IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 27 February 2023, accepted 11 March 2023, date of publication 14 March 2023, date of current version 17 March 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3257190

RESEARCH ARTICLE

A Novel Radiality Maintenance Algorithm for the Metaheuristic Based Co-Optimization of Network Reconfiguration With Battery Storage

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This work was supported by the Lahore University of Management Sciences through Faculty Initiative Fund under Grant FIF-750-2022.

ABSTRACT Network reconfiguration (NR) is a well-accepted technique to decrease power losses and enhance the voltage profile of the distribution network. The practical challenges in solving the NP-hard NR problem using metaheuristics are to randomly generate and, in each iteration, check and repair non-radial distribution network configurations without compromising on solution space in the least amount of time. Inefficient handling of non-radial configurations results in large computational time and high standard deviation. This paper mitigates the aforementioned challenges by proposing a novel radiality maintenance algorithm (RMA) that involves the novel concept of junction nodes and a selection set to produce only radial configurations. The proposed approach can potentially improve the standard deviation and computational efficiency of metaheuristics in solving the NR problem. The proposed RMA is generic, model-independent, and scalable, as it can be seamlessly integrated into any metaheuristic approach to solve the NR problem involving feeders of different sizes. The proposed RMA, combined with the accelerated particle swarm optimization, is implemented to solve: 1) the standard snapshot NR problem; and 2) the multiperiod co-optimization problem that simultaneously computes optimal network configuration and control setpoints of the photovoltaic system and battery energy storage system. Simulation results suggest a 27.3% standard deviation reduction in achieving the best results reported in the literature on NR-based power loss reduction within a comparable timeframe of 1.6 seconds. The effectiveness and reliability of the proposed algorithm are demonstrated on IEEE 33-bus test system.

INDEX TERMS Accelerated particle swarm optimization, battery energy storage system, distribution network reconfiguration, metaheuristic optimization, radial network.

I. INTRODUCTION

The inclusion of renewable energy sources and advancements in the remotely controlled operation of distribution grids have opened new avenues for economical and secure power delivery. The optimal network reconfiguration (ONR), first formulated in 1975 using the branch and bound method [1], is proving to be an effective approach in this modern era of technology to accomplish the goal of providing an economical and secure power supply [2]. The ONR in a distribution network (DN) determines the optimal open/close status of sectionalizing switches (normally closed) and tie lines (normally open) to ensure radial operation of the DN subjected to various operational constraints [3]. The ONR derives its essence from the fact that the DN is originally built in a weakly mesh structure but operated radially to limit short-circuit currents [4]. The mesh structure is realized by the available tie lines to increase the reliability of the DN. The ONR problem computes the optimal radial configuration among an exponentially large number of switching combinations comprising both feasible and infeasible solutions for the operation of DN. In addition, the feasible search space

The associate editor coordinating the review of this manuscript and approving it for publication was Fabio Mottola.

of the ONR problem is nonconvex due to the AC load flow constraints and binary nature of the switches [5]. Thus, finding the optimal switching combination subjected to different DN constraints is a challenging and computationally intensive task that places ONR in the category of combinatorial NP-hard mixed-integer nonlinear programming (MINLP) problems [6]. The non-deterministic polynomial-time (NP) problems are those whose solution can be verified in polynomial time but not necessarily be solved in polynomial time [7]. The non-deterministic polynomial-time hard (NP-hard) problems are at least as hard as the hardest problems in NP complexity class, but their solutions may not be verified in polynomial time [8].

The transition of distribution grids from conventional to smart ones incorporating distributed energy resources (DERs) yields numerous environmental and economic benefits [9]. However, this transition is accompanied by new technical challenges in operating DERs. The DERs in distribution grids mainly include battery energy storage system (BESS) and photovoltaic (PV) system. The optimized operation of the PV generation units and BESS is subjected to many equality, inequality, nonlinear, and time-coupled constraints [10]. Consequently, the co-optimization of ONR with the control of DERs in distribution grids becomes a highly multi-dimensional, nonconvex, and computationally intensive optimization problem, where co-optimization is an optimization approach that simultaneously optimizes multiple interconnected systems to achieve an overall optimal solution [11]. Several conventional optimization algorithms have been first applied to solve this type of NP-hard optimization problem. The limitations of conventional algorithms include the requirement of proper initial guesses and a high probability of being stuck at local optima. By contrast, the metaheuristic optimization algorithms have demonstrated their effectiveness in solving this NP-hard problem due to being gradient-independent with a very low probability of getting stuck at local optima [12]. The major challenge in co-optimizing the ONR with the control of DERs using metaheuristic algorithms is to ensure the radial structure of the distribution grids [13]. There are two main challenges in maintaining the radial topology of the DN using metaheuristic algorithms: 1) the generation of an initial radial random population to start the optimization process without compromising on solution space; and 2) the requirement to check and repair infeasible radial configurations that might be generated during the update process at each iteration.

Many algorithms have been proposed in the literature to initially generate the random/ordered radial topologies in distribution grids, but with limitations such as compromised solution space or with the possibility of providing infeasible radial topologies. For instance, the algorithm proposed in [4] to generate radial configurations showed acceptable performance in solving the ONR problem using Harris hawks optimization by reducing the generation rate of non-radial configurations but still could not guarantee to produce only radial topologies. Reference [2] employed a fundamental loops-based simplified network graph approach to generate and maintain radial topologies to solve the ONR problem. This fundamental loop approach suffered from the possibility of propagating non-radial DN configurations, as evident from the non-convergence of the load flow solution corresponding to some switching combinations. In [14], the penalty factor (PF) approach is used to maintain the radiality of the DN during the iterative process of finding optimal daily network configurations with a self-adaptive modified crow search algorithm. However, the PF approach is vulnerable to the selected penalty factors and inefficient in handling equality constraints, resulting in high convergence time and standard deviation. A fast nondominated sorting guided genetic algorithm was employed in [15] to reduce the DN's power losses, switching losses, and voltage deviation. The optimization process was initiated using the fundamental loop matrix to generate various random DN topologies, with the caveat that it may not always produce radial configurations. Although the approach in [15] optimized the aforementioned objectives effectively, the generation of non-radial configurations highlights a potential limitation of the fundamental loop matrix in generating radial DN topologies, causing a delay in the convergence of the applied optimizer. The ONR with static var compensators and distributed generation (DG) control was solved in [16] using a jellyfish search algorithm, and the multiobjective ONR with DG allocation was solved using an improved heap-based optimizer in [17]. To verify the radiality of the generated DN topologies in [16] and [17], the rank of the branch-bus incidence matrix for each generated topology has to be computed. Such an approach results in high computational time. In [18], the switch opening and exchange method was introduced to obtain the radial configurations by the sequential opening of the switches present in the loops of weakly mesh DN. However, the limitation of this method is that it is exhaustive and time intensive, as highlighted in [18]. To overcome this limitation, a heuristic strategy was implemented resulting in a compromised feasible solution search space. Reference [19] proposed an adaptive local search-based shuffled frog leaping algorithm to generate feasible radial topologies. This approach is not generic as it relies on the DN model and cannot be straightforwardly applied to problems involving different DN models. The above literature clearly indicates the lack of an algorithm that guarantees the generation of the radial configurations in an acceptable time without compromising on solution space.

