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Research Article

Parameter-Free Improved Best-Worst Optimizers and Their Application for Simultaneous Distributed Generation and Shunt Capacitors Allocation in Distribution Networks

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This paper proposes parameter-free two best-worst optimizers (BWOs) that combine the searching capabilities of Jaya and Rao-1 algorithms to intensify their exploration and exploitation capabilities. For the proposed first optimizer, BWO-1, parallel taxonomy has been adopted for the Jaya and Rao-1 combination to obtain dual sets of updated solutions for a given current solution set. For the proposed second optimizer, BWO-2, along with the parallel taxonomy, a subloop of random scaling factors has been introduced in the solution updating mechanism of both standard Jaya and Rao-1 algorithms to generate multiple sets of updated solutions in a single iteration. The best solutions from obtained multiple solution-sets will survive only and lead to the next iteration. Hence, the proposed solution updating mechanisms for BWO-1 and BWO-2 increase the probability of getting a quality solution under set conditions. The ability and scalability of BWO-1 and BWO-2 were assessed, solving the optimization problem of power loss reduction and voltage deviation minimization in the IEEE 33-bus and 69-bus test systems. The results show that the BWO-2 exhibited a lead of 2.97%, 1.83%, and 0.72% over the Rao-1, Jaya, and BWO-1 techniques, respectively. Besides, the BWO-2 achieves up to 38.76% more reduction in power losses against the existing standard, improved, and hybrid optimization techniques.

1. Introduction

Due to the rising power demand for electricity, utilities face challenges such as increased power losses, poor voltage regulation, reduced power quality, irregularity in power supply, high short-circuit levels, and poor power system stability. Generally, compared to the transmission lines, the current flows are higher in the distribution networks, which are usually radial. For these reasons, a significant amount of power losses are related to the distribution networks. It is reported that about 13% of the total generated power is wasted as power loss in distribution networks [1, 2]. The distributed generation (DG) and shunt capacitors (SCs) are generally installed into the radial distribution networks (RDNs) as an effective measure to reduce power losses and improve reliability. DGs are often used as the source of active and reactive powers while SCs are used only as a source of reactive power. Resultantly, SCs are considered less beneficial than DGs in reducing the active power losses in power systems. However, the DGs' capital cost is very high compared to the SCs. Thus, owing to the techno-economic benefits, the combined placement of DGs and SCs is the most effective solution to boost the functioning of the distribution networks [3]. However, an unoptimal allocation of DG and SCs may result in higher power loss and voltage divergence in the distribution network than when no DG or SC is installed. Therefore, an appropriate planning methodology must be used to integrate DG and SC units into the distribution network to attain potential benefits.

1.1. Existing Research and Its Limitations. In contemporary literature, several studies have focused on the simultaneous optimal allocation of DG and SC units into RDNs, considering various objective functions and the application of numerous metaheuristic optimization techniques. The most often used optimization techniques in this context are the genetic algorithm (GA) and particle swarm optimization (PSO). At the same time, power loss minimization and voltage profile improvement are typically optimized cost functions. In [4], the GA was employed to minimize the total power loss by optimizing the locations and capacities of DGs/SCs and the configuration of RDNs. In [5], the DG and SC allocations were optimized using GA to minimize the cost function comprised of the active power, reactive power, and voltage indices. To minimize a weighted-sum-based multicriterion function, the authors in [6] proposed a new GA to optimize the sizing and sitting of DG and SC units. A fuzzy-based GA (FGA) for the optimal allocation of DG and SC allocation has been proposed in [7]. In [8], to optimally place the DGs/SCs into the RDNs, the authors proposed the enhanced genetic algorithm (EGA) that combines the local search mechanism with GA to improve its exploration capability in finding the global optimum. In [9], the authors hybridize GA with an imperialist competitive algorithm (ICA) to solve the optimization problem of simultaneous DG/SC allocation. In [10], the GA has been hybridized with a moth swarm algorithm (MSA) to decrease the power losses with the simultaneous DG and SC allocation in RDNs.

In [11], the authors employed GA and PSO techniques to locate the DG and SC units and concluded that the PSO is more efficient than GA. To boost the RDNs' functioning by reconfiguring the network in the existence of DGs/SCs, improved variants of GA, PSO, and cat swarm optimization (CSO) have been proposed [12]. To optimally allocate the DGs and SCs in RDNs, some other studies [13–15] have also employed the PSO algorithm intending to minimize the power losses [13, 14], costs of DGs, SCs, energy loss, and the expected energy not supplied (EENS) [15]. In [16, 17], the discrete and binary versions of PSO (DPSO and BPSO) have been proposed, respectively. In [18], an application of the autonomous group PSO (AGPSO) has been proposed to minimize the power losses in RDNs by simultaneously allocating the DG and SC units with and without reconfiguring the network. Currently, to achieve the technical, economic, and environmental benefits, the water cycle algorithm (WCA) [19], salp swarm algorithm (SSA) [20], and spring search algorithm (SSA) [21] have been proposed for the optimal simultaneous allocation of DG and SC units. To optimize the technical indicators and operational cost of the RDN with simultaneous DG/SC allocation and network reconfiguration, Tolabi et al. [22] introduced a thief and police algorithm (TPA). To minimize the annual operating cost for RDNs, in [23], Das and Malakar proposed the opposition-based competitive swarm optimizer (OCSO) to optimize the placement of SCs under the uncertain load and wind power generation conditions. In another study [24], Elmitwally and Eldesouky employed the modified simulated annealing (MSA) to optimize the allocation of SCs in a wind-integrated distribution system to maximize the annual cost saving.

Furthermore, numerous other artificial intelligence-based optimization algorithms that have been proposed in literature for the simultaneous DG/SC allocation includes ant lion optimization (ALO) [25], biogeography-based optimization (BBO) [26], backtracking search algorithm (BSA) [27, 28], bacterial foraging optimization algorithm (BFOA) [29], binary collective animal behavior optimization (BCAO) [30], binary GSA (BGSA) [31], cuckoo search algorithm (CSA) [32], differential evolutionary algorithm (DEA) [33], discrete imperialistic competition algorithm (DICA) [34], intersect mutation differential evolution (IDME) [35], G_{best}-guided artificial bee colony algorithm (GABC) [36], memetic algorithm (MA) [37], symbiotic organisms search (SOS) [38], tabu search (TS) [39], and teaching-learning-based optimization [40]. The literature has also proposed several hybrid optimization techniques. These include the hybrid harmony search-particle artificial bee colony algorithm (HSA-PABC) [41] and hybrid configuration of weight-improved particle swarm optimization-gravitational search algorithm (WIPSO-GSA) [42]. In this connection, some modified and multiobjective versions of optimization techniques have also been proposed in the literature. These techniques include modified TLBO (MTLBO) [43, 44], multiobjective evolutionary algorithm based on decomposition (MOEA/D) [45], nondominated sorting GA (NSGA-II) [46, 47], and nondominated sorting multiobjective PSO (MOPSO) [48–50].

Most metaheuristic optimization techniques reported in the literature to solve the problem of simultaneous DG/SC allocation in RDNs require tuning of specific algorithm-defined parameters or involving two or more phases to update the solution. Considering that, such algorithms are comparatively challenging to implement. In literature, some parameterless optimization techniques have been proposed that do not require any algorithm-specific parameters, such as the Jaya algorithm [51] and Rao algorithms (Rao-1, Rao-2, and Rao-3) [52]. They are free from parameter tuning, making their implementation easier than other optimization methods. In contemporary literature, numerous studies [53–64] have proved the dominating performance of Jaya and Rao algorithms over different optimization algorithms applied in diverse fields. However, the Rao and Jaya algorithms also suffer from deficiencies of slow and premature convergence as they lose population diversity [63, 65–67]. Therefore, it is imperative to develop new parameter-free

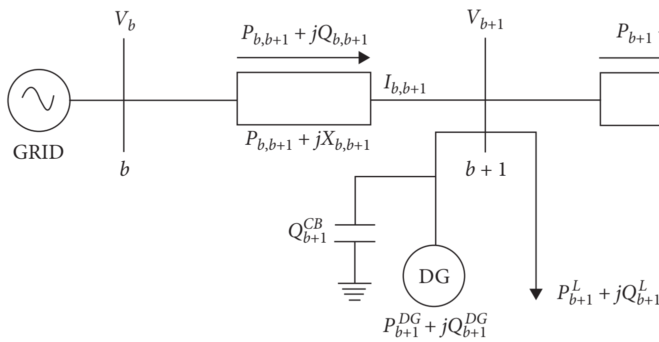


Figure 1: Single-line diagram of RDN with DG and SC installed at a bus.

metaheuristic algorithms and investigate their application in distribution networks for simultaneous DG-SC allocation.

1.2. Contributions of the Proposed Study. This study proposes two new optimization approaches, best-worst optimizer-1 (BWO-1) and best-worst optimizer-2 (BWO-2), to solve the problem of simultaneous DG/SC allocation in RDNs. The proposed optimizers utilize the solution updating equations of Rao-1 and Jaya algorithms. Using solution updating equations of both algorithms enables the first optimizer (BWO-1) to achieve two updated solutions in a single iteration, thus enhancing the likelihood of obtaining a quality solution under set conditions. To further intensify the exploration and exploitation capabilities, for BWO-2, a subloop of random scaling factors has been introduced that initializes different random numbers for the same solution set. The proposed mechanism allows the entire search cycle to start repeatedly by resetting different values of random numbers. This multistart approach enables the BWO-2 to obtain multiple sets of updated solutions ($2 \times$ pair of random scaling factors) in a single iteration, which potentially enhances the searching capabilities of BWO-2.

Thus, the main contributions of this study are as follows:

(i) A new parameter-free optimization technique, BWO-1, has been developed

(ii) An improved best-worst optimizer, BWO-2, has been developed

(iii) A bi-objective complex optimization problem of minimization of active power loss and voltage deviation (VD) has been solved using the proposed optimization techniques to assess the impact of optimal siting and sizing of DG and SC units in RDNs

2. Problem Formulation

Identifying the optimal sizes and nodes simultaneously for DG and SC units in RDNs is a complex combinatorial optimization problem [68]. The inappropriate selection of DGs' and SCs' sizes and locations will increase the system losses beyond a safe margin that will adversely affect the node voltages, thus raising the overall system expense [69]. Therefore, this study's main objective is to minimize the power loss in RDNs while maintaining the desired voltage at buses with simultaneous DG and SC placements. The ε-constraint approach has been adopted to turn this complex multiobjective optimization problem into a straightforward constraint optimization problem. The proposed method allows to keep one objective as the primary function and restrict rest of the objectives with user-specified values [70]. For this study, the minimization of active power loss is held as the main objective while the second objective, minimization of VD, is handled as a constraint with minimum and maximum bounds which are set to 0.95 p.u and 1.05 p.u, respectively. In an RDN embedded with DG and SC units, Figure 1, the power loss associated with branch between buses b and $b+1$ is computed as in the following equation:

$$P_{\text{loss}\,b,b+1} = \left|I_{b,b+1}\right|^2 R_{b,b+1}, \tag{1}$$

where current flow through that branch can be calculated as

$$I_{b,b+1} = \sqrt{\frac{P_{b,b+1}^2 + Q_{b,b+1}^2}{\left|V_b\right|^2}}. \tag{2}$$

The system's cumulative active power loss amounts to the summation of power losses across the distribution network branches. The mathematical form of the objective function is presented in the following equations:

$$P_{\text{loss}\,T} = \sum_{br=1}^{n\text{buses}-1} P_{\text{loss}\,b,b+1}, \tag{3}$$

$$F_1 = \min\left(P_{\text{loss}\,T}\right), \tag{4}$$

$$\text{subject to: } F_2 = \min(\text{VD}), \tag{5}$$

$$\text{where VD} = \left|V_b - V_{\text{rated}}\right| \leq \pm 5\%, \quad \forall\, b \in \left\{1, 2, \ldots, n_{\text{buses}}\right\}. \tag{6}$$

The equality and nonequality constraints considered for this optimization problem are power flow limits through the lines, Eqs. (7) and (8), and the position of the DGs and SCs (except slack bus), Eqs. (9) and (10); minimum and maximum installation capacities of each DG and SC unit are taken as 0% and 100% of the active and reactive power

Initialize the parameters of algorithm and optimization problem
Initialize the population
for $i = 1$: *maximum iterations*
    Compute the current values of *cost function*, $fobj(X_{d,c,i})$
    Obtain the *best* $(X_{d,c_{best},i})$ and *worst* $(X_{d,c_{worst},i})$ solutions
    for $c = 1$: *population size*
        for $d = 1$: *dimension*
            $X_{d,c,i}^{updated} = X_{d,c,i} + rand(X_{d,c_{best},i} - X_{d,c_{worst},i})$, for Rao-1
OR
            $X_{d,c,i}^{updated} = X_{d,c,i} + rand_{1,c,i}(X_{d,c_{best},i} - |X_{d,c,i}|) - rand_{2,c,i}(X_{d,c_{worst},i} - |X_{d,c,i}|)$, for Jaya
            if $X_{d,c,i}^{updated} < X_{lb}$ **then** $X_{d,c,i}^{updated} = X_{lb}$
            else if $X_{d,c,i}^{updated} > X_{ub}$ **then** $X_{d,c,i}^{updated} = X_{ub}$
            end
        end
        Compute the current values of *cost function*, $fobj(X_{d,c,i}^{updated})$
        if $fobj(X_{d,c,i}^{updated}) < fobj(X_{d,c,i})$ **then** $X_{d,c,i} = X_{d,c,i}^{updated}$
        else $X_{d,c,i} = X_{d,c,i}$
        end
    end
end

Figure 2: Pseudocode of the standard Rao-1 and Jaya algorithms.

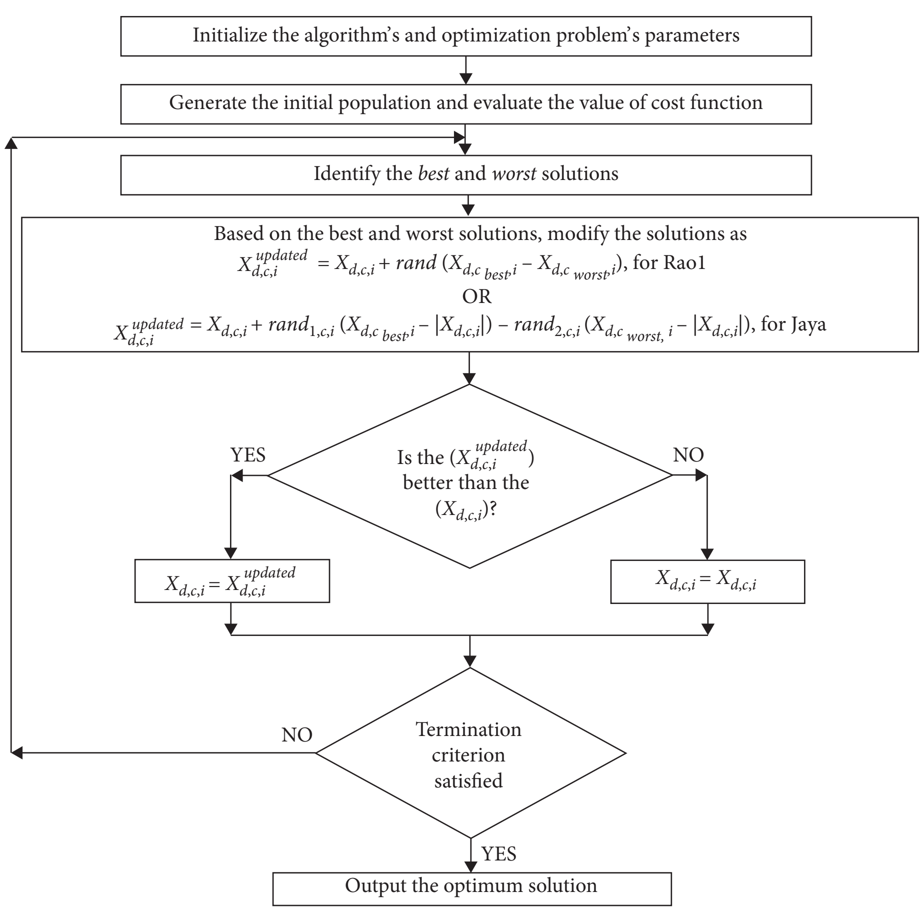


Figure 3: Flowchart of the Rao-1 and Jaya algorithms.

