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Butterfly optimizer assisted Max–Min based multi-objective approach for optimal connection of DGs and optimal network reconfiguration of distribution networks

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Abstract

Currently, the electrical distribution system is experiencing challenges such as low system efficiency due to substantial real power losses, a poor voltage profile, and inadequate system loadability as a result of the tremendous increase in system load demand. Therefore, distribution system operators are searching for ways to improve system efficiency and loadability. Distributed Generation technology has attracted a lot of researchers' interest in recent days because of its enormous technological advantages in dealing with the aforementioned issues. This work presents a Max–Min based multi-objective optimization approach for optimal connection of distributed generators (OCDG) in the presence of optimal distribution network reconfiguration (ODNR) to enhance the system loadability (λ_{\max}) and to reduce real power loss. Two scenarios are taken to achieve the proposed objectives. Scenario-1 deals with the enhancement of loss mitigation & system loadability. In scenario-2, to extract maximum benefits with less amount of real power injection by DGs into the system, DGs real power injection is taken as one of the objectives. Under each scenario, three cases are investigated. Case 1 and case 2 deal with single-objective optimization, whereas case 3 deals with multi-objective optimization. The butterfly Optimization (BO) technique is implemented for the optimization of proposed objectives. The proposed method is tested on 33 bus, 69 bus radial distribution test systems. To test the potential of the BO algorithm, the outcomes are contrasted with the suitable results that are accessible in the literature. From the outcomes, it was observed that real power loss of the system is reduced to (75–89)%, loadability enhanced to (94–121)% with the injection of 64% KVA by DGs into 33 & 69 bus systems.

Keywords: Max–Min method, Distributed generators (DGs), Power loss, Loadability, Butterfly optimizer

Introduction

The current scenario confronts electrical distribution system operators with tremendous challenges, such as an exponential rise in load demand, low distribution system efficiency caused by large real power losses, and poor network voltage profiles. Distribution system I^2R losses account for 13% of the total energy produced, according to recent

studies [1]. Distribution system reconfiguration, connection of DTATCOMs & DGs in the electrical distribution system have all been used in literature to reduce I^2R losses and improve system efficiency. Connecting DGs to the distribution system provides numerous additional advantages, including improved system loadability, reduced congestion in the T&D system, and enhanced EENS. These are just a few. As demand grows, it becomes imperative to increase the system's capacity in order to avoid the need for additional expansion of the infrastructure. These benefits can be harmed, however, by the incorrect positioning or size of DGs in the system. For this reason, in order to maximize the advantages while ensuring that various technical restrictions are met, it has been referred to as the "optimal connectivity of distributed generation (OCDG)" challenge.

The OCDG problem in radial distribution systems is discussed in depth in [2, 3]. The OCDG problem in the distribution system was addressed by certain researchers in order to reduce I^2R loss and improve the voltage profile of the network. For the OCDG problem, authors in [4–6] came up with a variety of analytical approaches. The radial distribution system's efficiency was hoped to be improved by a simulated annealing technique and a harmony search algorithm presented by authors in [7, 8]. DGs were located in the distribution system using loss-sensitivity indexes, and their sizes were employed as decision variables to optimize the intended outcomes. Mathematicians in [9] used a backtracking search optimization approach to reduce real power loss and enhance voltage distribution in a system. For DG placement, writers in [9] looked at the top (15–25%) of buses based on loss-sensitivity bus values, as opposed to the last two articles. Using the Firefly optimization technique and the Backtracking search optimization algorithm, authors in [10] tackled the OCDG and optimal capacitor problems at the same time. Authors in [11] used quasi-oppositional TLBO algorithm to solve a penalty-based multi-objective strategy to improve the OCDG problem's system efficiency, network voltage profile and stability index. Utilizing an optimization method to identify locations and DGs sizes is a better option than using loss-sensitivity indices and DGs sizes in an optimization algorithm to locate locations. DG locations and DG sizes are both treated as decision variables in this work, and an optimization approach is employed to obtain the best values for these variables.

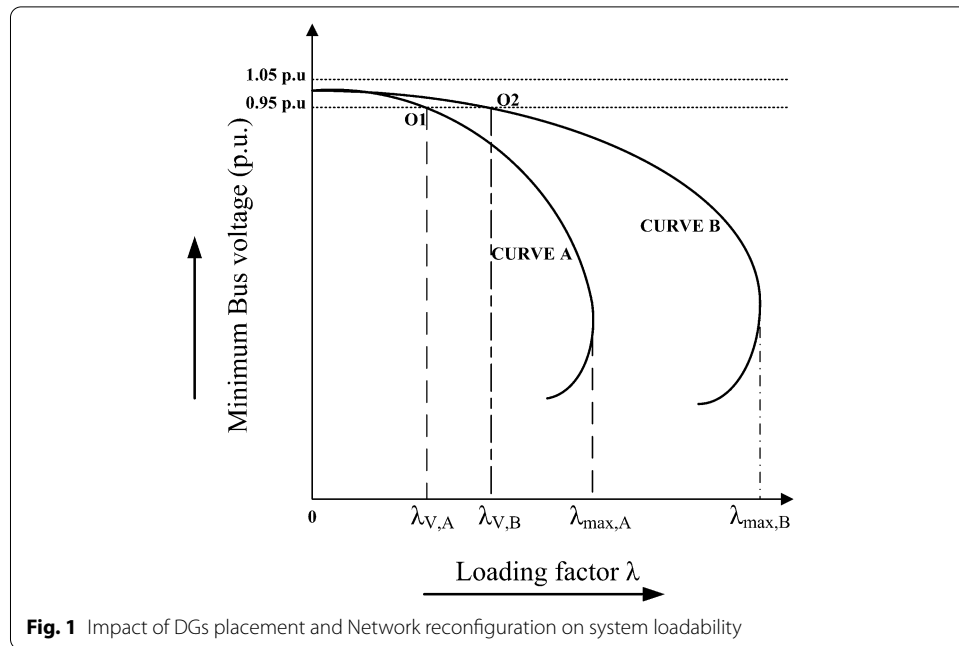
The Non-dominant enhanced differential search multi-objective algorithm for OCDG problem was addressed in [12] by the authors to reduce the I^2R loss, voltage deviation index, and network operation costs. To increase the real power loss reduction, voltage stability factor, and investment benefit of the distribution system, the authors of [13] used a Pareto-based multi-objective ant lion optimizer. A multi-objective approach has been found to be more effective in achieving all three objectives. With a multi-level load profile, the authors in [14] developed a novel objective function for loss mitigation and voltage profile improvement through the appropriate placement of DG and DSCs. To improve real power loss reduction and voltage stability margin in the distribution system, the authors in [15] looked at the OCDG problem under linear load changes from 0.5 to 1.5 times baseload. An algorithm for the best placement of dispatchable and non-dispatchable DGs to reduce energy loss and operating costs while also improving the distribution system's voltage profile under seasonal load variations was discussed in [16]. OCDG under varying distribution system loads was addressed in the last three articles, according to the authors. Authors in [17] used the HSA-PABC optimization algorithm to

find the best location for Type-1 DGs and Type-3 DGs (0.85 leading power factor) under three different load levels of the distribution network to reduce power loss. The best percentage of loss reduction is obtained when Type-3 DGs are placed optimally in the distribution network, according to the results. A TLBO-GWO optimization technique was used by the authors of [18] to place Type-1 DGs and Type-3 DGs with optimum power factors in the distribution network in order to reduce I²R loss and improve reliability. For Type-3 DGs operating with an optimized power factor, the appropriate placement of these DGs minimizes network power loss to the lowest possible value, as evidenced by the above-mentioned articles. Therefore, in this work, we have chosen the best possible placement of Type-3 DGs with an optimized power factor in order to meet our goals.

In order to fulfil the goals of reducing real power loss, improving voltage profile, and balancing the load, an optimal distribution network reconfiguration issue is designed to determine the on/off status of tie and section switches positioned in the system by satisfying the technological restrictions. Bacterial foraging optimization techniques [19, 20] are used to construct an improved selective BPSO algorithm for the optimal network reconfiguration problem to reduce I²R loss. In [21, 22], a mathematical objective function is devised to reduce real power loss and improve the voltage profile of the network. According to [23], there is a Multi-objective Max–Min strategy for minimizing I²R loss, load balancing between branches and feeders, and the amount of switch operations. Type-1 DGs have been handled in [8, 24] to reduce the system's I²R loss using simultaneous ODNr and appropriate connection of Type-1 DGs. With the novel UVDA optimization technique, researchers in [25] attempted to minimize the real power loss in the distribution system by connecting Type-3 DGs optimally while also addressing optimal network reconfiguration issues.