The normal practice in the available literature is to discard the non-radial generated topologies during the update process and temporarily stop the update process until the new radial topologies are generated [6]. For example, reference [20] restored the radiality of DN by opening the switches of the DN loops one by one until a new radial configuration is found. In [21], a similar sort of iterative technique is employed to find a new radial topology replacing the existing non-radial topology using the rain-fall optimization algorithm. Such an iterative technique in [20] and [21] is highly exhaustive and computationally expensive. Another approach adopted in the literature is to discard the non-radial generated topologies and replace them with previously obtained radial topologies. For instance, references [22] and [23] maintain the radiality of the DN by discarding the newly formed non-radial topologies and continuing the update process with the previously obtained radial topologies, which may cause a significant delay in the solution convergence. In [6], an attempt was made to avoid the generation of non-radial configurations during the update process using a heuristic technique combined with the genetic algorithm. However, the proposed technique was not generic as it cannot be seamlessly integrated into other metaheuristic algorithms to solve the ONR problem. The methods reported in the literature reviewed here for handling the non-radial topologies can compromise the performance, computational cost, and standard deviation of any metaheuristic algorithm in achieving the final solution to the ONR problem.

The hourly dispatch of BESS in a distribution grid with fixed topology was considered in the day-ahead scheduling problem [24], [25], [26]. The operating cost and power losses were minimized using metaheuristic algorithms for the entire scheduling period. However, a significant improvement in terms of objective values of [24], [25] and [26] can be achieved by exploiting the hourly ONR flexibility of distribution grids. References [9] and [27] performed the hourly co-optimization of ONR with BESS scheduling for a day-ahead forecasted load demand using mathematical optimization. Although encouraging results were achieved by formulating the problem as a mixed-integer linear program, the obtained results were greatly dependent on the selected initial states with a high probability of being stuck at local optima. In [20], an effort was made to avoid the limitations of conventional optimization algorithms by employing particle swarm optimization to co-optimize the hourly ONR with the control of BESS for a day-ahead scheduling problem. The cascaded implementation was realized by first scheduling the BESS followed by the hourly ONR, resulting in a large execution time. This computational cost can be reduced by simultaneous co-optimization of hourly ONR with BESS scheduling.

In view of the above discussion, this paper addresses the concerns related to the proper handling of radiality constraints with metaheuristic algorithms to solve the ONR problem. The reactive power support from DERs towards voltage profile improvement has been explored extensively in the literature (e.g., [28] and [29]) for fixed topology distribution grids. However, the co-optimization of hourly ONR with the control of BESS for a day-ahead scheduling problem using the metaheuristic algorithms has not been performed aptly in the literature with an acceptable execution time. The innovation and contributions of this paper are summarized as follows:

1) A novel radiality maintenance algorithm (RMA) is proposed that involves the novel concept of junction nodes and a selection set. The proposed RMA has the following attributes:
   - Randomly generates only radial configurations to start the optimization process in an acceptable time without compromising on solution space.
   - Ability to check and repair non-radial configurations that might be formed during the update process. This improves the overall performance and computational cost of metaheuristic algorithms as it results in radial topologies during the update process at each iteration.
   - Can be seamlessly integrated into any metaheuristic algorithm to solve the ONR problem involving feeders of different sizes.
   - Efficient and simple to be programmed in available software packages with very low computational time.
2) The co-optimization problem is formulated to reduce the power losses of DN. The proposed RMA is combined with an improved version of accelerated particle swarm optimization (APSO) to simultaneously compute the optimal set points of remotely controlled switches, PV systems, and BESS integrated into the day-ahead energy market.

II. PROBLEM FORMULATION

The ONR problem is an NP-hard combinatorial MINLP optimization problem. The ONR problem determines the optimal combination of open/closed switches of the DN to achieve a particular objective subjected to various constraints [4]. The co-optimization problem can be formulated as a single-objective or multiobjective problem based on the operational requirements of the distribution system operator [2].

A. OBJECTIVE FUNCTIONS

The single-objective ONR problem in this paper considers the minimization of power losses (1) or maximization of minimum voltage (2) of the DN. Let R_{ij} and I_t^{ij} be the branch resistance and the current flow in line (i, j), respectively. The V_t^i is the voltage at bus i at time instant t. Define the set of scheduling time instants as $\mathcal{T}$. The V_t^m denotes the minimum voltage value of the DN at instant t. The $\mathcal{N}_{br}$ and $\mathcal{N}_b$ represent the set of all the branches and buses of the DN, respectively. The objectives are given by

$$min\,(f_1) = min\left(\sum_{t\in\mathcal{T}}\sum_{ij\in\mathcal{N}_{br}} |I_t^{ij}|^2\, R_{ij}\right) \tag{1}$$

$$max\,(f_2) = max\left(\sum_{t\in\mathcal{T}} V_t^m\right) \tag{2}$$

The optimization of nominal voltage values of DN plays a crucial role in voltage profile enhancement and is widely employed in the literature on network reconfiguration [2]. In a multiobjective ONR problem, the main objective is to simultaneously minimize the power losses and maximize the minimum voltage of the DN, as given by (3).

$$min\,(f_3) = min\left(\frac{f_1}{min\,(f_1)} + \frac{V_s - f_2}{V_s - max\,(f_2)}\right) \tag{3}$$

where V_s is the rated voltage of the source in distribution grid.

The objectives f_1 and f_2 in multiobjective function (3) are conflicting in nature as we minimize f_1 and maximize f_2. To make them agreeable, the f_2 is subtracted from the V_s to construct a multiobjective function (3) that can be minimized. The weighted sum method with equal weights is employed to form the multiobjective function (3). The power losses and minimum voltage of distribution grids are normalized by their respective optimized single-objective values. The normalization in developing multiobjective functions gains its essence from the fact that objectives considered to form multiobjective functions differ in units and scale; therefore, dividing each objective function value by its corresponding optimal value ensures that all objectives are unitless, equally weighted, and bounded within the same scale. This enables multiobjective optimization to take place in a unitless and non-dimensional space.

B. OPERATIONAL CONSTRAINTS

Let N be the total number of buses. The y_{ij} is the admittance between buses i and j. The net active and reactive power injections at bus i are denoted by P_t^i and Q_t^i, respectively. The bus voltages of the DN can be determined by solving the nonconvex power flow equation (4) using any iterative technique [30]. Equation (5) calculates the current flows in line (i, j).

$$\frac{P_t^i - \imath Q_t^i}{V_t^{i*}} = V_t^i \sum_{j=1}^{N} y_{ij} - \sum_{j=2}^{N} V_t^j y_{ij} \quad j \neq i, \forall i \in \mathcal{N}_b \tag{4}$$

$$I_t^{ij} = y_{ij}\left(V_t^i - V_t^j\right) \quad \forall ij \in \mathcal{N}_{br} \tag{5}$$

The ONR optimization problem is subjected to the following constraints [2]:

1) ***Power balance*** The power supplied by the substation P_t^s must be equal to the sum of the load demand P_t^d and power losses P_t^l of the DN, as described by

$$P_t^s = P_t^d + P_t^l \tag{6}$$

2) ***Voltage limit*** The voltage at each bus in the DN should remain within the allowed maximum V_{max} and minimum V_{min} voltage limits, as given by

$$V_{min} \leq V_t^i \leq V_{max} \quad \forall i \in \mathcal{N}_b \tag{7}$$

3) ***Current limit*** The current flow in each branch of the DN should not exceed the maximum allowable current limit I_{max}, as expressed by

$$I_t^{ij} \leq I_{max} \quad \forall ij \in \mathcal{N}_{br} \tag{8}$$

4) ***Radiality maintenance*** The DN must be operated in a radial configuration. The following conditions must be satisfied to guarantee the radiality of the DN [13].
   a) The total number of closed branches B_c must be equal to one less than the total number of buses in the system, as described by

$$B_c = N - 1 \tag{9}$$

   b) All the buses in the DN must be energized, a requirement implicitly guaranteed by (7).