Table 1: Working mechanism of Rao-1 algorithm.

1st iteration						
Initially generated random solutions			Solution updated by Rao-1 $\begin{bmatrix} r_{11} \\ r_{21} \end{bmatrix} = \begin{bmatrix} 0.84 \\ 0.68 \end{bmatrix}$		Optimal values	
(x_1, x_2)	$fobj(z_j)$	Status	(x'_1, x'_2)	$fobj(z_j^{new})$	$fobj(z_j)$	Status
(-5, 18)	349		(-70.52, 26.84)	5693.46	349	
(14, 63)	4165		(-51.52, 71.84)	7815.30	4165	*worst*
(70, -6)	4936	*worst*	(4.48, 2.84)	28.14	28.14	*best*
(-8, 7)	113	*best*	(-73.52, 15.84)	5656.10	113	
(-12, -18)	468		(-77.52, -9.16)	6093.26	468	
2nd iteration						
Solutions obtained from 1st iteration			Solution updated by Rao-1 $\begin{bmatrix} r_{11} \\ r_{21} \end{bmatrix} = \begin{bmatrix} 0.31 \\ 0.22 \end{bmatrix}$		Optimal values	
(x_1, x_2)	$fobj(z_j)$	Status	(x'_1, x'_2)	$fobj(z_j^{new})$	$fobj(z_j)$	Status
(-5, 18)	349		(-7.95, 4.22)	81.04	81.04	
(14, 63)	4165	*worst*	(11.05, 49.22)	2544.82	2544.82	*worst*
(4.48, 2.84)	28.14	*best*	(1.53, -10.94)	121.99	28.14	*best*
(-8, 7)	113		(-10.95, -6.78)	165.88	113	
(-12, -18)	468		(-14.95, -31.78)	1233.42	468	

Table 2: Working mechanism of Jaya algorithm.

1st iteration						
Initially generated random solutions			Solution updated by JA $\begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} = \begin{bmatrix} 0.58 & 0.23 \\ 0.92 & 0.51 \end{bmatrix}$		Optimal values	
(x_1, x_2)	$fobj(z_j)$	Status	(x'_1, x'_2)	$fobj(z_j^{new})$	$fobj(z_j)$	Status
(-5, 18)	349		(-27.49, 20.12)	1160.51	349	
(14, 63)	4165		(-11.64, 46.67)	2313.58	2313.58	*worst*
(70, -6)	4936	*worst*	(24.76, 1.04)	614.14	614.14	
(-8, 7)	113	*best*	(-31.54, 13.63)	1180.55	113	*best*
(-12, -18)	468		(-36.94, -15.88)	1616.74	468	
2nd iteration						
Solutions obtained from 1st iteration			Solution updated by JA $\begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} = \begin{bmatrix} 0.27 & 0.81 \\ 0.38 & 0.49 \end{bmatrix}$		Optimal values	
(x_1, x_2)	$fobj(z_j)$	Status	(x'_1, x'_2)	$fobj(z_j^{new})$	$fobj(z_j)$	Status
(-5, 18)	349		(4.97, -0.23)	24.74	24.74	*best*
(-11.64, 46.67)	2313.58	*worst*	(1.91, 31.60)	1001.93	1001.93	*worst*
(24.76, 1.04)	614.14		(45.40, -19.05)	2424.10	614.14	
(-8, 7)	113	*best*	(3.59, -12.44)	167.59	113	
(-12, -18)	468		(1.75, -36.23)	1315.55	468	

where

= **Accepted solutions** = **Rejected solutions**

= **Obtained *best* solution in an iteration** = **Obtained *worst* solution in an iteration**

```
Initialize the parameters of algorithm and optimization problem
Initialize the population
for i = 1: maximum iterations
    Compute the current values of cost function, fobj(X_{d,c,i})
    Obtain the best (X_{d,c_best,i}) and worst (X_{d,c_worst,i}) solutions
    for c = 1: population size
        for d = 1: dimension
        X1^{updated}_{d,c,i} = X_{d,c,i} + rand(X_{d,c_best,i} − X_{d,c_worst,i})
        X2^{updated}_{d,c,i} = X_{d,c,i} + rand_{1,c,i}(X_{d,c_best,i} − |X_{d,c,i}|) − rand_{2,c,i}(X_{d,c_worst,i} − |X_{d,c,i}|)
            if X1^{updated}_{d,c,i} / X2^{updated}_{d,c,i} < X_lb then X1^{updated}_{d,c,i} / X2^{updated}_{d,c,i} = X_lb
            else if X1^{updated}_{d,c,i} / X2^{updated}_{d,c,i} > X_ub then X1^{updated}_{d,c,i} / X2^{updated}_{d,c,i} = X_ub
            end
        end
        Compute the current values of cost function,
        fobj(X1^{updated}_{d,c,i}) && fobj(X2^{updated}_{d,c,i})
        if fobj(X1^{updated}_{d,c,i}) < fobj(X2^{updated}_{d,c,i})
            if fobj(X1^{updated}_{d,c,i}) < fobj(X_{d,c,i}) then X_{d,c,i} = X1^{updated}_{d,c,i}
            else X_{d,c,i} = X_{d,c,i}
            end
        else if fobj(X2^{updated}_{d,c,i}) < fobj(X_{d,c,i}) then X_{d,c,i} = X2^{updated}_{d,c,i}
            else X_{d,c,i} = X_{d,c,i}
        end
    end
end
```

Figure 4: Pseudocode of BWO-1.

demands ($P_{\text{load}}, Q_{\text{load}}$), respectively, as in Eqs. (11) and (12), whereas the penetration level of DGs and SCs ($P_{\text{DG}}^{\text{Total}}, Q_{\text{SC}}^{\text{Total}}$) is set to 20% to 100% of the P_{load} and Q_{load}, respectively, Eqs. (13) and (14), as follows:

$$P_{\text{SS}} + \sum P_{\text{DG}} = \sum P_{\text{load}} + \sum P_{\text{loss}}, \tag{7}$$

$$Q_{\text{SS}} + \sum Q_{\text{DG/SC}} = \sum Q_{\text{load}} + \sum Q_{\text{loss}}, \tag{8}$$

$$2 \leq \text{DG}_{\text{location}} \leq n_{\text{buses}}, \tag{9}$$

$$2 \leq \text{SC}_{\text{location}} \leq n_{\text{buses}}, \tag{10}$$

$$P_{\min}^{\text{DG}} \leq P_{\text{DG}} \leq P_{\max}^{\text{DG}}, \tag{11}$$

$$Q_{\min}^{\text{SC}} \leq Q_{\text{SC}} \leq Q_{\max}^{\text{SC}}, \tag{12}$$

$$0.2 * P_{\text{load}} \leq P_{\text{DG}}^{\text{Total}} \leq 1.0 * P_{\text{load}}, \tag{13}$$

$$0.2 * Q_{\text{load}} \leq Q_{\text{SC}}^{\text{Total}} \leq 1.0 * Q_{\text{load}}. \tag{14}$$

3. Proposed Optimization Techniques

This section discusses the proposed optimization techniques, BWO-1 and BWO-2, which combine two parameter-free optimization approaches, Jaya and Rao-1 algorithms. The need to improve an existing optimization technique or combine it with another method arises to address a couple of significant concerns, including the following:

(i) How to quickly access suitable regions of the solution space with the maximum probability of optimum global existence?
(ii) How can these regions be effectively exploited?
(iii) How can the candidate solution jump to a different location in the search space if it becomes trapped in a local optimum or effectively explore the entire search space?

Another issue that researchers are interested in is how to choose two optimization techniques that are most suited for hybridization. Although there is no set guideline for choosing two methods, however, the main goal behind combining two approaches is that they must aid each other in overcoming their weaknesses. Hence, uniting different algorithms is to reap the benefits of their combined properties, such as potent exploration and exploitation capabilities, or preserve population diversity. With these considerations in mind, in this study, the authors chose Rao-1 and Jaya algorithms for hybridization as both fall into the same category of single-stage and parameter-free optimization techniques. Furthermore, both algorithms' operating mechanisms are founded on the idea that candidate solutions should continuously

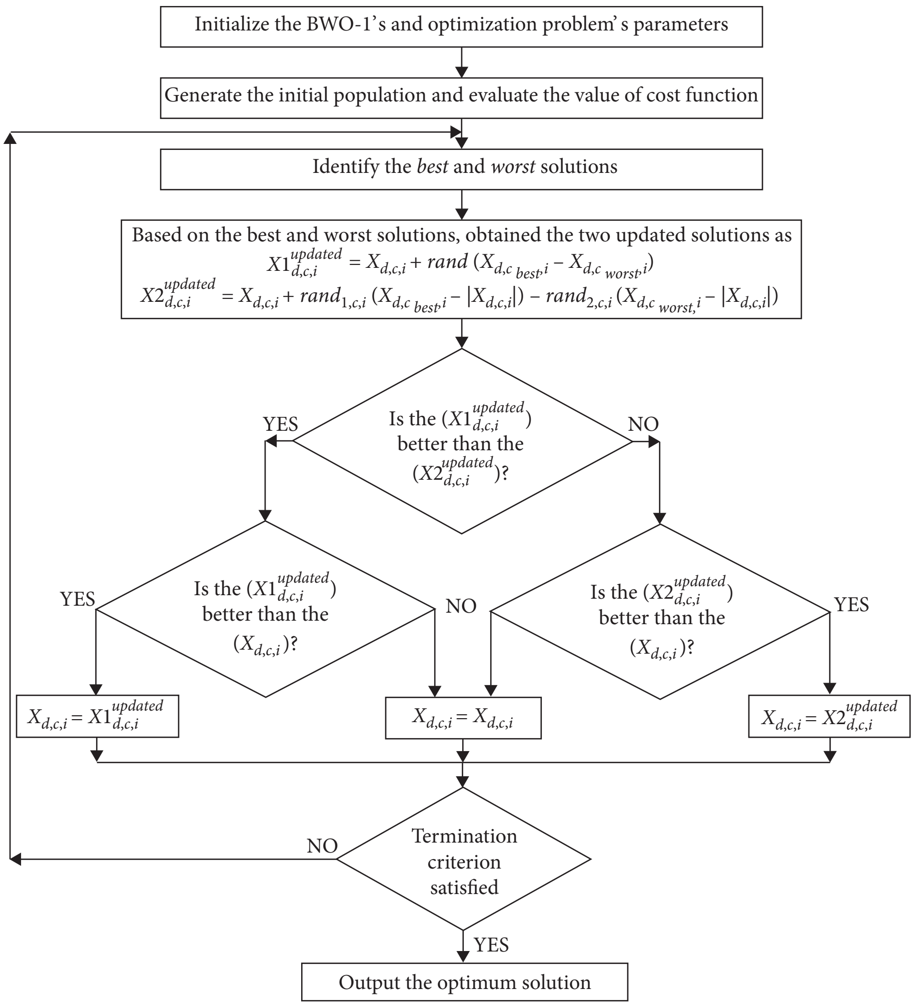


Figure 5: Flowchart of BWO-1.

advance towards the best agent while avoiding the worst. Except for a minor difference in the solution updating equations of both algorithms, there is no significant change in their working mechanisms, as demonstrated in (15) and (16). As a result, the pseudocode and flowcharts for both algorithms are identical. Besides, the design variables used in both algorithms have the same meanings, which significantly decrease the difficulty of combining these two techniques. The pseudocode for the Rao-1 and Jaya algorithms is given in Figure 2, and the flowchart is presented in Figure 3.

Solution updating equation for Rao-1 algorithm:

$$X_{d,c,i}^{\text{updated}} = X_{d,c,i} + \text{rand}\left(X_{d,c_{\text{best}},i} - X_{d,c_{\text{worst}},i}\right). \tag{15}$$

Solution updating equation for Jaya algorithm:

$$\begin{aligned} X_{d,c,i}^{\text{updated}} &= X_{d,c,i} + \text{rand}_{1,c,i}\left(X_{d,c_{\text{best}},i} - \left|X_{d,c,i}\right|\right) \\ &\quad - \text{rand}_{2,c,i}\left(X_{d,c_{\text{worst}},i} - \left|X_{d,c,i}\right|\right). \end{aligned} \tag{16}$$

Although the execution cycles and working mechanisms of Jaya and Rao-1 algorithms are similar, they also have different abilities to solve the same optimization problem. For the same solution vector of a given optimization problem, both techniques seek the optimal solution in distinct patterns by searching different regions of the solution space. It is because of the variation in their solution updating expressions and the performance dependence of these algorithms on arbitrarily selected random numbers (r_1, r_2). This phenomenon can better be understood from Tables 1 and 2, elaborating the working mechanisms and searching capabilities of Jaya and Rao-1 algorithms, respectively.

To demonstrate the operations of Jaya's and Rao-1's algorithms and the difference in their working mechanism, an unconstrained sphere function with the mathematical formulation of $F(x) = \sum_{i=1}^{\dim} x_i^2$ has been employed. It is a minimization function with a known solution of zero for all x_i equal to zero. Let's assume two decision variables x_1 and x_2, a population size of five solutions, and the termination criteria of two iterations. Since the sphere is a minimization function, the lowest value will be the *best* solution, and in contrast, its highest value will be considered the *worst* solution. Table 1 shows that, for the Rao-1 algorithm, the best value of $F(x)$ decreased from 113 to 28.14 in two iterations, whereas, for the initially generated same solution

Initialize the parameters of algorithm and optimization problem
Initialize the population
for $i = 1$: *maximum iterations*
  Compute the current values of *cost function*, $fobj(X_{d,c,i})$
  Obtain the *best* ($X_{d,c_{best},i}$) and *worst* ($X_{d,c_{worst},i}$) solutions
  for $c = 1$: *population size*
    for $s = 1$: *number of random scaling pairs*
      Initialize the random numbers ($rand$, $rand_1$, $rand_2$)
      for $d = 1$: *dimension*
        $X1_{d,c,i}^{updated} = X_{d,c,i} + rand(X_{d,c_{best},i} - X_{d,c_{worst},i})$
        $X2_{d,c,i}^{updated} = X_{d,c,i} + rand_{1,c,i}(X_{d,c_{best},i} - |X_{d,c,i}|) - rand_{2,c,i}(X_{d,c_{worst},i} - |X_{d,c,i}|)$
        if $X1_{d,c,i}^{updated} / X2_{d,c,i}^{updated} < X_{lb}$ **then** $X1_{d,c,i}^{updated} / X2_{d,c,i}^{updated} = X_{lb}$
        else if $X1_{d,c,i}^{updated} / X2_{d,c,i}^{updated} > X_{ub}$ **then** $X1_{d,c,i}^{updated} / X2_{d,c,i}^{updated} = X_{ub}$
        end
      end
      Compute the current values of *cost function*, $fobj(X1_{d,c,i}^{updated})$ && $fobj(X2_{d,c,i}^{updated})$
      if $fobj(X1_{d,c,i}^{updated}) < fobj(X2_{d,c,i}^{updated})$
        if $fobj(X1_{d,c,i}^{updated}) < fobj(X_{d,c,i})$ **then** $X_{d,c,i} = X1_{d,c,i}^{updated}$
        else $X_{d,c,i} = X_{d,c,i}$
        end
      else if $fobj(X2_{d,c,i}^{updated}) < fobj(X_{d,c,i})$ **then** $X_{d,c,i} = X2_{d,c,i}^{updated}$
        else $X_{d,c,i} = X_{d,c,i}$
      end
    end
  end
end

Figure 6: Pseudocode of BWO-2.

set, the Jaya algorithm succeeds in reaching a farther lowest value of 24.74 as shown in Table 2. This clearly shows the difference in the searching capabilities of Jaya and Rao-1 algorithms.

