A Two-Phase Framework with Loop Reduction and Meta-Heuristic Evaluation for Distribution Network Reconfiguration

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ABSTRACT

This paper presents a novel two-phase framework for solving the Distribution Network Reconfiguration (DNR) problem by combining loop-based search-space reduction with Meta-Heuristic (MH) algorithms. In Phase #1, fundamental loops are identified using Dijkstra's algorithm, and duplicated switches are eliminated through a winner–loser rule, which drastically reduces the search space while preserving feasible topologies. In Phase #2, multiple MH algorithms are simultaneously applied to the reduced search space, allowing an efficient evaluation of their suitability for DNR. The proposed approach was validated on three benchmark systems: IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus distribution networks. In all cases, the method consistently identified optimal network configurations with active power loss reductions of up to 36.4%, 32.8%, and 28.9% for the IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus systems, respectively, while improving the minimum bus voltage by 2–6% compared to the original configurations. The results also reveal algorithm-specific behaviors, highlighting that some MH algorithms (e.g., SADE, JADE, HS, GWO) perform robustly across all network sizes, while others are more problem-dependent. Importantly, the loop-reduction step leads to a substantial reduction of the search space, thereby facilitating faster convergence and enhancing scalability. These findings confirm that the proposed framework provides a practical, flexible, and effective solution to the DNR problem in both small-scale and large-scale distribution networks.

Keywords-distribution network reconfiguration; power losses reduction; branch exchange; meta-heuristic algorithms; mealpy; pandapower; IEEE 33-bus / IEEE 69-bus / IEEE 118-bus distribution systems

I. INTRODUCTION

Energy losses are inevitable in electrical systems, with Distribution Networks (DNs) accounting for the largest portion due to conductor resistance. Reducing these losses has long been a central objective in the optimization of power systems. Various techniques have been proposed, including optimal conductor sizing, reactive power compensation, Distributed Generation (DG) allocation, and Distribution Network Reconfiguration (DNR) [1]. Among them, DNR is particularly promising because it reconfigures the topology by opening or closing sectionalizing and tie switches to optimize power flows and minimize losses [2]. Although the physical structure of a distribution system is meshed, it is typically operated in a radial configuration for protection and control purposes. Consequently, DNR becomes a discrete combinatorial optimization problem, in which the goal is to minimize losses, balance loads, or enhance reliability while maintaining radiality [3]. This problem is NP-hard due to the exponential number of possible switching combinations, which makes Meta-Heuristic (MH) algorithms a practical choice to achieve near-optimal solutions efficiently [4].

A. Related Works

Numerous MH algorithms have been successfully applied to solve the DNR problem [5]. In [6], Harris Hawks Optimization (HHO) was benchmarked against Particle Swarm Optimization (PSO) and Cuckoo Search (CSA). In [7], an Improved CSA (ICSA) with local search achieved faster convergence and better global optima. In [8], a GA-PSO-

TLBO scheme was tailored to faulted-feeder reconfiguration, achieving a competitive loss reduction on the IEEE 33-bus system. In [9], an SA-GA method incorporated transmission-cost terms to improve economic efficiency in standard feeders.

Other methods include Tabu Search (TS) [10, 11], Moth Swarm Algorithm (MSA) [12], Harmony Search (HS) [13, 14], Whale Optimization Algorithm (WOA) [15], Sine–Cosine Algorithm (SCA) [16], and Fireworks Algorithm (FWA) [17]. These works confirm the efficiency of MH approaches in handling the nonlinear and non-differentiable nature of DNR. Despite these efforts, challenges remain:

- Discrete handling: Most MH algorithms are originally designed for continuous optimization. Only a limited number of discrete or binary variants (e.g., TS, ACO, GA, SA) [18], [19] exist, and adapting continuous-domain algorithms to the discrete DNR search space often requires ad-hoc modifications that may reduce generalization.
- Search space reduction: The combinatorial nature of DNR leads to a vast number of switching combinations. Although approaches such as integer encoding [7] and Dijkstra-based initialization [20, 21] have been explored, overlapping loops or redundant switches often result in infeasible configurations.
- Comparative assessment: Prior studies generally evaluate one or two MH algorithms in isolation, making it difficult to identify which methods are most effective across various DNs. A unified benchmarking framework is lacking, limiting both reproducibility and methodological insights.

B. *Research Contributions*

This study addresses the above challenges with the following contributions:

- Generalized framework: Presents a unified approach that integrates a broad family of MH algorithms for DNR, enabling fair performance comparison and principled selection of the most suitable method.
- Novel discrete-handling strategy: Introduces a method that allows continuous-domain MH algorithms to operate directly on the discrete DNR search space without binary/discrete variants, improving exploration while preserving problem feasibility.
- Enhanced initialization: Fundamental loops are generated using Dijkstra's algorithm, and shared switches are systematically eliminated through a winner-loser rule to shrink the search space and avoid infeasible configurations.
- Extensive evaluation: The approach is validated on three IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus networks, with results benchmarked against state-of-the-art studies to evaluate effectiveness and robustness.

II. PROBLEM FORMULATION

The DNR task aims to find a switching pattern that meets operational limits while minimizing losses. The network has sectionalizing switches (SS, normally closed) and tie switches (TS, normally open). Reconfiguration closes selected TSs and, for any loop created, opens one SS in that loop to preserve radiality. By modeling the feeder as a graph (buses = nodes, branches = edges), each TS induces a fundamental loop, so the number of loops equals the number of TSs. The search thus explores feasible radial topologies generated by SS/TS operations, which simplifies protection and limits fault currents.

A. *Objective Function*

DNR mostly aims to minimize active power losses, typically high in radial feeders. A mono-objective function is formulated as:

$$f = min(P_{loss}) = min\left(\sum_{i=1}^{N_{br}} |I_i|^2 R_i\right) \quad (1)$$

where P_{loss} denotes the total active power losses, N_{br} is the total number of branches, $|I_i|$ is the absolute value of the current passing through the i^{th} branch, and R_i is the resistance of the i^{th} branch.

B. *Constraints*

Optimization is subject to standard operational and topological constraints, as the following.