C. DETAILED MODELING OF DERs

The BESS model for the day-ahead scheduling problem is presented in (10)−(14) [10], [25]. The BESS state-of-charge SOC_t is calculated using (10), which is a dynamic linear equality constraint as each interval value depends upon the previous interval value. Equation (11) computes the increment/decrement in the BESS state-of-charge during an interval of operation Δt. To ensure the optimal performance of BESS, the allowable range of the BESS state-of-charge and active power charge/discharge rate are defined by the double-sided linear inequalities (12) and (13), respectively. The linear inequalities provide a flexible framework for constraining the system within acceptable limits. The reactive power capability of BESS is described by the convex quadratic inequality constraint (14).

$$SOC_t = SOC_{t-1} - \Delta SOC_t \tag{10}$$

$$\Delta SOC_t = \begin{cases} \dfrac{p_t^{BESS}\ \Delta t}{\eta_{dsc}}, & \text{if } p_t^{BESS} \geq 0 \\ p_t^{BESS}\ \eta_{ch}\ \Delta t, & \text{if } p_t^{BESS} < 0 \end{cases} \tag{11}$$

$$SOC_{min} \leq SOC_t \leq SOC_{max} \tag{12}$$

$$p_{min}^{BESS} \leq p_t^{BESS} \leq p_{max}^{BESS} \tag{13}$$

$$(p_t^{BESS})^2 + (q_t^{BESS})^2 \leq (S_{max}^{BESS})^2 \tag{14}$$

where p_t^{BESS} is the BESS active power charge/discharge rate and q_t^{BESS} is the reactive power output. The S_{max}^{BESS} denotes the apparent power rating of battery storage. The maximum (minimum) values of SOC_t and p_t^{BESS} are expressed by SOC_{max} (SOC_{min}) and p_{max}^{BESS} (p_{min}^{BESS}), respectively. The η_{ch} and η_{dsc} are the BESS charging and discharging efficiencies, respectively.

Let p_t^{PV}, q_t^{PV}, and S_{max}^{PV} be the PV active power, reactive power, and apparent power rating, respectively. The PV reactive power capability to operate the DN more effectively is described by the following quadratic inequality constraint:

$$(p_t^{PV})^2 + (q_t^{PV})^2 \leq (S_{max}^{PV})^2 \tag{15}$$

This article solves the snapshot ONR problem for the objectives (1)−(3) subject to constraints (4)−(9). The co-optimization of ONR with the coordinated control of PV reactive power and BESS is performed to minimize the power losses (1) subject to constraints (4)−(15).

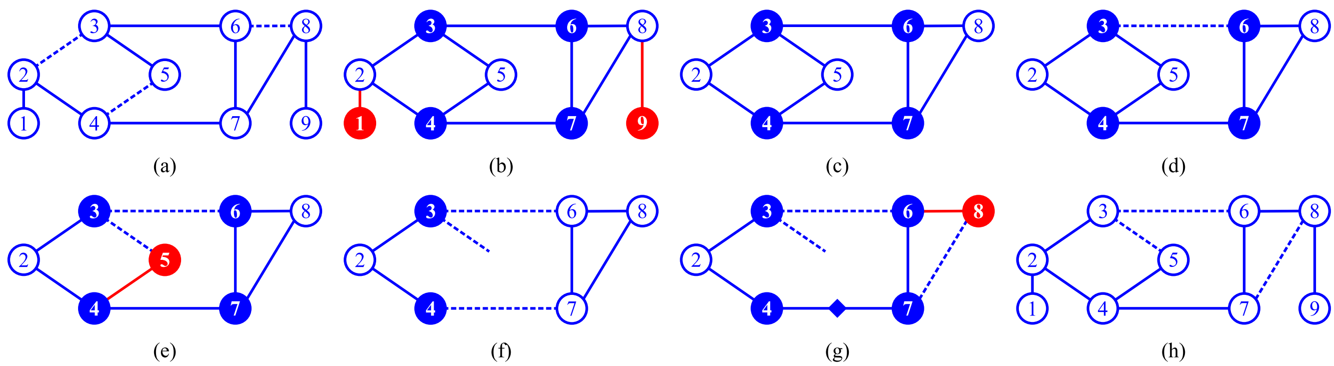

FIGURE 1. Network example for the illustration of the proposed RMA.

III. PROPOSED RADIALITY MAINTENANCE ALGORITHM

The core concept of the proposed radiality maintenance algorithm involves the following conditions:

1) Total number of open branches B_o must be equal to the difference between the total branches T_b and total number of nodes N of the network minus one [13], as given by
$$B_o = T_b - (N - 1) \tag{16}$$
2) The opening branches must not be the ones connecting the dangling node(s) of the network. The dangling node(s) are the network nodes connected to the source/root node through a unique path.
3) All the junction nodes directly or indirectly through other junction nodes must be connected to the source/root node of the network. Note that a junction node is a node connected to at least three other nodes of the network, excluding dangling nodes.

The first point presents the necessary condition that must hold for the network to be radial but it is not a sufficient condition to guarantee the radial structure of the DN [13], [31].

To elaborate on the second point, consider that all the network branches are initially closed. It can be seen that most (if not all) of the network's non-junction nodes lie along the path formed by the branches between junction nodes. The remaining non-junction nodes (if any), that do not lie on the path between junction nodes, are connected to junction nodes in a dangling configuration. Note that opening any branch along the path between junction nodes breaks the path (or loop) and results in a dangling configuration. Opening any further branch on the already broken path would result in an isolated network [2], [4]. It is pertinent to mention that the existence of unpowered islands (i.e., isolated networks) is prohibited in the ONR problem.

The third point highlights the novel aspect of this work. Intuitively, each node is connected to the junction nodes of the network either in a loop or dangling configuration. Therefore, the existence of a path between these junction nodes and the source/root node (either directly or indirectly via other junction nodes) is sufficient to guarantee the existence of a path between every network node and the source/root node. This aspect prohibits any isolated node in the network.

Note that any configuration of DN with the aforementioned three attributes would definitely result in a radial structure. The proposed RMA algorithm, due to the novel aspect, has a very small computational time as the total number of junction nodes is usually far less than the total number of nodes in the entire network. There is a need to check the connectivity of only two adjacent junction nodes (instead of all junction nodes) with the source/root node when we open a branch, which further speeds up the proposed algorithm.