It is also worth noting that both algorithms have flaws in that they do not fully utilize population data. Both techniques' learning approach uses the current best and worst solutions to guide the population's search direction. As a result, once the current best individual has been stuck in the local optimum, additional individuals will be drawn to approach this local optimum gradually, and population diversity will be lost. Therefore, before deploying Jaya or Rao-1 algorithms to solve the optimization problem of simultaneous DG and SC allocation in RDNs, it is imperative to propose a mechanism for improving their performance and intelligently utilize the searching capabilities of both techniques.

Thus, combining these two techniques will enable them to use their combined properties and assist each other in overcoming their weaknesses. It increases the likelihood of finding the best solution for a given set of common parameters.

3.1. Best-Worst Optimizer-1 (BWO-1). To effectively utilize the best and worst solutions to enhance search agents' exploration and exploitation capabilities, the proposed BWO-1 uses the solution updating equations of both Jaya and Rao-1 algorithms. For BWO-1, the parallel taxonomy has been adopted for the Jaya and Rao-1 combination instead of the sequential approach (i.e., one-after-another). As a well-known fact that every technique has certain limitations and no algorithm is ideal for the simultaneous DG-SC allocation problem, the unoptimized selection of size or location using a particular algorithm will result in undesirable outcomes. In contrast, the proposed parallel taxonomy provides an equal opportunity for both algorithms to search for optimal sizes and locations individually. The BWO-1 runs Rao-1 and Jaya algorithms in parallel for a given solution set and selects the best one from the obtained two solution sets. By doing so, instead of a single updated solution, the BWO-1 attains two new solutions in a single iteration, $X1_{d,c,i}^{\text{updated}}$ from Rao-1 and $X2_{d,c,i}^{\text{updated}}$ from Jaya. From the generated two updated solutions, the best solution will survive. In the next stage, the BWO-1 compares the resultant best-

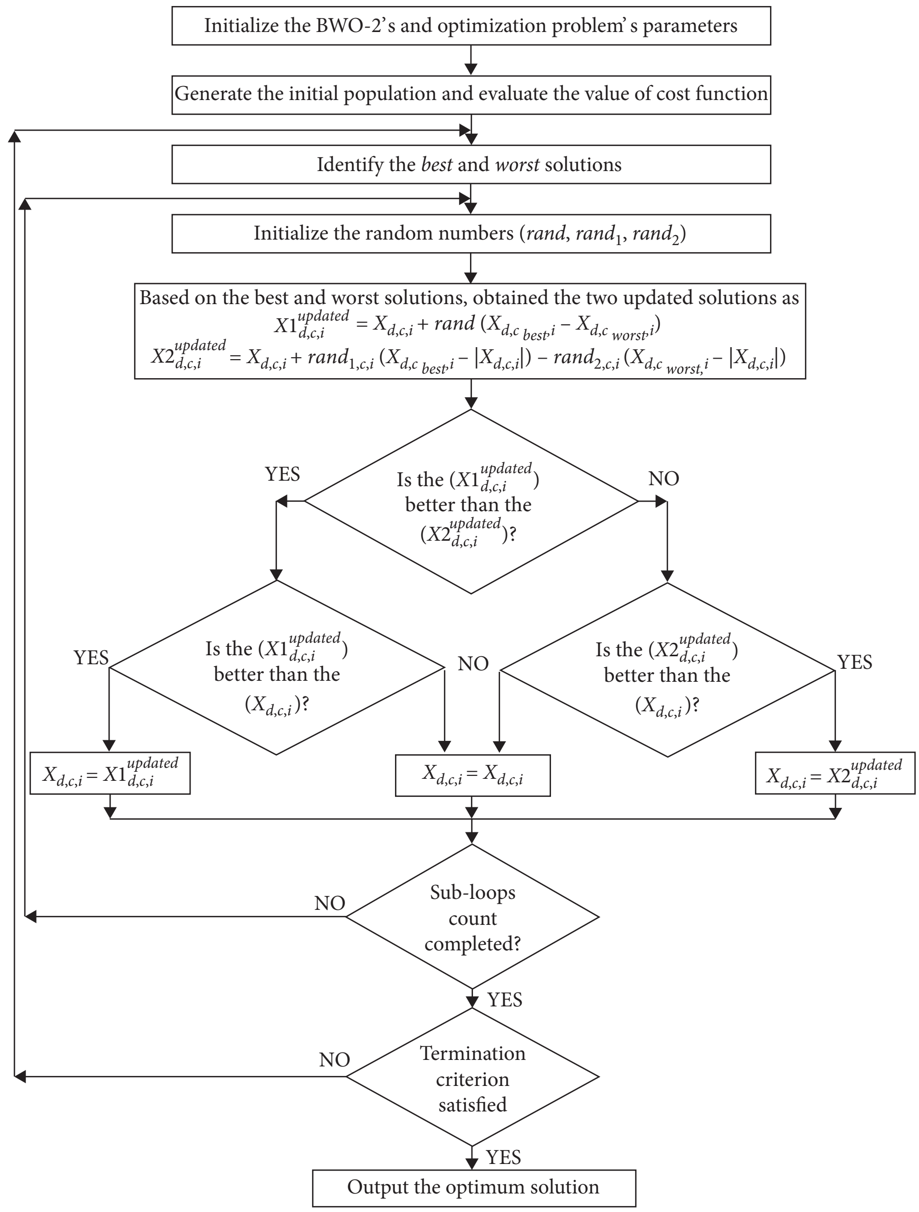


Figure 7: Flowchart of BWO-2.

updated solution with the previous solution and proceeds to the next iteration with a quality solution survived among them. The BWO-1's characteristic of obtaining dual sets of updated solutions enhances the probability of avoiding premature convergence. Combining these two techniques in a parallel hierarchy allows jointly use their potentials and aid each other in overcoming their weaknesses. Thus, it increases the likelihood of finding the best solution for a given set of common parameters. The pseudocode and flowchart of the BWO-1 are presented in Figures 4 and 5, respectively.

3.2. Best-Worst Optimizer-2 (BWO-2). As part of the transforming equation, the Rao-1 and Jaya algorithms exploit both best and worst solutions (X_{best}, X_{worst}). To ensure a better exploration of the search space, the terms "rand $(X_{d,c_{\text{best}},i} - X_{d,c_{\text{worst}},i})$" for Rao-1 and "$\text{rand}_{1,c,i}\,(X_{d,c_{\text{best}},i} - |X_{d,c,i}|) - \text{rand}_{2,c,i}\,(X_{d,c_{\text{worst}},i} - |X_{d,c,i}|)$" for Jaya algorithm have to be large enough. Likewise, these terms must be small to allow steady exploitation. The search process appears to be trapped in local optima when the difference between the mentioned terms is minimal, preventing further exploration. The search strategy roams throughout the search space at first, during the exploration phase, to maximize the chances of locating the optimal region. The search method must settle down and exploit the current best solution during the exploitation phase. Ideally, the search should be able to switch to another place of the solution space when there is no progress, thus re-explore the search space to find a better solution. Considering this fact, it seems that the Rao-1 and Jaya algorithms have poor control over the exploration and exploitation as they do not offer any mechanism to allow the local optima to jump out.

Table 3: Working mechanism of BWO-1.

1st iteration								
Randomly generated initial solutions			**Solution updated by JA** $\begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} = \begin{bmatrix} 0.58 & 0.23 \\ 0.92 & 0.51 \end{bmatrix}$		**Solution updated by Rao-1** $\begin{bmatrix} r_{11} \\ r_{21} \end{bmatrix} = \begin{bmatrix} 0.84 \\ 0.68 \end{bmatrix}$		**Optimal values**	
(x_1, x_2)	$fobj(z_j)$	**Status**	(x_1', x_2')	$fobj(z_j^{new})_{JA}$	(x_1', x_2')	$fobj(z_j^{new})_{Rao1}$	$fobj(z_j)$	**Status**
(-5, 18)	349		(-27.49, 20.12)	1160.51	(-70.52, 26.84)	5693.46	349	
(14, 63)	4165		(-11.64, 46.67)	2313.58	(-51.52, 71.84)	7815.30	2313.58	*worst*
(70, -6)	4936	*worst*	(24.76, 1.04)	614.14	(4.48, 2.84)	28.14	28.14	*best*
(-8, 7)	113	*best*	(-31.54, 13.63)	1180.55	(-73.52, 15.84)	5656.10	113	
(-12, -18)	468		(-36.94, -15.88)	1616.74	(-77.52, -9.16)	6093.26	468	
2nd iteration								
Solutions obtained from 1st iteration			**Solution updated by JA** $\begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} = \begin{bmatrix} 0.27 & 0.81 \\ 0.38 & 0.49 \end{bmatrix}$		**Solution updated by Rao-1** $\begin{bmatrix} r_{11} \\ r_{21} \end{bmatrix} = \begin{bmatrix} 0.31 \\ 0.22 \end{bmatrix}$		**Optimal values**	
(x_1, x_2)	$fobj(z_j)$	**Status**	(x_1', x_2')	$fobj(z_j^{new})_{JA}$	(x_1', x_2')	$fobj(z_j^{new})_{Rao1}$	$fobj(z_j)$	**Status**
(-5, 18)	349		(8.34, -1.81)	72.80	(-0.003, 8.36)	69.85	69.85	
(-11.64, 46.67)	2313.58	*worst*	(5.28, 30.01)	928.79	(-6.64, 37.03)	1415.16	928.79	*worst*
(4.48, 2.84)	28.14	*best*	(17.54, -18.64)	654.88	(9.48, -6.80)	136.09	28.14	
(-8, 7)	113		(6.96, -14.02)	244.95	(-3, -2.64)	16	16	*best*
(-12, -18)	468		(5.12, -37.81)	1455.72	(-7, -27.64)	813.15	468	

Table 4: Working mechanism of BWO-2.

1st iteration								
Randomly generated initial solutions			**Solution updated by JA using 1st set of random numbers** $\begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} = \begin{bmatrix} 0.58 & 0.23 \\ 0.92 & 0.51 \end{bmatrix}$		**Solution updated by Rao-1 using 1st set of random numbers** $\begin{bmatrix} r_{11} \\ r_{21} \end{bmatrix} = \begin{bmatrix} 0.84 \\ 0.68 \end{bmatrix}$		**Optimal values**	
(x_1, x_2)	$fobj(z_j)$	**Status**	(x_1', x_2')	$fobj(z_j^{new})_{JA}$	(x_1', x_2')	$fobj(z_j^{new})_{Rao1}$		
(-5, 18)	349		(-27.49, 20.12)	1160.51	(-70.52, 26.84)	5693.46		
(14, 63)	4165		(-11.64, 46.67)	2313.58	(-51.52, 71.84)	7815.30		
(70, -6)	4936	*worst*	(24.76, 1.04)	614.14	(4.48, 2.84)	28.14		
(-8, 7)	113	*best*	(-31.54, 13.63)	1180.55	(-73.52, 15.84)	5656.10		
(-12, -18)	468		(-36.94, -15.88)	1616.74	(-77.52, -9.16)	6093.26		
			Solution updated by JA using 2nd set of random numbers $\begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} = \begin{bmatrix} 0.85 & 0.32 \\ 0.29 & 0.47 \end{bmatrix}$		**Solution updated by Rao-1 using 2nd set of random numbers** $\begin{bmatrix} r_{11} \\ r_{21} \end{bmatrix} = \begin{bmatrix} 0.89 \\ 0.58 \end{bmatrix}$			
			(x_1'', x_2'')	$fobj(z_j^{new})_{JA}$	(x_1'', x_2'')	$fobj(z_j^{new})_{Rao1}$	$fobj(z_j)$	**Status**
			(-36.85, 26.09)	2038.61	(-74.42, 25.54)	6190.63	349	
			(-22.62, 79.19)	6782.72	(-55.42, 70.54)	8047.27	2313.58	*worst*
			(3.7, -0.07)	13.69	(0.58, 1.54)	2.71	2.71	*best*
			(-41.44, 13.11)	1889.15	(-77.42, 14.54)	6205.27	113	
			(-47.56, -9.91)	2360.16	(-81.42, -10.46)	6738.63	468	
2nd iteration								
Solutions obtained from 1st iteration			**Solution updated by JA using 1st set of random numbers** $\begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} = \begin{bmatrix} 0.27 & 0.81 \\ 0.38 & 0.49 \end{bmatrix}$		**Solution updated by Rao-1 using 1st set of random numbers** $\begin{bmatrix} r_{11} \\ r_{21} \end{bmatrix} = \begin{bmatrix} 0.31 \\ 0.22 \end{bmatrix}$		**Optimal values**	
(x_1, x_2)	$fobj(z_j)$	**Status**	(x_1', x_2')	$fobj(z_j^{new})_{JA}$	(x_1', x_2')	$fobj(z_j^{new})_{Rao1}$		
(-5, 18)	349		(7.29, -2.30)	58.38	(-1.21, 8.07)	66.62		
(-11.64, 46.67)	2313.58	*worst*	(4.23, 29.52)	889.36	(-7.85, 36.74)	1411.58		
(0.58, 1.54)	2.71	*best*	(10.48, -20.57)	533.07	(4.37, -8.39)	89.45		
(-8, 7)	113		(5.91, -14.51)	245.50	(-4.21, -2.93)	26.32		
(-12, -18)	468		(4.07, -38.30)	1483.65	(-8.21, -27.93)	847.44		
			Solution updated by JA using 2nd set of random numbers $\begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} = \begin{bmatrix} 0.72 & 0.44 \\ 0.24 & 0.51 \end{bmatrix}$		**Solution updated by Rao-1 using 2nd set of random numbers** $\begin{bmatrix} r_{11} \\ r_{21} \end{bmatrix} = \begin{bmatrix} 0.39 \\ 0.17 \end{bmatrix}$			
			(x_1'', x_2'')	$fobj(z_j^{new})_{JA}$	(x_1'', x_2'')	$fobj(z_j^{new})_{Rao1}$	$fobj(z_j)$	**Status**
			(-0.86, -0.57)	1.07	(-0.23, 10.33)	106.72	1.07	*best*
			(-9.36, 35.84)	1372.03	(-6.87, 39)	1568.09	889.36	*worst*
			(5.96, -21.48)	496.71	(5.35, -6.13)	66.18	2.71	
			(-4.70, -14.54)	233.57	(-3.23, -0.67)	10.91	10.91	
			(-9.82, -36.57)	1433.97	(-7.23, -25.67)	711.39	468	

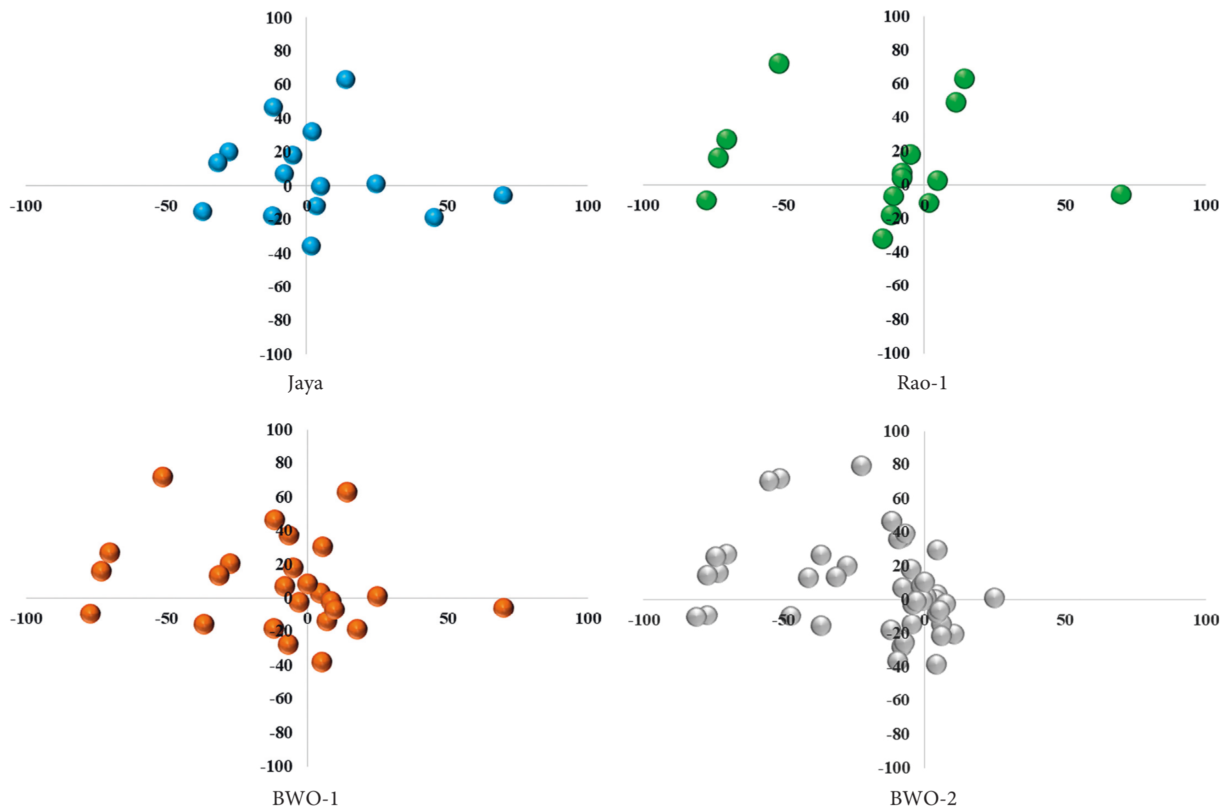


Figure 8: Search the history of agents for the Jaya, Rao-1, BWO-1, and BWO-2 algorithms.