1) *Bus Voltage Limits*

Bus voltage magnitudes must lie within acceptable bounds to ensure proper operation of equipment:

$$Vm_{min} \le Vm_i \le Vm_{max} \quad (2)$$

2) *Branch Current Limits*

The current in each branch must not exceed its rated capacity:

$$Im_i \le Im_{max} \quad (3)$$

3) *Radiality Constraint*

The final configuration must maintain radial topology. This condition is verified using the branch-to-bus incidence matrix Â based on Kirchhoff's method. The reduced incidence matrix A is obtained by omitting the reference bus column. The determinant of A indicates the network structure:

$$det(A) = \pm 1 \Rightarrow Radial$$

$$det(\text{A}) = 0 \Rightarrow Nonradial \text{ or } disconnected \quad (1)$$

This criterion is employed for validating radiality in three IEEE benchmark systems.

III. PROPOSED METHOD

The DNR problem is inherently combinatorial: with N_S switches, the total number of configurations is 2^{N_S}, most of which are infeasible. Viewing the network as a connectivity graph, loops encode alternative switching options. Infeasibility arises when radiality is violated or power flow fails to converge. Thus, two needs emerge:

- Search space reduction: Efficient methods are needed to extract fundamental loops and eliminate redundant or infeasible candidates, particularly for large-scale networks.

- Efficient optimization handling: Since the problem is discrete by nature, but most MH algorithms are designed for continuous spaces, an appropriate strategy is necessary to adapt MH algorithms without relying solely on binary/discrete variants.

A general two-phase framework is used to address these issues (Figure 1). In Phase #1, the search space is reduced by identifying fundamental loops and eliminating infeasible or overlapping configurations. In Phase #2, MH algorithms in the continuous domain are adapted to handle the discrete DNR problem, enabling efficient exploration of the reduced search space while maintaining solution quality and radiality.

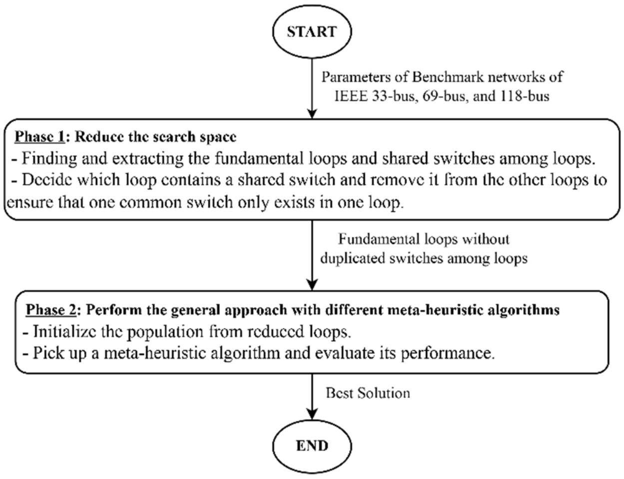

Fig. 1. Two-phase general approach for network reconfiguration.

A. Phase #1: Reducing the Search Space

This phase aims to reduce the size of the search space by systematically extracting non-duplicated fundamental loops. This process involves two main steps.

- Step 1 - Identification of fundamental loops using Dijkstra's algorithm: This algorithm is widely used to determine shortest paths in graph-based models. The DN is modeled as a graph with unit edge weights, so that the shortest means the fewest edges. For each TS, the shortest path between its terminal nodes is computed, and the process is repeated for all TSs. The fundamental loops of the network are formed by closing all TSs along their corresponding shortest paths, with the number of loops equal to the number of TSs.
- Step 2 - Elimination of duplicated switches across loops:

Algorithm 1: Remove duplicated switches from two fundamental loops
Inputs:
  ID_{L1}, ID_{L2}: the IDs of loops #1 and #2
1. SW_{L1} ← get the set of switches for loop #1 from ID_{L1}
2. SW_{L2} ← get the set of switches for loop #2 from ID_{L2}
3. SW_C ← $SW_{L1} \cap SW_{L2}$ // get common switches
4. $LOSS_1$ ← $-\infty$ // store the lowest power // loss between a switch in loop #1 and //a common switch
5. $LOSS_2$ ← $-\infty$ // store the lowest power // loss between a switch in loop #2 and // a common switch
6. for S_C in SW_C do
   // loop on all common switches
7.   for S_1 in $SW_{L1} \backslash SW_C$ do
     // switches of loop #1 that are not
     // in common switches
8.   open two switches S_C, S_1 and close remaining switches
9. L_{tmp} ← calculate the power losses after running a power flow analysis (Newton-Raphson) with pandapower
10.   if $L_{tmp} < LOSS_1$ then
11. $LOSS_1$ ← L_{tmp}
12. for S_2 in $SW_{L2} \backslash SW_C$ do
     // switches of loop #2 that are not
     // in common switches
13.   open two switches S_C, S_2 and close remaining switches
14. L_{tmp} ← calculate the power losses after running a power flow analysis (Newton-Raphson) with pandapower
15.   if $L_{tmp} < LOSS_2$ then
16. $LOSS_2$ ← L_{tmp}
17. if $LOSS_1 < LOSS_2$ then
18. SW_{L1} ← $SW_{L1} \backslash SW_C$
      // remove all common switches from
      // loop #1
19. else
20. SW_{L2} ← $SW_{L2} \backslash SW_C$
      // remove all common switches from
      // loop #2
Outputs: SW_{L1}, SW_{L2}
// common switches are removed from one of
// two input loops

Shortest-path loops may share switches, creating redundant configurations. Algorithm 1 assigns each shared switch to exactly one loop. For a shared switch, two cases are tested: treat it as belonging to one loop and pair it with each non-shared switch in the other loop. The algorithm keeps the best combination in each case (by active loss), compares the two best values, then assigns the switch to the loop with the lower loss and removes it from the other. This is repeated for all shared switches until no overlaps remain. The resulting non-overlapping loops preserve radiality and sharply reduce the search space for subsequent optimization.

B. Phase #2 – Optimization With MH Algorithms

Most existing works addressing the DNR problem represent switches by their numerical identifiers. In this formulation, the position values of agents in non-binary MH algorithms are expressed in the real-valued space, whereas the switches themselves are inherently integer-valued (e.g., FWA [17], or CSA [22]). Although switches can be numbered sequentially in the network, members of a fundamental loop are rarely consecutive; uneven ID gaps skew selection probabilities and increase the risk of premature convergence. This study adopts per-loop renumbering: instead of original switch IDs, each loop's switches are stored in an array, and agents use the array's sequential indices as decision values. For example, in the IEEE 33-bus system, the first loop contains switches (3, 5, 25, 26, 29, 31). These are stored in an array with indices (0, 1, 2, 3,4, 5), ensuring a uniform discrete distribution and equal selection probability. Figure 2 presents the switch numbers in a loop stored in an array and their indexes.