Some researchers took the OCDG and ODNr problems for enhancing the loadability of the network. Loadability (λ_{\max}) of the system is termed as the maximum increase in network load level before the system voltage instability occurs. Figure 1 depicts loading curves A & B of a system without & with the connection of DGs, respectively. From Fig. 1, it is observed that curve B has a better system loadability than curve A, due to the connection of DGs optimally in the system and reconfigured network. And also from Fig. 1, it is noticed that enhancement in system loadability also improves the network voltage profile, i.e., at each loading level, curve B has a better voltage magnitude in comparison with curve A.

Authors in [26–28] addressed the ODNr problem to enhance the system loadability make use of a fuzzy adaptation of the optimization algorithm, discrete ABC algorithm, enhanced HSO algorithm, respectively, and deduced that the ODNr enhances system loadability. In [29], the OCDG problem has used for the improvement of system loadability employing the hybrid PSO—k-matrix algorithm and drawn a conclusion that with 40% of real power injection by DGs into the system, real power loss mitigated to 65–70%, loadability improved to 15–40%. Researchers in [30], taken the OCDG and ODNr problems at a time for enhancement of system loadability and concluded that utmost enhancement of system loadability is noted in the case of DGs connected optimally in the optimal reconfigured network. From the latter two papers, it was observed that even though the system loadability is improved to utmost value but the percentage of real power loss mitigation is not up to the mark. And also, from



the papers [29, 30], it was observed that improving the loadability of the system also improves the voltage profile of the system. Therefore, in this work authors considered the improvement of real power loss reduction and loadability of the system only which in turn also improves the voltage profile of the system. Since loadability of the system should be improved concerning the 100% load level of the system, in this work authors had not considered the load variations of the system. To extract the maximum number of benefits with less amount of power injected by DGs into the system, in this work authors have taken DGs penetration level as one of the objectives. To improve more than one objective at a time, researchers in [7, 10–12, 17] used either weighted-factor or Pareto-based or Max–Min based multi-objective methods. Among them, Max–Min based multi-objective method had advantages like no need to bother about weights or formation of the fronts. And also, since DGs penetration level is taken as one of the objectives, drive the authors of this work for selecting max–min multi-objective method rather than pareto-based multi-objective method.

Therefore, in this work, the multi-objective approach with the Max–Min method is used to mitigate the real power loss and maximize the system loadability (λ_{\max}). To improve the desired objectives two scenarios are considered, i.e., without and with DGs real power injection objective function. Under each scenario three cases are considered, i.e., optimization of single objectives is considered in case-1 & case-2, multi-objective optimization is considered in case-3. And each case having two sub-cases, the optimal connection of DGs in the initial configured network and the optimal connection of DGs in the optimal reconfigured network. BO algorithm is chosen to optimize the proposed objectives. The rest of the paper is organized as follows, section-2 introduces the mathematical formulation aspects of the work done in this work, section-3 will give brief insights of the BO optimization technique and thorough implementation aspects of it, Sect. 4 will illustrate the scenarios taken in this work and the associated results.

Problem formulation

Network real power loss

Real power loss (P_{loss}) have to be minimized for the enhancement of distribution system efficiency.

$$f_1 = \text{minimize}(P_{loss}) \quad (1)$$

$$P_{loss} = J * R^T \quad (2)$$

where, J and R are branch current and branch resistance vectors of size nbr (number of branches). Backward/forward sweep-based load flow [31] is used to obtain P_{loss} .

Loadability of the system

System loadability (λ_{max}) have to be maximized with a view for future load enhancement on the system.

$$f_2 = \text{maximize}(\lambda_{max}) \quad (3)$$

To obtain the λ_{max} of the system, authors had used the method developed in [32].

DGs penetration level

Placing of Distributed Generators in the distribution network changes the distribution system characteristics [33, 34] as bi-directional power flows, changing the passive distribution system network to active distribution network, change in fault current levels, etc. Therefore, to maintain the quality of the network, some of the authors in the literature limited the DG's real power injection into the distribution system. Authors in [9, 29, 35] limited the DGs real power penetration into the distribution system to 40% and 50%, respectively, and Authors in [36] taken DGs penetration level as one of the objectives and limited the DGs real power penetration into the system without violating stability margins. And also, from the literature, it was observed that at lower DGs penetration levels, a significant increase in DGs penetration level results in significant improvement in technical parameters. But at higher DGs penetration levels, a significant increase in DGs penetration level results in an insignificant improvement in benefits of the system.

Therefore, in this paper, instead of limiting DGs real power injection to a fixed percentage say 40% or 50%, authors considered DGs penetration level as one of the objectives in scenario-2 along with the objectives considered in scenario-1, and a detailed analysis is presented in result section between scenario-1 and scenario-2 outcomes.

The mathematical modeling of the DGs real power injection into the system is taken as one of the objectives.

$$f_3 = \text{minimize} \left(\sum_{k=1}^{ndg} P_{DG,k} = P_{T,DG} \right) \quad (4)$$

where $P_{DG,k}$ is the real power delivered by the k th DG unit, $P_{T,DG}$ is the total real power delivered by the DGs units.

Max–Min method

In [23], the authors addressed the multi-objective Max–Min method for optimal network reconfiguration problem to select the comprised solutions between the objectives. The Max–Min method contains a Membership function for each objective function and has a value in the range [0–1]. The membership function for the minimization of the k th objective function is given as follows.

$$MF_k = \begin{cases} 1, & F_k \leq F_k^{min} \\ \frac{F_k^{max} - F_k}{F_k^{max} - F_k^{min}}, & F_k^{min} \leq F_k \leq F_k^{max} \\ 0, & F_k \geq F_k^{max} \end{cases} \quad (5)$$

where F_k, F_k^{max} , and F_k^{min} are the k th objective function value, maximum and minimum values of the k th objective function, respectively. For maximization of the k th objective function, reciprocal of k th objective function value, minimum and maximum values of the k th objective function have to take to get F_k, F_k^{min} , and F_k^{max} , respectively. The value of F_k^{min} is taken from the outcome of that single-objective optimization, the value of F_k^{max} is taken from the base load flow results.

Since the F_k^{max} is subtracted from the F_k in the numerator of the Membership value (MF_k) of an objective function, the objective function with the highest MF_k value is well improved and the objective function with the lowest MF_k value is less improved in terms of minimizing the objective function. Then a fuzzy decision for a comprised solution is defined as the choice of maximizing the lowest MF_k value. In other words, the multi-objective function is transformed into a single objective by maximizing the minimum value among all membership values as follows:

$$\text{Maximize of} = \{\min\{MF_k\}\} \quad (6)$$

The above maximization problem is converted into a minimization problem is as follows

$$\text{Minimize of} = \{1 - \{\min\{MF_k\}\}\} \quad (7)$$

Constraints

The following constraints need to satisfy for the optimal network reconfiguration and connection of DGs to the distribution system.

- The voltage magnitude of the buses in the system should be within the permissible limits.

$$|V_{min}| < |V_i| < |V_{max}| \quad i = 1, 2 \dots nb \quad (8)$$

where nb is the total number of buses are there in test system. In this paper, we have taken.

$$|V_{min}| = 0.95 \text{ p.u. and } |V_{max}| = 1.05 \text{ p.u.}$$

- The magnitude of current in each branch should be less than the maximum current rating of the respective branch.

$$I_j \leq I_j^{max} \quad j = 1, 2 \dots nbr \quad (9)$$

where nbr is the total number of branches.

- c. Power injected by each DG ($P_{DG,k}$) must be less than the maximum power limit of DGs.

$$P_{DG,k} \leq P_{DG,k}^{max} \quad k = 1, 2 \dots ndg \quad (10)$$

where ndg is the number of DGs connected to the system. In this paper, the maximum real power injection by DGs ($P_{DG,k}^{max}$) limited to the total real power demand supplied by the DGs.

- d. Power factor of DGs must be between the minimum (pf_k^{min}) and unity power factor limits.

$$pf_k^{min} \leq pf_k \leq 1 \quad k = 1, 2 \dots ndg \quad (11)$$

In this paper, the minimum power factor of the DG unit is limited to 0.8.

- e. Total real power ($P_{T,DG}$) and reactive power injected ($Q_{T,DG}$) by DGs must be less than the distribution system real (P_{load}) and reactive power (Q_{load}) demand.

$$\sum_{k=1}^{ndg} P_{DG,k} = P_{T,DG} \leq P_{load} \quad (12)$$

$$\sum_{k=1}^{ndg} Q_{DG,k} = Q_{T,DG} \leq Q_{load} \quad (13)$$

- f. Power balance constraints.

$$P_{sub} + P_{T,DG} = P_{load} + P_{loss} \quad (14)$$

$$Q_{sub} + Q_{T,DG} = Q_{load} + Q_{loss} \quad (15)$$

where P_{sub} , Q_{sub} are the real and reactive power demands at the substation.

