active power losses from 202.68 kW to 132.43 kW while improving voltage profiles—achieved solely through network reconfiguration, without additional devices.

4.2. Optimal network reconfiguration in IEEE 69-bus system

This section employs the WOA and SSA algorithms to determine the best ONR for the IEEE 69 bus system illustrated in Figure 6. The RDS parameters investigated in this study are 100 MVA and 12.66 kV. Figure 7 illustrates the voltage profile outcomes utilizing WOA optimization prior to the incorporation of the ONR and subsequent to the selection of the ONR within the IEEE 69 network. The figure illustrates that the voltage of the buses was augmented utilizing the ONR, resulting in a voltage value of 0.9476 p.u. and a reduction in active power losses to an acceptable level of 104.396 KW. The voltage profile utilizing the SSA technique is depicted in Figure 8. The SSA optimization demonstrates superior bus voltage enhancement compared to the WOA, with the minimum voltage value obtained in this technique being 0.988 p.u.

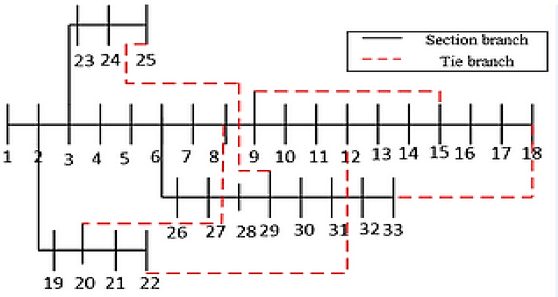

Figure 3. Block diagram of IEEE 33-bus RDS system

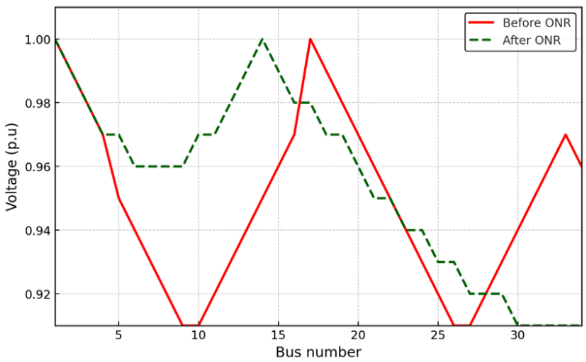

Figure 4. Bus voltage with bus number for the IEEE 33 bus network using WOA optimization

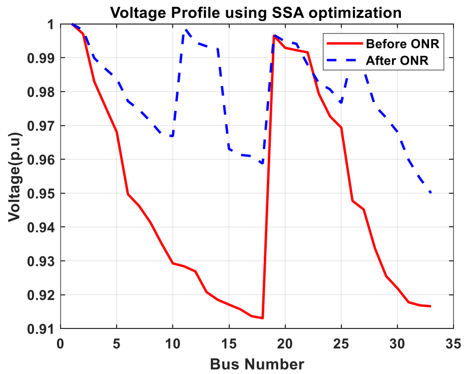

Figure 5. IEEE 33 bus voltage profile using SSA optimization

Table 1. Comparison and results of the IEEE 33-bus system-based reconfiguration technique

Optimization	Tie switch number	Total power loss	Maximum voltage $(p.u)$	Voltage minimum $(p.u)$
Base case	[33, 34, 35, 36, 37]	202.6771	1	0.91306
BPSO [27]	[7, 10, 28, 14, 32]	140.5	1	0.941
GSA [28]	[7,14, 28, 9, 32]	134.6	1	0.96
FA [29]	[7, 14, 9, 32, 28]	139.98	1	0.9413
ACO [30]	[7, 9, 13, 14, 32]	139.5	1	0.943
Proposed WOA	[28, 14, 33, 32, 9]	139.56	1	0.938
Proposed SSA	[28, 11, 32, 14, 7]	132.43	1	0.95

Table 2 presents the simulation outcomes of the proposed algorithms alongside comparative findings with other published algorithms, focusing on the number of tie switches, actual power losses, maximum voltage, and minimum voltage. According to the table, the suggested SSA algorithm provides optimal solutions for both the voltage profile and network losses following the ONR.