Fig. 2. Switch numbers stored in an array and their indices.

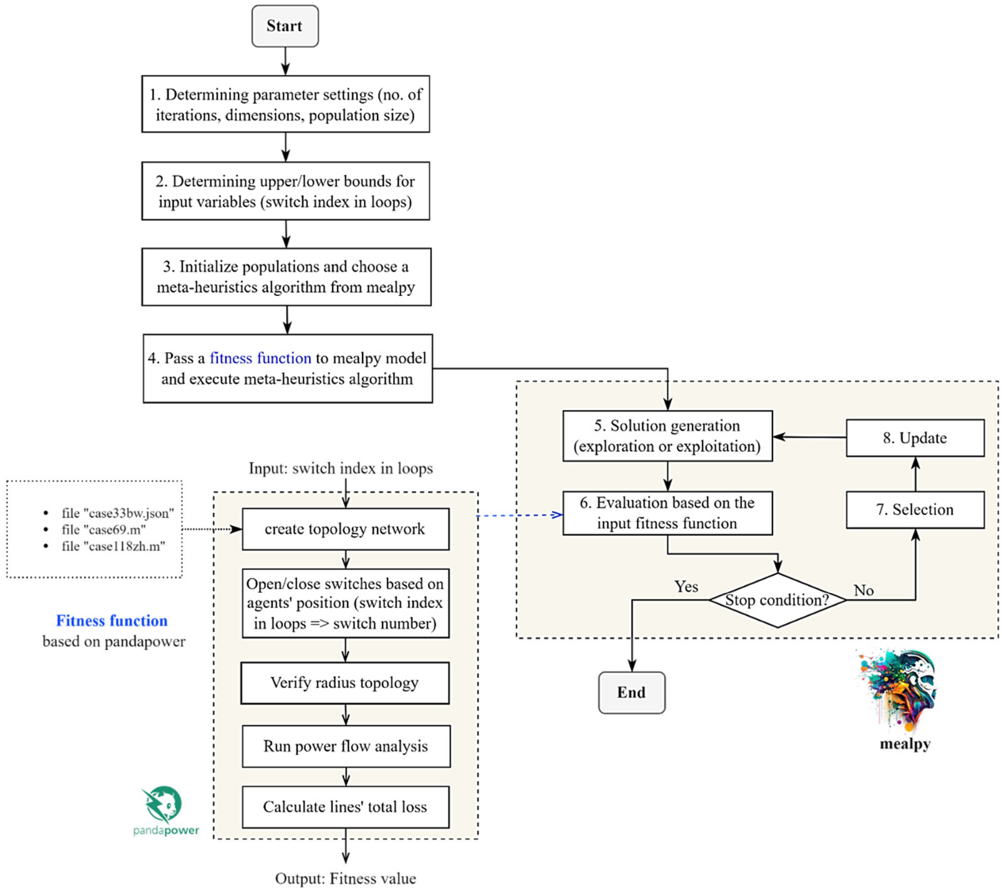

Fig. 3. Flowchart of the proposed method (phase #2).

Building on the reduced search space from Phase #1, Phase #2 proceeds with the following workflow (Figure 2):

- Step 1: Define key parameters, including the number of dimensions, iterations, and population size. The number of dimensions corresponds to the number of TSs in the benchmark network (e.g., 15 dimensions for the IEEE 118-bus system).
- Step 2: Assign the upper and lower bounds of each dimension according to the number of switches in the corresponding loop obtained from Phase #1. For instance, if the first loop has 9 switches, its bound is [0, 8]; if the second has 12 switches, the bound is [0, 11].
- Step 3: Initialize the population. In this study, random initialization is adopted.
- Step 4: Define a general fitness function for power loss minimization.
- Step 5–8: Execute the MH algorithm from the Mealpy library. The exploration-exploitation process iteratively updates the population to improve fitness values. Each candidate solution is represented by a k-dimensional vector, where each element is a continuous variable generated by the MH algorithm. Since the switch positions are discrete, each element is converted into a valid switch index by rounding it to the nearest integer: $s_d = round(x_d),\ d = 0, 1, \ldots, k-1$, where x_d is the continuous decision variable and s_d is the corresponding discrete switch index.

Candidate solutions are evaluated in Pandapower: for each MH-generated switch configuration, radiality is checked; if radial, an AC power flow (Newton–Raphson) is solved, and fitness is the total active power loss; otherwise, a large penalty is assigned. This filters infeasible topologies and steers the search toward feasible, loss-minimizing configurations.

IV. SIMULATION RESULTS AND DISCUSSIONS

Experiments were implemented in Python using Pandapower for AC power-flow and Mealpy as the MH runtime, both unmodified; this allows focusing on loop-based search-space reduction and problem-aware discrete encoding. Three benchmark distribution networks, the IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus systems, are employed to validate the effectiveness of the proposed approach. Table I summarizes the general parameter settings for the MH algorithms ID_{L2}, and the key features of the three test networks. For each simulation scenario, every MH algorithm is executed ten independent runs under identical parameter settings. The final results are obtained by averaging across all runs, thereby mitigating the effect of random initialization. The proposed approach was experimentally validated using a broad set of MH algorithms. The algorithms that exhibit superior performance in solving the RN problem on both small-scale networks (IEEE 33-bus and IEEE 69-bus systems) and a large-scale network (IEEE 118-bus system) are highlighted and compared against existing approaches.

A. IEEE 33-Bus Distribution Network

The IEEE 33-bus distribution network is a 12.66 kV radial system comprising 37 branches with 32 SSs and 5 TSs [23].

1) Phase #1: Loop Identification and Reduction of Search Space

In Phase #1, Dijkstra's algorithm is applied to determine the shortest paths associated with each TS. For example, from TS #33, the shortest path between bus 8 and bus 21 is identified, yielding the loop consisting of switches {8, 9, 10, 11, 35, 21, 33}. Repeating this process for all five TSs results in five initial fundamental loops, as summarized in Table II.