From the solution updating expressions of Rao-1 and Jaya, it is clear that their exploration and exploitation capabilities are proportional to the values of randomly generated numbers (rand, rand_1, and rand_2). While the random numbers help update the diversity, their inappropriate combination may unnecessarily make the algorithms wander back and forth between exploration and exploitation. Therefore, for the proposed BWO-2, a subloop has been introduced to initialize the different values of random numbers for the same solution set. Thus, the BWO-2 allows the entire search cycle to start repeatedly by resetting different values of random numbers. This multistart approach potentially enhances the ability of BWO-2 to get a better solution within the search space at a new location. Resetting the random numbers can generate the new values of "$\text{rand}\,(X_{d,c_{\text{best}},i} - X_{d,c_{\text{worst}},i})$" and "$\text{rand}_{1,c,i}\,(X_{d,c_{\text{best}},i} - |X_{d,c,i}|) - \text{rand}_{2,c,i}\,(X_{d,c_{\text{worst}},i} - |X_{d,c,i}|)$" This allows BWO-2 to switch out of the current location and re-explore the search space with a new position. Unlike the BWO-1, which produces only two sets of updated solutions in a single iteration, the BWO-2's multistart approach enables it to produce "$2 \times$ pair of random scaling factors" sets of updated solutions in a single iteration, which potentially enhances the searching capabilities of BWO-2. This multistart approach is the unique property of BWO-2, making it superior not only against the conventional Jaya and Rao-1 algorithms but also against the BWO-1. The pseudocode and flowchart of the BWO-2 are presented in Figures 6 and 7, respectively.

Further, the working mechanisms of proposed BWO-1 and BWO-2 are illustrated in Tables 3 and 4, respectively. Table 3 demonstrates that for an initially generated random solution set, the BWO-1 generates two sets of updated solutions: first using the Jaya algorithm's solution updating equation and second using the Rao-1 algorithm's equation. This mechanism allows the BWO-1 to concurrently search for the optimal solution in two different regions of the search space. As a result, in comparison to the Jaya and Rao-1, the BWO-1 achieves a much improved optimal solution for the initially generated same solution set.

On the other hand, for the proposed BWO-2, a subloop of two random number sets has been introduced, allowing it to produce four sets of updated solutions (two for the Jaya algorithm and two for the Rao-1 algorithm) in each iteration. The proposed mechanism enables the BWO-2 to explore four different regions of the solution space and select the best solutions from these regions. Hence, this multiregion exploration strategy enhances the BWO-2's probability of being trapped in local optima. Besides, it also enables it to attain a better optimal solution in the same number of iterations. The phenomenon is also proved in Table 4, showing that in comparison to BWO-1's optimal answer of 16, Table 3, the BWO-2 attains an optimum outcome of 1.07, which is very close to the ideal 0 output of the sphere minimization function.

The search history of agents for the Jaya, Rao-1, BWO-1, and BWO-2 algorithms is presented in Figure 8, which displays the position history of all agents during the

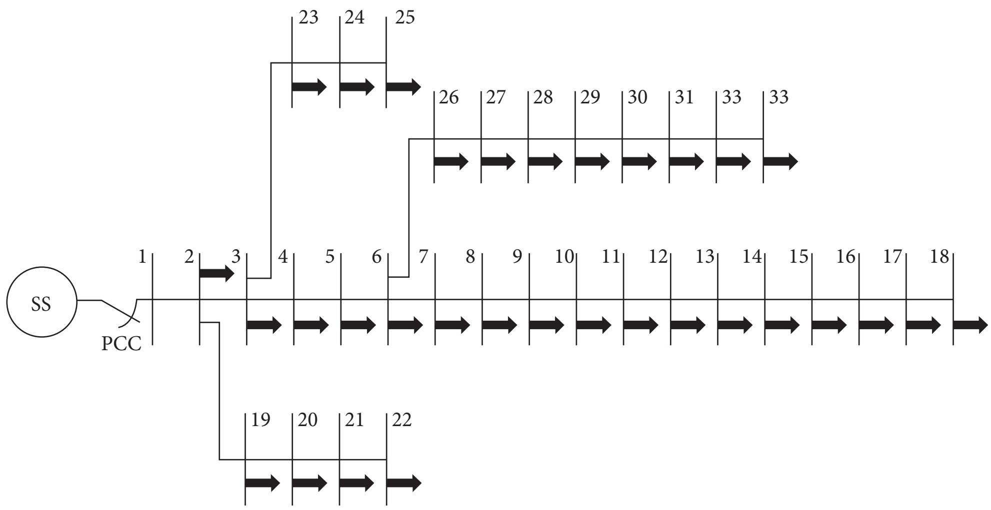


FIGURE 9: Single-line diagram of the standard IEEE 33-bus RDN.

TABLE 5: Performance comparison of the Rao-1, Jaya, BWO-1, and BWO-2 for the 33-bus test system.

Cases	Parameters	Optimization techniques			
		Rao-1	Jaya	BWO-1	BWO-2
Base case	P_{loss} (kW)	211	211	211	211
	V_{min} (p.u)	0.9038	0.9038	0.9038	0.9038
Case 1 (1 DG + 1 SC)	DG size in MW (node)	2.5 (6)	2.5 (6)	2.532 (6)	2.532 (6)
	SC size in MVAr (node)	1.256 (30)	1.255 (30)	1.256 (30)	1.256 (30)
	P_{loss} (kW)	58.464	58.464	58.451	**58.451**
	V_{min} (p.u)	0.9532	0.9532	0.9536	**0.9536**
	P_{loss} reduction (%)	72.29	72.29	72.30	**72.30**
Case 2 (2 DGs + 2 SCs)	DGs size in MW (nodes)	0.893 (13)	0.811 (13)	0.86 (13)	0.846 (13)
		1.118 (30)	1.16 (30)	1.147 (30)	1.138 (30)
	SCs size in MVAr (nodes)	0.448 (14)	0.374 (14)	0.446 (12)	0.446 (12)
		1.024 (30)	1.022 (30)	1.033 (30)	1.044 (30)
	P_{loss} (kW)	28.874	28.713	28.512	**28.493**
	V_{min} (p.u)	0.9804	0.9802	0.9804	**0.9804**
	P_{loss} reduction (%)	86.32	86.39	86.48	**86.50**
Case 3 (3 DGs + 3 SCs)	DGs size in MW (nodes)	0.7 (14)	0.992 (11)	0.856 (13)	0.766 (14)
		0.958 (24)	0.987 (24)	1.103 (24)	1.075 (24)
		0.907 (32)	0.836 (32)	0.881 (31)	1.042 (30)
	SCs size in MVAr (nodes)	0.475 (13)	0.914 (3)	0.299 (15)	0.421 (12)
		0.448 (30)	0.317 (16)	0.310 (25)	0.409 (25)
		0.603 (31)	0.882 (30)	1.001 (30)	1.004 (30)
	P_{loss} (kW)	18.207	15.805	13.461	**11.95**
	V_{min} (p.u)	0.9890	0.9897	0.9898	0.9923
	P_{loss} reduction (%)	91.37	92.51	93.62	**94.34**

optimization process. By saving and illustrating the history of agents' positions, we can observe the sampled regions of search space by an algorithm and the probable search patterns in the swarm. It has been demonstrated that all proposed algorithms follow different searching patterns for the initially generated solution set. Moreover, the BWO-1 and BWO-2 have more search points in solution space due to their searching mechanism that allows them to produce dual and multiple sets of updated solutions, respectively.

4. Results and Discussion

To illustrate the efficacy of BWO-1 and BWO-2, their results have been compared to the traditional Rao-1 and Jaya algorithms. Later, performance comparison with

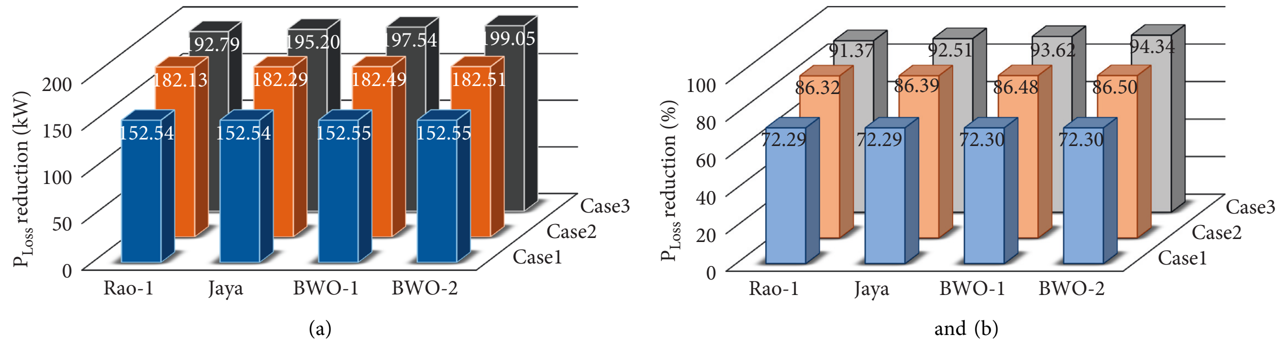


FIGURE 10: The power loss reductions obtained in 33-bus RDN for the studied three cases: (a) in kW and (b) in percentage.

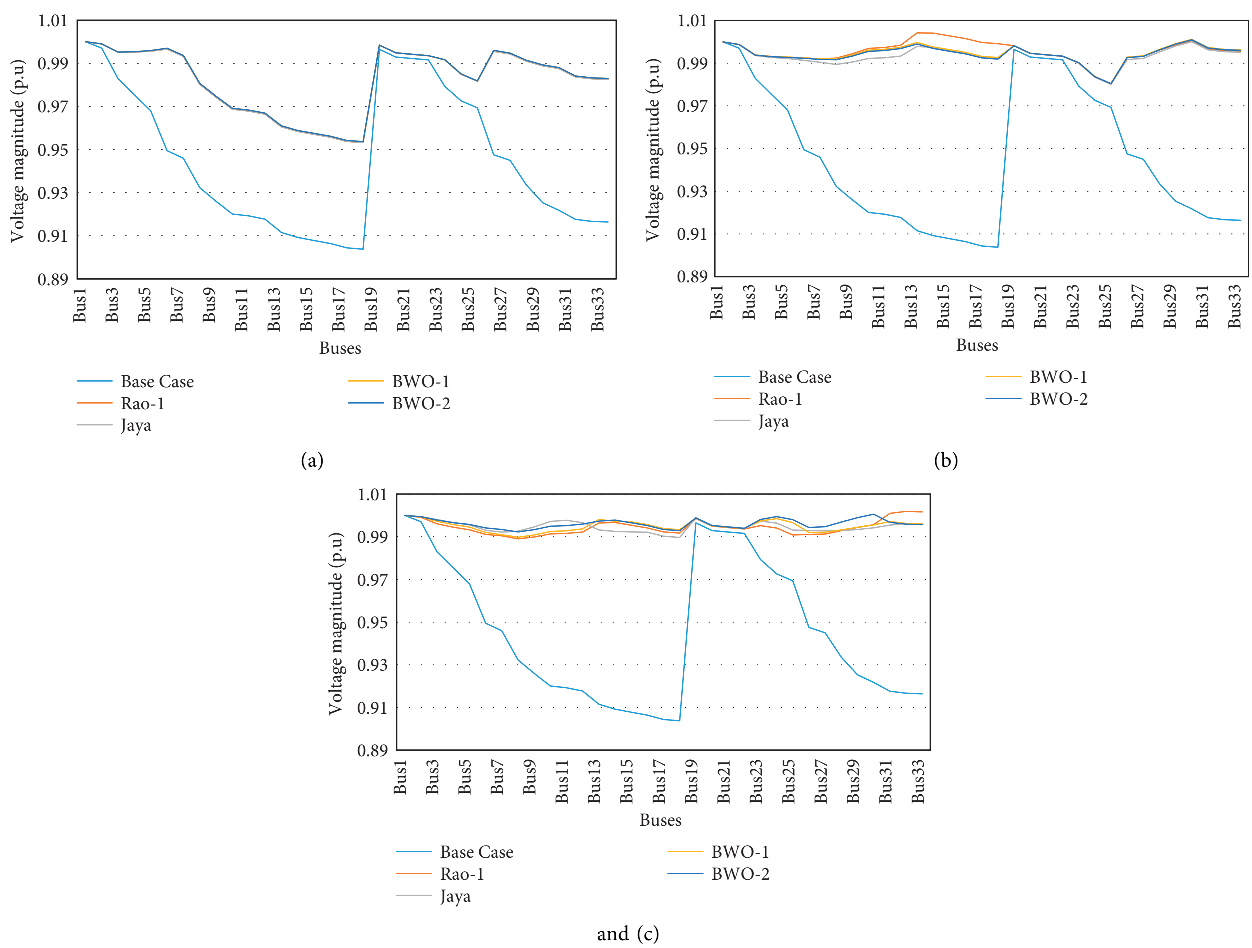


FIGURE 11: Comparison of bus voltages for the IEEE 33-bus test system with the simultaneous allocation of (a) 1DG and 1SC, (b) 2DGs and 2SCs, and (c) 3DGs and 3SCs.

various optimization techniques reported in the literature has been provided. The input parameters set for the Rao-1, Jaya, BWO-1, and BWO-2 were *nPop*: 50 and *MaxItr*: 200, whereas for BWO-2, the number of subloops for the random scaling factors is set to two, which means that for the same solution set the BWO-2 obtains two updated solutions twice the time (i.e., total four updated solutions). IEEE 33-bus and 69-bus test systems were used to evaluate the effectiveness of the proposed techniques for simultaneous DG and SC allocation. Due to the moderate structures, the opted test systems are commonly used in the literature; for this reason, they were selected mainly for this study. The computational experiments for the proposed optimization problem were carried out in the MATLAB environment R2016a version installed in the Intel i3, 1.90 GHz, 4 GB RAM.

DGs considered in this study are in the form that has deterministic output operating at the unity power factor, such as diesel generators, small gas turbines, converter-based wind energy sources or photovoltaic systems equipped with

Table 6: Performance comparison of the BWO-2 against the established optimization techniques for 33-bus test system.