- g. The ODNR problem requires checking the radiality status of the network. In this work spanning tree technique is used for checking the status of network radiality [37].

DG Placement performance indices

The following performance indices are considered to evaluate the impact of optimal DGs connection and optimal network configuration on the distribution system.

- a. Percentage Real power loss reduction

$$\%PLR = \frac{P_{loss}^b - P_{loss}^{(DG+NR)}}{P_{loss}^b} \quad (16)$$

where P_{loss}^b is the base case real power loss of the system, $P_{loss}^{(DG+NR)}$ is the real power loss of the system after placement of DGs and network reconfiguration.

b. Percentage Maximum Loadability improvement

$$\%MLI = \frac{\lambda_{max}^{(DG+NR)} - \lambda_{max}^b}{\lambda_{max}^b} \quad (17)$$

Where λ_{max}^b is the base case maximum loadability of the system, $\lambda_{max}^{(DG+NR)}$ is the maximum loadability of the system after placement of DGs and network reconfiguration.

Butterfly optimization algorithm

In the literature, various researchers have taken several optimization algorithms for the OCDG and ODNr problems. According to the “No Free lunch theorem,” no optimization algorithm gives exceptional results for all optimization problems. An optimization algorithm may give admirable results for some set of optimization problems and may give inferior results for another set of optimization problems. Performance-wise, all optimization algorithms are indistinguishable while solving a whole set of optimization problems. However, while choosing an optimization problem author of this paper have taken care of few things like since finding loadability of the distribution system is a very tedious process, authors try to avoid optimization algorithms with a two-stage evolutionary process like in cuckoo search algorithm, TLBO algorithm, etc., and algorithm should be easy in implementation. Since the Butterfly optimization (BO) algorithm is a new one and advantages like the ease in implementation have driven the authors to use this algorithm [38–40].

Sankalp A and S Singh developed the butterfly optimization (BO) method, a population-based meta-heuristic optimization strategy [41]. By drawing inspiration from butterfly mating and food seeking habits, the algorithm was created. They will rely on their sense of smell to find food and a partner for mating. In the process of searching for food, butterflies will release aromas with some force, and the potential of the scents/aromas is relative to the quantity of food source in the butterfly’s neighborhood. It will emit a scent that will be picked up by others. If the other butterflies in the cluster are able to detect the aroma, they will move toward it. From one location to the next, butterflies will travel about in search of a good food source in this manner.

It is assumed that all butterflies are searching agents in the BO algorithm. Each agent will be assigned a specific location and a distinct fragrance. The scent of the agents is linked to the performance of the objective functions. In Eq. 18, the aroma’s mathematical representation is provided.

$$f = cI^a \quad (18)$$

where f , I , c & a are the magnitude of the aroma, stimulus intensity, sensor modality and power exponent. In the algorithm, I is taken as the fitness of the respective searching agent.

All agents will move to the new positions as per mathematical formulated Eqs. 19 & 20.

Update the position of i th agent using for global search Eq. 19 if $randomvalue[0, 1] < P$

$$x_i^d(t+1) = x_i^d(t) + \left(r^2 * gbest - x_i^d(t) \right) \quad * f_i i = 1 \dots N \quad (19)$$

or Update the position of i^{th} agent for local search using Eq. 20

$$x_i^d(t+1) = x_i^d(t) + \left(r^2 * x_j^d(t) - x_k^d(t) \right) \quad * f_i i = 1 \dots N \quad (20)$$

where $x_j^d(t)$ and $x_k^d(t)$ are random J th and k th butterflies and N, d, r, p are Number of agents, Number of decision variables, arbitrary random number & switching probability lies in the range $[0, 1]$.

The detailed step-by-step implementation procedure of the proposed multi-objective Max–Min BO optimization technique for finding befitting DGs sizes, locations and power factors to obtain the desired objectives are given as follows.

1. Initialize optimization technique parameters N, d, p, c, a , Maximum number of iterations.
2. Read the test system line data and load data. Run the load flow algorithm for the base case to get F_k^{max} values for objectives power loss, system loadability & run single-objective optimization programs to get F_k^{min} values.
3. Initialize minimum and maximum limit values of decision variables. For optimal connection of DGs with optimized power factors problem, the total number of decision variables is equal to three times the number of DGs to be connected (DGs locations, DGs sizes, DGs power factors) in the system. Therefore, decision variables minimum and maximum variable limit vectors are shown in Eq. 21 and 22.

$$X_{min} = [L_{1min} L_{2min} \dots L_{dmin}, S_{1min} S_{2min} \dots S_{dmin}, pf_{1min} pf_{2min} \dots pf_{dmin}] \quad (21)$$

$$X_{max} = [L_{1max} L_{2max} \dots L_{dmax}, S_{1max} S_{2max} \dots S_{dmax}, pf_{1max} pf_{2min} \dots pf_{dmax}] \quad (22)$$

where in the above vectors, L indicates DGs locations, S indicates DGs sizes and pf indicates DGs power factors.

4. Generate initial solutions using Eq. 23 as follows

$$x_j^i = [X_{min,j} + (X_{max,j} - X_{min,j}) * rand] \quad i = 1 \dots N, j = 1 \dots \text{length}(X_{min}) \quad (23)$$

A set of initial solutions generated using Eq. 23 is depicted in the matrix as follows

$$X = \begin{bmatrix} L_1^1 \dots L_j^1 \dots L_d^1, S_1^1 \dots S_j^1 \dots S_d^1, pf_1^1 \dots pf_j^1 \dots pf_d^1 \\ \vdots \\ L_1^i \dots L_j^i \dots L_d^i, S_1^i \dots S_j^i \dots S_d^i, pf_1^i \dots pf_j^i \dots pf_d^i \\ \vdots \\ L_1^N \dots L_j^N \dots L_d^N, S_1^N \dots S_j^N \dots S_d^N, pf_1^N \dots pf_j^N \dots pf_d^N \end{bmatrix} \quad (24)$$

5. Run the load flow program for each solution in matrix X and get power loss, system loadability and then calculate membership values for objectives in each solution set using Eq. 25 as follows

$$MF_{i,k} = \begin{cases} 1, & F_{i,k} \leq F_k^{min} \\ \frac{F_k^{max} - F_{i,k}}{F_k^{max} - F_k^{min}}, & F_k^{min} \leq F_{i,k} \leq F_k^{max} \\ 0, & F_{i,k} \geq F_k^{max} \end{cases} \quad \text{for } i = 1 \dots N, k = 1 \dots M \quad (25)$$

And then calculate objective function value or fitness value for each solution set in the matrix X using Eq. 26.

$$of_i = 1 - \{ \min \{ MF_{i,1} \dots MF_{i,k} \dots MF_{i,M} \} \} \quad (26)$$

As a whole, the whole fitness calculation method for all the agents is depicted in Eq. 27

$$OF = \begin{bmatrix} F_{1,1} \dots F_{1,k} \dots F_{1,M} \rightarrow MF_{1,1} \dots MF_{1,k} \dots MF_{1,M} \rightarrow of_1 \\ \vdots \\ F_{i,1} \dots F_{i,k} \dots F_{i,M} \rightarrow MF_{i,1} \dots MF_{i,k} \dots MF_{i,M} \rightarrow of_i \\ \vdots \\ F_{N,1} \dots F_{N,k} \dots F_{N,M} \rightarrow MF_{N,1} \dots MF_{N,k} \dots MF_{N,M} \rightarrow of_N \end{bmatrix} \quad (27)$$

Find the solution with minimum objective function value (*of*) value and declare the corresponding solution set from matrix X as the global best solution.

6. Set iteration count = 0.
7. Update the aroma/fragrance of butterflies using Eq. 18.
8. Update the solutions of each agent using Eq. 19 & Eq. 20.
9. Calculate the objective function value or fitness value of each updated agent using the sequential process followed in Step 5.
10. Perform greedy selection between updated solutions and old solutions.
11. Update global best solution.
12. If the iteration count is less than the maximum number of iterations repeat steps 6–11 else print out the results such as global best solution, objective function values.

Results and discussion

In this section, the proposed BO technique for enhancement of the system loadability (λ_{max}) and real power loss mitigation is applied on 33 & 69 bus distribution test systems for the scenarios and cases shown in Table 1. In turn, each case is divided into two sub-cases a) optimal connection of DGs in the initial network without application of ODNR problem b) Optimal connection of DGs in the optimal reconfigured network which is obtained from the ODNR problem. The tuned BO algorithm parameters are shown in Table 2. All the simulations are implemented in MATLAB R2017a platform and carried out in computer having Core i7 7200U 3.10 GHz, 16 GB RAM.

