

## Research Article

# A Quasioppositional-Chaotic Symbiotic Organisms Search Algorithm for Distribution Network Reconfiguration with Distributed Generations

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This study suggests an enhanced metaheuristic method based on the Symbiotic Organisms Search (SOS) algorithm, namely, Quasioppositional Chaotic Symbiotic Organisms Search (QOCSOS). It aims to optimize the network configuration simultaneously and allocate distributed generation (DG) subject to the minimum real power loss in radial distribution networks (RDNs). The suggested method is developed by integrating the Quasiopposition-Based Learning (QOBL) as well as Chaotic Local Search (CLS) approaches into the original SOS algorithm to obtain better global search capacity. The proposed QOCSOS algorithm is tested on 33-, 69-, and 119-bus RDNs to verify its effectiveness. The findings demonstrate that the suggested QOCSOS technique outperformed the original SOS and provided higher-quality alternatives than many other methods studied. Accordingly, the proposed QOCSOS algorithm is favourable in adapting to the DG placement problems and optimal distribution network reconfiguration.

## 1. Introduction

In distribution networks, reconfiguration is a traditional technique to minimize power loss in the system by opening/closing switches to establish the latest optimal network structure. Recently, distributed generation (DG) has been swiftly implemented in distribution networks caused by its great economic, environmental, and technical benefits. The DG unit's optimal allocation in the distribution network can reduce power loss and other risks such as excess reverse power flow, harmonic distortion, overload in line, and overvoltage in the operation of the network [1]. It is realized that the combination of the optimal network reconfiguration and DG placement problems would significantly decrease power loss and enhance

the performance of the distribution network. Nevertheless, the distribution network reconfiguration (DNR) is a complex optimization problem since this problem has  $2^n$  candidate solutions ( $n$  is the number of switches) [2]. Finding the optimal solution among these solutions while satisfying the radial structure and operating constraints is a barrier to problem-solving techniques. In addition, the optimal DG placement (ODGP) problem refers to a complex mixed-integer nonlinear optimization problem. Moreover, this is deemed as an obstacle for optimization methods. Therefore, the issues with ODGP and DNR in combination (DNG-DG) become a more complex optimization problem for the optimization solving approach. This research aims to propose a successful optimization method in solving the DNR-DG problem.

Merlin and Back initially solved the DNR problem for power loss decrement [3]. In this study, the authors expressed the DNR as a mixed-integer nonlinear optimization problem and overcame it with a discrete branch-and-bound method. In [4], Civanlar et al. recommended a branch exchange scheme to address the DNR problem for minimizing balancing load and power loss. In [5], Martín and Gil developed a novel heuristic methodology of branch exchange depending on the branch power flow's direction to decrease the real power loss for the DNR issue. In [6], Gohokar et al. formulated the DNR problem by a network topology concept, in which nodes and branches can be numbered in any order. The single loop optimization procedure was developed to find the optimum network topology. The aforementioned heuristic methods are simple implementation and provide an excellent solution for small-scale problems. Nevertheless, they expose limitations when facing complex optimization problems of changing objective functions. Therefore, these methods have not really attracted researchers.

Advanced optimization methods (i.e., metaheuristics) have been developed and applied to various engineering fields. They are capable of handling various complex constraints and different objective functions. Genetic algorithm (GA) is deemed a well-known metaheuristic, thrivingly implemented on the DNR problem. In [7], a modified GA was suggested for the DNR alongside the power loss reduction objective for 16- and 33-bus RDNs. In [8], GA was enhanced by utilizing the edge-window-decoder encoding system to minimize the power loss via the DNR problem. Another famous metaheuristic approach is particle swarm optimization (PSO). In [9], an adaptive PSO was presented for the RDN's reconfiguration for the real power loss reduction. In [10], the niche binary PSO algorithm was developed to optimally reconfigure the RDN. This algorithm overcame the prematurity of the original PSO for a better-obtained solution. In [11], improved selective binary PSO was offered as an alternative to the DNR to decrease the power loss. Other metaheuristic algorithms have been implemented effectively to the DNR problem, for instance, ant colony search algorithm [12], cuckoo search algorithm (CSA) [13], fireworks algorithm [14], honeybee mating optimization [15], stochastic fractal search [16], and binary group search optimization [17].

The DNR problem becomes more complex when DG units are integrated into distribution networks. Thus, the metaheuristic-based approaches are more suitable than heuristic methods for an optimal solution. Several metaheuristic methods have been recommended for the DNR-DG problem. In [2], a harmony search algorithm (HSA) was proposed in solving the DNR-DG problem for the 33- and 69-bus RDNs. The aim of this research was voltage profile increment and real power loss reduction. Also, in studies [18,19], fireworks algorithm (FWA) and adaptive cuckoo search algorithm (ACSA) were, respectively, presented for the DNR-DG within the similar coverage in the research [2]. In [20], the DNR-DG problem was fixed by the adaptive shuffled frogs leaping algorithm (ASFLA). In this study, the simulated outcomes from 33-bus and 69-bus RDNs for

various circumstances found that the ASFLA was efficient than ACSA, FWA, and SFLA. In [21], the salp swarm algorithm (SSA) was suggested for handling the DNR problem with the DG placement. The effectiveness of SSA was also tested on 33- and 69-bus RDNs. Generally, the aforementioned metaheuristic methods were implemented in small- and medium-scale test systems. The research did not take into account large-scale systems. Moreover, the majority of the research employed metaheuristic approaches to tackle the DNR-DG issue. Despite these techniques having a significant search capacity for an optimal solution, there is no guarantee that they would be effective for all optimization problems. A metaheuristic method can effectively solve a specific optimization problem; however, it may not be effective for others. Therefore, there is always room to suggest new effective metaheuristic methods for dealing with complex optimization problems.

This research suggests a powerful optimization strategy to manage the DNR-DG problem towards minimum real power loss. The suggested approach is the Quasioppositional Chaotic Symbiotic Organisms Search (QOCSOS) method developed in our previous work [22]. The QOCSOS algorithm embedded QOBL and CLS search strategies to boost the obtained solution quality and convergence speed of the original SOS. In QOCSOS, the QOBL strategy helps the algorithm to explore more promising domains; thus, it increases the chance of obtaining a better solution. As a result, the algorithm's exploration capacity is enhanced. In addition to QOBL, the CLS strategy also helps the algorithm to avoid trapping in local optima. It locally explores the neighbourhood of the current best solution for better exploitation. Consequently, the integration of both QOBL and CLS strategies would keep a balance between exploration and exploitation and significantly improve the performance of the SOS algorithm. The suggested QOCSOS technique is applied to simultaneously obtain the optimal configuration and DG placement in the 33-, 69-, and 119-bus RDNs.

This research's contributions are outlined as the statements as follows:

- (i) The QOCSOS was modified to the DNR-DG problem for power loss decrement.
- (ii) The QOCSOS was successfully applied to 119-bus large-scale system for the DNR-DG problem.
- (iii) The simulation results showed that the simultaneous consideration of optimal network reconfiguration and DG placement substantially enhanced the distribution networks' performance with regard to voltage profile and power loss compared to only network reconfiguration or DG placement.
- (iv) The outcome comparison illustrated that the QOCSOS technique is more successful than the original SOS and other compared approaches for the acquired excellent solution standard.