A. GRAPHICAL ILLUSTRATION OF PROPOSED RMA

This section provides a detailed graphical illustration of the proposed RMA using a small radial network [4] as manifested in Fig. 1(a). The objective here is to construct another possible radial topology of the network by using the aforementioned attributes of the proposed RMA.

The network has 9 nodes and 11 branches. The dashed line represents an open branch while the solid line depicts a closed branch. As per the first attribute of the RMA, the total number of open branches is 3 to realize a radial structure. Now close all the network branches to identify the junction nodes $\{3, 4, 6, 7\}$ and determine the dangling nodes $\{1, 9\}$ with their associated branches as shown in Fig. 1(b). Here, the network junction nodes are highlighted with blue color while the red color is used for the dangling nodes and their associated branches. As per the second attribute of the RMA, temporarily remove the dangling nodes along with their associated branches from the network as shown in Fig. 1(c). At this stage, randomly select any network node as the source/root node. This graphical illustration assumes node 2 as the source/root node. Any other node can be selected as a source/root node as the final result would remain the same.

Next, open any available branch in the network. For instance, open the branch between nodes 3 and 6. As per the third attribute of the RMA, check whether the path exists between adjacent junction nodes $\{3, 6\}$ and the source/root node either directly or indirectly via other junction nodes.

The adjacent junction nodes {3, 6} are still connected to the source/root node as shown in Fig. 1(d). Therefore, select this branch as the first opened branch of the network. As per the second attribute of the RMA, temporarily remove the nodes and branches (if any) that are present between the junction nodes {3, 6}.

Again, open any available branch in the network (e.g., branch between nodes 3 and 5). Fig. 1(e) shows that the adjacent junction nodes {3, 4} are still connected to the source/root node, thus, satisfying the third attribute of the RMA. Select this branch as the second opened branch of the network. Fig. 1(f) shows the temporary removal of the nodes and branches present between the junction nodes {3, 4}, thus, complying with the second attribute of the RMA.

Next, the branch between nodes 4 and 7 is arbitrarily selected as open. As per the third attribute of the RMA, check whether the adjacent junction nodes {4, 7} are still connected to the source/root node either directly or indirectly via other junction nodes. Fig. 1(f) clearly shows that the junction node 7 is not connected to the source/root node anymore, which is distinguished by temporarily removing the blue color. Therefore, the branches present on the path between the junction nodes {4, 7} are assumed to be unavailable (marked with a diamond symbol) for further selection as an opened branch.

Again, randomly select the branch between nodes 7 and 8 to be opened. Fig. 1(g) shows that the adjacent junction nodes {6, 7} are still connected to the source/root node either directly or indirectly via other junction nodes, thus, satisfying the third attribute of the RMA. Therefore, select this branch as the third opened branch of the network. As mentioned earlier, the total number of open branches to make the network radial is 3. As a final step, add all the temporarily removed nodes and branches back to the network. The resultant network is the desired network with a new radial topology as shown in Fig. 1(h).

B. PSEUDO-CODES FOR THE PROPOSED RMA

The proposed RMA can be extended to ensure the radial topology of distribution feeders of different sizes. Table 1 presents the generalized pseudo-code based on the proposed RMA for the random radial population generation of any network. Table 2 describes the pseudo-code for the checking and repairing of non-radial configurations of any network that might be formed during the update process. The algorithms developed in Tables 1 and 2 ensure the particles' radiality by utilizing the novel concept of junction nodes set $\mathcal{J}$ and a selection set $\mathcal{S}$ of branches connected to non-dangling nodes. Table 1 can be applied to randomly generate the networks' radial configurations of any population size P, and Table 2 can be applied to check/repair the networks' non-radial configurations for any set $\mathcal{I}$ of open branches having elements found using (16).

In summary, the very need for an algorithm that can generate only random radial topologies and check/repair non-radial topologies for any feeder size without compromising

TABLE 1. Pseudo-code for the random radial population generation of any network.

Input: $P \leftarrow$ Population
1 : $p \leftarrow 0$
2 : $b \leftarrow 0$
3 : $B \leftarrow$ Required number of open branches, calculated from (16)
4 : $\mathcal{O} \leftarrow$ Matrix of order $P \times B$
5 : $\mathcal{C} \leftarrow$ Matrix with information that among which junction nodes the branches are present
6 : **while** $p \neq P$ **do**
7 : $\mathcal{S} \leftarrow$ Set of branches not connecting the network dangling node(s)
8 : $\mathcal{J} \leftarrow$ Matrix with information on the junction nodes' connection with each other and the root node
9 :   **while** $b \neq B$ **do**
10 : $o \leftarrow$ Randomly select any branch from $\mathcal{S}$
11 :   Determine from $\mathcal{C}$ the junction nodes $J_1 \& J_2$ among which o is present
12 :   Update $\mathcal{J}$ to disjoint the connection between $J_1 \& J_2$
13 :   From $\mathcal{J}$ check $J_1 \& J_2$ connection with a root node
14 :   **if** $J_1 \& J_2$ are connected to the root node **do**
15 : $b = b + 1$
16 :   Add value of o in $\mathcal{O}$ at p^{th} row and b^{th} column
17 :   **else do**
18 :   Reverse the last update of $\mathcal{J}$ that took place in step 12
19 :   **end if**
20 :   From $\mathcal{C}$ determine branches present between $J_1 \& J_2$
21 :   Update $\mathcal{S}$ by removing branches determined in step 20
22 :   **end while**
23 : $p = p + 1$
24 : **end while**
Output: $\mathcal{O}$

on solution space is a major problem in network reconfiguration with metaheuristics, and the proposed RMA fulfills this need. Moreover, the RMA is not only efficient in terms of time but also flexible enough to integrate with any metaheuristic algorithm to enhance the metaheuristics algorithmic performance.

IV. IMPROVED APSO ALGORITHM

The accelerated particle swarm optimization algorithm is an advanced variant of the canonical particle swarm optimization, proposed in [32], an improved version suggested in [33], and its statistical performance superiority over other metaheuristic algorithms in solving optimization problems is established in [34], [35], and [36]. The major advantages of the improved APSO algorithm include fast convergence behavior with a very low probability of premature convergence, better/similar solutions compared to other optimizers with less computational cost, and the ability to be easily tuned and programmed for any optimization problem [33]. These advantages are mainly attributed to its efficient objective-oriented algorithmic structure involving only one update equation (17) with two tuning parameters α and β.

Let x_k^{n+1} be the next calculated position of the k^{th} particle at iteration n. The L_k^n is the local best position of the k^{th} particle at iteration n and G^n is the global best position achieved among all the particles till iteration n. The update equation

TABLE 2. Pseudo-code for the non-radial configuration checking and repairing of any network.