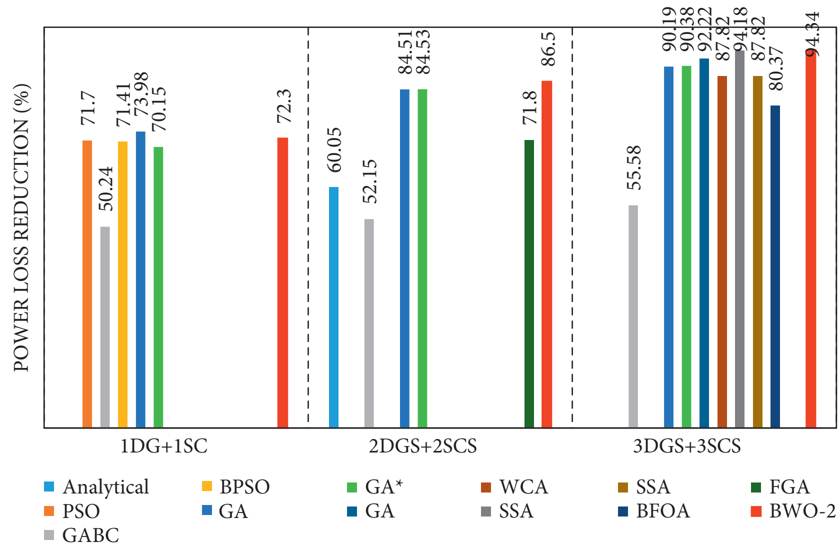
Cases	Parameters	Optimization techniques						
		Analytical [72]	PSO [14]	GABC [36]	BPSO [17]	BSA [28]	GA [8]	GA* [8]
Base case	P_{loss} (kW)	211	211	210.97	211		202.69	211*
	V_{min} (p.u)	0.904	0.904	0.9038	0.904		0.9130	0.9038*
Case 1 (1 DG + 1 SC)	DG size in MW (node)		2.511 (6)	1.539 (30)	2.5 (6)	2.5 (6)	1.90574 (7)	1.90574 (7)
	SC size in MVAr (node)		1.457 (30)	0.45 (18)	1.5 (30)	1.2436 (6)	1.2484 (30)	1.2484 (30)
	P_{loss} (kW)		59.7	104.99	60.33*	71.55*	52.73	62.99*
	V_{min} (p.u)		0.955	0.9527	0.955*		0.9616	0.9471*
	P_{loss} reduction (%)		71.7	50.24	71.41*		73.98	70.15*
Case 2 (2 DGs + 2 SCs)	DGs size in MW (nodes)	0.559 (17)		1.015 (29)			1.0079 (12)	1.0079 (12)
		0.447 (18)		0.626 (30)			0.93083 (30)	0.93083 (30)
	SCs size in MVAr (nodes)	0.5 (32)		0.3 (17)			0.57818 (26)	0.57818 (26)
		0.4 (33)		0.15 (18)			0.94795 (30)	0.94795 (30)
	P_{loss} (kW)	84.28		100.95			31.39	32.65*
	V_{min} (p.u)	0.961		0.9542			0.9802	0.9783*
	P_{loss} reduction (%)	60.05		52.15			84.51	84.53*
Case 3 (3 DGs + 3 SCs)	DGs size in MW (nodes)			1.098 (28)			1.7299 (6)	1.7299(6)
				0.132 (29)			0.64542 (14)	0.64542 (14)
				0.609 (30)			0.90217 (24)	0.90217 (24)
	SCs size in MVAr (nodes)			0.3 (16)			0.51604 (10)	0.51604 (10)
				0.15 (17)			0.46827 (24)	0.46827 (24)
				0.15 (18)			0.81145 (30)	0.81145 (30)
	P_{loss} (kW)			93.72			19.88	20.30*
	V_{min} (p.u)			0.9629			0.9803	0.9803*
	P_{loss} reduction (%)			55.58			90.19	90.38*

Cases	Parameters	Optimization techniques						
		GA [10]	WCA [19]	SSA [20]	SSA [21]	BFOA [29]	FGA [7]	BWO-2
Base case	P_{loss} (kW)	210.98	202.67	202.6	202.67	211	211	211
	V_{min} (p.u)	0.9036				0.904	0.904	0.9038
Case 1 (1 DG + 1 SC)	DG size in MW (node)							2.532 (6)
	SC size in MVAr (node)							1.256 (30)
	P_{loss} (kW)							**58.451**
	V_{min} (p.u)							**0.9536**
	P_{loss} reduction (%)							**72.30**
Case 2 (2 DGs + 2 SCs)	DGs size in MW (nodes)						0.6 (7)	0.846 (13)
							1.1 (32)	1.138 (30)
	SCs size in MVAr (nodes)						0.65 (16)	0.446 (12)
							0.8 (33)	1.044 (30)
	P_{loss} (kW)						59.5	**28.493**
	V_{min} (p.u)						0.96	**0.9804**
	P_{loss} reduction (%)						71.8	**86.50**

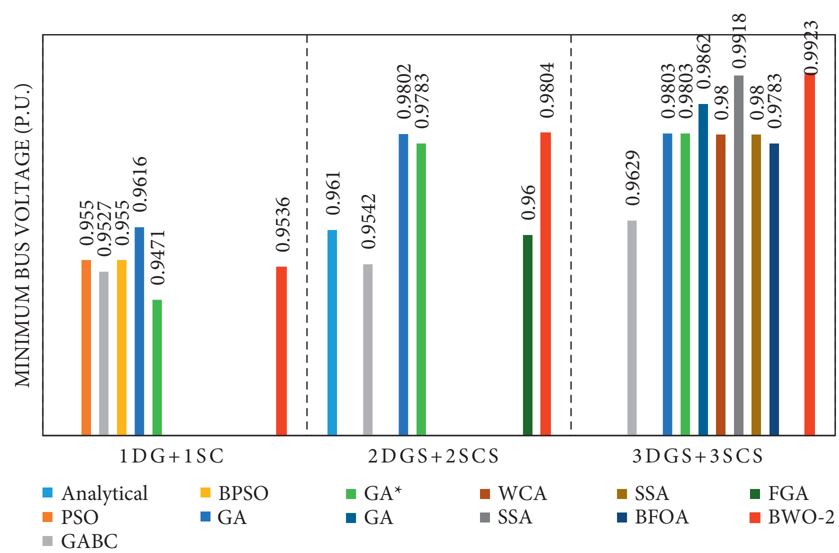
Table 6: Continued.

Cases	Parameters	Optimization techniques						
		Analytical [72]	PSO [14]	GABC [36]	BPSO [17]	BSA [28]	GA [8]	GA* [8]
Case 3 (3 DGs + 3 SCs)	DGs size in MW (nodes)	0.4937 (8)	0.563 (11)	0.7466 (13)	0.563 (11)	0.542 (17)		0.766 (14)
		0.4953 (14)	0.973 (25)	1.079 (23)	0.973 (25)	0.160 (18)		1.075 (24)
		0.4953 (25)	1.04 (29)	1.049 (29)	1.04 (29)	0.895 (33)		1.042 (30)
	SCs size in MVAr (nodes)	0.45 (6)	0.535 (14)	0.3 (13)	0.535 (14)	0.163 (18)		0.421 (12)
		0.45 (12)	0.465 (23)	0.6 (23)	0.465 (23)	0.541 (30)		0.409 (25)
		0.75 (33)	0.565 (30)	1.05 (29)	0.565 (30)	0.338 (33)		1.004 (30)
	P_{loss} (kW)	16.41	24.688	11.8	24.688	41.41		**11.95**
	V_{min} (p.u)	0.9862	0.980	0.9918	0.980	0.9783		0.9923
	P_{loss} reduction (%)	92.22	87.82*	94.18	87.82	80.37		**94.34**

*Values are recomputed by using the proposed values of DG/SC sizes and locations.



(a)



and (b)

Figure 12: Performance comparison of BWO-2 against the established optimization algorithms for (a) power loss reduction and (b) minimum bus voltage.

energy storage devices, or any other hybrid combination of renewable and conventional energy sources. The reactive power demand for the load was met through the grid and SCs. Furthermore, several scenarios of simultaneous DG and SC allocation have been investigated in this study, which are given as follows:

Case 1: Simultaneous allocation of a single unit for each DG and SC

Case 2: Simultaneous allocation of two units for each DG and SC

Case 3: Simultaneous allocation of three units for each DG and SC

4.1. IEEE 33-Bus Test System. The IEEE 33-bus test system is a balanced three-phase RDN that consists of 33-buses and 32-branches and operates at the voltage of 12.66 kV. The system's active and reactive power demands are 3.715 MW and 2.30 MVAR, respectively. Further details of the 33-bus system, such as the line data and the load connected per bus, are provided in [71]. The single-line diagram of the IEEE 33-bus system is shown in Figure 9.

An analysis of the obtained best optimal allocation for the installed DGs and SCs and the improvement in network performance as attained by the standard Rao-1, Jaya, BWO-1, and BWO-2 algorithms after 50 independent runs (each algorithm run 50 times starting from the randomly

Table 7: Performance comparison of the BWO-2 against the improved and hybrid optimization techniques for 33-bus test system.

Cases	Parameters	Optimization techniques IPSO [12]	IGA [12]	ICSO [12]	ITLBO [44]	HSA-PABC [41]
Base case	P_{loss} (kW)	202.67	202.67	202.67	202.67	211
	V_{min} (p.u)	0.9038*	0.9131	0.9131	0.9131	
Case 1 (1 DG + 1 SC)	DG size in MW (node)					2.531 (6)
	SC size in MVAr (node)					1.25 (30)
	P_{loss} (kW)					58.45
	V_{min} (p.u)					0.9536
	P_{loss} reduction (%)					72.29
Case 2 (2 DGs + 2 SCs)	DGs size in MW (nodes)					
	SCs size in MVAr (nodes)					
	P_{loss} (kW)					
	V_{min} (p.u)					
	P_{loss} reduction (%)					
Case 3 (3 DGs + 3 SCs)	DGs size in MW (nodes)	0.748 (14)	0.748 (14)	0.745 (14)	0.747 (14)	
		1.003 (24)	1.079 (24)	1.045 (24)	1.074 (24)	
		1.057 (30)	1.043 (30)	1.052 (30)	1.054 (30)	
	SCs size in MVAr (nodes)	0.3 (14)	0.3 (15)	0.5 (10)	0.3 (15)	
		0.5 (24)	0.3 (25)	0.6 (24)	0.5 (24)	
		1.0 (30)	1.1 (30)	0.9 (30)	1.0 (30)	
	P_{loss} (kW)	12.682*	12.547*	12.33*	11.94	
	V_{min} (p.u)	0.9879*	0.9900*	0.9930*	0.9911	
	P_{loss} reduction (%)	93.74*	93.81*	93.92*	94.10	

Cases	Parameters	Optimization techniques IMDE [35]	EGA [8]	EGA* [8]	WIPSO-GSA [42]	BWO-2
Base case	P_{loss} (kW)	211	202.69	211*	211	211
	V_{min} (p.u)	0.904	0.9130	0.9038*		0.9038
Case 1 (1 DG + 1 SC)	DG size in MW (node)		2.4999 (6)	2.4999 (6)		2.532 (6)
	SC size in MVAr (node)		1.2532 (30)	1.2532 (30)		1.256 (30)
	P_{loss} (kW)		51.80	58.464*		58.451
	V_{min} (p.u)		0.9619	0.9532*		0.9536
	P_{loss} reduction (%)		74.44	72.29*		72.30
Case 2 (2 DGs + 2 SCs)	DGs size in MW (nodes)	1.08 (10)	0.83566 (13)	0.83566 (13)	0.96 (12)	0.846 (13)
		0.8964 (31)	1.1617 (30)	1.1617 (30)	1.06 (30)	1.138 (30)
	SCs size in MVAr (nodes)	0.2548 (16)	0.43857 (13)	0.43857 (13)	0.53 (11)	0.446 (12)
		0.9323 (30)	1.0474 (30)	1.0474 (30)	0.81 (30)	1.044 (30)
	P_{loss} (kW)	32.08	28.50	28.594*	30.15	28.493
	V_{min} (p.u)	0.979	0.9804	0.9804*	0.9802*	0.9804
	P_{loss} reduction (%)	84.79	85.94	86.45*	85.71	86.50
Case 3 (3 DGs + 3 SCs)	DGs size in MW (nodes)		0.76774 (14)	0.76774 (14)	0.85 (13)	0.766 (14)
			1.09496 (24)	1.09496 (24)	0.86 (25)	1.075 (24)
			0.96422 (30)	0.96422 (30)	0.87 (30)	1.042 (30)
	SCs size in MVAr (nodes)		0.33477 (14)	0.33477 (14)	0.48 (12)	0.421 (12)
			0.38875 (25)	0.38875 (25)	0.49 (29)	0.409 (25)
			1.18991 (30)	1.18991 (30)	0.51 (30)	1.004 (30)
	P_{loss} (kW)		12.70	12.828*	16.89	11.95
	V_{min} (p.u)		0.9924	0.9912*	0.9895*	0.9923
	P_{loss} reduction (%)		93.73	93.92*	91.99	94.34

*Values are recomputed by using the proposed values of DG/SC sizes and locations.

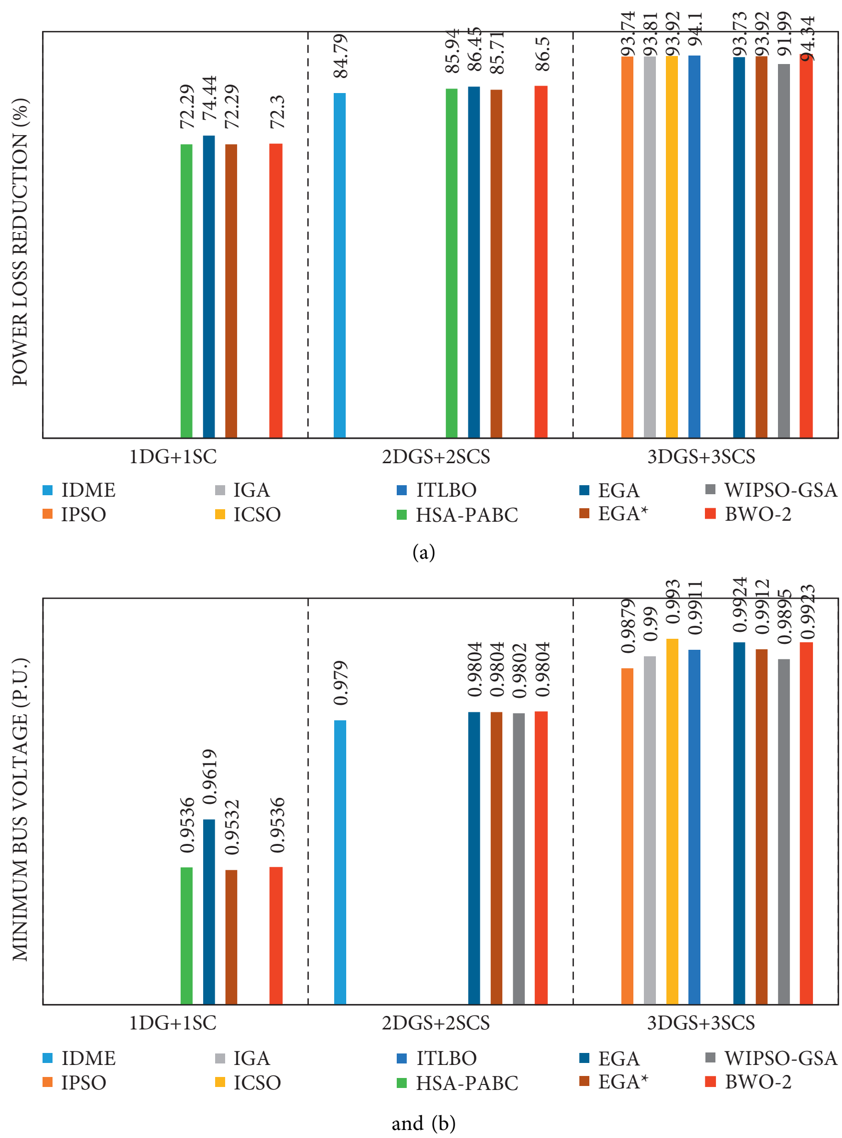


FIGURE 13: Performance comparison of BWO-2 against the improved variants of optimization algorithms for (a) power loss reduction and (b) minimum bus voltage.

generated populations) is presented in Table 5. The table compares the power loss, minimum bus voltages, and the percentage reduction in power loss obtained before and after integrating the DGs and SCs. The bold numbers in tables show the best solutions attained in 50 independent runs. The graphical illustration of the effectiveness of these methods in reducing power losses is provided in Figure 10. For the first case, all algorithms show a comparable performance when the single unit of each DG and SC was placed simultaneously in the network. For the simultaneous allocation of two units of each, the BWO-2 outperforms the Rao-1, Jaya, and BWO-1 in percentage power loss reduction by 0.18%, 0.11%, and 0.02%, respectively. However, the BWO-2 shows a significant lead over the competitive algorithms for the last case, when the complexity of the problem increased with the placement of more DG and SC units. In this case, the percentage loss reduction attained by the BWO-2 is greater than the Rao-1, Jaya, and BWO-1 algorithms by 2.97%, 1.83%, and 0.72%, respectively. This is because working mechanism of the BWO-2 enables it to jump out of the local optima even if the complexity of the optimization problem is higher, thus allowing it to explore and exploit the search space efficiently.