The remaining sections of the paper are as follows. Section 2 describes the problem formulation of the DNR-DG. Section 3 presents the QOCSOS algorithm, in which the original SOS, QOBL, and CLS are introduced. Section 4

explains the implementation of the proposed QOCSOS to the DNR-DG problem. The results of numerical simulations are presented in Section 5. Finally, the conclusions are given in Section 6.

## 2. Problem Formulation

The main goal of the DNR-DG problem is to minimize real power loss ( $P_L$ ) in RDNs, while all operating constraints are satisfied as follows:

$$\begin{aligned} OF &= \text{Min}(P)_L \\ &= \text{Min}\left(\sum_{k=1}^{N_L} R_k I_k^2\right), \end{aligned} \quad (1)$$

where  $R_k$  is the resistance of the  $k^{\text{th}}$  branch,  $I_k$  is the current passing through that branch, and  $N_L$  is the number of branches in an RDN.

The operational constraints for the objective function in equation (1) are given as follows:

i. Power balance constraints:

$$\begin{aligned} P_{SS} + \sum_{i=1}^{N_{DG}} P_{DG,i} &= \sum_{j=1}^{N_B} P_{D,j} + \sum_{k=1}^{N_L} P_{L,k}, \\ Q_{SS} + \sum_{i=1}^{N_{DG}} Q_{DG,i} &= \sum_{j=1}^{N_B} Q_{D,j} + \sum_{k=1}^{N_L} Q_{L,k}, \end{aligned} \quad (2)$$

where  $N_{DG}$  is the number of DGs;  $N_B$  is the number of buses in RDN;  $P_{D,j}$  and  $Q_{D,j}$  are the active and reactive power of load demands at the  $j^{\text{th}}$  bus, respectively;  $P_{L,k}$  and  $Q_{L,k}$  are the active and reactive power losses in the  $k^{\text{th}}$  branch, respectively;  $P_{SS}$  and  $Q_{SS}$  are the active and reactive power outputs at the slack bus, respectively;  $P_{DG,i}$  and  $Q_{DG,i}$  are the active and reactive power outputs of the  $i^{\text{th}}$  DG, respectively.

ii. Voltage constraint:

$$V_{\min,i} \leq V_i \leq V_{\max,i}; \quad i = 1, \dots, N_B, \quad (3)$$

where  $V_{\min,i}$  and  $V_{\max,i}$  denote the voltage bounds at the  $i^{\text{th}}$  bus.

iii. Thermal limit:

$$|I_k| \leq |I_{\max,k}|; \quad k = 1, \dots, N_L, \quad (4)$$

where  $I_{\max,k}$  represents the maximum current allowed to flow through the  $k^{\text{th}}$  branch.

iv. DG generation constraint:

$$P_{DG\min,i} \leq P_{DG,i} \leq P_{DG\max,i}; \quad i = 1, \dots, N_{DG}, \quad (5)$$

where  $P_{DG\min,i}$  and  $P_{DG\max,i}$  denote the capacity limit of the  $i^{\text{th}}$  DG, respectively.

v. DG penetration constraint:

$$\sum_{i=1}^{N_{DG}} P_{DG,i} \leq \sum_{j=1}^{N_B} P_{D,j}. \quad (6)$$

vi. Radial configuration constraint:

The radial topology must be maintained after reconfiguration as follows [23]:

$$\det(A) = 1 \text{ or } -1, \quad (7)$$

where  $A$  represents a matrix for the connection of branches and buses in the RDN [23]:

$$A_{ij} = \begin{cases} 1, & \text{if branch } i \text{ connects from bus } j, \\ -1, & \text{if branch } i \text{ connects to bus } j, \\ 0, & \text{otherwise.} \end{cases} \quad (8)$$

## 3. QOCSOS Algorithm

**3.1. Original SOS Algorithm.** The SOS method was developed based on a natural ecosystem with symbiotic relations between two different organisms [24]. The search process is started by randomly generating a population of organisms (ecosystem) as follows:

$$O_i = O_{\min} + \text{rand}(0, 1) \times (O_{\max} - O_{\min}), \quad i = 1, 2, \dots, N, \quad (9)$$

where  $O_i = [o_{i1}, o_{i2}, \dots, o_{iD}]$ ;  $D$  is the dimension of optimization problem;  $O_{\min}$  and  $O_{\max}$  are the upper and lower limits of the  $i^{\text{th}}$  organism, respectively;  $N$  is the size of the ecosystem.

In the population, each organism represents a solution. For each iteration, the population is updated based on mutualism, commensalism, and parasitism phases. Each phase is defined as follows.

**3.1.1. Mutualism.** Based on mutualistic relationships, the  $j^{\text{th}}$  random organism is assigned from the population to associate with the  $i^{\text{th}}$  organism during this phase. Vectors  $O_i$  and  $O_j$  are the  $i^{\text{th}}$  and  $j^{\text{th}}$  organisms in the population, respectively. New organisms are created as follows [24]:

$$\begin{aligned} O_i^{\text{new}} &= O_i + \text{rand}(0, 1) \times (O_{\text{best}} - MV \times bf_1), \\ O_j^{\text{new}} &= O_j + \text{rand}(0, 1) \times (O_{\text{best}} - MV \times bf_2), \end{aligned} \quad (10)$$

$$MV = \frac{O_i + O_j}{2},$$

where  $MV$  is the average of the  $i^{\text{th}}$  and  $j^{\text{th}}$  organisms, representing a mutualistic relationship;  $bf_1$  and  $bf_2$  are randomly chosen as 1 or 2;  $O_{\text{best}}$  denotes the best organism in the population.

The fitness value is calculated for each organism. The new organism is updated as follows:

$$O_i = \begin{cases} O_i^{\text{new}}, & \text{if } f(O_i^{\text{new}}) < f(O_i), \\ O_i, & O_i \text{ otherwise.} \end{cases} \quad (11)$$

3.1.2. *Commensalism*. In this phase, the  $i^{\text{th}}$  organism interacts with the  $j^{\text{th}}$  organism, which is randomly selected from the population based on commensalism interaction. A new organism is generated as follows [24]:

$$O_i^{\text{new}} = O_i + \text{rand}(-1, 1) \times (O_{\text{best}} - O_j). \quad (12)$$

The new organism is updated as described by equation (10).