Input: $\mathcal{I} \leftarrow$ Set of open branches of the network
1 : $b \leftarrow 0$
2 : $c \leftarrow 1$
3 : $B \leftarrow$ Required number of open branches, calculated from (16)
4 : $\mathcal{O} \leftarrow$ Matrix of order $1 \times B$
5 : $\mathcal{C} \leftarrow$ Matrix with information that among which junction nodes the branches are present
6 : $\mathcal{S} \leftarrow$ Set of branches not connecting the network dangling node(s)
7 : $\mathcal{J} \leftarrow$ Matrix with information on the junction nodes' connection with each other and the root node
8 : **while** $b \neq B$ **do**
9 :   **if** $c \leq$ size of $\mathcal{I}$ **do**
10 : $o \leftarrow$ Select branch from $\mathcal{I}$ at c^{th} column
11 :   **else do**
12 : $o \leftarrow$ Randomly select any branch from $\mathcal{S}$
13 :   **end if**
14 :   **if** o is present in $\mathcal{S}$ **do**
15 :   Determine from $\mathcal{C}$ the junction nodes $J_1 \& J_2$ among which o is present
16 :   Update $\mathcal{J}$ to disjoint the connection between $J_1 \& J_2$
17 :   From $\mathcal{J}$ check $J_1 \& J_2$ connection with a root node
18 :   **if** $J_1 \& J_2$ are connected to the root node **do**
19 : $b = b + 1$
20 :   Add value of o in $\mathcal{O}$ at b^{th} column
21 :   **else do**
22 :   Reverse the last update of $\mathcal{J}$ that took place in step 16
23 :   **end if**
24 :   From $\mathcal{C}$ determine branches present between $J_1 \& J_2$
25 :   Update $\mathcal{S}$ by removing branches determined in step 24
26 :   **end if**
27 : $c = c + 1$
28 : **end while**
Output: $\mathcal{O}$

is given by

$$x_k^{n+1} = (1 - \beta(n))L_k^n + \beta(n)G^n + \alpha(n)R_k^n \tag{17}$$

The R_k^n is a $p \times c$ matrix of normally distributed random numbers with 0 mean and standard deviation equal to the standard deviation of the local best position values of all the particles at iteration n [33]. For the ONR problem considered in this work, p is the total number of particles generated and c is the total number of switches that should be opened during the operation of the distribution grids. The α is the exploration coefficient while β is the exploitation coefficient. These coefficients can either be fixed or varied during the iterative process. However, good performance has been observed in [37] by varying the values of α and β with iterations. Therefore, the parameter control technique from [37] for the tuning parameters is utilized in this work and is given by (18)-(19).

$$\alpha(n) = \alpha_{max} - \left((\alpha_{max} - \alpha_{min}) \times \frac{n}{n_t} \right) \tag{18}$$

$$\beta(n) = \beta_{min} + \left((\beta_{max} - \beta_{min}) \times \sin\left(\frac{\pi}{2} \times \frac{n}{n_t} \right) \right) \tag{19}$$

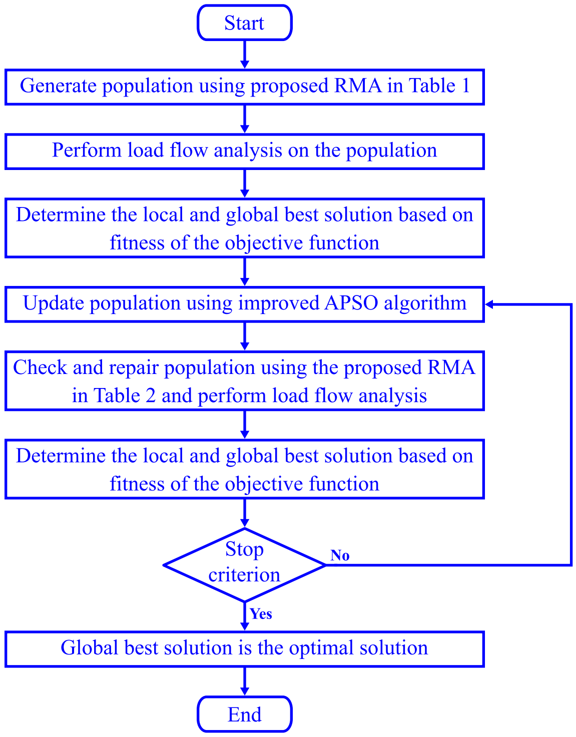

FIGURE 2. Flowchart of the improved APSO integrating the proposed RMA applied to the ONR problem.

where α_{max}, α_{min}, β_{max}, and β_{min} are taken as 0.81, 0.62, 0.81, and 0.62, respectively. The n is the current iteration number and n_t denotes the total number of iterations.

The α is monotonically dropped from a higher value to a lower value to have greater exploration at the start of the iterative process. The linear step reduction is made towards the conclusion of iterations to make the APSO algorithm converge [37]. The β increases from a lower value to a higher value with a sinusoidal step increment to realize greater influence from the particles' local best at the start of the iterative process. Also, it keeps the solution space diversity alive and enables more influence from the global best at the end of iterations to make the algorithm converge [37]. Fig. 2 depicts the complete flowchart for implementing the improved APSO in combination with the proposed RMA applied to the ONR problem.

V. RESULTS AND DISCUSSIONS

This paper considers the IEEE 33-bus test system [38] to demonstrate the effectiveness and reliability of the proposed RMA in improving the performance of the metaheuristic algorithm applied to the ONR problem. The IEEE 33-bus test system has a network of 33 buses and 37 distribution lines as shown in Fig. 3. The initial configuration of the IEEE 33-bus test system is radial with 1 to 32 normally closed sectionalizing switches and 33 to 37 normally open tie lines. The nominal voltage of the network is 12.66 kV with an allowable voltage limit between 0.9 pu and 1.0 pu at each bus.

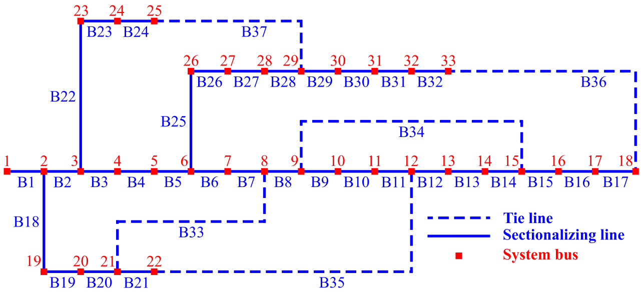

FIGURE 3. IEEE 33-bus test system.

TABLE 3. Simulation results of the FONR problem.

Optimal open branches			B7, B9, B14, B32, B37		
Power Loss (PL)			139.5508 kW		
Minimum Voltage (MV)			0.9378 pu		
Iter.	Pop.	Standard deviation		Time (s)	
		PL (kW)	MV (pu)	50 trials	Per trial
50	5	2.207	0.0023	80	1.6
	10	1.5728	0.0017	179	3.58
	15	1.0093	0.0017	299	5.98
	20	0.3386	0.0018	326	6.52
100	5	3.5425	0.0036	150	3
	10	1.4043	0.0024	281	5.62
	15	0.5507	0.0017	427	8.54
	20	0.2521	0.0017	544	10.88
150	5	3.4138	0.0034	171	3.42
	10	1.0789	0.0017	333	6.66
	15	0.2324	0.0018	541	10.82
	20	0.1937	0.0016	774	15.48

* Iter. → Iteration | Pop. → Population.