Table 1 Scenarios and cases considered in this paper

Type of scenario/ Cases	Case-1	Case-2	Case-3
Scenario-1 Objectives	Power loss Minimization (f_1)	Loadability Maximization (f_2)	Optimization of (f_1) & (f_2) using Max–Min Method
Scenario-2 Objectives	Power loss Minimization (f_1) + Minimization of Total Real power supplied by DGs & (f_3) using the Max–Min method	Loadability Maximization (f_2) + Minimization of Total Real power supplied by DGs (f_3) using the Max–Min method	Optimization of (f_1), (f_2) & (f_3) Using the Max–Min Method

Table 2 BO algorithm parameters

Parameter Description	Assigned Value
Number of Agents	150 for 33 & 69 Bus systems 300 for 199 Bus system
Dimension	Depends on Test System
Maximum number of iterations	150 for 33 & 69 Bus systems 300 for 119 Bus system
Modular modality 'c'	0.01
Power exponent 'a'	0.3
Probability switch 'P'	0.7

33 Bus radial distribution system

The line & load data of the system is taken from [29]. The system has 33 section switches and 5 tie switches. Normally tie switches are in open condition. The load on the system is 3.715 MW + j 2.3 MVAR. The base case real power loss is 210.98 kW, system loadability is 3.4, and the minimum voltage is 0.9038 p.u.

From the results of the ODNR problem, the points observed are.

1. In case of f_1 optimization, the real power loss is reduced to 138.5513 kW. And also, in this case, system loadability is improved to 4.87. For this case, switches given by the algorithm are 7, 9, 14, 32, and 37.
2. In case of f_2 optimization, the system loadability is enhanced to 5.23. And also, in this case, system network power loss is reduced to 139.9782 kW. For this case, switches given by the algorithm are 7, 9, 14, 28, and 32.
3. From the above observations, it is perceived that in the case of f_2 maximization, both objectives is improved. Therefore, the optimal switches determined by the algorithm for enhancement of f_2 are considered for case-3b.

Table 3 shows the outcomes of the OCDG problem for scenario 1. From the outcomes tabulated in Table 3, the succeeding points are observed. In case-1a & case-1b, the real power loss is reduced to 12.7458 kW & 18.7531 kW, respectively. It is observed that the real power loss of the system is reduced to the lowest value in the case of DGs placed in the initial configured network. In Case-2a & case-2b, system loadability is improved to 5.1 & 7.23 from 3.4 & 5.23, respectively. It is noticed that system loadability is improved

Table 3 Simulation results of 33 bus system for scenario-1

Parameters/ Cases	Initial configured network Open Switch positions 33 34 35 36 37			Optimal Reconfigured Network Open Switch positions 7 9 14 28 32		
	Case-1a	Case-2a	Case-3a	Case-1b	Case-2b	Case-3b
DG sizes in kW/Bus/ power factor	1044/24/0.88 1156/30/0.8 737/14/0.88	1832/31/0.8 550/17/1 792/14/0.82	1009/15/0.89 837/7/0.8 1097/31/0.8	414/33/0.92 573/12/0.88 1520/29/0.8	356/32/0.8 2519/30/0.83 828/33/0.93	969/31/0.8 1164/29/0.8 564/33/0.91
Minimum and Maximum voltage in p.u	0.9916 & 1.0007	0.9853 & 1.0498	0.9848 & 1.0371	0.9884 & 1.001	0.978 & 1.0495	0.9732 & 1.028
λ_{max}	4.4	5.1	4.78	6.15	7.23	6.76
λ_V	1.49	2.04	1.85	1.75	1.68	1.56
Real power loss in kW	12.7458	86.5804	39.1317	18.7531	98.8904	42.7188
OF value	–	–	0.1364	–	–	0.1894
% KVA DG INJECTION	79.17	84.97	81.014	68.4	99.6	74.92
% PLR	93.95	58.96	81.45	91.11	53.12	79.75
% MLI	29.41	50	40.58	80.88	112.64	98.82

to the utmost value in the case of DGs connected optimally in the optimal reconfigured network, i.e., in case-2b. From the outcomes of case-2a & case-2b, it is also noticed that real power loss is only reduced to 86.5804 kW and 98.8904 kW, respectively. To improve both loss reduction and system loadability, a multi-objective approach with the Max–Min method is taken in case-3. For case-3a, the minimum (F_k^{max}) and maximum (F_k^{min}) objective function values taken for real power loss are 12 kW, 210.98 kW and for maximum loadability are 1/5.1, 1/3.4. For case-3b, the minimum and maximum objective function values taken for real power loss are 18 kW, 139.9782 kW, for maximum loadability are 1/7.23, 1/5.23. The convergence graphs for all cases of scenario-1 are shown in Fig. 2.

From the results of case-3a & 3b, the points observed are as follows.

1. In case-3a, the system loadability is enhanced to 4.78 from 3.4, and loss is reduced to 39.1317 kW from 210.98 kW shows an improvement in both the objectives unlike in case-1a & case-2a.
2. In case-3b, the system loadability is enhanced to 6.76 from 5.23 and loss is reduced to 42.7188 kW from 139.9782 kW shows an improvement in both the objectives unlike in case-1b & case-2b.
3. In scenario-1, the utmost percentage of improvement in both the objectives is observed in case-3b, i.e., in the case of DGs optimally connected in the optimal reconfigured network while optimizing f_1 and f_2 using the Max–Min method.

The minimum (F_k^{min}) and maximum (F_k^{max}) objective function values taken in scenario-2 for case-1a are 12 kW, 210.98 kW, for case-1b are 1/5.1, 1/3.4, for case-2a are 18 kW, 139.9782 kW and for case-2b are 1/7.23, 1/5.23 for system loadability. The minimum limit for DGs real power injection is taken as 50% of the system real power demand i.e., $3715 \times 0.5 = 1857$ kW, and the maximum real power injective power limit by DGs is taken as 100% injection level.