3.1.3. *Parasitism*. In this phase, the  $i^{\text{th}}$  organism acts as a parasite, and the  $j^{\text{th}}$  random organism acts as the host. In the parasitism interaction of two different organisms, the parasite gets benefits, while the host gets harm. Vector  $O_i$  is duplicated to create a *Parasite\_Vector* (PV). A new candidate solution ( $O_{PV}$ ) is created by randomly modifying some variables of the PV vector [24]. The  $O_{PV}$  vector is updated or discarded as follows:

$$O_j = \begin{cases} O_{PV}, & \text{if } f(O_{PV}) < f(O_j), \\ O_j, & O_i \text{ otherwise.} \end{cases} \quad (13)$$

3.2. *QOBL Strategy*. The QOBL strategy is performed when SOS generates a new population of organisms. The QOBL approach is also applied when the initial population is randomly initialized. The opposite point  $O_i^o$  of each organism  $O_i$  is calculated as follows [25]:

$$O_i^o = O_{\text{imin}} + O_{\text{imax}} - O_i. \quad (14)$$

Then, the quasiopposite point  $O_i^{qo}$  is given by the following equation [22]:

$$O_i^{qo} = \text{rand}\left(\frac{O_{\text{imin}} + O_{\text{imax}}}{2}, O_i^o\right). \quad (15)$$

The pseudocode of QOBL (Algorithm 1) is illustrated in Figure 1.

3.3. *CLS Strategy*. For increasing the likelihood of finding better solutions, the CLS approach is utilized to explore the vicinity of the current best solution. A new candidate solution is created via the CLS strategy as follows [27]:

$$O_{\text{best},k}^{\text{new}} = O_{\text{best},k} + (Z_k - 0.5) \times (O_{i,k} - O_{j,k}), \quad (16)$$

where  $O_{\text{best},k}^{\text{new}}$  is the new organism created via CLS at the  $k^{\text{th}}$  iteration;  $O_{\text{best},k}$  is the current best organism;  $O_{i,k}$  and  $O_{j,k}$  denote the two random organisms selected from the population, respectively;  $Z_k$  is generated from ‘‘logistic map’’ [28].

The fitness values are computed for the organisms  $O_{\text{best},k}^{\text{new}}$  and  $O_{\text{best},k}$ . The new organism is updated as follows:

Algorithm 1: Pseudocode of QOBL	
%	$O_{ij}$ is current population
%	$O_{ij}^o$ is opposite of $O_{ij}$
%	$O_{ij}^{qo}$ is quasi-opposite of $O_{ij}$
%	[LB, UB] is search boundary
1:	for $i=1:N$
2:	for $j=1:D$
3:	$O_{ij}^o = LB_j + UB_j - O_{ij}$ ;
4:	$C_{ij} = (LB_j + UB_j)/2$
5:	if ( $O_{ij} < C_{ij}$ )
6:	$O_{ij}^{qo} = C_{ij} + (O_{ij}^o - C_{ij}) \times \text{rand}$ ;
7:	else
8:	$O_{ij}^{qo} = O_{ij}^o + (C_{ij} - O_{ij}^o) \times \text{rand}$ ;
9:	end if
10:	end for
11:	end for

FIGURE 1: QOBL pseudocode.

$$O_{\text{best},k} = \begin{cases} O_{\text{best},k}^{\text{new}}, & \text{if } f(O_{\text{best},k}^{\text{new}}) < f(O_{\text{best},k}), \\ O_{\text{best},k}, & \text{otherwise.} \end{cases} \quad (17)$$

3.4. *QOCSOS*. The QOCSOS method is developed based on the original SOS with the integration of QOBL and CLS strategies. Firstly, QOCSOS generates a population of organisms  $O$ . Afterwards, the quasiopposite population  $O^{qo}$  is created via the QOBL strategy. From the set  $[O, O^{qo}]$ , QOCSOS selects  $N$  (i.e., size of the ecosystem) of best organisms as an initial population according to their best fitness values. Next, the operation of SOS is performed. At the end of this stage, when a new population is created, a jumping rate  $j_r$  parameter determines whether to implement the QOBL approach or to keep the current population. Lastly, the CLS approach is used to obtain the best organism. The QOCSOS operation is implemented until the stopping condition is satisfied. Figure 2 shows the pseudocode of the QOCSOS method.

## 4. Implementation of QOCSOS to DNR-DG Problem

This section discussed how QOCSOS was deployed to the DNR-DG issue to minimize real power loss in RDNs. Therefore, three scenarios are considered as follows:

- (i) Case 1: considering only the DNR.
- (ii) Case 2: considering only the optimal DG location.
- (iii) Case 3: simultaneous consideration of DNR and optimal DG location (DNR-DG problem).

4.1. *Initialization of Population*. In the population of QOCSOS, each organism  $O_i$  ( $i = 1, \dots, N$ ) denotes a solution vector, which consists of opened switches, locations, and

Algorithm 2: Pseudocode of the QOCSOS algorithm	
1: Set control parameters ( $D, N, maxIter, j_r, K$ );	%QOBL based generation jumping%
2: Initialize (randomly) population of oraganisms $O_{i,j}$ ;	16: if (rand < $j_r$ )
3: Calculate fitness value for $O_{i,j}$ ;	17: Perform QOBL using Algorithm 1 to obtain
%QQBL based population initialization%	$O_{i,j}^{qo}$
4: Perform QOBL using Algorithm 1 to obtain $O_{i,j}^{qo}$	18: Calculate fitness value for $O_{i,j}^{qo}$ ;
5: Calculate fitness value for $O_{i,j}^{qo}$ ;	19: Select $N$ of best organisms from the set $[O_{i,j},$
6: Select $N$ of best organisms from the set $[O_{i,j}, O_{i,j}^{qo}]$ as	$O_{i,j}^{qo}]$ as current population;
initial population;	20: Identity best organism ( $O_{best}$ ) in ecosystem;
7: Set $Iter = 0$ ; % Iteration Counter;	21: else
8: while ( $Iter < maxIter$ )	22: Identity best organism ( $O_{best}$ ) in ecosystem;
9: $Iter = Iter + 1$ ;	23: end if
10: for $i = 1; N$	24: %Chaotic local search%
11: Identity the best organism $X_{best}$ in ecosystem;	25: for $j = 1:K$
12: Perform Mutualism Phase;	26: Update chaotic number $Ch$ vi logistic map;
13: Perform Commensalism Phase;	27: Randomly select two organisms from
14: Perform Parasitism Phase;	current population;
15: end for	28: Calculate new organism using Eq. (20);
	29: Calculate fitness value of new organism;
	30: Update new solution if fitness is better;
	31: end for
	32: end while

FIGURE 2: Pseudocode of the QOCSOS algorithm.

capacities of DGs. Equations (18), (19), and (20) express a solution for Cases 1, 2, and 3, respectively.

$$O_i = [SW_1, \dots, SW_{N_{SW}}], \quad (18)$$

$$O_i = [L_{DG,1}, \dots, L_{DG,N_{DG}}, P_{DG,1}, \dots, P_{DG,N_{DG}}], \quad (19)$$

$$O_i = [SW_1, \dots, SW_{N_{SW}}, L_{DG,1}, \dots, L_{DG,N_{DG}}, P_{DG,1}, \dots, P_{DG,N_{DG}}], \quad (20)$$

in which  $N_{SW}$  denotes the number of opened switches.