TABLE I. PARAMETERS OF BENCHMARK NETWORKS AND MH ALGORITHMS

Benchmark Distribution Networks			
Parameters	**IEEE 33-bus**	**IEEE 69-bus**	**IEEE 118-bus**
Number of buses	33	69	118
Number of branches	37	73	132
External grid	1	1	1
Number of loads	32	48	117
Number of TSs	5	5	15
Initial position of tie switches	33, 34, 35, 36, 37	69, 70, 71, 72, 73	118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132
Base voltage level (kV)	12.66	12.66	11.0
Active load (MW)	3.715	3.8021	22.70972
Reactive load (MVAr)	2.3	2.6947	17.041068
MH algorithms			
Dimensions	5	5	15
Population size	30	30	30
Number of iterations	100	100	100

TABLE II. FUNDAMENTAL LOOPS IN THE IEEE 33-BUS NETWORK FOUND BY THE DIJKSTRA ALGORITHM

No.	**Switches**
Loop #1	[8, 9, 10, 11, 21, 33, 35]
Loop #2	[2, 3, 4, 5, 6, 7, 18, 19, 20, 33]
Loop #3	[9, 10, 11, 12, 13, 14, 34]
Loop #4	[6, 7, 8, 15, 16, 17, 25, 26, 27, 28, 29, 30, 31, 32, 34, 36]
Loop #5	[3, 4, 5, 22, 23, 24, 25, 26, 27, 28, 37]

TABLE III. FUNDAMENTAL LOOPS WITHOUT DUPLICATED SWITCHES OF THE IEEE 33-BUS NETWORK FOUND BY ALGORITHM 1

Steps	**Action**	**Identifier**	**Value**	**New value**	**Remarks**
1	Initialize fundamental loops with switches	Loop #1	[8, 9, 10, 11, 21, 33, 35]		
		Loop #2	[2, 3, 4, 5, 6, 7, 18, 19, 20, 33]		
		Loop #3	[9, 10, 11, 12, 13, 14, 34]		
		Loop #4	[6, 7, 8, 15, 16, 17, 25, 26, 27, 28, 29, 30, 31, 32, 34, 36]		
		Loop #5	[3, 4, 5, 22, 23, 24, 25, 26, 27, 28, 37]		
2	Run Algorithm 1 with two input loops #1 and #2	Loop #1	[8, 9, 10, 11, 21, 33, 35]	[8, 9, 10, 11, 21, 35]	The winner is loop #2. Switch [33] is removed from loop #1.
3	Run Algorithm 1 with two input loops #1 and #3	Loop #3	[9, 10, 11, 12, 13, 14, 34]	[12, 13, 14, 34]	The winner is loop #1. Switches [9, 10, 11] are removed from loop #3.
4	Run Algorithm 1 with two input loops #1 and #4	Loop #4	[6, 7, 8, 15, 16, 17, 25, 26, 27, 28, 29, 30, 31, 32, 34, 36]	[6, 7, 15, 16, 17, 25, 26, 27, 28, 29, 30, 31, 32, 34, 36]	The winner is loop #1. Switch [8] is removed from loop #4.
5	Run Algorithm 1 with two input loops #3 and #4	Loop #4	[6, 7, 15, 16, 17, 25, 26, 27, 28, 29, 30, 31, 32, 34, 36]	[6, 7, 15, 16, 17, 25, 26, 27, 28, 29, 30, 31, 32, 36]	The winner is loop #3. Switch [34] is removed from loop #4.
6	Run Algorithm 1 with two input loops #2 and #4	Loop #4	[6, 7, 15, 16, 17, 25, 26, 27, 28, 29, 30, 31, 32, 36]	[15, 16, 17, 25, 26, 27, 28, 29, 30, 31, 32, 36]	The winner is loop #2. Switches [6, 7] are removed from loop #4.
7	Run Algorithm 1 with two input loops #2 and #5	Loop #5	[3, 4, 5, 22, 23, 24, 25, 26, 27, 28, 37]	[22, 23, 24, 25, 26, 27, 28, 37]	The winner is loop #2. Switches [3, 4, 5] are removed from loop #5.
8	Run Algorithm 1 with two input loops #4 and #5	Loop #4	[15, 16, 17, 25, 26, 27, 28, 29, 30, 31, 32, 36]	[15, 16, 17, 29, 30, 31, 32, 36]	The winner is loop #5. Switches [25, 26, 27, 28] are removed from loop #4.
9	Get the final fundamental loops without duplicated switches	Loop #1	[8, 9, 10, 11, 21, 35]		
		Loop #2	[2, 3, 4, 5, 6, 7, 18, 19, 20, 33]		
		Loop #3	[12, 13, 14, 34]		
		Loop #4	[15, 16, 17, 29, 30, 31, 32, 36]		
		Loop #5	[22, 23, 24, 25, 26, 27, 28, 37]		

Subsequently, Algorithm 1 is employed to eliminate duplicate switches across loops. Through pairwise comparisons of loops with common switches, the winner-loser strategy ensures that each switch is uniquely assigned. The iterative reduction procedure, detailed in Table III, reduces the number of candidate solutions significantly: from an initial search space of 86,240 (7×10×7×16×11) to only 15,360 (6×10×4×8×8). This reduction highlights the efficiency of Phase #1 in simplifying the optimization process while retaining feasible reconfiguration options.

2) Phase #2: Meta-Heuristic Optimization

In Phase #2, the reduced 5-dimensional search space is explored by a variety of MH algorithms. Table IV presents the performance of ten selected MH algorithms compared with several state-of-the-art approaches. Remarkably, all ten MH algorithms identified the same optimal configuration, with opened switches {7, 9, 14, 32, 37} yielding a minimum power loss of 139.551 kW. This solution is consistent with the best results reported in prior works, such as ICSA [7], HSA [24], and SCA [16], confirming the robustness of the proposed method. Notably, HSA achieved a slightly lower reported loss (138.06 kW), which may be attributed to differences in simulation tools or load-flow calculation methods. The ability of the proposed approach to uniformly recover the optimal configuration across diverse MH algorithms emphasizes its flexibility and effectiveness.