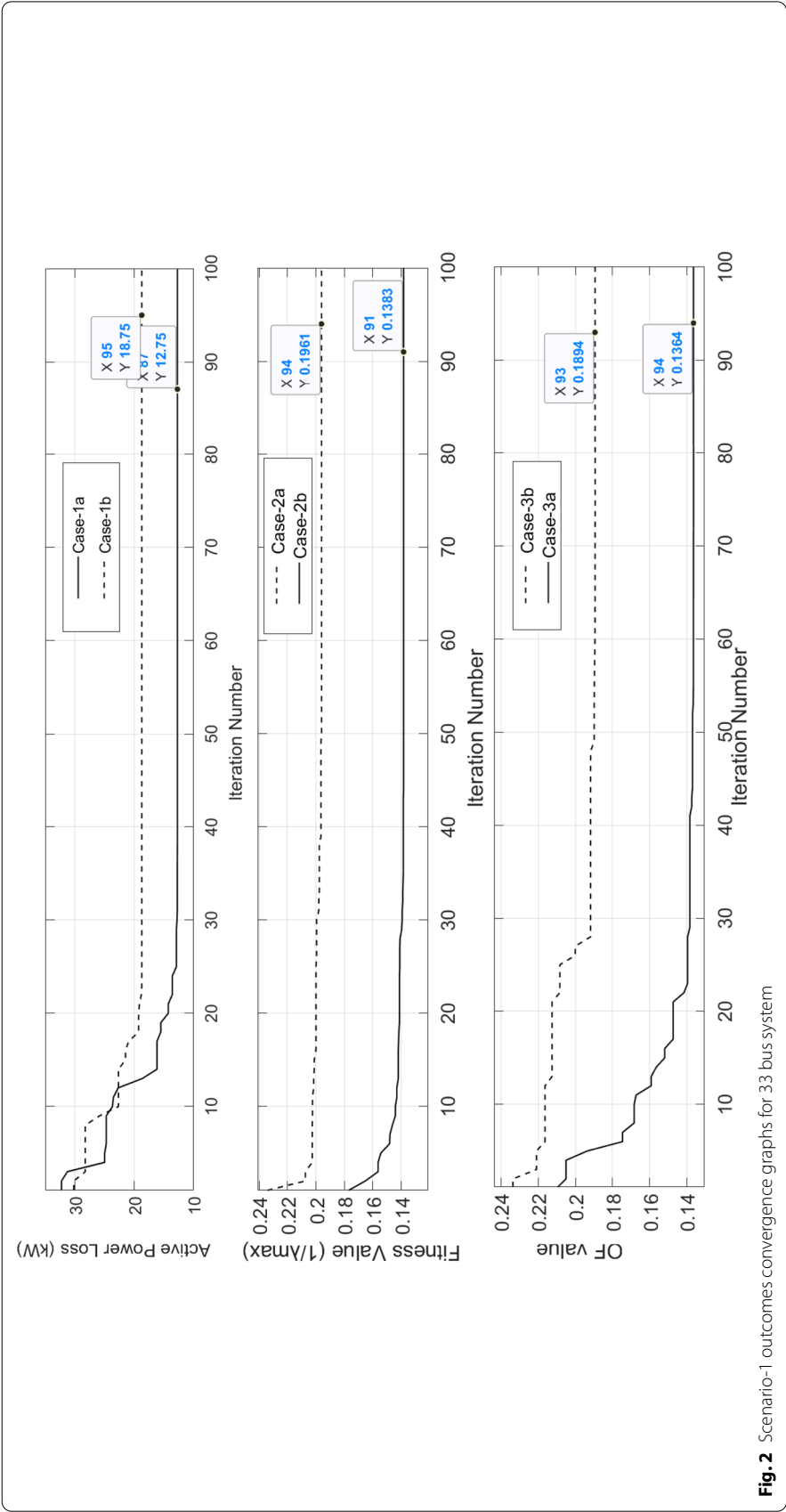


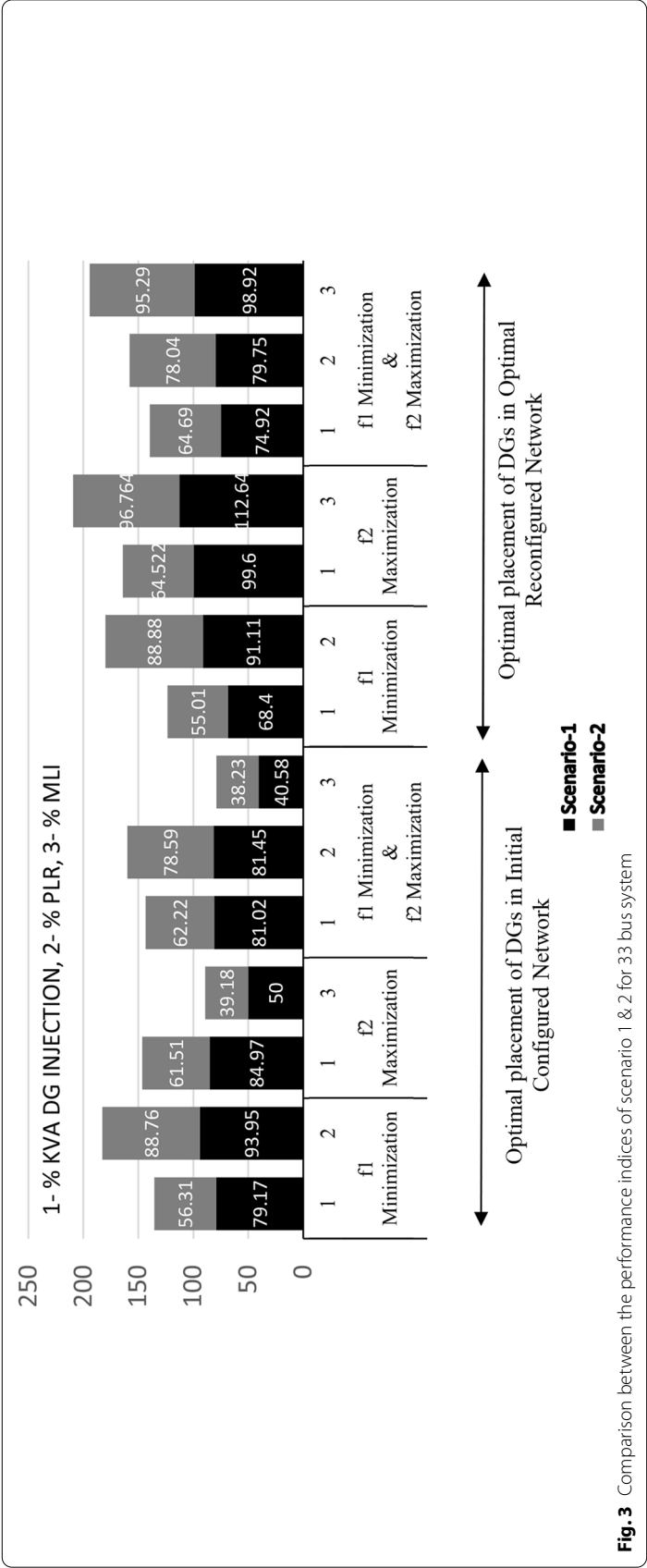
Fig. 2 Scenario-1 outcomes convergence graphs for 33 bus system

Table 4 shows the outcomes of the OCDG problem for scenario 2. Figure 3 depicts the comparison between the performance indices of scenario-1 & 2. From Fig. 3 it is observed that even though there is a significant difference between the % KVA injection by DGs into the distribution system in scenario-1 & scenario-2 cases, but the difference between the performance indices is very less. Therefore, it can be concluded that the optimal placement of DGs in scenario-2 gives a better improvement in objectives (% PLR & % MLI) with less amount of % KVA injection by the DGs into the system.

From Table 4, the succeeding points are noticed. In the case of f_1 and f_3 optimization, loss is reduced to 23.715 kW & 23.446 kW in case-1a & case-1b, respectively. It is noticed that the amount of loss reduction is almost the same for both cases. In the case of f_2 and f_3 optimization, system loadability is improved to 4.73 & 6.69 in case-2a & case-2b, respectively, but the loss is reduced to 55.4613 kW and 56.2606 kW only. Therefore, to improve the real power loss reduction along with loadability, optimization of f_1, f_2 , and f_3 are considered in case-3a & case-3b. The points observed from case-3a & case-3b are real power loss is reduced to 45.1702 kW, 46.3242 kW, respectively, system loadability is increased to 4.7, 6.64. From case-3a & 3b of scenario-2, it is concluded that the optimal connection of DGs in the reconfigured network shows better improvement in both the objectives, i.e., loss reduction and system loadability enhancement. The convergence graphs for all cases of scenario-2 are shown in Fig. 4. Based on the above discussions it can be concluded that among all the cases in scenario-1 & 2, the highest percentage of improvement in both the objectives is observed in case-3b of scenario-1, i.e., by the injection of 74.92% kVA into the system, real power loss is reduced to 79.75%, system loadability is increased by 98.92%. An almost equal percentage of improvement in both objectives with less amount of % kVA injection by DGs into the system is observed in case-3b of scenario-2, i.e., with 64.69% kVA injection into the system, the loss is reduced to 78.04%, system loadability is increased by 95.29%.

Table 4 Simulation results of 33 bus system for scenario-2

Parameters/ Cases	Initial configured network Open Switch positions 33 34 35 36 37			Optimal Reconfigured Network Open Switch positions 7 9 14 28 32		
	Case-1a	Case-2a	Case-3a	Case-1b	Case-2b	Case-3b
DG sizes in kW/ Bus/power factor	556/14/0.8 500/25/0.8 913/30/0.8	505/16/0.8 543/18/0.8 1102/32/0.8	640/32/0.8 1027/16/0.8 508/30/0.8	500/16/0.92 1026/30/0.8 500/12/0.85	500/33/0.8 1210/32/0.8 545/31/0.8	494/33/0.84 209/25/0.82 1588/31/0.8
Minimum and Maximum volt- age in p.u	0.9793 & 1	0.9811 & 1.0465	0.9813 & 1.0361	0.9825 & 1	0.9735 & 1.0305	0.9727 & 1.0249
λ_{max}	4.2	4.73	4.7	5.97	6.69	6.64
λ_V	1.31	1.66	1.69	1.55	1.56	1.55
Real power loss in kW	23.715	55.4613	45.1702	23.446	56.2606	46.3242
OF value	0.0587	0.1564	0.1702	0.0895	0.2129	0.2196
% KVA DG INJECTION	56.31	61.51	62.22	55.006	64.522	64.69
% PLR	88.76	73.71	78.59	88.88	73.33	78.04
% MLI	23.529	39.18	38.23	75.58	96.764	95.29