Each organism is randomly generated in its boundaries, in which the opened switches and locations of DGs are natural numbers. Hence, the designed variables are generated as follows:

$$\begin{aligned} SW_i &= \text{round} [SW_{\min,i} + \text{rand}(0, 1) \times (SW_{\max,i} - SW_{\min,i})], \\ L_{DG,j} &= \text{round} [L_{DG\min,j} + \text{rand}(0, 1) \times (L_{DG\max,j} - L_{DG\min,j})], \\ P_{DG,j} &= P_{DG\min,j} + \text{rand}(0, 1) \times (P_{DG\max,j} - P_{DG\min,j}), \end{aligned} \quad (21)$$

in which  $i = 1, 2, \dots, N_{SW}$ ;  $j = 1, 2, \dots, N_{DG}$ ;  $SW_{\min,i} = 1$  for all variables;  $SW_{\max,i}$  denotes the length of the  $i^{\text{th}}$  fundamental loop vectors. The principle of finding the fundamental loop vectors can be found in [29];  $L_{DG\min,j} = 2$  for all variables, which means that DG units can be installed at all buses except the slack bus.

**4.2. Fitness Value.** Fitness values for organisms of QOCSOS are calculated as follows:

$$F_T = OF + K_p \sum_{i=1}^{N_B} (V_i - V_i^{\text{lim}})^2 + K_q \sum_{k=1}^{N_L} (I_k - I_k^{\text{lim}})^2, \quad (22)$$

in which  $K_p$  and  $K_q$  denote penalty coefficients for voltage and thermal current, respectively;  $x^{\text{lim}}$  denotes the limit value of the dependent variable  $x$  (bus voltages and currents) as follows:

$$x^{\text{lim}} = \begin{cases} x_{\max}, & \text{if } x > x_{\max}, \\ x_{\min}, & \text{if } x < x_{\min}, \\ x, & \text{otherwise.} \end{cases} \quad (23)$$

where  $x$  denotes the  $V_i$  and  $I_k$  values;  $x^{\text{lim}}$  denotes the limitations of  $V_i$  and  $I_k$ .

**4.3. Overall Procedure.** The QOCSOS implementation to the DNR-DG problem can be drawn as follows:

*Step 1.* set QOCSOS parameters ( $D, N, maxIter, j_r, K$ ).

*Step 2.* perform the fundamental loops to define the lower and upper bounds of  $SW_i$

*Step 3.* randomly create a population of organisms  $O_{i,j}$ . Execute the QOBL approach to acquire  $O_{i,j}^{qo}$ . Calculate fitness values using equation (22) for the set  $[O_i, O_{i,j}^{qo}]$ . Choose  $N$  of best organisms from the set  $[O_i, O_{i,j}^{qo}]$  as initial population. Check the radial structure for all organisms. Set  $Iter = 0$ .

*Step 4.* set  $Iter = Iter + 1$ . Start the main loop.

*Step 5.* define the best organism  $O_{\text{best}}$  having the best fitness value.

*Step 6.* execute the mutualism phase.

*Step 7.* execute the commensalism phase.

*Step 8.* execute the parasitism phase.

(In each phase, check the radial condition and constraints for new organisms and apply an approach using equation (23) if any organism violates its limits.)

*Step 9.* move to Step 5 if organism  $O_i$  is not the final organism of the ecosystem ( $O_N$ ). Otherwise, continue to the next step. Check the radial constraint and apply the repairing strategy if necessary.

*Step 10.* if  $\text{rand}() < j_r$ , implement the QOBL approach to obtain quasiopposite points of the current population. Check the radial constraint and deploy the repairing strategy. Calculate fitness value and define the best organism  $O_{\text{best}}$ . Otherwise, define the best organism  $O_{\text{best}}$  from Step 9.

*Step 11.* implement the CLS approach to obtain the best organism  $O_{\text{best}}$ . Check the radial constraint and apply the repairing strategy

*Step 12.* if  $\text{Iter} < \text{maxIter}$ , go to Step 4. Else, the process is done.

## 5. Simulation Results

In this study, 33-bus, 69-bus, and 118-bus RDNs were used to test the QOCSOS method with three scenarios. The QOCSOS technique was performed in thirty separate trials for each case study to find the optimum solution. Besides, the SOS approach was also applied to the same problem for result comparisons. QOCSOS's initial parameters were chosen in Table 1.

*5.1. 33-Bus Test Network.* The proposed QOCSOS method was initially implemented on the 33-bus RDN. The comprehensive data of this network was obtained from [30]. For Case 1, the QOCSOS method obtained the opened switches: 7-9-14-32-37, where the real power loss of the network was decreased from 202.67 kW (base case) to 139.5513 kW in relation to 31.14% of the power loss reduction (PLR). The system's minimum voltage amplitude was raised from 0.9131 p.u. to 0.9378 p.u. Table 2 shows the reconfiguration results acquired using various optimization methods for the 33-bus RDN. For accurate comparison of the best obtained result improvement (power loss), the following equation can be used to assess quantitatively the result improvement:

$$RI_{\text{QOCSOS}}\% = \frac{R_{\text{compared\_method}} - R_{\text{QOCSOS}}}{R_{\text{compared\_method}}} \times 100\%, \quad (24)$$

where  $RI_{\text{QOCSOS}}$  is the QOCSOS result improvement compared to other methods;  $R_{\text{compared\_method}}$  is the power loss obtained by other compared methods;  $R_{\text{QOCSOS}}$  is the power loss obtained by the QOCSOS method.

In equation (24), the best result improvement ( $RI$ ) can be the plus sign (+) or minus sign (-). If  $RI$  has a plus sign (+), the result obtained by QOCSOS is better than the compared method; otherwise, the compared method has a better result than QOCSOS. Besides, if  $RI$  is zero, QOCSOS and compared methods have the same result.

From Table 2, the  $RI$  values show that the real power loss acquired by the QOCSOS was slightly better than FWA [14], ACSA [19], HSA [31], and ITS [31] (the result improvement is from 0.3079% to 2.0211%). The methods including SOS, ICSA [13], RGA [7], SSA [21], and SFS [16] have similar power loss compared to the proposed QOCSOS.

For Case 2, where three DG units were installed in the network, the QOCSOS determined the optimum positions to place the DG units at buses 14, 24, and 30 with capacities of 0.7540 MW, 1.0994 MW, and 1.0714 MW. Consequently, a minimal real power loss of 71.4572 kW (64.74% PLR) and a minimal voltage of 0.9687 p.u. were established. Table 3 portrays the findings of optimal DG placement obtained by QOCSOS and distinct methods for the 33-bus RDN. It can be displayed that QOCSOS had the same power loss as SSA [21] and was lower than those of other methods in the table. The observation of  $RI$  shows the proposed QOCSOS method can improve the result of 0.0179%, 26.1501%, 19.4213%, and 3.7743% compared to SFS [16], HSA [2], FWA [14], and ACSA [19], respectively.