The current flow limit of each distribution line is assumed to be 500 A [5]. The total connected active and reactive load demands are 3.715 MW and 2.300 MVAR, respectively. The OpenDSS [39] software is used to perform the load flow studies. For the initial radial configuration, the calculated power losses are 202.67 kW while the minimum voltage of the system is 0.9131 pu.

The improved APSO algorithm, in combination with the proposed RMA, is applied to optimize: 1) three snapshot cases (categorized based on the objective criteria) of the IEEE 33-bus benchmark ONR problem; and 2) a multiperiod co-optimization problem of hourly ONR with the optimal dispatch of DERs in a day-ahead electricity market. The simulations are performed on a core i5-7500 system with 3.40 GHz CPU and 8 GB RAM.

A. SNAPSHOT OPTIMIZATION WITH IEEE 33-BUS BENCHMARK CASES

The first ONR (FONR) case solved using the proposed RMA with improved APSO is a single-objective optimization problem minimizing the power losses (1) of the DN subject to constraints (4)–(9). Table 3 summarizes the results of the FONR problem for different iterations and population sizes.

TABLE 4. Simulation results of the SONR problem.

Optimal open branches			B7, B9, B14, B28, B32		
Power Loss (PL)			139.9778 kW		
Minimum Voltage (MV)			0.9413 pu		
Iter.	Pop.	Standard deviation		Time (s)	
		PL (kW)	MV (pu)	50 trials	Per trial
50	5	9.3192	0.0023	94	1.88
	10	5.0255	0.0013	194	3.88
	15	1.5739	0.0008	254	5.08
	20	1.1329	0.0006	329	6.58
100	5	9.1285	0.0022	150	3
	10	3.8775	0.0011	270	5.4
	15	0.475	0.0004	423	8.46
	20	0.8914	0.0004	551	11.02
150	5	10.0468	0.0021	187	3.74
	10	5.062	0.0012	349	6.98
	15	0.4907	0.0004	571	11.42
	20	0.175	10^{-06}	790	15.8

* Iter. → Iteration | Pop. → Population.

For all the combinations of iterations and population sizes, the same best optimal solution is achieved with an open branch combination of {B7, B9, B14, B32, B37} resulting in 139.55 kW of power losses. Note that the frequency of occurrence of the best optimal solution varies with iterations and population sizes as evident from the calculated standard deviation for 50 trials in Table 3. There are no constraint violations at the optimal solution, which reflects the promising effectiveness and reliability of the proposed algorithm.

The second ONR (SONR) case solved is also a single-objective optimization problem maximizing the minimum voltage (2) of the DN subject to constraints (4)–(9). Table 4 summarizes the results obtained for the SONR problem. It is noticeable that the same best optimal solution is achieved with an open branch combination of {B7, B9, B14, B28, B32} resulting in a minimum voltage of 0.9413 pu for all the combinations of iterations and population sizes. Furthermore, no constraint is violated at the optimal solution indicating the effectiveness and dependability of the proposed algorithm.

The third ONR (TONR) case solved is a multiobjective optimization problem that simultaneously optimizes the objectives considered in the FONR and SONR problems (i.e., equation (3)) subject to constraints (4)–(9). Table 5 illustrates the results of the TONR problem. It is evident that for all employed combinations of population sizes and iterations, the same best optimal solution is achieved with an open branch combination of {B7, B9, B14, B28, B32} resulting in a minimum voltage of 0.9413 pu with 139.98 kW power losses. Again, no constraint is violated at the optimal solution highlighting the strong potential and dependability of the proposed algorithm.

Fig. 4 shows the convergence characteristics of the proposed RMA with improved APSO for a population size of 20 and 150 iterations. The fast convergence behavior of the

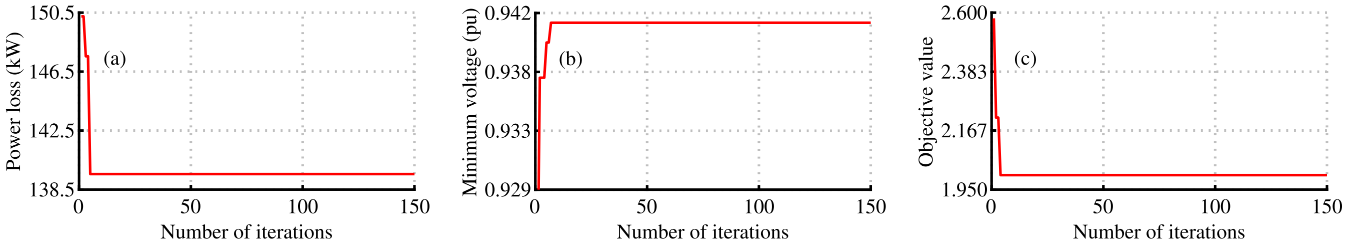

FIGURE 4. Convergence behavior: (a) FONR problem. (b) SONR problem. (c) TONR problem.

TABLE 5. Simulation results of the TONR problem.

Optimal open branches			B7, B9, B14, B28, B32		
Power Loss (PL)			139.9778 kW		
Minimum Voltage (MV)			0.9413 pu		
Iter.	Pop.	Standard deviation		Time (s)	
		PL (kW)	MV (pu)	50 trials	Per trial
50	5	4.8167	0.0021	94	1.88
	10	1.872	0.0012	172	3.44
	15	0.8923	0.0005	252	5.04
	20	0.8344	0.0005	326	6.52
100	5	3.0843	0.0032	136	2.72
	10	0.7508	0.0004	257	5.14
	15	0.4832	0.0004	414	8.28
	20	0.144	10^{-06}	548	10.96
150	5	4.2846	0.0033	170	3.4
	10	1.164	0.0014	355	7.1
	15	0.175	10^{-06}	529	10.58
	20	0.103	10^{-07}	716	14.32

* Iter. → Iteration | Pop. → Population.

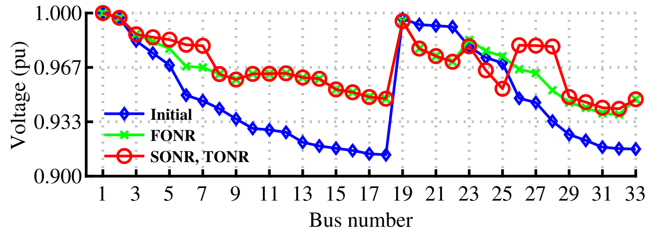

FIGURE 5. Voltage profile before and after snapshot reconfiguration of the IEEE 33-bus test system.

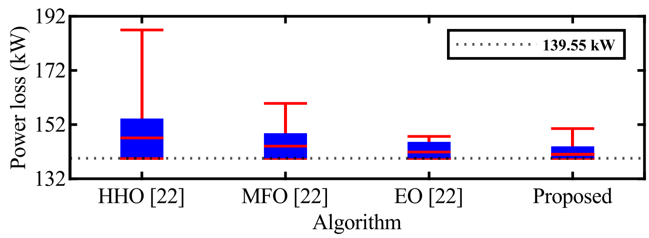

FIGURE 6. Boxplot of the algorithms for FONR case.

proposed optimizer applied to the three ONR cases is apparent from Fig. 4. The voltage profiles before and after solving the three ONR cases are illustrated in Fig. 5.