TABLE IV. COMPARISON OF EXISTING METHODS AND THE TEN BEST MH ALGORITHMS IN THE IEEE 33-BUS NETWORK

No.	Algorithm	Optimum value $min(P_{loss})$ (kW)	Opened switches
Results of recent state-of-the-art methods			
1	ICSA [7]	139.55	[7, 9, 14, 32, 37]
2	HSA [24]	138.06	[7, 9, 14, 32, 37]
3	SCA [16]	139.55	[7, 9, 14, 32, 37]
4	WOA [15]	139.57	[7, 9, 14, 32, 37]
5	FWA [17]	139.98	[7, 9, 14, 28, 32]
Results of the proposed approach with some MH algorithms			
1	SADE	139.55	[7, 9, 14, 32, 37]
2	JADE	139.55	[7, 9, 14, 32, 37]
3	Original HS	139.55	[7, 9, 14, 32, 37]
4	Original GWO	139.55	[7, 9, 14, 32, 37]
5	IGWO	139.55	[7, 9, 14, 32, 37]
6	Original ABC	139.55	[7, 9, 14, 32, 37]
7	GA	139.55	[7, 9, 14, 32, 37]
8	Original EO	139.55	[7, 9, 14, 32, 37]
9	Original PSO	139.55	[7, 9, 14, 32, 37]
10	GWO_WOA	139.55	[7, 9, 14, 32, 37]

a) Convergence Performance

Figure 4 illustrates the convergence performance of the ten best MH algorithms under both the original and reduced search spaces for the IEEE 33-bus network. As observed, all algorithms converge significantly faster after applying the loop-reduction procedure in Phase #1. In the reduced search space, every MH algorithm achieves stability within the first 20 iterations, compared to noticeably slower convergence in the original space. Among them, PSO shows the fastest convergence, stabilizing after only four iterations. These results clearly demonstrate that the proposed search-space reduction substantially enhances the computational efficiency and convergence rate of various MH algorithms while maintaining consistent optimal fitness values.

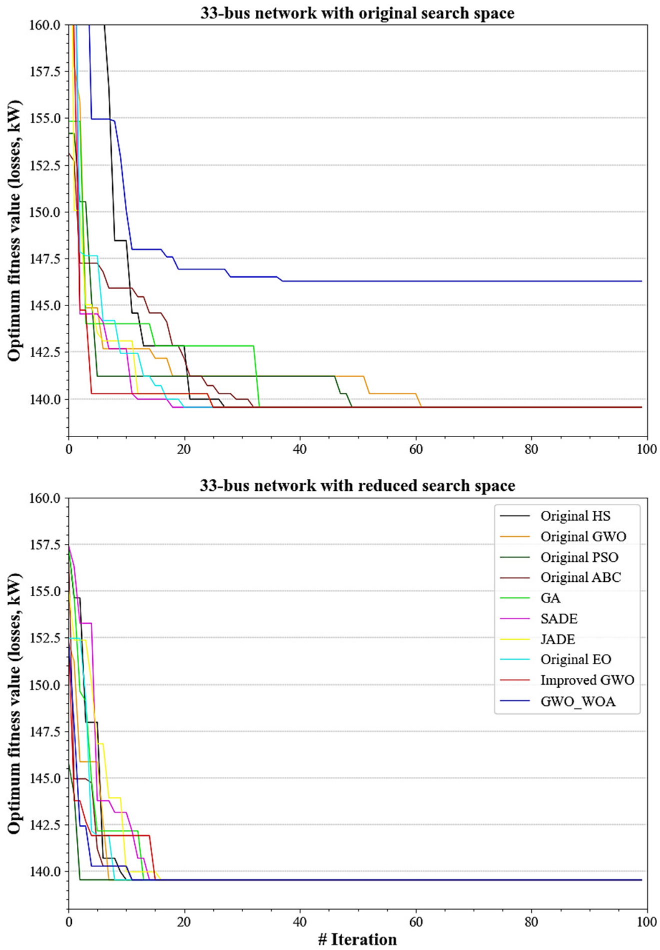

Fig. 4. Convergence speed of the ten best MH algorithms in the IEEE 33-bus network with reduced and original search space.

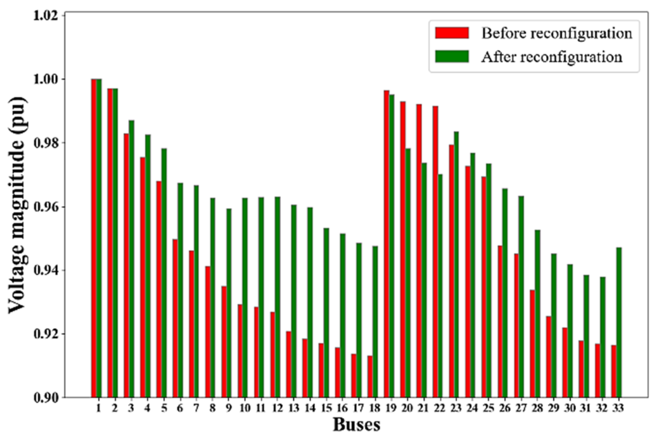

Fig. 5. Node voltage before and after reconfiguration in the IEEE 33-bus network.

b) Voltage Profile Enhancement

Figure 5 shows the voltage profile before and after reconfiguration. In the original configuration, the minimum bus voltage was 0.913 pu (at bus #18). After applying the optimal reconfiguration, the minimum voltage increased to 0.9378 pu (at bus #32). This improvement not only enhances overall voltage stability but also ensures that the voltage constraint (≥ 0.93 pu) is satisfied across the entire system. Thus, the reconfiguration yields a dual benefit: minimizing active power losses while simultaneously reinforcing system reliability.

B. IEEE 69-Bus Distribution Network

The IEEE 69-bus distribution network is a 12.66 kV radial system with 73 branches, including 68 SSs and 5 TSs [25].

1) Phase #1: Loop Identification and Search-Space Reduction

In Phase #1, Dijkstra's algorithm was applied to determine the shortest paths corresponding to each tie switch, initially generating five fundamental loops. Algorithm 1 was then used to eliminate duplicate switches among these loops. After successive removals of overlapping elements, the final set of five non-overlapping loops was obtained, as summarized in Table V.

TABLE V. FUNDAMENTAL LOOPS OF IEEE 69-BUS NETWORK IN PHASE #1

No.	Switches
Fundamental loops found by the Dijkstra algorithm	
Loop #1	[11, 12, 13, 14, 43, 44, 45, 69, 71]
Loop #2	[4, 5, 6, 7, 8, 46, 47, 48, 49, 52, 53, 54, 55, 56, 57, 58, 72]
Loop #3	[3, 4, 5, 6, 7, 8, 9, 10, 35, 36, 37, 38, 39, 40, 41, 42, 69]
Loop #4	[9, 10, 11, 12, 21, 22, 23, 24, 25, 26, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 70, 73]
Loop #5	[13, 14, 15, 16, 17, 18, 19, 20, 70]
Fundamental loops found by Algorithm 1	
Loop #1	[11, 12, 13, 14, 43, 44, 45, 71]
Loop #2	[46, 47, 48, 49, 52, 53, 54, 55, 56, 57, 58, 72]
Loop #3	[3, 4, 5, 6, 7, 8, 9, 10, 35, 36, 37, 38, 39, 40, 41, 42, 69]
Loop #4	[21, 22, 23, 24, 25, 26, 59, 60, 61, 62, 63, 64, 73]
Loop #5	[15, 16, 17, 18, 19, 20, 70]

This process drastically reduced the dimensionality of the optimization problem. Without applying Algorithm 1, the search space comprised 682,344 candidate solutions. After loop refinement, the search space was reduced to 206,388 candidates, representing a reduction of nearly 70%. This demonstrates the efficiency of the proposed loop reduction mechanism in lowering computational complexity.