For Case 3, QOCSOS acquired the best network configuration using the opened switches: 10-28-31-33-34. Concurrently, DGs were deployed to positions at buses 7, 18, and 25 having capacities of 0.8708 MW, 0.7118 MW, and 1.2274 MW. After optimal DNR-DG problem, the minimum real power loss for this case obtained by the QOCSOS was 51.5388 kW, corresponding to a PLR of 74.57%. Table 4 displays the findings of DNR-DG obtained by QOCSOS and different methods for the 33-bus RDN. Based on the  $RI$  values with the plus sign "+," the QOCSOS method obtained the best real power loss results among the other compared methods for this case.

Tables 2–4 show that the PLR percentages for Cases 1–3 were 31.14%, 64.74%, and 74.57%, accordingly. The PLR of Case 3 was the largest of the three instances. This demonstrated that considering DNR and ODGP at the same time has a substantial influence on power loss reduction. The convergence curves of the QOCSOS and the original SOS are shown in Figure 3. For Cases 1 and 2, both the SOS and QOCSOS algorithms yielded the equivalent real power loss outcome. Nevertheless, the QOCSOS's convergence speeds for optimal outcomes were faster than SOS in all scenarios. Moreover, the voltage profiles of the 33-bus test network for Cases 1, 2, and 3 are illustrated in Figure 4. When the scenario of simultaneous consideration of ODGP and DNR (Case 3) was addressed, the network's voltage profile was greatly enhanced.

TABLE 1: Setting parameters of QOCSOS and SOS for three test networks.

33-bus RDN	69-bus RDN	118-bus RDN
$N = 20$ ; maxIter = 50	$N = 20$ ; maxIter = 100	$N = 100$ and maxIter = 100 for case 1 and case 2; $N = 100$ and maxIter = 200 for case 3

TABLE 2: Optimal configuration obtained by QOCSOS and other techniques for Case 1 of the 33-bus RDN.

Method	Opened switches	$P_L$ (kW)	$RI$ (%)	$PLR$ (%)	$V_{\min}$ (p.u.)
Base case	33-34-35-36-37	202.68	—	—	0.9131
RGA [7]	7-9-14-32-37	139.55	-0.0009	31.15	0.9378
ITS [31]	7-9-14-36-37	142.17	+1.8419	29.86	0.9336
HSA [31]	7-10-14-28-36	142.43	+2.0211	29.73	0.9377
ACSA [19]	7-9-14-28-32	139.9823	+0.3079	30.94	0.9412
FWA [14]	7-9-14-28-32	139.9823	+0.3079	30.94	0.9412
ICSA [13]	7-9-14-32-37	139.55	-0.0009	31.14	0.9378
SSA [21]	7-9-14-32-37	139.55	-0.0009	31.14	0.9378
SFS [16]	7-9-14-32-37	139.55	-0.0009	31.14	0.9378
SOS	7-9-14-32-37	139.5513	0.0000	31.14	0.9378
QOCSOS	7-9-14-32-37	139.5513	—	31.14	0.9378

5.2. *69-Bus Test Network.* The QOCSOS technique was used on the 69-bus RDN to verify its scalability. The data are presented and tabulated in [32]. Table 5 portrays the findings of the DNR problem obtained by QOCSOS and other techniques for the 69-bus RDN. For Case 1, the switches, 14-57-61-69-70, were opened by the QOCSOS to form the system's optimal configuration. Then, the system's real power loss was 98.6062 kW, which corresponds to a PLR of 56.17% in comparison to the baseline case. According to the  $RI$  values, the real power loss obtained by QOCSOS is slightly better than SFS [16], SSA [21], and HSA [2] and close to that of other methods, as seen in Table 5.

Table 6 presents the results of the ODGP problem obtained by QOCSOS, SOS, ACSA [19], FWA [14], HSA [2], SSA [21], and SFS [16]. For Case 2, QOCSOS found three buses, 11, 18, and 61, to install three DGs. The corresponding DGs capacities were 0.5268 MW, 0.3804 MW, and 1.7190 MW. The system's real power loss is reduced from 225.0005 kW (base case) to 69.4284 kW with the DG installation, which is equal to SOS, close to SSA [21], and better than other methods.

Table 7 reports the results of the DNR-DG problem yielded by QOCSOS and other algorithms for the 69-bus network. QOCSOS simultaneously obtained the optimal opened switches: 14-58-61-69-70. Moreover, three DGs of capacities 0.5376 MW, 1.4340 MW, and 0.4903 MW were located at buses 11, 61, and 164, correspondingly. As a result, the obtained real power loss was 35.1624 kW, which is the same as SOS and SFS [16] and better than other compared methods.

From Tables 4–7, the QOCSOS generated the real power losses of 98.6062 kW, 69.4284 kW, and 35.1624 kW for the cases of 1 to 3, accordingly. In comparison to Cases 1 and 2, the real power loss from Case 3 was the smallest. This demonstrated that simultaneously considering ODGP and DNR problems greatly decreased the system's real power loss. Figure 5 shows the QOCSOS and SOS's convergence characteristics for Cases 1–3. In every case, QOCSOS

outperformed SOS in terms of convergence speed. The network's minimal voltage value was 0.9495 p.u., 0.9790 p.u., and 0.9813 p.u. for Cases 1–3, accordingly, after optimization for three cases. These reduced voltage values were enhanced from 0.9092 p.u. (base case), indicating that the network's voltage profile has improved significantly (Figure 6). Case 3 had the greatest minimum voltage out of the three cases. This indicated that taking into account both DNR and ODGP concurrently boosted the system's voltage profile tremendously.

5.3. *119-Bus Test Network.* The effectiveness of the QOCSOS technique was justified on the large-scale 119-bus RDN. The data for branch and network load was provided in [33]. Table 8 demonstrates the outcomes of QOCSOS and other techniques for the DNR problem of the 119-bus RDN. As observed from this table, QOCSOS acquired the opened switches, 23-25-34-39-42-50-58-71-74-95-97-109-121-129-130, generating a real power loss of 854.0309 kW. It can be from  $RI$  values that this result was slightly better than that of SFS [16] and better than other compared methods.

Table 9 presents the results offered by QOCSOS and other methods for the ODGP problem. For this case, QOCSOS found that three DGs were located at buses 50, 71, and 109, along with the corresponding capacities of 2.8833 MW, 2.9785 MW, and 3.1199 MW. The power loss result acquired by QOCSOS was identical to those of SOS and SFS [16] methods.

Table 10 tabulates the results gathered by QOCSOS and various approaches for the DNR-DG problem. For this case, QOCSOS obtained the opened switches: 23-26-34-39-42-50-61-70-74-85-86-107-121-125-129, where three DGs were located at buses 4, 91, and 110 with capacities of 9.3909 MW, 4.1078 MW, and 2.5599 MW, accordingly. When both ODGP and DNR were implemented at the same time, the obtained real power loss of QOCSOS was 565.0605 kW,

TABLE 3: Optimal DG placement results obtained by QOCSOS and other techniques for Case 2 of 33-bus RDN.