The thorough performance investigation of the proposed RMA with improved APSO for the three ONR cases is carried out by simulating the test cases for 50 trials. The parallel computing toolbox of MATLAB is employed to calculate the standard deviation in power losses and minimum voltage of the DN along with their execution times as presented in Tables 3, 4, and 5. The standard deviation of both power losses and minimum voltage approaches (nearly) zero in Tables 4 and 5 with a small increment in execution time as the population size and the number of iterations increased. The supremacy of the proposed technique is established by comparing the results of the FONR and TONR problems with the reported results as presented in Tables 6 and 7. It can be seen in Table 6 that statistically, the proposed technique has surpassed the existing methods in attaining low standard deviation within a comparable time frame while achieving the best results reported in the literature. The standard deviation is reduced by 27.3% compared to the literature-reported standard deviation for the FONR case, as evident from Table 6. The boxplot showing the proposed method's strength compared to other algorithms for FONR case is presented in Fig. 6. Table 7 shows the comparison of the best, worst, and average results of the proposed method for TONR with other algorithms. It can be observed that the proposed method in the TONR case showed its statistical strength in attaining the best solution reported in the literature while maintaining a low standard deviation. The comparison of the SONR problem is not made as it is solved for the first time in this paper. It is evident from the comparison that the proposed technique has achieved the best-reported results in an acceptable time with either better or comparable standard deviation.

B. MULTIPERIOD CO-OPTIMIZATION WITH DISTRIBUTED ENERGY RESOURCES

This section considers the co-optimization of hourly ONR with PV reactive power control and BESS scheduling for a day-ahead electricity market to minimize the DN power losses. The co-optimization problem is investigated using a modified IEEE 33-bus test system. The problem formulated results in an exponential increase in the optimal number of open switches, requiring 120 open switches for the radial operation of the DN during the entire 24-hour scheduling period and making it a large optimization problem. The PV units of 605 kVA ratings are assumed to be installed at

TABLE 6. Comparison of simulation results of FONR problem with the literature for IEEE 33-bus system.

Algorithm applied	Open branches combination	Power loss (kW)				Minimum voltage (pu)	Time (s)	Power loss reduction (%)
		Best	Worst	Average	Std.			
BPSOGSA [40]	B7, B11, B14, B32, B37	141.19	–	156.00	68.52	0.9378	31.32	30.34
PSO [23]	B7, B9, B14, B32, B37	139.55	–	–	–	0.9378	120.25	31.14
AMPL [5]	B7, B9, B14, B32, B37	139.55	–	–	–	0.9378	2.28	31.14
HHO [22]	B7, B9, B14, B32, B37	139.55	186.95	147.08	7.161	0.9378	5.38	31.14
MFO [22]	B7, B9, B14, B32, B37	139.55	159.83	144.04	4.637	0.9378	1.96	31.14
EO [22]	B7, B9, B14, B32, B37	139.55	147.64	141.87	3.036	0.9378	1.18	31.14
Proposed	**B7, B9, B14, B32, B37**	**139.55**	**150.53**	**141.00**	**2.207**	**0.9378**	**1.60**	**31.14**

* Std. → Standard deviation.

TABLE 7. Comparison of simulation results of TONR problem with the literature for IEEE 33-bus system.

Algorithm applied	Open branches combination	Power loss (kW) ∣ Minimum voltage (pu)				Power loss reduction (%)	Voltage improvement (%)
		Best	Worst	Average	Std.		
HSA [3]	B7, B10, B14, B36, B37	142.68 ∣ 0.9336	195.10 ∣ –	152.23 ∣ –	11.28 ∣ –	29.60	2.25
FWA [41]	B7, B9, B14, B28, B32	139.98 ∣ 0.9413	155.75 ∣ –	145.63 ∣ –	5.490 ∣ –	30.93	3.09
AWIDPSO [42]	B7, B11, B14, B28, B32	141.63 ∣ 0.9413	– ∣ –	– ∣ –	– ∣ –	30.12	3.09
FA [2]	B7, B9, B14, B28, B32	139.98 ∣ 0.9413	155.04 ∣ –	143.81 ∣ –	4.190 ∣ –	30.93	3.09
Two-stage FA [2]	B7, B9, B14, B28, B32	139.98 ∣ 0.9413	140.71 ∣ –	139.99 ∣ –	0.101 ∣ –	30.93	3.09
NRNM [21]	B7, B9, B14, B28, B32	139.98 ∣ –	– ∣ –	– ∣ –	– ∣ –	30.93	3.09
Proposed	**B7, B9, B14, B28, B32**	**139.98 ∣ 0.9413**	**140.71 ∣ 0.9413**	**139.99 ∣ 0.9413**	**0.103 ∣ 10^{-07}**	**30.93**	**3.09**

* Std. → Standard deviation.

buses 11, 12, 22, and 29. The BESS with 1.1 MVA/5 MWh capacity is assumed to be installed at bus 33. The shunt capacitors of 300 kVAR are assumed to be installed at buses 2, 3, 6, 13, 23, and 32. The load and solar irradiance profiles on 4th September 2022 are inferred from the domestic load profile of Southern California Edison [43] and NREL [44], respectively. It should be noted that the scope of the study in this work is relevant to power system operation optimization and assumes that the DG locations provided as input data are optimized before solving the hourly ONR with PV reactive power control and BESS scheduling for a day-ahead electricity market.

The objective is to minimize the DN power losses (1) subject to constraints (4)−(15). The BESS initial state-of-charge is considered to be 20%. The BESS charge and discharge rates of 1 MW with 95% converter efficiency are assumed. The allowed voltage range is 0.9−1.05 pu while the current limit is 500 A. The injection/extraction rate of the PV reactive power is assumed to be 1 MVAR. Note that the multiperiod co-optimization problem is solved for 24 hours with 11 control variables in each hour. These control variables include the BESS active and reactive powers, four PV reactive powers, and five opened switches. This essentially results in a total of 264 decision variables that need to be optimized simultaneously. The BESS constraints in solving the co-optimization problem are handled according to [25]. The proposed RMA, in combination with the improved APSO, achieves a total power loss of 2.4859 MW with a population size of 50 and 200 iterations. It is important to note that due to the NP-hard nature of the problem, the optimization process can continue indefinitely in search of a better solution [45]. Hence,

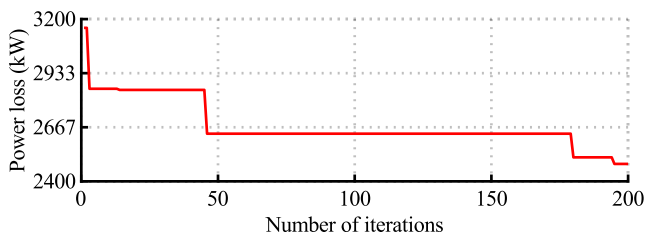

FIGURE 7. Convergence behavior of the multiperiod co-optimization problem.

we must stop the process at a reasonable point to achieve a healthy, robust solution, which we selected empirically to be 200 iterations. Fig. 7 shows the convergence behavior while the optimized switching combinations and hourly losses for each interval are given in Table 8.