2) Phase #2: Meta-Heuristic Optimization

In Phase #2, several MH algorithms were employed to solve the DNR problem within the reduced search space. As summarized in Table VI, all ten evaluated MH algorithms consistently identified the same optimal solution, with opened switches {14, 57, 61, 69, 70} and an active power loss of 98.5875 kW. This result is identical to the best-reported outcomes achieved by recent methods such as ICSA [7] and IAICA [26], and is competitive with other approaches like FWA [17], SCA [16], HSA [14], and WOA [15].

a) Convergence Performance

Figure 6 illustrates the convergence performance of the ten best MH algorithms for the IEEE 69-bus network under both the original and reduced search spaces. When operating in the original search space, most algorithms required 30–60 iterations to converge, with some (e.g., BBO and AOA) stabilizing only after approximately 50 iterations. In contrast, after applying the proposed loop-reduction procedure in Phase #1, all algorithms achieved stability within 20–40 iterations, while JADE reached the optimal fitness value after only 6 iterations. This demonstrates that the search-space reduction not only preserves solution accuracy but also accelerates convergence by nearly a factor of 2×, thereby improving computational efficiency across different MH strategies.

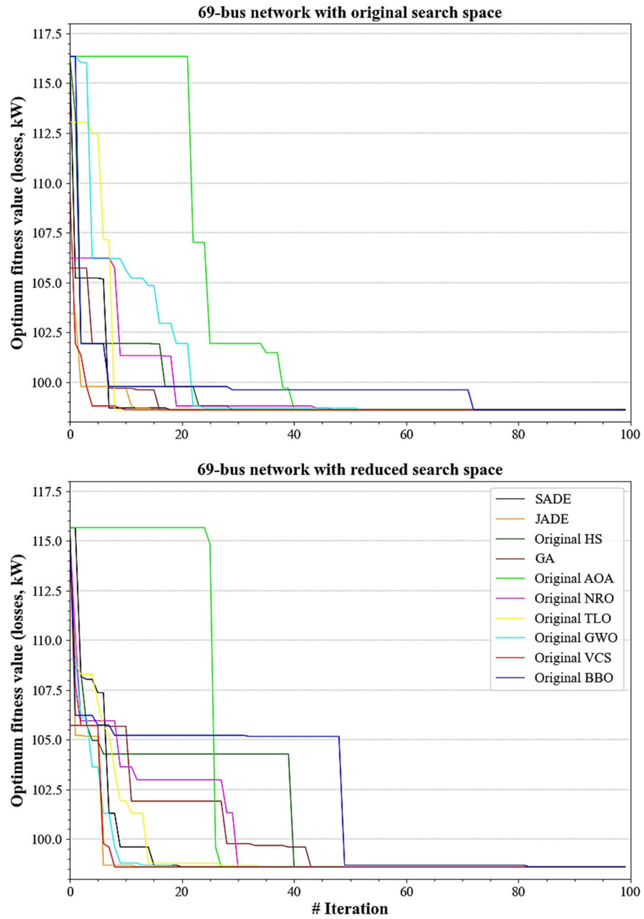

Fig. 6. Convergence speed of the ten best MH algorithms in the IEEE 69-bus network with reduced and original search space.

b) Voltage Profile Enhancement

Figure 9 shows the voltage profiles before and after reconfiguration. In the original configuration, the lowest bus voltage was 0.909 pu (at bus #65). After reconfiguration, the minimum voltage improved significantly to 0.949 pu (at bus #61). Furthermore, all buses satisfied the operational constraint of voltage magnitude (≥ 0.93 pu), highlighting the positive impact of the proposed method on system reliability and voltage stability.

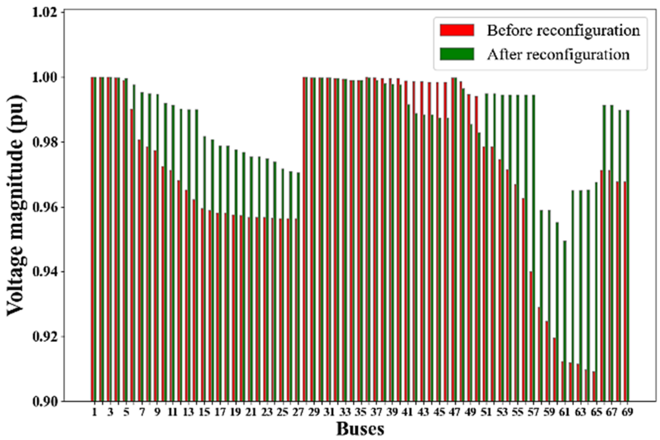

Fig. 7. Node voltage before and after reconfiguration in the IEEE 69-bus network.

TABLE VI. COMPARISON OF EXISTING METHODS AND THE TEN BEST MH ALGORITHMS IN THE IEEE 69-BUS NETWORK

No.	Algorithm	Optimum value $min(P_{loss})$ (kW)	Opened switches
Results of recent state-of-the-art methods			
1	ICSA [7]	98.5875	[14, 57, 61, 69, 70]
2	IAICA [26]	98.5875	[14, 57, 61, 69, 70]
3	FWA [17]	98.59	[14, 57, 61, 69, 70]
4	SCA [16]	98.6	[14, 55, 61, 69, 70]
5	HSA [14]	99.45	[14, 15, 61, 69, 70]
6	WOA [15]	99.95	[12, 13, 55, 61, 69]
Results of the proposed approach on some MH algorithms			
1	SADE	98.5875	[14, 57, 61, 69, 70]
2	JADE	98.5875	[14, 57, 61, 69, 70]
3	Original HSA	98.5875	[14, 57, 61, 69, 70]
4	Original GWO	98.5875	[14, 57, 61, 69, 70]
5	Original PSO	98.5875	[14, 57, 61, 69, 70]
6	Original ABC	98.5875	[14, 57, 61, 69, 70]
7	GA	98.5875	[14, 57, 61, 69, 70]
8	Original BBO	98.5875	[14, 57, 61, 69, 70]
9	Original VCS	98.5875	[14, 57, 61, 69, 70]
10	Original GCO	98.5875	[14, 57, 61, 69, 70]

C. IEEE 118-Bus Distribution Network

The IEEE 118-bus distribution network is an 11.0 kV radial system comprising 132 branches, with 117 SSs and 15 TSs.