Method	$P_{DG}$ (MW)/(bus)	$P_L$ (kW)	RI (%)	PLR (%)	$V_{min}$ (p.u.)
ACSA [19]	0.7798/(14); 1.1251/(24); 1.3496/(30)	74.26	+3.7743	63.26	0.9778
FWA [14]	0.5897/(14); 0.1895/(18); 1.0146/(32)	88.68	+19.4213	56.24	0.9680
HSA [2]	0.1070/(18); 0.5724/(17); 1.0462/(33)	96.76	+26.1501	52.26	0.9670
SSA [21]	-	71.45	-0.0101	64.74	0.9687
SFS [16]	0.7540/(14); 1.0994/(24); 1.0714/(30)	71.47	+0.0179	64.74	0.9687
SOS	0.7539/(14); 1.0994/(24); 1.0717/(30)	71.4572	0.0000	64.74	0.9687
QOCSOS	0.7540/(14); 1.0994/(24); 1.0714/(30)	71.4572		64.74	0.9687

TABLE 4: Optimal DRN-DG problem results obtained by QOCSOS and other techniques for Case 3 of 33-bus RDN.

Method	Opened switches	$P_{DG}$ (MW)/(bus)	$P_L$ (kW)	RI (%)	PLR (%)	$V_{min}$ (p.u.)
ACSA [19]	33-34-11-31-28	0.8968/(18); 1.4381/(25); 0.9646/(7)	53.21	+3.1408	73.75	0.9806
SSA [21]	6-14-11-17-28	-	56.42	+8.6515	72.16	0.9762
SFS [16]	7-9-14-27-30	0.7753/(22); 0.7356/(33); 1.2858/(25)	53.01	+2.7753	73.85	0.9720
SOS	6-34-11-31-28	0.7082/(17); 1.4072/(25); 0.7051/(8)	53.0662	+2.8783	73.82	0.9690
QOCSOS	10-28-31-33-34	0.8708/(7); 0.7118/(18); 1.2274/(25)	51.5388		74.57	0.9719

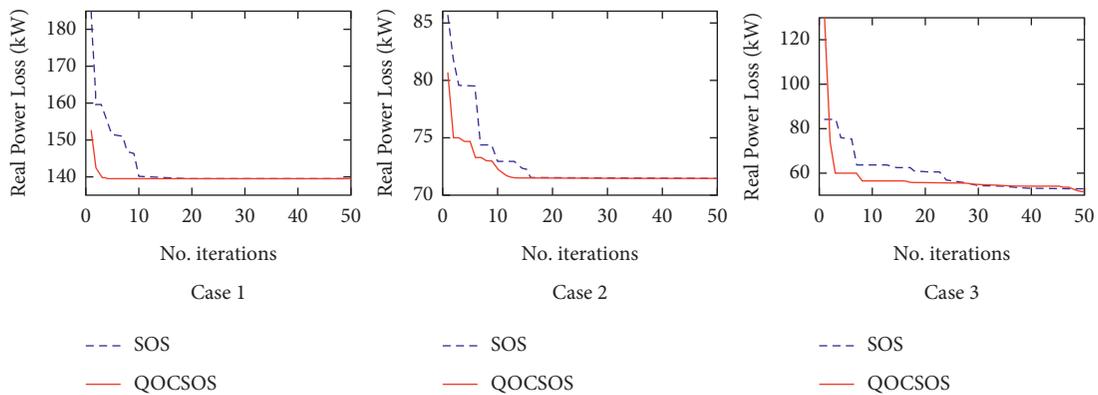


FIGURE 3: Convergence curves by QOCSOS and SOS for all cases of 33-bus network. (a) Case 1. (b) Case 2. (c) Case 3.

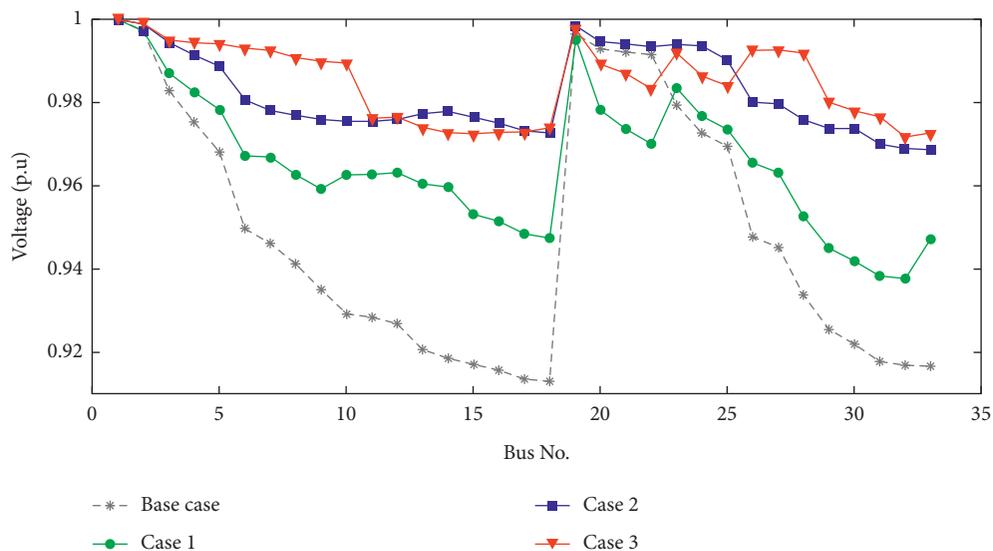


FIGURE 4: Voltage profile for all cases for 33-bus network.

TABLE 5: Optimal configuration obtained by QOCSOS and other techniques for Case 1 of the 69-bus RDN.

Method	Opened switches	$P_L$ (kW)	$RI$ (%)	$PLR$ (%)	$V_{min}$ (p.u.)
Base case	69-70-71-72-73	225.0005		-	0.9092
ASFLA [20]	69-71-14-57-61	98.59	-0.0164	56.16	0.9495
HSA [2]	69-18-13-56-61	99.35	+0.7487	55.85	0.9428
ACSA [19]	69-70-14-57-61	98.59	-0.0164	56.16	0.9495
FWA [14]	69-70-14-56-61	98.56	-0.0469	56.16	0.9495
SSA [21]	69-14-71-61-58	98.63	+0.0241	56.15	0.9492
SFS [16]	14-55-61-69-70	98.62	+0.0140	56.17	0.9495
SOS	14-57-61-69-70	98.6062	0.0000	56.17	0.9495
QOCSOS	14-57-61-69-70	98.6062		56.17	0.9495

TABLE 6: Optimal DG placement results obtained by QOCSOS and other techniques of Case 2 of 33-bus RDN.

Method	$P_{DG}$ (MW)/(bus)	$P_L$ (kW)	$RI$ (%)	$PLR$ (%)	$V_{min}$ (p.u.)
ACSA [19]	0.6022/(11); 0.3804/(18); 2.0000/(61)	72.44	+4.1574	67.79	0.9890
FWA [14]	0.4085/(65); 1.1986/(61); 0.2258/(27)	77.85	+10.8177	65.39	0.9740
HSA [2]	0.1018/(65); 0.3690/(64); 1.3024/(63)	86.77	+19.9857	61.43	0.9677
SSA [21]	-	69.41	-0.0265	69.14	0.9789
SFS [16]	0.5268/(11); 0.3804/(18); 1.7190/(61)	69.44	+0.0167	69.14	0.9790
SOS	0.5268/(11); 0.3804/(18); 1.7190/(61)	69.4284	0.0000	64.74	0.9687
QOCSOS	0.5268/(11); 0.3804/(18); 1.7190/(61)	69.4284		69.14	0.9790

TABLE 7: Optimal DRN-DG problem results obtained by QOCSOS and other techniques of Case 3 for 69-bus RDN.