Fig. 8 shows the optimal dispatch of BESS active and reactive powers. Similarly, the PV reactive power output is depicted in Fig. 9. The minimum and maximum voltage profiles of the DN are represented in Fig. 10. The feeder voltage profiles during the intervals at which the lowest (time = 23h) and highest (time = 12h) voltages occur are shown in Fig. 11.

It is pertinent to mention that all the state and control variables are within the defined limits in Figs. 8-11 with no constraint violations. Furthermore, the radiality of the DN remained intact in each interval. The execution time for simulating one trial is approximately 660 seconds which is reasonable for this kind of nonconvex, nonlinear, and NP-hard co-optimization problem with 264 decision variables. It is not possible to compare the results of the proposed

TABLE 8. Multiperiod co-optimization ONR solution set and power loss.

Int. (h)	Open branches combination	Power loss (kW)	Int. (h)	Open branches combination	Power loss (kW)
1	B3, B9, B14, B27, B36	72.3812	13	B5, B7, B8, B11, B20	65.6376
2	B4, B11, B13, B15, B28	127.4880	14	B6, B11, B15, B23, B33	41.4717
3	B3, B10, B12, B29, B33	228.3389	15	B6, B8, B14, B18, B22	75.1222
4	B3, B14, B15, B28, B33	82.8494	16	B4, B6, B8, B13, B17	100.0546
5	B6, B8, B10, B18, B25	150.1478	17	B4, B7, B10, B14, B20	50.6817
6	B4, B8, B12, B16, B33	123.8900	18	B4, B7, B8, B12, B29	248.5434
7	B6, B8, B12, B15, B24	63.4029	19	B6, B9, B13, B24, B29	128.8376
8	B7, B9, B12, B22, B30	57.7434	20	B4, B6, B11, B13, B15	58.7722
9	B3, B6, B8, B14, B32	137.5628	21	B3, B6, B11, B12, B29	105.0774
10	B3, B6, B9, B13, B16	61.5148	22	B7, B11, B15, B24, B33	226.4416
11	B5, B7, B11, B19, B35	56.5505	23	B4, B6, B14, B21, B32	104.4168
12	B4, B8, B13, B18, B27	37.2814	24	B7, B15, B24, B34, B35	81.7084
* Int. → Interval				Total power loss (kW)	2485.9153

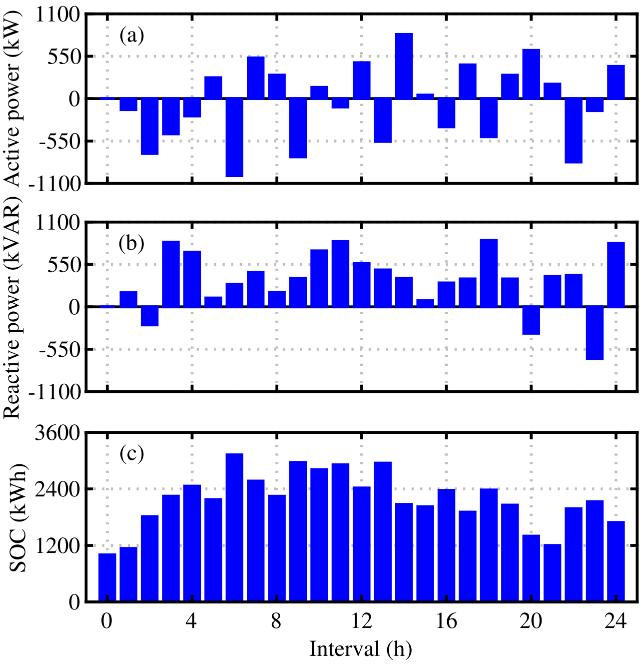

FIGURE 8. BESS scheduling: (a) Active power charge/discharge rate. (b) Reactive power injection/extraction rate. (c) State-of-charge (SOC) profile.

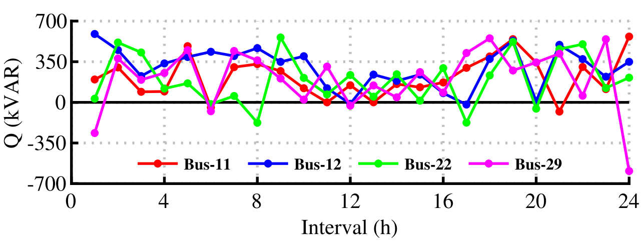

FIGURE 9. PV reactive power (Q) control set point values.

multiperiod co-optimization problem with the literature as it is considered for the first time in this paper. However, to make an analogy, in [24], a different NP-hard co-optimization problem of energy management with BESS having 192 decision variables is solved with a hybrid particle swarm and grey wolf

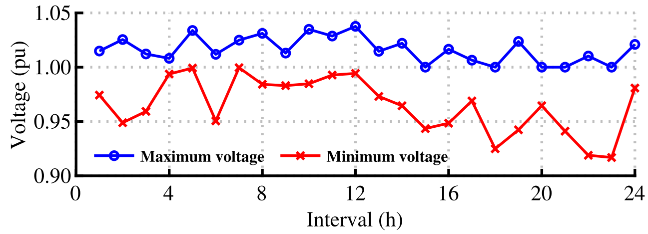

FIGURE 10. Maximum and minimum voltage profiles.

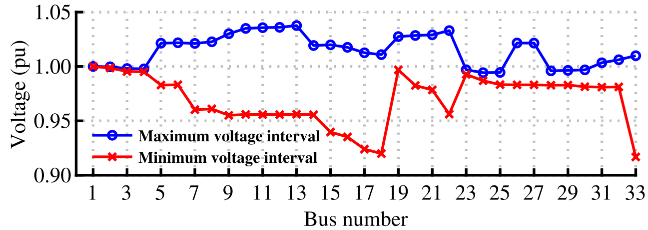

FIGURE 11. Feeder voltage profiles corresponding to the intervals with maximum and minimum voltages for the multiperiod co-optimization problem.

optimization algorithm in 864 seconds. Therefore, it can be said with a certain level of confidence that the novel RMA, in combination with the improved APSO, has solved the hourly co-optimization of ONR with the optimal control of PV reactive power and BESS scheduling in an acceptable time.

VI. CONCLUSION

The proposed RMA, in combination with the improved APSO algorithm, minimized the power losses of the snapshot ONR problem as well as the multiperiod co-optimization problem involving hourly ONR with the optimal control of PV reactive power and BESS scheduling. The proposed novel RMA guarantees the initial random radial population generation and has the capability to check and repair non-radial configurations of DN during the update process without compromising on the solution space in the least amount of time. The proposed technique is tested and validated using a standard IEEE 33-bus test system. The results obtained for the snapshot ONR are relatively persistent and computationally efficient, resulting in a 31.14% reduction in power losses compared to the initial configuration of the DN.

The effectiveness of the proposed technique for the day-ahead scheduling problem is established by solving a high-dimensional multiperiod co-optimization problem in an acceptable time. It is concluded that the proposed RMA is time-effective, increases the performance of the metaheuristic algorithm by lowering the standard deviation, and can be programmed with any metaheuristic algorithm to solve the ONR problem involving DN feeders of different sizes.

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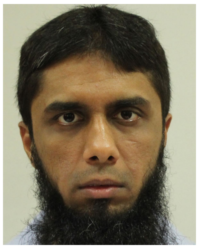

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