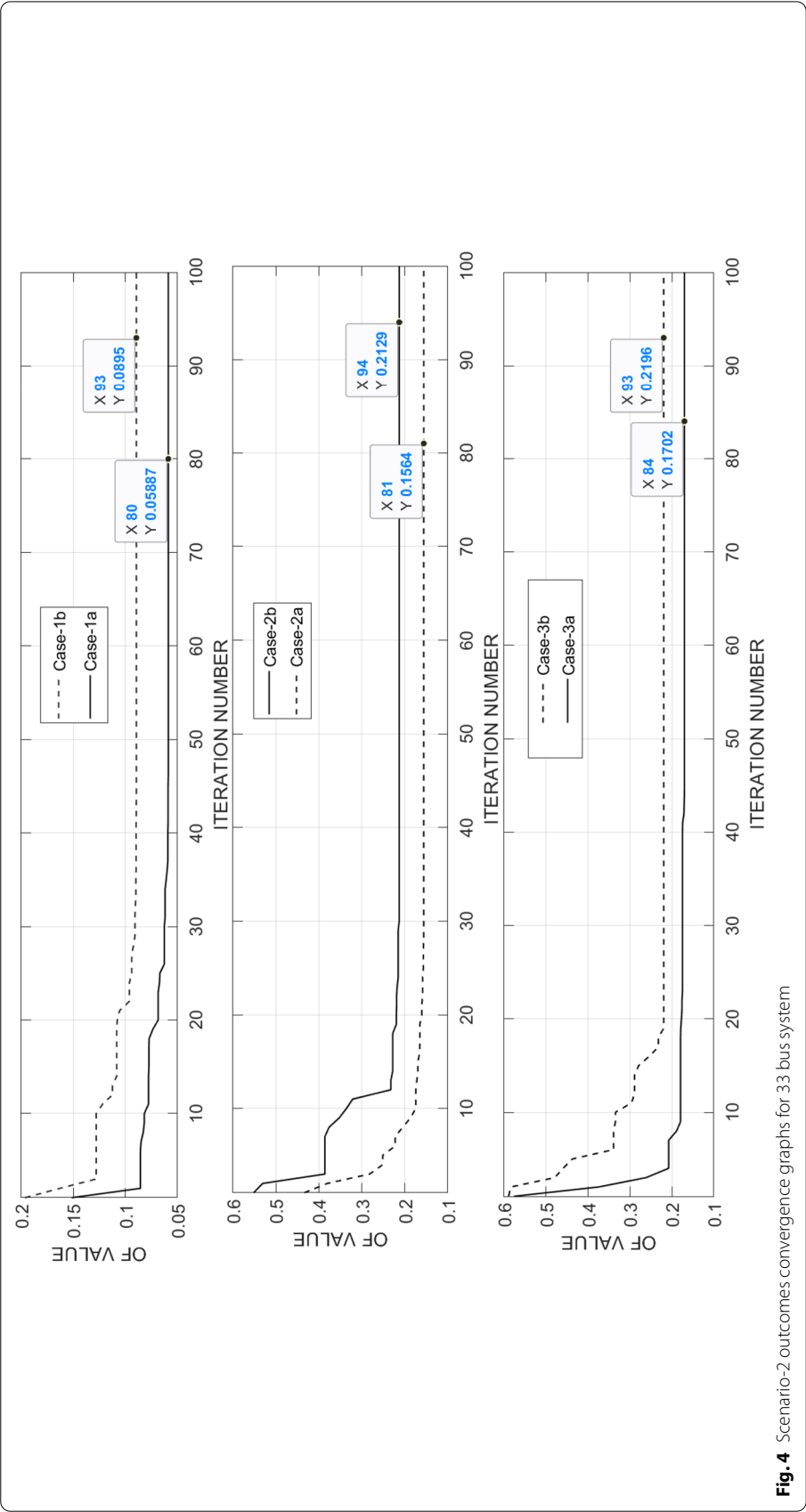


Fig. 4 Scenario-2 outcomes convergence graphs for 33 bus system

To access the capability of the BO optimization technique to the proposed methodology, the results obtained are contrasted with the befitting methods and algorithms that are accessible in the literature and shown in Table 5. From Table 5, it is observed that in case of power loss minimization by the optimal placing of DGs in the initial configured case & optimal reconfigured case, the proposed BO algorithm reduces the real power loss to 93.95% & 91.11, respectively, whereas HTLBO-GWO, HAS-PABC, UVDA reduces real power loss to 93.51%, 92.51%, and 87.98%, respectively. In the case of loadability maximization, the BO algorithm improves it to 50% whereas HPSO improves it to 48.23% only. In scenario-2, in the case of loss minimization, the loss is reduced to 88.76% with 53.01 kW injection by DGs into the system, whereas the BSOA algorithm reduces it to 85.94% with % 50 kW real power injection by DGs into the system. In [29], with 40% kW or 47.05 kVA injection by DGs into the system, real power loss reduced to 71.75%, system loadability increased to 26.76%. But with the proposed method in this paper, with 64.69% kVA injection by DGs into the system, real power loss reduced to 78.09%, maximum loadability increased to 95.29% that shows an improvement in both the objectives unlike the method in [29] which shows the efficacy of the proposed method.

69 Bus radial distribution System

The line & load data of the system are taken from [29]. The system has 69 section switches and 5 tie switches. Normally tie switches are in open condition. The load on the system is 3.801 MW + j 2.693 MVAR. The base case real power loss is 224.9515 kW, loadability of the system is 3.21 and the minimum voltage is 0.9091 p.u.

From the results of the ODNR problem, the following points are observed. In the case of individual optimization of objective functions f_1 & f_2 , switches given by the algorithm are the same, i.e., they are 14, 58, 61, 69, and 70. For these switch combinations real

Table 5 Comparison results of 33 bus system

Method	DGs sizes in kW/BUS/ p.f	% DG kW or kVA	% PLR	%MLI
Scenario-1/ Power loss Minimization / Initial Configured Network				
Proposed BO algorithm	(1044/24/0.88), (1156/30/0.8), (737/14/0.88)	NA	93.95	NA
HTLBO-GWO [18]	(997/30/0.86), (1000/13/0.81), (789/24/0.87)	NA	93.51	NA
HAS-PABC [17]	(862/12/0.85), (1159/30/0.85), (816/25/0.85)	NA	92.45	NA
Scenario-1/ Power loss Minimization / Optimal Reconfigured Network				
Proposed BO algorithm	(414/33/0.92), (573/12/0.88), (1520/29/0.8)	NA	91.11	NA
UVDA Method [25]	(1.125 + j1.034/30), (0.592 + j0.252/15) (0.526 + j0.280/12)	NA	87.98	NA
Scenario-1/ Loadability Maximization / Initial Configured Network				
Proposed BO algorithm	(1832/31/0.8), (550/17/1), (792/14/0.82)	NA	NA	50
HPSO Algorithm [29]	(377/29/0.85), (1160/15/0.85), (1677/31/0.85)	NA	NA	48.23
Scenario-2/Power loss Minimization / Initial Configured Network				
Proposed BO algorithm	(556/14/0.8), (500/25/0.8), (913/30/0.8)	%56.31 KVA/% 53.01 kW	88.76	NA
BSOA algorithm	(698/13/0.86), (402/29/0.71), (658/31/0.7)	% 50 kW	85.94	NA
Scenario-2/ Loadability Maximization / Initial Configured Network				
Proposed BO algorithm	(505/16/0.8), (543/18/0.8), (1102/32/0.8)	%57.87 kW/ % 61.51 kVA	NA	39.18
HPSO Algorithm [29]	(583/14/0.85), (583,18,0.85), (583,32,0.85)	% 40 kW	NA	26.76

power loss is mitigated to 98.55 kW, loadability enhanced to 5.23. Therefore, the above-mentioned optimal switches are considered for the OCDG problem in the optimal reconfigured network case.

Table 6 shows the outcomes of the OCDG problem for scenario 1. In case-1a & 1b, the power loss is reduced to 4.487 kW & 5.3082 kW. It is observed that the power loss is reduced to the lowest value in the case of DGs connected optimally in the initial configured network. In case-2a & case-2b, the system loadability is improved to 4.91 & 7.71, respectively, but the real power loss is only reduced to 89.8601 kW & 93.9651 kW. In case-3a & 3b, the system loadability is improved to 4.61 & 7.07 and real power loss is reduced to 30.2921 kW & 25.313, respectively. From scenario-1 outcomes, it can be deduced that both the loadability and real power loss reduction are well improved in case-3b. The convergence graphs for all cases of scenario-1 are shown in Fig. 5. Figure 6 depicts the comparison between the performance indices of scenario-1 & 2. From Fig. 6, it is noticed that the optimal connection of DGs in scenario-2 gives a better improvement in objectives (% PLR & % MLI) with less amount of % KVA injection by the DGs into the system.

Table 7 shows the outcomes of the OCDG problem for scenario 2. In case-1a & 1b, the real power loss is reduced to 9.6078 & 7.0345 kW, respectively, but the system loadability is improved to 4.09 & 6.4 only. In case-2a & 2b, the system loadability is enhanced to 4.51 & 7.04, respectively, but the power loss is reduced to 35.096 kW & 46.448 kW only. Among case-3a & case-3b, better enhancement in both objectives is observed in optimal connection of DGs in optimal network reconfigured case, i.e., real power loss is reduced to 23.8112 kW and system loadability is enhanced to 6.94. The convergence graphs for all cases of scenario-2 are shown in Fig. 7. Based on the above discussions it can be concluded that among all the cases in scenario-1 & 2, better improvement in both objectives with less % KVA injection by DGs is observed in case-3b of scenario-2, i.e., real power loss is reduced to 89.414%, maximum loadability is increased to 116.19%.