Method	Opened switches	$P_{DG}$ (MW)/(bus)	$P_L$ (kW)	$RI$ (%)	$PLR$ (%)	$V_{min}$ (p.u.)
ACSA [19]	69-70-14-58-61	0.5413/(11); 0.5536/(65); 1.7240/(61)	37.02	+5.0178	83.54	0.9869
SSA [21]	69-14-70-63-58	-	35.81	-1.8084	84.08	0.9808
SFS [16]	14-56-61-69-70	0.4903/(64); 0.5376/(11); 1.4340/(61)	35.16	-0.0068	84.37	0.9810
SOS	14-58-61-69-70	1.4428/(61); 0.5398/(11); 0.5304/(65)	35.1624	0.0000	84.37	0.9690
QOCSOS	14-58-61-69-70	0.5376/(11); 1.4340/(61); 0.4903/(64)	35.1624		84.37	0.9813

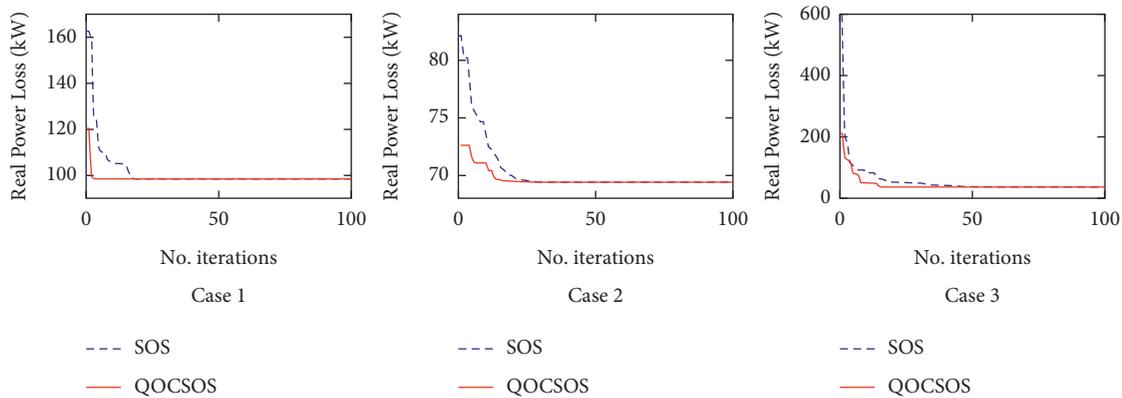


FIGURE 5: Convergence curves by QOCSOS and SOS for all cases of 69-bus network. (a) Case 1. (b) Case 2. (c) Case 3.

which is better than those of SOS, SFS [16], and ACSA [19]. The QOCSOS method can improve the result 1.0250%, 0.7155%, 0.3702%, and 3.6128% compared to SOS, SFS [16], and ACSA [19], respectively.

The real power losses produced by QOCSOS in Cases 1–3 were 854.0309 kW (34.21% PLR), 667.2940 kW (48.59% PLR), and 565.0605 kW (56.47% PLR), according to Tables 8–10. It is shown that Case 3 had the greatest PLR value. This claimed that when the ODGP and DNR problems were examined together, the system’s real power loss was

significantly decreased. In terms of convergence rate, QOCSOS converged to the near-optimal solution at a quicker pace than SOS, as portrayed in Figure 7. The 119-bus network’s voltage profiles are shown in Figure 8 for all cases. The minimal voltage values produced by QOCSOS after solving the DNR-DG issue were 0.9323 p.u., 0.9541 p.u., and 0.9599 p.u. for Cases 1–3, respectively. In addition, Case 3 substantially enhanced the voltage profile after simultaneously considering the ODGP and DNR problems, as seen in Figure 8.

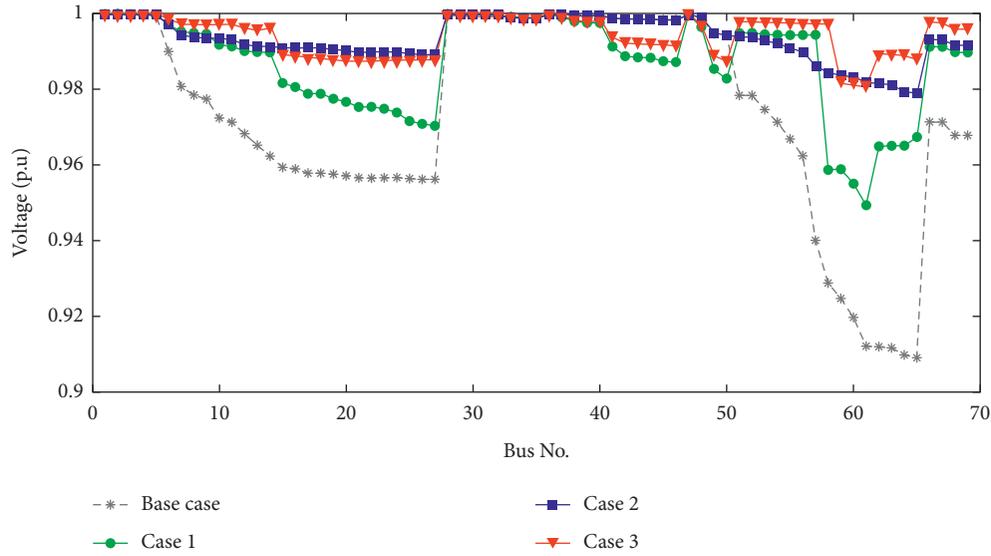


FIGURE 6: Voltage profile for all cases for 69-bus network.

TABLE 8: Optimal configuration obtained by QOCSOS and other techniques for Case 1 of the 119-bus RDN.

Method	Opened switches	$P_L$ (kW)	RI (%)	PLR (%)	$V_{min}$ (p.u.)
Base case	118-119-120-121-122-123-124-125-126-127-128-129-130-131-132	1298.09	—	—	0.8688
ITS [33]	42-26-23-51-122-58-39-95-74-71-97-129-130-109-34	867.4	+1.5413	33.18	0.9323
MTS [34]	42-26-23-51-122-58-39-95-74-71-97-129-130-109-34	867.4	+1.5413	33.18	0.9323
HSA [31]	23-27-33-43-53-62-72-75-123-125-126-129-130-131-132	854.21	+0.0210	34.19	0.9323
ACSA [19]	42-25-23-121-50-58-39-95-71-74-97-129-130-109-34	854.06	+0.0034	34.21	0.9298
FWA [14]	42-25-23-121-50-58-39-95-71-74-97-129-130-109-34	854.06	+0.0034	33.18	0.9298
SFS [16]	42-25-23-121-50-58-39-95-71-74-97-129-130-109-34	854.04	+0.0011	34.21	0.932
SOS	23-25-34-39-42-50-59-71-74-95-97-109-128-129-130	857.1404	+0.3628	33.97	0.9323
QOCSOS	23-25-34-39-42-50-58-71-74-95-97-109-121-129-130	854.0309	—	34.21	0.9323

TABLE 9: Optimal DG placement results obtained by QOCSOS and other techniques for Case 2 of 119-bus RDN.