For the proposed cases, a comparison of the bus voltage profiles before and after optimally integrating the DGs-SCs using proposed optimization techniques is presented in Figure 11. It can be observed from the figure that the voltage across all the nodes is significantly improved in each case. The proposed methods improve the voltage profile by approximately the same margin against the base-case condition. Moreover, using these techniques for each case, the bus voltages are maintained within the permissible limits.

The performance comparison of the proposed BWO-2 algorithm against the numerous established optimization

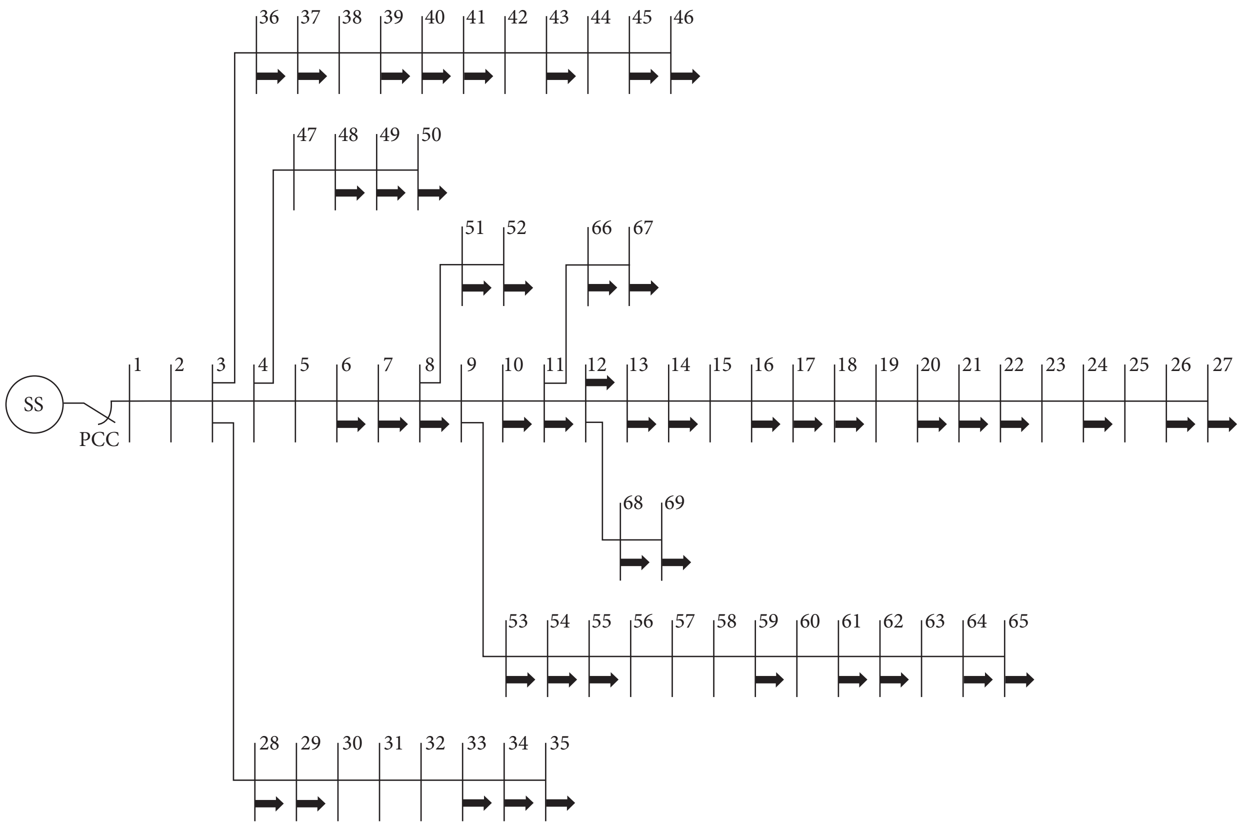


Figure 14: Single-line diagram of the standard IEEE 69-bus RDN.

Table 8: Performance comparison of the Rao-1, Jaya, BWO-1, and BWO-2 for the 69-bus test system.

Cases	Parameters	Optimization techniques			
		Rao-1	Jaya	BWO-1	BWO-2
Base case	P_{loss} (kW)	225	225	225	225
	V_{min} (p.u)	0.9092	0.9092	0.9092	0.9092
Case 1 (1 DG + 1 SC)	DG size in MW (node)	1.8285 (61)	1.8285 (61)	1.8285 (61)	1.8285 (61)
	SC size in MVAr (node)	1.3006 (61)	1.3006 (61)	1.3006 (61)	1.3006 (61)
	P_{loss} (kW)	23.171	23.171	23.171	23.171
	V_{min} (p.u)	0.9725	0.9725	0.9725	0.9725
	P_{loss} reduction (%)	89.70	89.70	89.70	89.70
Case 2 (2 DGs + 2 SCs)	DGs size in MW (nodes)	0.523 (17)	0.505 (17)	0.522 (17)	0.522 (17)
		1.734 (61)	1.732 (61)	1.726 (61)	1.734 (61)
	SCs size in MVAr (nodes)	1.226 (61)	0.355 (17)	0.353 (17)	0.353 (17)
		0.428 (69)	1.228 (61)	1.235 (61)	1.238 (61)
	P_{loss} (kW)	8.396	7.22	7.21	**7.20**
	V_{min} (p.u)	0.9941	0.9940	0.9942	**0.9943**
	P_{loss} reduction (%)	96.27	96.79	96.80	**96.80**
Case 3 (3 DGs + 3 SCs)	DGs size in MW (nodes)	0.465 (17)	0.392 (21)	0.393 (18)	0.495 (11)
		1.772 (61)	1.677 (61)	1.697 (61)	0.379 (18)
		0.244 (69)	0.340 (66)	0.317 (69)	1.674 (61)
	SCs size in MVAr (nodes)	0.0173 (56)	0.191 (18)	0.235 (20)	0.334 (12)
		1.282 (61)	1.225 (61)	1.223 (61)	0.207 (21)
		0.549 (66)	0.292 (69)	0.320 (67)	1.206 (61)
	P_{loss} (kW)	7.481	5.158	4.997	**4.300**
	V_{min} (p.u)	0.9943	0.9943	0.9943	**0.9943**
	P_{loss} reduction (%)	96.68	97.71	97.78	**98.09**

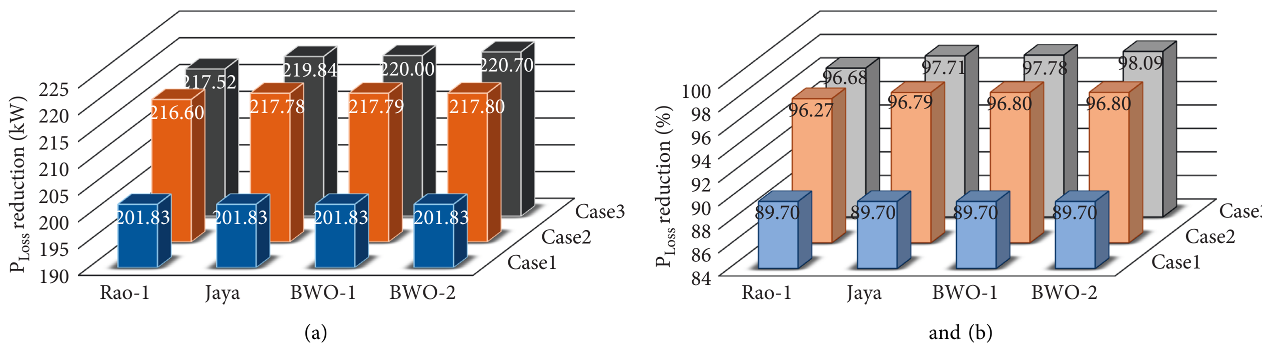


Figure 15: The power loss reductions obtained in the 69-bus distribution network for the studied three cases (a) in kW and (b) in percentage.

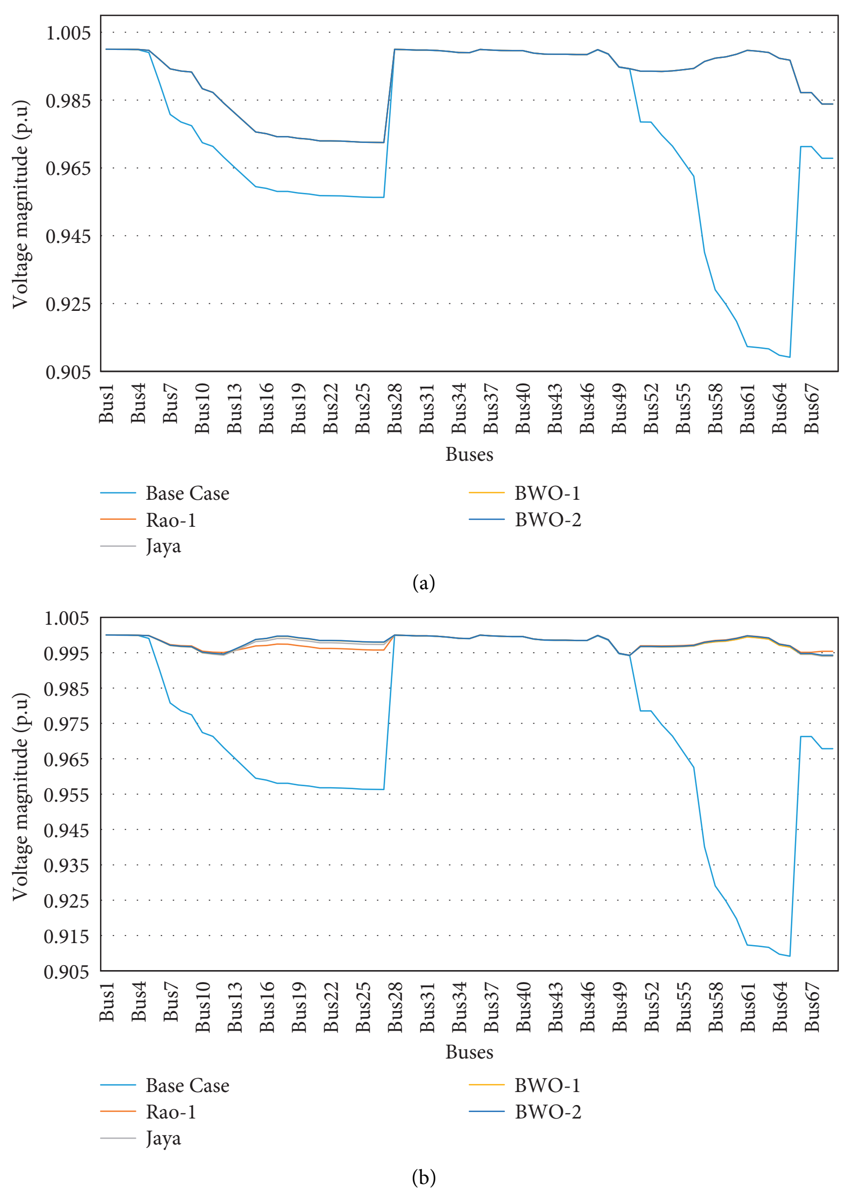
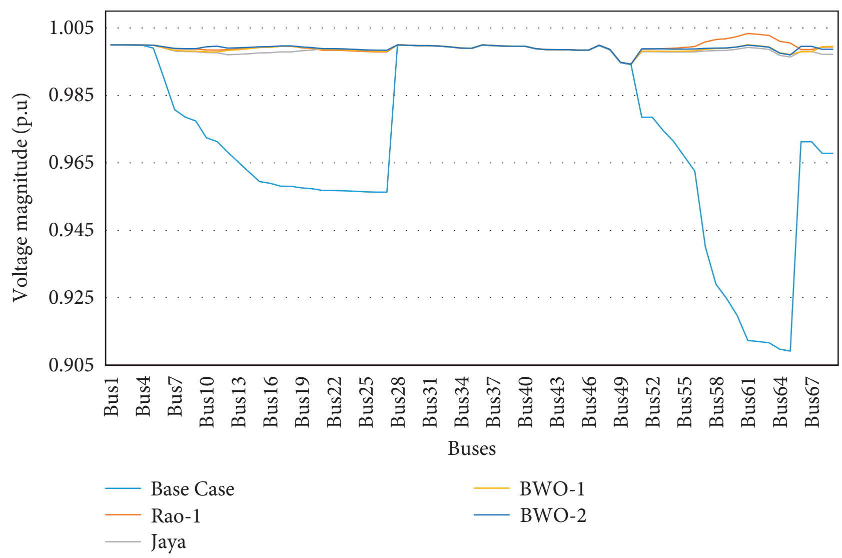


Figure 16: Continued.



and (c)

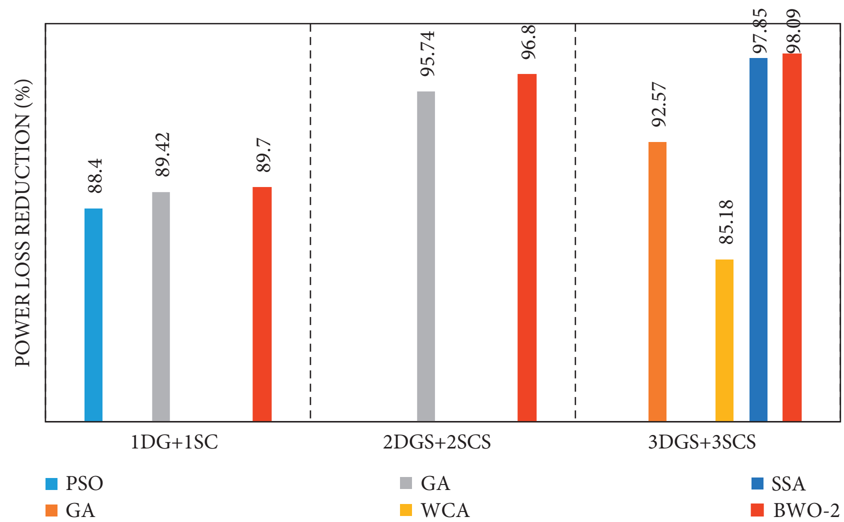
Figure 16: Comparison of bus voltages for the 69-bus test system with the simultaneous allocation of (a) 1DG and 1SC, (b) 2DGs and 2SCs, and (c) 3DGs and 3SCs.

Table 9: Performance comparison of the BWO-2 against the established optimization techniques for the 69-bus test system.