1) Phase #1: Fundamental-Loop Identification and Search-Space Reduction

The shortest paths associated with each tie switch were first identified using Dijkstra's algorithm to generate the initial fundamental loops. Then, Algorithm 1 was employed to remove duplicated switches across loops through a winner-loser elimination strategy. The resulting non-overlapping loops, shown in Table VII, significantly reduced the search space. This refinement led to substantial efficiency gains: without Algorithm 1, the search space consisted of $\approx 7.317 \times 10^{17}$ candidate configurations, whereas after loop reduction it was decreased to $\approx 1.242 \times 10^{13}$. This corresponds to a reduction by a factor of approximately 5.89×10^4, which is crucial for ensuring computational tractability in large-scale distribution networks while still preserving feasible topologies.

TABLE VII. FUNDAMENTAL LOOPS OF IEEE 118-BUS NETWORK IN PHASE #1

No.	Switches
Fundamental loops found by the Dijkstra algorithm	
Loop #1	[43, 44, 45, 118, 27, 28, 37, 38, 39, 40, 41, 42, 26, 25, 24, 23, 22, 21, 20, 19, 18, 17, 10, 9]
Loop #2	[11, 12, 13, 14, 15, 16, 119, 26, 25, 24, 23, 22, 21, 20, 19, 18, 17]
Loop #3	[120, 4, 5, 6, 7, 23, 22, 21, 20, 19, 18, 17, 10, 9]
Loop #4	[121, 29, 30, 31, 32, 33, 34, 46, 47, 48, 49, 50, 51, 52, 53, 42, 41, 40, 39, 38, 37]
Loop #5	[122, 29, 30, 31, 32, 33, 34, 46, 47, 48, 49, 50, 51, 52, 53, 61, 60,59, 58, 57, 56, 55, 54]
Loop #6	[35, 36, 123, 29, 61, 60, 59, 58, 57, 56, 55, 54]
Loop #7	[8, 124, 4, 5, 6, 7, 39, 38, 37, 28, 27]
Loop #8	[125, 27, 28, 54, 55, 56, 57, 95, 90, 89, 88, 64]
Loop #9	[126, 65, 66, 67, 68, 69, 70, 71, 72, 90, 89, 88]
Loop #10	[127, 87, 86, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 85, 78, 77]
Loop #11	[75, 76, 128, 98, 97, 96, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 95, 90, 89, 88]
Loop #12	[79, 80, 81, 82, 129, 77, 78, 107, 106, 105, 104, 103, 102, 101, 100]
Loop #13	[130, 77, 78, 85, 104, 103, 102, 101, 100]
Loop #14	[108, 109, 131, 117, 116, 115, 114, 113, 100, 101, 102, 103, 104, 105, 106, 107]
Loop #15	[132, 27, 28, 29, 30, 31, 32, 33, 34, 24, 23, 22, 21, 20, 19, 18, 17, 10, 9]
Fundamental loops found by Algorithm 1	
Loop #1	[40, 41, 42, 43, 44, 45, 118]
Loop #2	[11, 12, 13, 14, 15, 16, 24, 25, 26, 119]
Loop #3	[9, 10, 17, 18, 19, 20, 21, 22, 23, 120]
Loop #4	[121]
Loop #5	[46, 47, 48, 49, 50, 51, 52, 53, 122]
Loop #6	[29, 35, 36, 54, 55, 56, 57, 58, 59, 60, 61, 123]
Loop #7	[4, 5, 6, 7, 8, 27, 28, 37, 38, 39, 124]
Loop #8	[27, 28, 64, 88, 89, 90, 95, 125]
Loop #9	[65, 66, 67, 68, 69, 70, 71, 72, 126]
Loop #10	[64, 73, 74, 86, 87, 127]
Loop #11	[75, 76, 96, 97, 98, 128]
Loop #12	[79, 80, 81, 82, 105, 106, 107, 129]
Loop #13	[77, 78, 85, 100, 101, 102, 103, 104, 130]
Loop #14	[108, 109, 113, 114, 115, 116, 117, 131]
Loop #15	[24, 27, 28, 29, 30, 31, 32, 33, 34, 132]

2) Phase #2: Meta-Heuristic Optimization

Within the reduced 15-dimensional space, multiple MH algorithms were executed. Table VIII summarizes the results of the ten best performers and comparisons with recent methods. Most MH algorithms (SADE, JADE, original HS, original BBO, original SHADE, original VCS, GA, original EO) consistently discovered the same optimal open-switch set [23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130] and an average active-loss value of 854.03 kW over ten independent runs. This configuration matches those reported by ICSA [7], HSA [14], and FWA [17].

3) Convergence Performance

Figure 8 presents the convergence behavior of the ten best MH algorithms for the IEEE 118-bus network under both the original and reduced search spaces. The difference in convergence speed becomes even more pronounced in this large-scale system. In the original search space, most algorithms required 60–100 iterations to stabilize, and several methods (e.g., EO, HS, and BBO) exhibited slow or irregular convergence trends. In contrast, after applying the proposed loop-reduction step in Phase #1, all algorithms achieved rapid and smooth convergence within 30–50 iterations, while maintaining identical optimal loss values. This result highlights that the search-space reduction technique is especially effective for large networks, significantly improving computational efficiency and scalability of MH algorithms without compromising solution quality.