Method	$P_{DG}$ (MW)/(bus)	$P_L$ (kW)	RI (%)	PLR (%)	$V_{min}$ (p.u.)
SFS [16]	2.9786/(71); 3.1199/(109); 2.8833/(50)	667.29	-0.0006	48.59	0.9541
SOS	2.8833/(50); 2.9785/(71); 3.1199/(109)	667.2940	0.0000	48.59	0.9541
QOCSOS	2.8833/(50); 2.9785/(71); 3.1199/(109)	667.2940	—	48.59	0.9541

TABLE 10: Optimal DRN-DG problem results obtained by QOCSOS and other techniques for Case 3 of 119-bus RDN.

Method	Opened switches	$P_{DG}$ (MW)/(bus)	$P_L$ (kW)	RI (%)	PLR (%)	$V_{min}$ (p.u.)
ACSA [19]	42-25-22-121-122-58-39-125-70-127-128-81-130-131-33	2.5331 (50); 3.6819 (109); 3.7043 (73)	586.24	+3.6128	53.97	0.9644
SFS [16]	43-16-23-42-50-61-124-125-70-74-75-82-130-108-34	2.3133/(110); 4.0392/(91); 8.7132/(29)	567.16	+0.3702	56.31	0.9595
SOS	42-25-22-121-122-58-39-125-70-127-74-129-130-108-33-42	2.6517/(50); 4.0922/(91); 2.3055/(110)	570.9123	+1.0250	56.02	0.9591
QOCSOS	23-26-34-39-42-50-61-70-74-85-86-107-121-125-129	9.3909/(4); 4.1078/(91); 2.5599/(110)	565.0605	—	56.47	0.9599

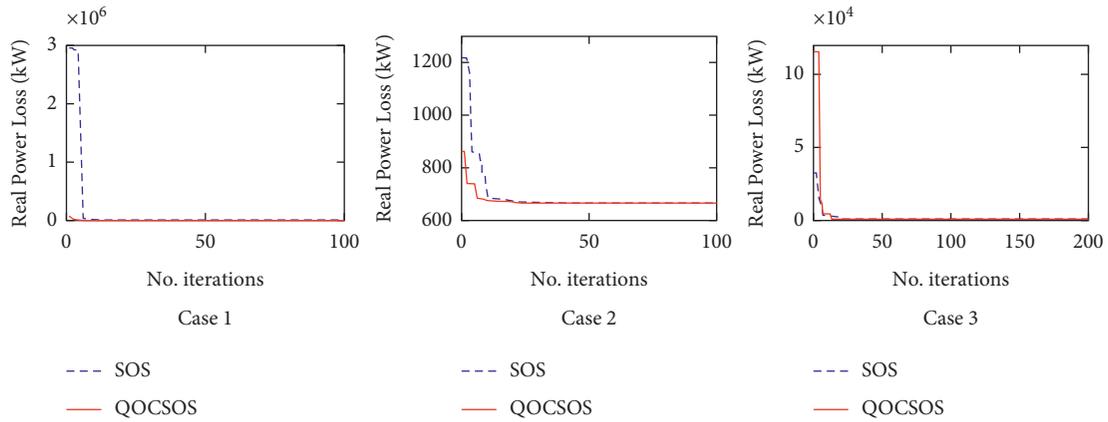


FIGURE 7: Convergence curves by QOCSOS and SOS for all cases of 119-bus network. (a) Case 1. (b) Case 2. (c) Case 3.

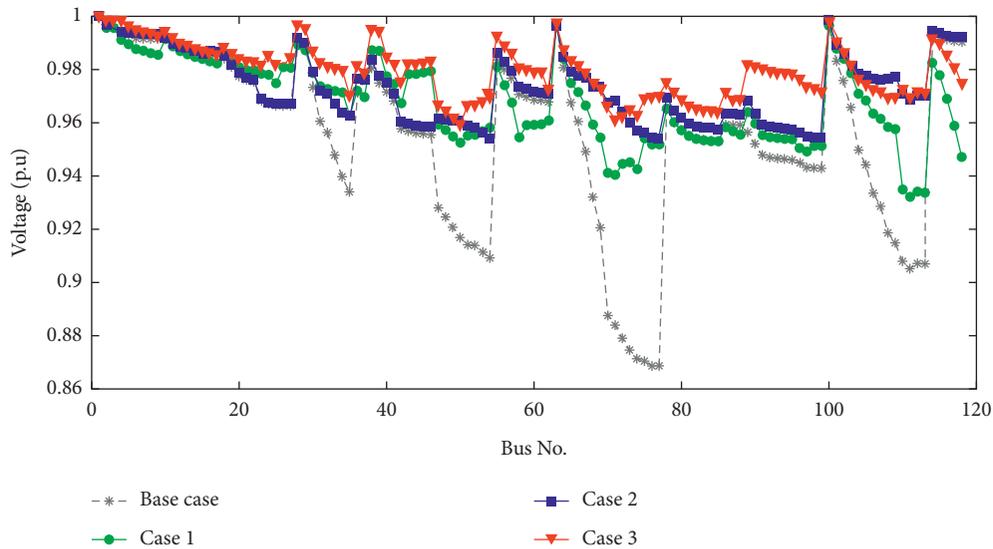


FIGURE 8: Voltage profile for all cases for 119-bus network.

In this case, QOCSOS outperformed the comparable techniques with regard to the solution quality, demonstrating its suitability for a large-scale system.

### 6. Conclusion

In the study, the improved QOCSOS is successfully implemented to solve the simultaneous problems of network reconfiguration and DG allocation in RDNs to reduce the real power loss. The efficacy of QOCSOS has been carried out on the 33-bus, 69-bus, and 119-bus RDNs. It was found that Case 3 (combination of optimal network reconfiguration and DG allocation) offered the best real power loss and minimum voltage amplitude compared to Case 1 (only network reconfiguration) or Case 2 (only optimal DG placement). For this case, the power loss reductions were 74.57%, 84.37%, and 56.47% for the 33-bus, 69-bus, and 119-bus RDNs. Furthermore, the findings showed that the suggested QOCSOS algorithm delivered higher solution quality with regard to loss

minimization than the original SOS and several other optimization approaches, particularly for large-scale systems, as seen from the outcome evaluations. As a result, the QOCSOS algorithm provides a viable solution for the DNR-DG problem in RDNs.

### Data Availability

No data were used to support this study.

### Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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