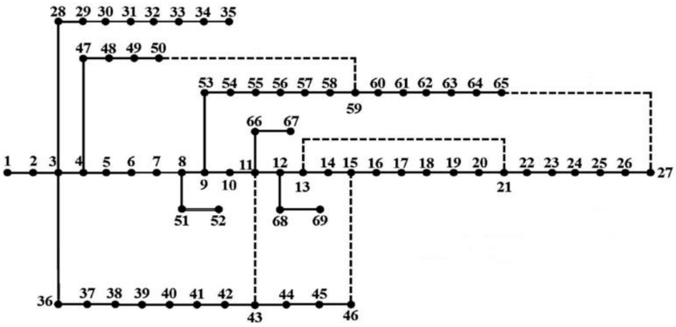

Figure 6. IEEE 69 bus network single-line diagram

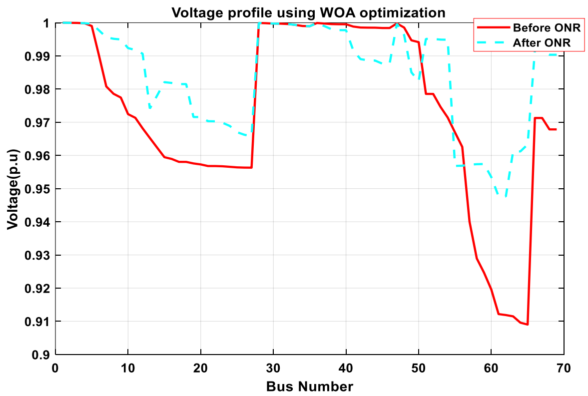

Figure 7. Bus voltage with bus numbers of the IEEE 69 bus system using WOA optimization

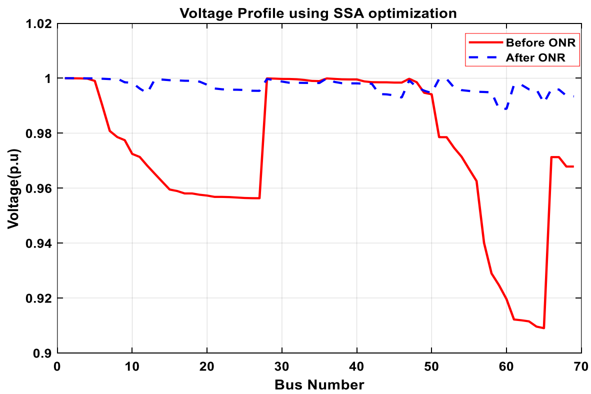

Figure 8. IEEE 69-bus network voltage profile using SSA optimization

Table 2. Comparison and results of IEEE 69-bus system-based reconfiguration technique

Optimization type	Tie switch number	Power loss (KW)	Maximum voltage (p.u)	Minimum voltage (p.u)
Base case	[33, 34, 35, 36]	224.9606	1	0.90901
BTLBO [31]	[12, 60,15,6,10]	154.326	1	0.98856
GWO [32]	[58,12,61,69,70]	99.82	1	0.945
WOA [22]	[12,13,55,61,69]	99.94	1	0.909
Proposed WOA	[62, 18, 54, 12, 69]	104.396	1	0.9476
Proposed SSA	[7, 60, 16, 10, 12]	95.8	1	0.988

5. CONCLUSION

This study seeks to mitigate the losses in the RDS and enhance the bus voltage of the network through optimal network reconfiguration (ONR) employing two heuristic methods: slime swarm optimization (SSA) and whale optimization algorithm (WOA). The mathematical formulations of the objective functions for the suggested two algorithms are initially presented, followed by an analysis of the processes of the WOA and SSA to identify the optimal solution through reconfiguration. The MATLAB environment is utilized to implement the algorithms for the IEEE 33 and 69 bus networks. The archived findings demonstrated that the proposed SSA algorithm is the most effective approach for minimizing losses and improving bus voltages in comparison to other contemporary methods. Additionally, the minimum bus voltage prior to the ONR was 0.91306 p.u. (base case), which rose to 0.95 following the ONR for 33 bus systems utilizing the SSA technique. The minimum voltage in the 69-bus network was 0.90901 p.u. prior to determining the ONR, and this voltage increased to 0.988 p.u. The actual power losses were reduced from 202.6771 KW in the base scenario to 132.43 KW in the IEEE 33 bus system, and from 224.9606 KW to 95.8 KW in the 69-bus system.

The results demonstrate that reconfiguration considerably reduces power losses in the RDS and enhances the voltage profile when employing the SSA optimization technique.

Despite their strengths, WOA and SSA have limitations: i) High computational complexity in large-scale systems wastes resources; ii) SSA's strong exploitation risks local optima, while WOA suffers from slow convergence; iii) Performance is highly parameter-dependent, reducing effectiveness if poorly tuned; iv) Scalability declines with system size, hindering practical use; v) Real-world complexities (e.g., time-varying loads, uncertainties) are overlooked, limiting applicability. Addressing these issues could enhance their reliability for power system optimization.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data availability is not applicable to this paper as no new data were created or analyzed in this study.

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