To access the capability of the BO optimization technique to the proposed methodology, the results obtained are contrasted with the befitting methods and algorithms that

Table 6 Simulation results of 69 bus system for scenario-1

Parameters/Cases	Initial configured network Open Switch positions 69 70 71 72 73			Optimal Reconfigured Network Open Switch positions 14 58 61 69 70		
	Case-1a	Case-2a	Case-3a	Case-1b	Case-2b	Case-3b
DG sizes in kW/Bus/ power factor	500/11/0.82 1652/61/0.81 500/18/0.89	2292/61/0.8 500/36/0.8 724/62/0.84	2405/61/0.8 503/22/0.96 604/49/0.92	1411/61/0.81 500/64/0.83 534/11/0.81	214/69/0.83 378/62/0.8 3207/61/0.83	500/64/0.84 500/11/0.84 2193/61/0.8
Minimum and Maxi- mum voltage in p.u	0.9943 & 1.0047	0.9818 & 1.0497	0.9972 & 1.0287	0.9938 & 1	0.9899 & 1.05	0.9936 & 1.0229
λ_{max}	4.2	4.91	4.61	6.49	7.71	7.07
λ_V	1.53	1.74	1.89	1.93	2.18	2.37
Real power loss in kW	4.847	89.8601	30.2921	5.3082	93.9651	25.313
OF value	–	–	0.1229	–	–	0.2254
% KVA DG INJECTION	68.79	93.56	89.01	64.45	98.58	84.33
% PLR	97.84	60.05	86.53	97.64	58.22	88.74
% MLI	30.84	52.95	43.61	102.18	140.18	120.249