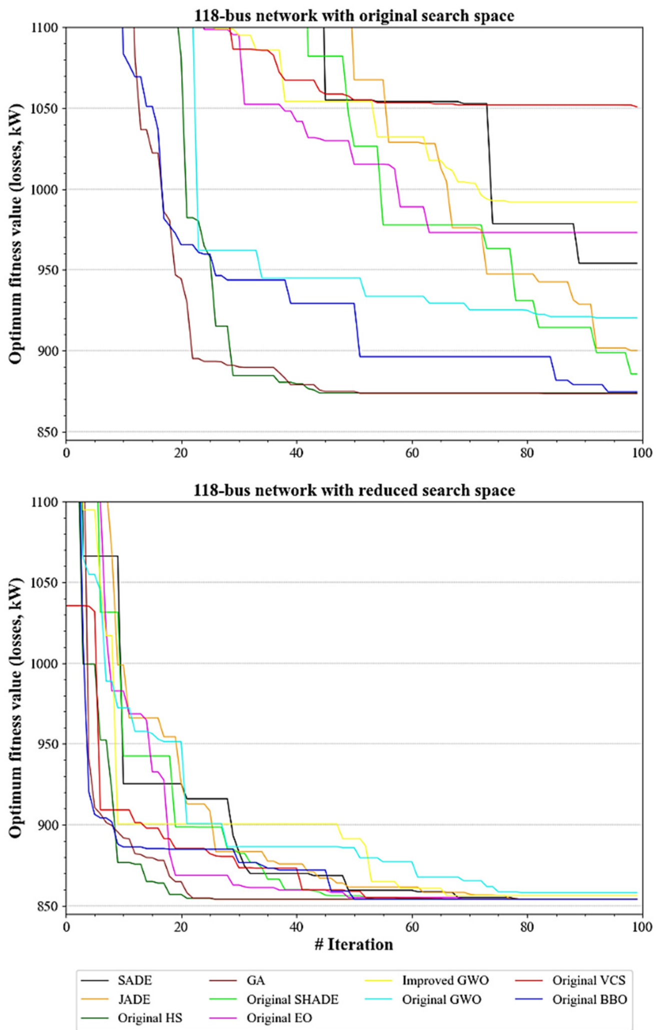

Fig. 8. Convergence speed of the ten best MH algorithms in the IEEE 118-bus network with reduced and original search space.

4) *Voltage Profile Enhancement*

Figure 9 compares bus voltages before and after reconfiguration. The minimum voltage improves from 0.869 pu (bus #55) to 0.931 pu (bus #71), ensuring that the operational constraint $V \geq 0.93$ pu is satisfied at all buses post-reconfiguration. Thus, the proposed approach achieves a twofold benefit on a large network: loss minimization and system-wide voltage stabilization.

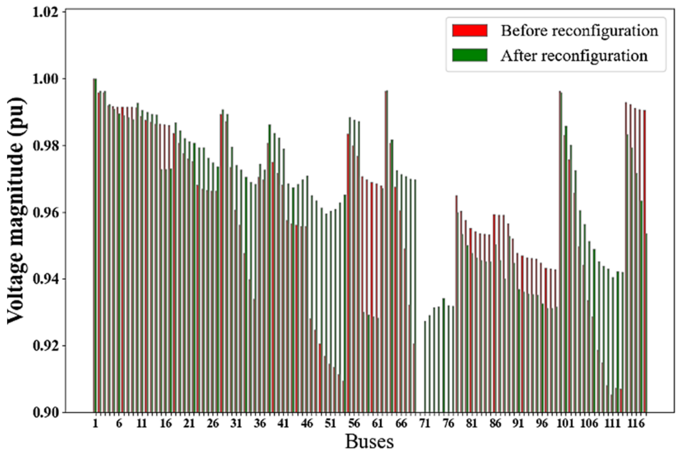

Fig. 9. Node voltage before and after reconfiguration in the IEEE 118-bus network.

TABLE VIII. COMPARISON OF EXISTING METHODS AND TEN BEST MH ALGORITHMS IN THE IEEE 118-BUS NETWORK

No.	Algorithm	Optimum value ($min(P_{loss})$) (kW)	Opened switches
Results of recent state-of-the-art methods			
1	ICSA [7]	855.04	[23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
2	HSA [14]	852.3	[23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
3	FWA [17]	855.04	[23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
4	MTS [11]	865.86	[23, 27, 35, 41, 45, 54, 61, 65, 74, 77, 86, 89, 95, 101, 114]
5	CSA [7]	886.77	[22, 39, 42, 50, 59, 71, 74, 95, 97, 109, 119, 122, 129, 130, 132]
Results of the proposed approach on some MH algorithms			
1	SADE	854.03	[23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
2	JADE	854.03	[23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
3	Original HSA	854.03	[23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
4	Original BBO	854.03	[23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
5	Original SHADE	854.03	[23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
6	Original VCS	854.03	[23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
7	GA	854.03	[23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
8	Original EO	854.03	[23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
9	IGWO	856.427	[23, 25, 34, 39, 43, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130]
10	Original GWO	858.13	[23, 25, 34, 39, 42, 50, 58, 71, 74, 82, 95, 97, 109, 121, 130]

Overall, the proposed two-phase framework demonstrates strong and consistent performance in the IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus systems. Since MH algorithms exhibit problem-dependent and experimentally driven behavior, their suitability must be verified empirically. The proposed framework provides a unified platform for parallel evaluation and systematic comparison under consistent operating conditions. Simulation results reveal distinct algorithm-specific patterns: SADE, JADE, HS, GWO, and GA perform robustly across all three systems, while PSO and ABC maintain good performance on the IEEE 33-bus network and IEEE 69-bus network but show reduced stability on the larger IEEE 118-bus network. Conversely, IGWO and EO (original) remain competitive on the IEEE 33-bus network and the IEEE 118-bus network but are less effective for the IEEE 69-bus network. The proposed loop-reduction mechanism significantly enhances scalability, ensuring efficient convergence and feasible computation even for large-scale distribution networks such as the IEEE 118-bus network. These findings confirm both the adaptability of the proposed framework and its practical value for large and complex DNR problems.

V. CONCLUSIONS

This work presented an integrated DNR framework that combines loop-based search-space reduction with MH evaluation in two phases. This design sharply reduces the problem dimensionality and lets continuous-domain MHs operate without binary/discrete variants. Compared to previous studies that typically apply a single or limited set of MH algorithms, this work introduces a generalized benchmarking platform that enables fair and parallel evaluation of multiple MHs under identical conditions. Furthermore, the loop-reduction phase provides a systematic method to eliminate redundant configurations, reducing the search space by several orders of magnitude—an innovation not reported in earlier DNR frameworks. Simulation results on IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus networks confirm that the proposed method achieves comparable or superior loss reductions and voltage improvements relative to state-of-the-art methods such as ICSA, HSA, and FWA, while requiring fewer iterations and offering better scalability. Overall, the approach delivers computational efficiency and high-quality solutions, making it suitable for large-scale practice. Future work will extend to multi-objective settings, real-time reconfiguration under dynamic loads, and integration with smart-grid operations.

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