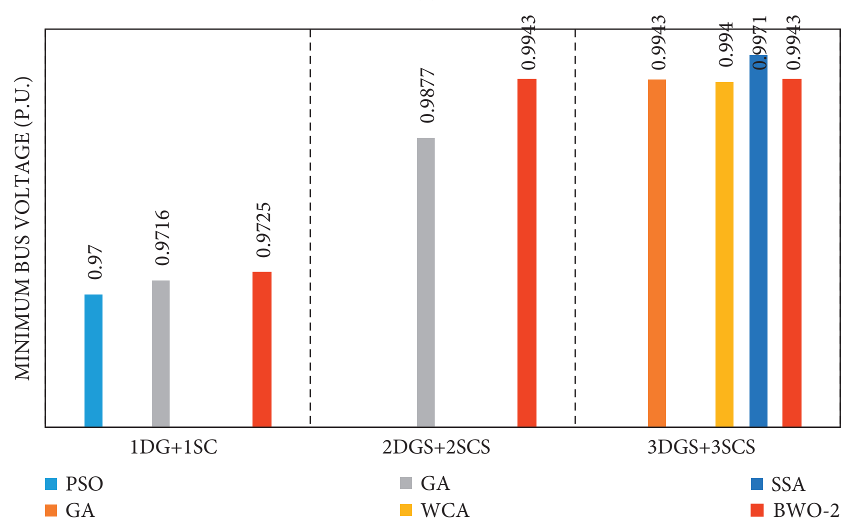
Cases	Parameters	Optimization techniques					
		PSO [14]	GA [10]	GA [8]	WCA [19]	SSA [20]	BWO-2
Base case	P_{loss} (kW)		224.98	224.95	225	225	225
	V_{min} (p.u)		0.9092	0.9092			0.9092
Case 1 (1 DG + 1 SC)	DG size in MW (node)	1.566 (61)		1.6945 (61)			1.8285 (61)
	SC size in MVAr (node)	1.4013 (61)		1.2688 (61)			1.3006 (61)
	P_{loss} (kW)	25.9		23.79			23.171
	V_{min} (p.u)	0.97		0.9716			0.9725
	P_{loss} reduction (%)	88.4		89.42			89.70
Case 2 (2 DGs + 2 SCs)	DGs size in MW (nodes)			0.53237 (18)			0.522 (17)
				1.50724 (61)			1.734 (61)
	SCs size in MVAr (nodes)			0.43728 (15)			0.353 (17)
				1.11621 (61)			1.238 (61)
	P_{loss} (kW)			9.58			**7.20**
	V_{min} (p.u)			0.9877			**0.9943**
	P_{loss} reduction (%)			95.74			**96.80**
Case 3 (3 DGs + 3 SCs)	DGs size in MW (nodes)		0.3984 (22)		0.5408 (17)	0.518 (10)	0.495 (11)
			0.3184 (58)		2.0 (61)	0.358 (19)	0.379 (18)
			0.1374 (36)		1.1592 (69)	1.6735 (60)	1.674 (61)
	SCs size in MVAr (nodes)		1.35 (2)		1.1879 (2)	0.6 (11)	0.334 (12)
			0.45 (24)		1.2373 (62)	0.6 (48)	0.207 (21)
			0.15 (69)		0.2697 (69)	1.2 (60)	1.206 (61)
	P_{loss} (kW)		16.72		33.339	4.837	**4.300**
	V_{min} (p.u)		0.9943		0.994	0.9971	**0.9943**
	P_{loss} reduction (%)		92.57		85.18*	97.85*	**98.09**

*Values are recomputed by using the presented values of DG/SC sizes and locations.

techniques has been carried out, and the results are presented in Table 6 [7, 8, 10, 14, 17, 19–21, 28, 29, 36, 72]. For the first case, except for GA [8], the BWO-2 method produces much improved results than the PSO, GABC, and BPSO. For the second case, the GA [8] is the only algorithm that produces closer results to the BWO-2 but still lags behind it, approximately by 2% in power loss reduction, whereas, for the third case, only SSA [20] produces closer results to BWO-2 but falls short behind it by 0.16% in the percentage power loss reduction. Thus, for all the cases, the BWO-2 attains a much better percentage reduction in power loss and improvement in minimum bus voltages than the competitive algorithms. A similar conclusion can also be drawn from Figure 12, showing the percentage



(a)



and (b)

Figure 17: Performance comparison of BWO-2 against the established optimization algorithms for (a) power loss reduction and (b) minimum bus voltage.

power loss reductions and the minimum voltages at the nodes.

In the literature, the application of various improved [8, 12, 35, 44] and hybrid [41, 42] optimization techniques have been presented for the simultaneous DG and SC allocation. BWO-2's findings and its performance comparison against the modified and hybrid methods are tabulated in Table 7, and the graphical view is illustrated in Figure 13. For the first case, the BWO-2 produces comparable results to that of the EGA and HSA-PABC. For the second case, the BWO-2 shows an edge over the contending algorithms IMDE, EGA, and WIPSO-GSA in terms of the power loss reduction and achieves comparable outputs for the minimum bus voltages. For the third case, the performance of the proposed BWO-2 is compared with the results reported for IPSO, IGA, ICSO, ITLBO, EGA, and WIPSO-GSA. Among all the contending algorithms, the findings reported for the ITLBO are comparable to the BWO-2 but fall short by 0.24%. Hence, the BWO-2 outperformed these improved variants in terms of the power loss reduction, whereas it achieves comparable outcomes for the minimum bus voltages.

4.2. IEEE 69-Bus Test System. The IEEE 69-bus test system is a balanced three-phase RDN that consists of 69 buses, 68 branches, and operates at the voltage of 12.66 kV. The system's active and reactive power demands are 3.8022 MW and 2.6947 MVAR, respectively. The 69-bus system's further details, such as the line data and the load connected per bus, are provided in [14]. The single-line diagram of the IEEE 69-bus system is shown in Figure 14.

An assessment of the best optimal allocation of DGs-SCs in the 69-bus RDN for the improvement in network performance achieved by the standard Rao-1, Jaya, BWO-1, and BWO-2 algorithms after the 50 independent runs is

Table 10: Performance comparison of the BWO-2 against the improved optimization techniques for the 69-bus test system.

Cases	Parameters	Optimization techniques						
		EGA [8]	IMDE [35]	IPSO [12]	IGA [12]	ICSO [12]	ITLBO [44]	BWO-2
Base case	P_{loss} (kW)	224.95		225	225	225	225	225
	V_{min} (p.u)	0.9092		0.9092	0.9092	0.9092	0.9092	0.9092
Case 1 (1 DG + 1 SC)	DG size in MW (node)	1.83871 (61)						1.8285 (61)
	SC size in MVAr (node)	1.30626 (61)						1.3006 (61)
	P_{loss} (kW)	23.15						23.171
	V_{min} (p.u)	0.9726						0.9725
	P_{loss} reduction (%)	89.71						89.70
Case 2 (2 DGs + 2 SCs)	DGs size in MW (nodes)	0.52285 (18)	0.4790 (24)					0.522 (17)
		1.7341 (61)	1.7380 (62)					1.734 (61)
	SCs size in MVAr (nodes)	0.35508 (17)	1.1920 (61)					0.353 (17)
		1.24366 (61)	0.1090 (63)					1.238 (61)
	P_{loss} (kW)	7.20	13.833					**7.20**
	V_{min} (p.u)	0.9943	0.9915					**0.9943**
	P_{loss} reduction (%)	96.80	93.84					**96.80**
Case 3 (3 DGs + 3 SCs)	DGs size in MW (nodes)			0.557 (11)	0.313 (12)	0.486 (11)	0.485 (11)	0.495 (11)
				0.321 (21)	0.396 (18)	0.381 (18)	0.382 (18)	0.379 (18)
				1.672 (61)	1.7 (61)	1.822 (61)	1.675 (61)	1.674 (61)
	SCs size in MVAr (nodes)			0.3 (11)	0.3 (11)	0.3 (18)	0.3 (11)	0.334 (12)
				0.3 (18)	0.3 (17)	1.2 (61)	0.3 (18)	0.207 (21)
				1.2 (61)	1.2 (61)	0.3 (66)	1.2 (61)	1.206 (61)
	P_{loss} (kW)			4.372*	4.621*	5.146*	4.3311	**4.300**
	V_{min} (p.u)			0.9943*	0.9943*	0.9943*	0.9943	**0.9943**
	P_{loss} reduction (%)			98.06*	97.95*	97.71*	98.08	**98.09**

*Values are recomputed by using the presented values of DG/SC sizes and locations.

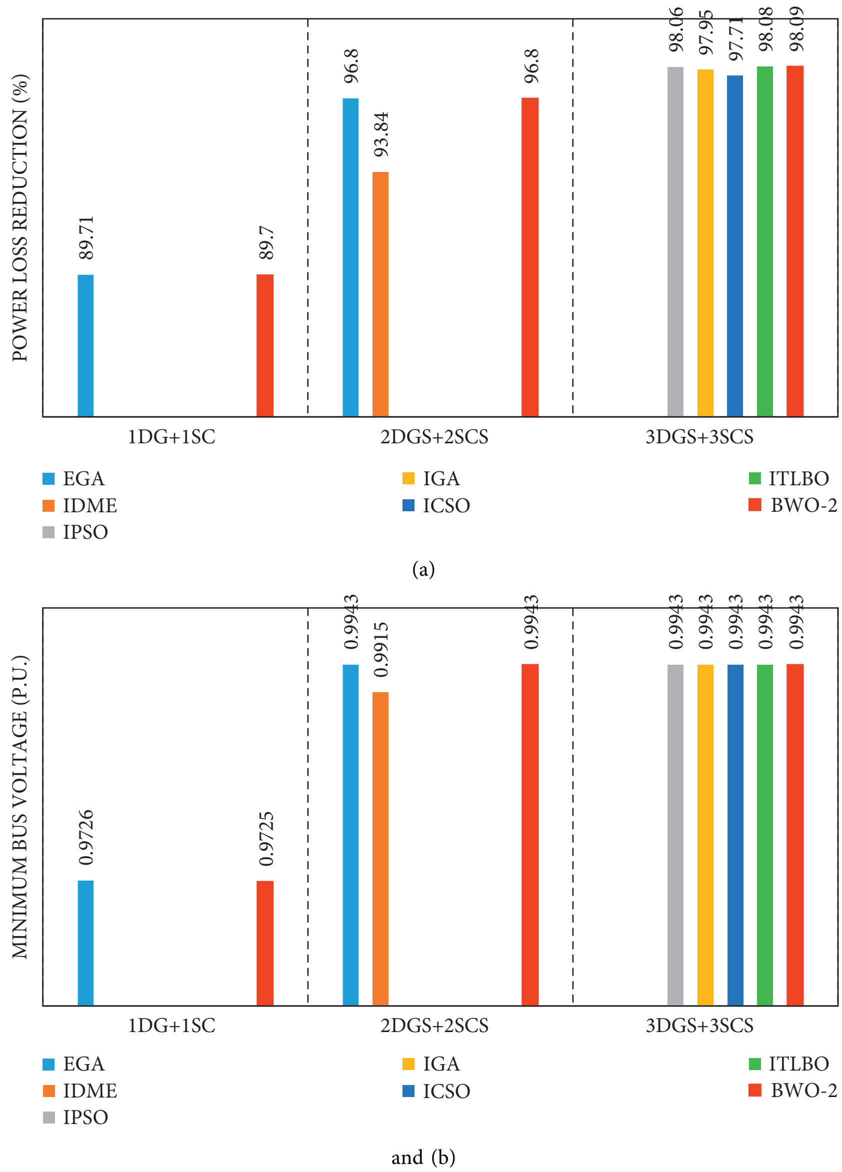


Figure 18: Performance comparison of BWO-2 against other optimization algorithms for (a) power loss reduction and (b) minimum bus voltage.

provided in Table 8. The table compares the power loss reduction and minimum bus voltages achieved after installing the DGs-SCs. The pictorial view of the efficacy of these methods in minimizing power losses is demonstrated in Figure 15. The table and figures show that the proposed techniques produce comparable outputs for the first case. For the second case, the Jaya, BWO-1, and BWO-2 nearly achieved the same outcomes and showed a significant upper hand over the Rao-1 algorithm in the power loss reduction. However, for the last case, the BWO-2 exhibited a substantial lead over the competitive algorithms by producing 1.41%, 0.38%, and 0.31% more loss reductions compared to the Rao-1, Jaya, and BWO-1 techniques, respectively. This proves that the proposed BWO-2 can efficiently solve the optimization problem of optimal DG and SC allocation, even if the complexity of the problem will be raised by adding more DG and SC units.

A comparison of the bus voltage profiles for the proposed cases pre- and postinstalling the DGs/SCs using proposed optimization methods is displayed in Figure 16. From the figure, it can be noticed that in each case, the voltage across all the nodes improved significantly. The proposed methods enhance the voltage profiles by nearly the same margin against the base case. Furthermore, using these techniques, the bus voltages are retained within the allowable limits for each case.

For the 69-bus test system, a performance comparison of the BWO-2 against several standard optimization techniques is presented in Table 9. For the examined first two cases, the GA [8] produces closer results to that of BWO-2 but falls short behind it by 0.28% and 1.06%, respectively. Furthermore, for both cases, the BWO-2 also shows a significant improvement in minimum bus voltages. In the third case, the BWO-2 generated more reduction in power losses than the

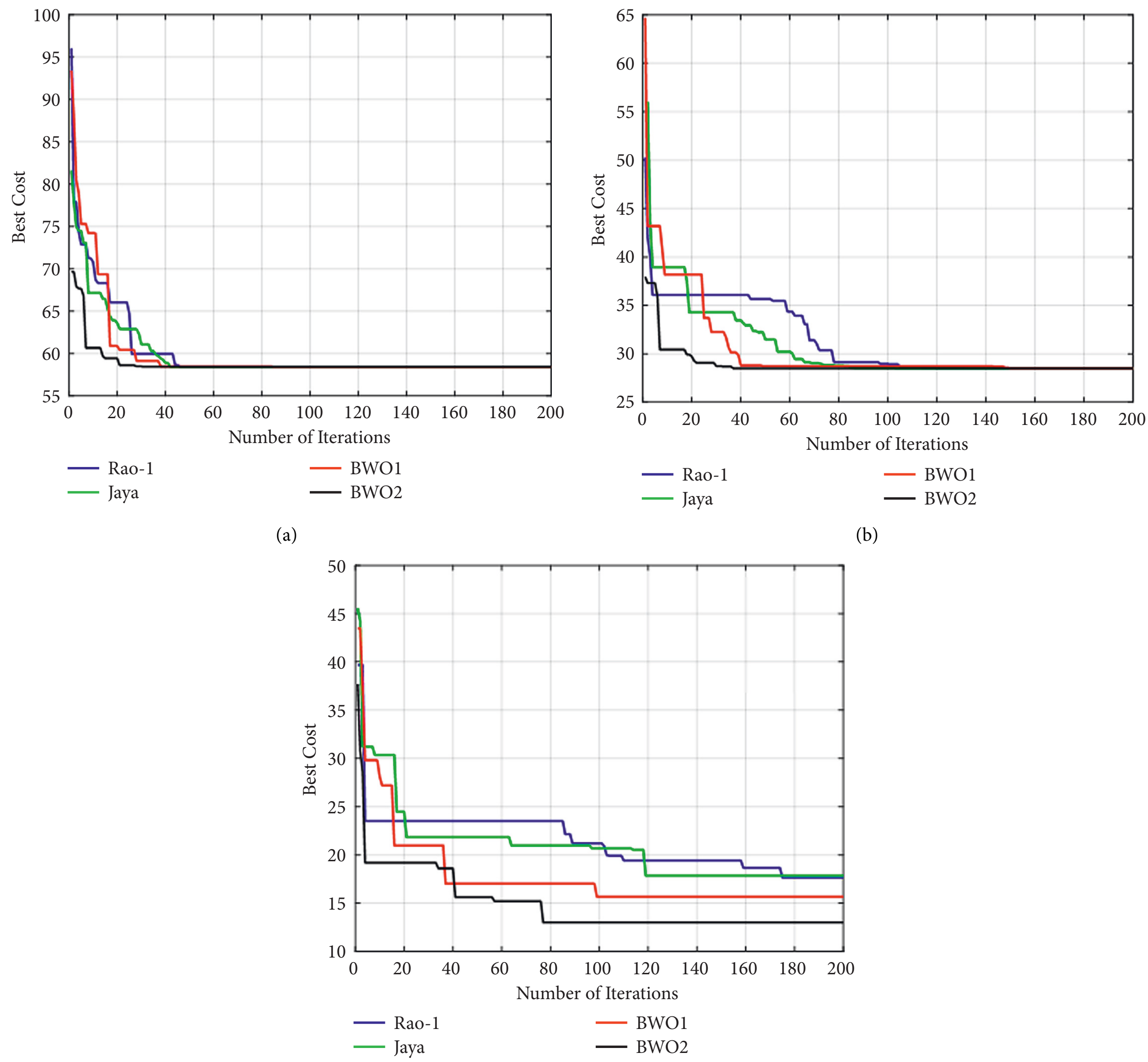


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Figure 19: Convergence characteristics of Rao-1, Jaya, BWO-1, and BWO-2 for the 33-bus test system for simultaneous allocation of (a) 1DG and 1SC, (b) 2DGs and 2SCs, and (c) 3DGs and 3SCs.

competing algorithms, ranging from 0.24% against the SSA [20] to 12.91% against the WCA. The BWO-2's dominant performance against the established optimization techniques is also evident in Figure 17, showing the percentage power loss reductions and the minimum voltages at the buses.