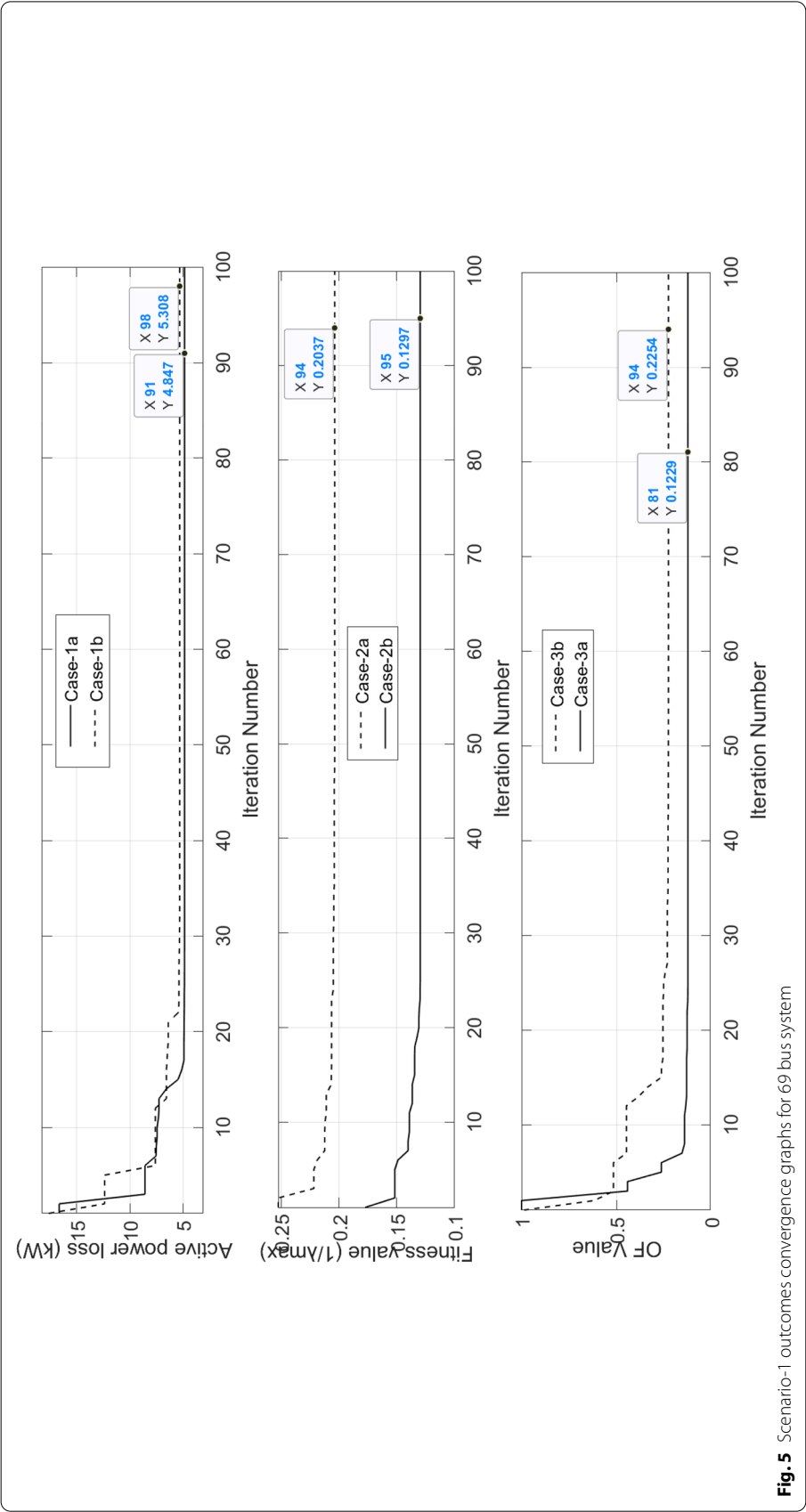


Fig. 5 Scenario-1 outcomes convergence graphs for 69 bus system

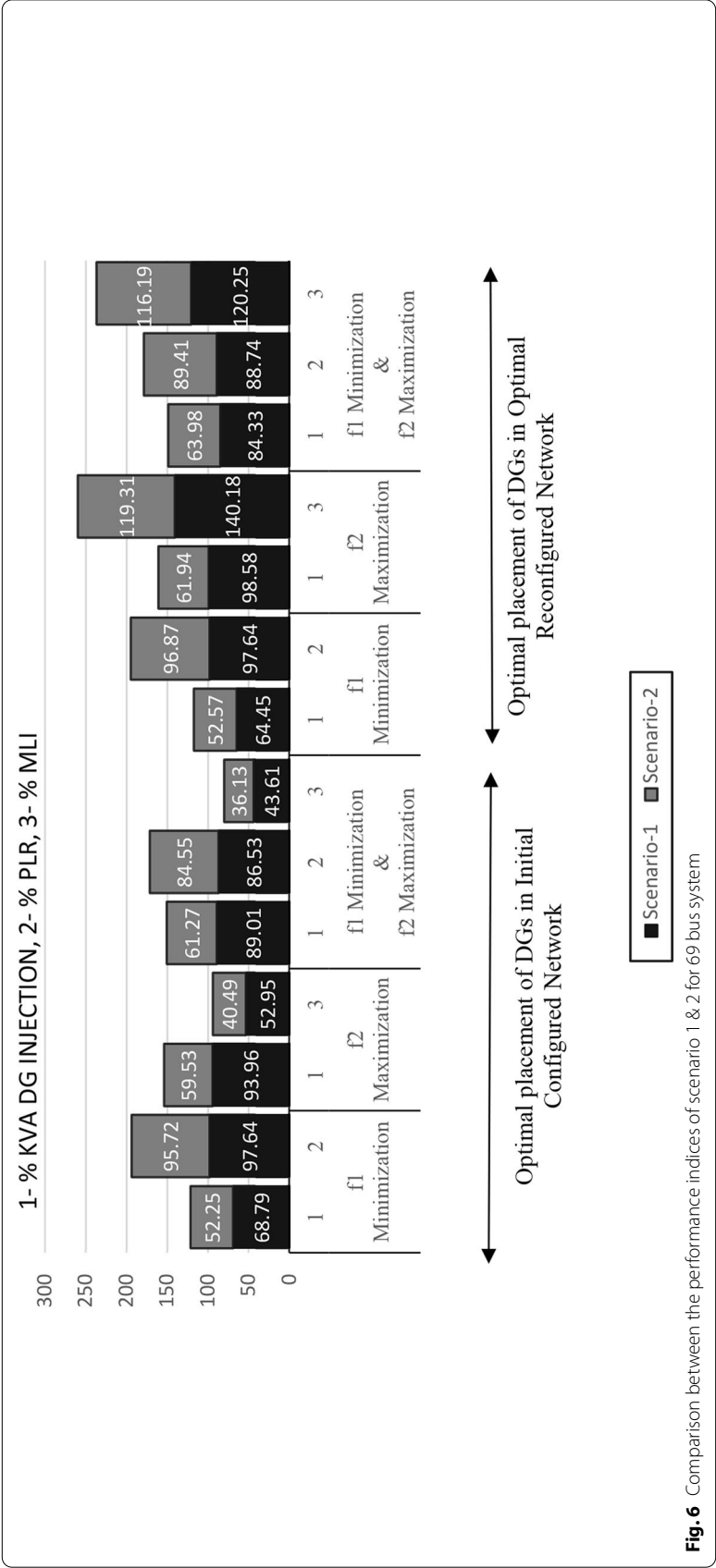


Table 7 Simulation results of 69 bus system for scenario-2

Parameters/ Cases	Initial configured network Open Switch positions 69 70 71 72 73			Optimal Reconfigured Network Open Switch positions 14 58 61 69 70		
	Case-1a	Case-2a	Case-3a	Case-1b	Case-2b	Case-3b
DG sizes in kW/ Bus/power factor	1496/61/0.8 252/21/0.8 200/68/0.8	1113/61/0.8 209/62/0.8 897/64/0.8	200/18/0.85 1943/64/0.8 200/15/0.97	277/12/0.8 419/64/0.8 1264/61/0.8	2152/61/0.8 200/2/0.96	200/64/0.8 200/23/0.91 2013/61/0.8
Minimum and Maximum volt- age in p.u	0.9867 & 1	0.9759 & 1.0225	0.9916 & 1.0209	0.9915 & 1	0.9652 & 1.0216	0.9862 & 1.0172
λ_{max}	4.09	4.51	4.37	6.4	7.04	6.94
λ_V	1.41	1.59	1.69	1.85	1.41	2.01
Real power loss in kW	9.6078	35.096	34.7448	7.0345	46.448	23.8112
OF value	0.0254	0.1675	0.2333	0.0321	0.2379	0.2744
% KVA DG INJECTION	52.25	59.53	61.27	52.57	61.94	63.98
% PLR	95.72	84.39	84.55	96.87	79.35	89.414
% MLI	27.41	40.49	36.13	99.37	119.31	116.19

are accessible in the literature and shown in Table 8. The proposed algorithm yields to produce the same result produced by the HPSO algorithm in the literature concerning loadability of the system as an objective function and the proposed algorithm performs well in mitigating the real power with comparison to the HTLBO-GWO algorithm. In [29], with 40% KW or 47.06 KVA injection by DGs into the system, real power loss reduced to 87.206%, system loadability increased to 27.72%. But with the proposed method in this paper, with 63.98% KVA injection by DGs into the system, real power loss reduced to 89.414%, system loadability increased to 116.19% that shows an improvement in both the objectives unlike the method in [29] which shows the efficacy of the proposed method.

Conclusion

In this work, OCDG and ODNR problems on radial distribution systems have been addressed to enhance the system efficiency and too apt upcoming load growth via I^2R loss mitigation and system loadability enhancement. To achieve the objectives, two scenarios each consisting of three cases and each case having two sub-cases are considered. The concept of a spanning tree has been taken for confirming the radiality status of the system. BO optimization technique has been taken to optimize the proposed objective functions and implemented on 33 & 69 bus test systems. In both the test systems, the highest percentage of improvement in both the objectives with less amount of % KVA injection by DGs into the system is observed in case-3b of scenario-2. From the outcomes, it has observed that loss of the system is reduced to (75–89) %, loadability enhanced to (94–121) % with the injection of 64% KVA by DGs in 33 & 69 bus systems. BO algorithm has performed well in optimizing the proposed objectives when compared with the other algorithms in the literature.

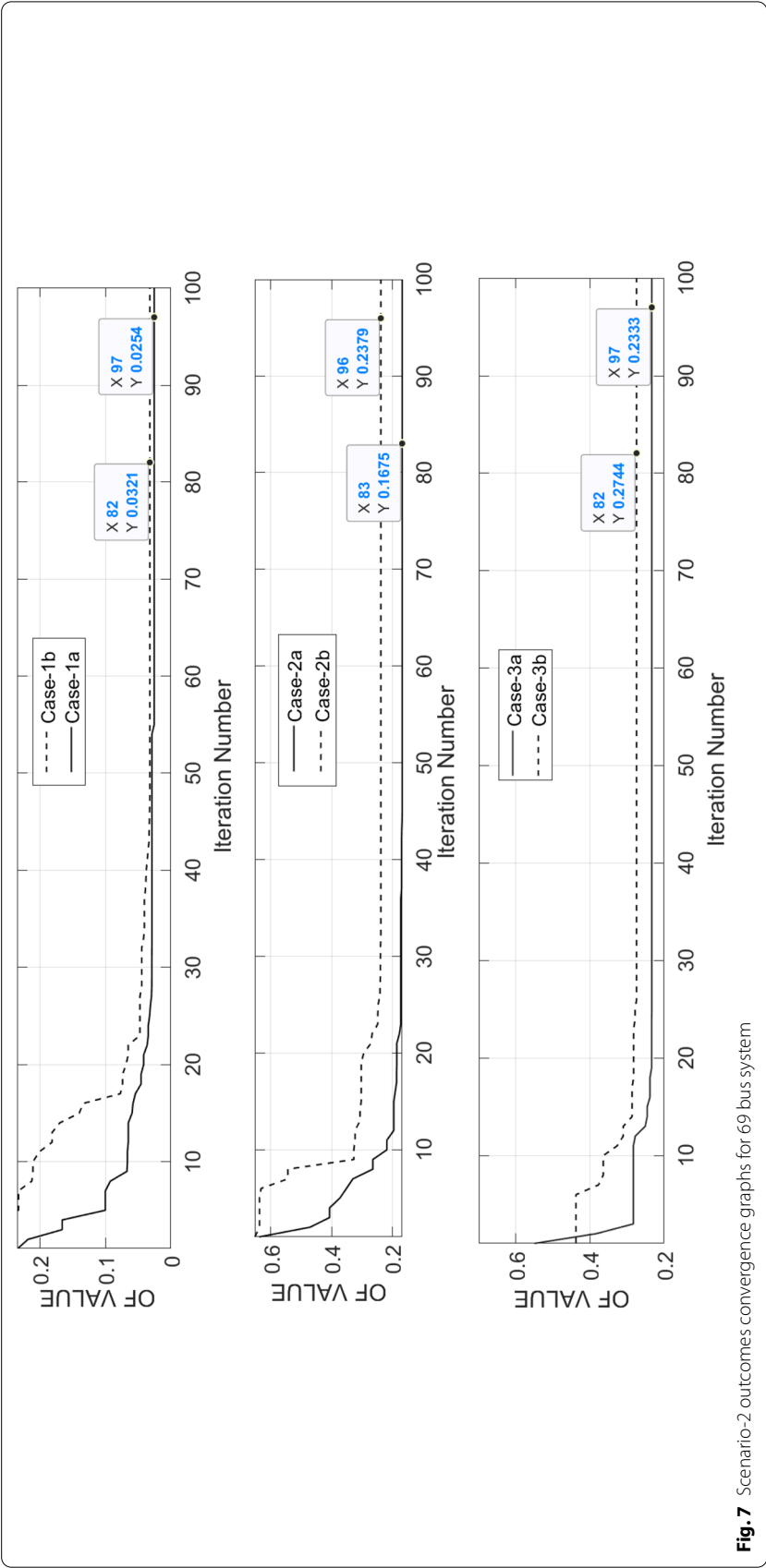


Fig. 7 Scenario-2 outcomes convergence graphs for 69 bus system

Table 8 Comparison results of 69 bus system

Method	DGs sizes in kW/BUS/ p.f	% PLR	% MLI
Scenario-1/ Power loss Minimization / Initial Configured Network			
Proposed BO algorithm	(500/11/0.82), (1652/61/0.81), (500/18/0.89)	97.84	NA
HTLBO-GWO [18]	(523/18/0.83), (1000/61/0.82), (723/62/0.80)	96.76	NA
Scenario-1/ Power loss Minimization / Optimal Reconfigured Network			
Proposed BO algorithm	(1411/61/0.81), (500/64/0.83), (534/11/0.81)	97.64	NA
UVDA Method [25]	(1.378 + j0.984/61), (0.62 + j0.443/11) (0.722 + j0.514/64)	95.84	NA
Scenario-1/ Loadability Maximization / Initial Configured Network			
Proposed BO algorithm	(2292/61/0.8), (500/36/0.8), (724/62/0.84)	NA	52.95
HPSO Algorithm [29]	(3105/61/0.85), (27/63/0.85), (130/46/0.85)	NA	52.95

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