For the 69-bus test system, the comparative performance analysis of the BWO-2 versus several improved optimization techniques is provided in Table 10 and Figure 18. For the first two cases, only EGA produces comparable results to that of BWO-2. The BWO-2 showed a marginal edge over the IPSO and ITLBO in the third case. On the other hand, it outperformed the IGA and ICSO by 0.14% and 0.38%, respectively.

To prove the convergence characteristics of the BWO-1 and BWO-2, their convergence efficiency was compared with the Rao-1 and Jaya algorithms. For the 33-bus test system, the convergence curves obtained for three case studies have been presented in Figure 19. The figure shows that, while most of the algorithms achieve the same optimal value in the first two cases, the BWO-2 converges quickly to the optimal point in the first few iterations. The proposed BWO-2 outperforms the competing algorithms in the third case of simultaneous allocation of three units of DG and SC. This is due to the BWO-2's proposed process, which allows it to obtain numerous sets of updated solutions and choose the best among them. Only the better solutions will survive from the multiple sets of

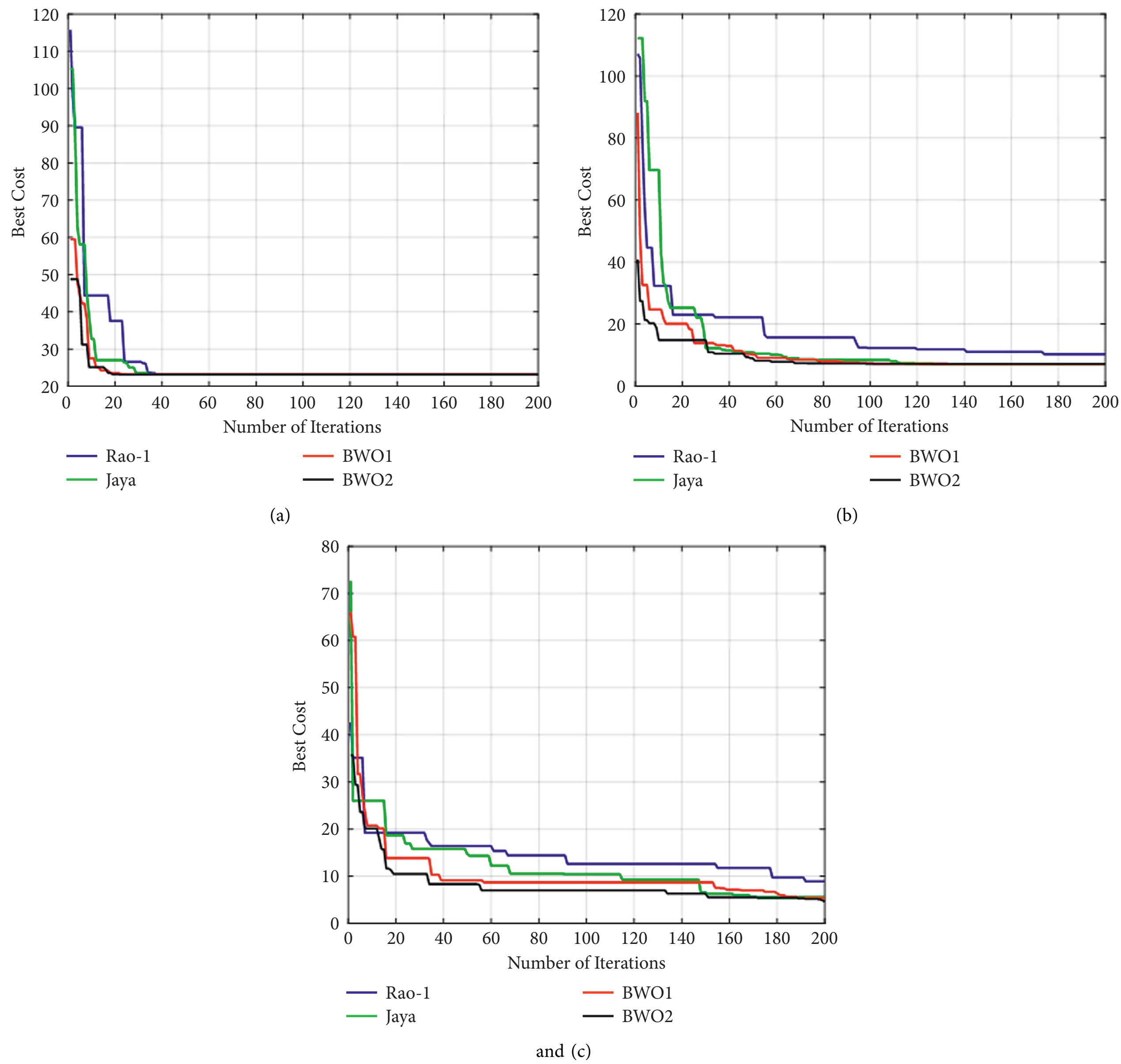

Figure 20: Convergence characteristics of Rao-1, Jaya, BWO-1, and BWO-2 for the 69-bus test system for simultaneous allocation of (a) 1DG and 1SC, (b) 2DGs and 2SCs, and (c) 3DGs and 3SCs.

updated solutions found and progress to the next iteration via the greedy search method. From the presented figures, it can be observed that in all the cases, the BWO-1 stood second and showed better convergence characteristics over the standard Rao-1 and Jaya algorithms. This is expected because, unlike the Rao-1 and Jaya techniques, the proposed BWO-1 attains the two updated solutions for each current solution and therefore converges quickly to the optimal solution by adopting the best one from the available solutions. Although the *MaxItr* set for this analysis is 200, the BWO-2 converges very fast to the optimal solution in less than 100 iterations.

The convergence characteristics of the Rao-1, Jaya, BWO-1, and BWO-2 for the 69-bus test system are comparable to the 33-bus system, as shown in Figure 20. For the studied cases of simultaneous DG and SC allocations, the BWO-2 stood first in convergence performance, followed by BWO-1, Jaya, and Rao-1 techniques.

Besides the convergence analysis, the statistical analysis of the Rao-1, Jaya, BWO-1, and BWO-2 algorithms has also been carried out to observe the solution quality of the studied algorithms. The solution quality of these techniques is analyzed in terms of the obtained best, worst, average, and standard deviation (SD) on the optimized cost function of power loss reduction. The results obtained from this statistical analysis for the 33-bus and 69-bus test systems are illustrated in Tables 11 and 12, respectively. From the tables, it can be observed that the BWO-2 attains the best average values for all three cases studied and shows minimum deviations in the optimized costs. For the 33-bus system, both BWO-1 and BWO-2

Table 11: Statistical analysis of Rao-1, Jaya, BWO-1, and BWO-2 for 33-bus test system.

Parameter	Optimization techniques			
	Rao-1	Jaya	BWO-1	BWO-2
Case1 (1 DG + 1 SC)				
Best solution	58.464	58.464	58.451	58.451
Worst solution	67.862	67.862	58.451	58.451
Average solution	60.344	59.415	58.451	58.451
SD	3.759 E + 00	2.816 E + 00	0.00 E + 00	0.00 E + 00
Case2 (2 DGs + 2 SCs)				
Best solution	28.874	28.713	28.512	28.493
Worst solution	33.803	31.745	30.302	29.282
Average solution	29.790	29.639	29.071	28.696
SD	1.778 E + 00	1.209 E + 00	5.530E − 01	2.516 E − 01
Case3 (3 DGs + 3 SCs)				
Best solution	18.207	15.805	13.461	11.95
Worst solution	24.212	20.732	18.297	15.689
Average solution	20.525	17.968	15.771	13.945
SD	1.667 E + 00	1.50 E + 00	1.469 E + 00	1.314 E + 00

Table 12: Statistical analysis of Rao-1, Jaya, BWO-1, and BWO-2 for 69-bus test system.

Parameter	Optimization technique			
	Rao-1	Jaya	BWO-1	BWO-2
Case1 (1 DG + 1 SC)				
Best solution	23.171	23.171	23.171	23.171
Worst solution	23.171	23.171	23.171	23.171
Average solution	23.171	23.171	23.171	23.171
SD	0.00 E + 00	0.00 E + 00	0.00 E + 00	0.00 E + 00
Case2 (2 DGs + 2 SCs)				
Best solution	8.396	7.22	7.21	7.20
Worst solution	16.317	11.326	11.31	10.115
Average solution	10.437	8.474	8.131	8.012
SD	2.692 E + 00	1.630 E + 00	1.144 E + 00	1.107 E + 00
Case3 (3 DGs + 3 SCs)				
Best solution	7.481	5.158	4.997	4.300
Worst solution	14.675	14.247	10.601	8.37
Average solution	10.806	7.212	6.838	5.235
SD	2.154 E + 00	2.698 E + 00	1.805 E + 00	1.317 E + 00

achieve the same results in the first case, whereas for the remaining two cases, the BWO-2 shows dominance over the contending algorithms.

Similar to the 33-bus test system, all algorithms produce the same outcomes while allocating the single unit of each DG and SC in the 69-bus test system. For the second case, although Jaya, BWO-1, and BWO-2 reach the same value of the best solution in 50 independent optimization runs, the BWO-2 has again proved its superiority in terms of the obtained minimum values of the average optimized cost and SD on the optimized cost. Furthermore, in the third case, the BWO-2 attains the best values for all computed parameters followed by the BWO-1.

5. Conclusion and Future Road Maps

This research presents new parameter-free improved best-worst optimizers, BWO-1 and BWO-2, to site and size the DG and SC units into the RDNs. The proposed algorithms utilize the solution updating equations of parameterless Rao-1 and Jaya optimization techniques. Using solution updating equations of both algorithms enables the BWO-1 to achieve two updated solutions in a single iteration. To further improve the exploration and exploitation capabilities for BWO-2, a subloop has also been introduced in the execution process that initializes the different values of random numbers for the same solution set. The introduced loop allows the BWO-2 to start the entire search process several times by resetting different values of random numbers. The proposed optimizers were employed to solve the optimization problem that involves the minimization functions of active power loss and voltage deviation by allocating the single and multiple DG and SC units in the 33-bus and 69-bus RDNs.

The performance comparison of the proposed BWO-1 and BWO-2 has been carried out against the standard Rao-1, Jaya, and several established, improved, and hybrid optimization methods, which have proved their comparative and promising performance over the contending algorithms. For the 33-bus system, the BWO-2 technique outperformed the Rao-1, Jaya, and BWO-1 techniques by 2.97%, 1.83%, and 0.72%, respectively. Compared to the existing standard, modified, and hybrid optimization techniques, the BWO-2 achieves up to 38.76% higher reduction in power losses. For the 69-bus test system, against the Rao-1, Jaya, BWO-1, and other optimization strategies, the BWO-2 achieved an enhanced reduction in power losses of 1.41%, 0.38%, 0.31%, and 12.91%, respectively. In addition, the convergence and statistical analysis of the BWO-1 and BWO-2 optimizers also acknowledged the marked performance of both optimizers.

In the future, the proposed optimization technique can be employed for different types of DGs and evaluate the uncertainties associated with the power generations. Besides, the economic and environmental impacts of the DGs and SCs installation can be included in the objective function. It is also recommended to solve the discrete single- and multiobjective optimization problems in different applications using the BWO-1 and BWO-2. Furthermore, it is recommended to study the impacts of various constraint-handling approaches on the findings of the proposed optimizers.

Nomenclature

br: Branch
c: Candidate solution
$\mathrm{SC}_{\mathrm{location}}$: Location of the capacitor bank
d: Decision variable
$\mathrm{DG}_{\mathrm{location}}$: Location of distributed generation
dim: Number of decision variables
i: Iteration
$I_{b,b+1}$: Branch current between buses b and $b+1$
n_{buses}: Number of buses
nPop: Number of population (population size)
Max Itr: Maximum number of iterations
P_{b+1}: The real power of the $b+1$th bus
P_{b+1}^{L}: The real power of the load at $b+1$th bus
P_{b+1}^{DG}: Real power supplied by DG at $b+1$th bus
P_{min}^{DG}: Minimum real power generated by DG
$P_{\mathrm{max}}^{\mathrm{DG}}$: Maximum real power generated by DG
$P_{b,b+1}$: Real power flow between buses b and $b+1$
$P_{\mathrm{loss}\,b,b+1}$: Real power loss in the branch between buses b and $b+1$
$P_{\mathrm{loss}\,T}$: Total active power loss
P_{SS}: Real power supplied by the substation
P_{DG}: Real power supplied by the DG
$P_{\mathrm{DG}}^{\mathrm{Total}}$: Total real power jointly supplied by all DG units
P_{load}: Real power consumed by the load
P_{loss}: Real power loss
Q_{b+1}: Reactive power of the $b+1$th bus
Q_{b+1}^{L}: Reactive power of the load at $b+1$th bus
$Q_{\mathrm{b+1}}^{\mathrm{DG}}$: Reactive power supplied by DG at $b+1$th bus
$Q_{\mathrm{b+1}}^{\mathrm{SC}}$: Reactive power supplied by SC at $b+1$th bus
$Q_{\mathrm{min}}^{\mathrm{SC}}$: Minimum reactive power generated by SC
$Q_{\mathrm{max}}^{\mathrm{SC}}$: Maximum reactive power generated by SC
$Q_{b,b+1}$: Reactive power flow between buses b and $b+1$
Q_{SS}: Reactive power supplied by the substation
$Q_{\mathrm{DG/SC}}$: Reactive power supplied by the DG and/or SC
$Q_{\mathrm{SC}}^{\mathrm{Total}}$: Total reactive power jointly supplied by all SC units
Q_{load}: Reactive power consumed by the load
Q_{loss}: Reactive power loss
R: Resistance
r/rand: Random number
$\mathrm{rand}_{1,c,i}$: The first random number for the cth candidate solution during ith iteration
$\mathrm{rand}_{2,c,i}$: The second random number for the cth candidate solution during ith iteration
$R_{b,b+1}$: The resistance of the branch between buses b and $b+1$
V_b: The voltage at bth bus
V_{rated}: Rated voltage
VD: Voltage deviation
X: Reactance
$X_{b,b+1}$: The reactance of the branch between buses b and $b+1$
$X_{d,c,i}$: Value of dth decision variable for cth candidate solution during ith iteration
$X_{d,c_{\mathrm{best}},i}$: Value of dth decision variable for best candidate solution during ith iteration
$X_{d,c_{\mathrm{worst}},i}$: Value of dth decision variable for worst candidate solution during ith iteration
X_{lb}: Lower bound for the decision variable
X_{ub}: Upper bound for the decision variable
$X_{d,c,i}^{\mathrm{updated}}$: The updated value of dth decision variable for cth candidate solution in ith iteration.

Data Availability

No data were used to support the study.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this research work.

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