

Optimal Site and Size of Distributed Generation Allocation in Radial Distribution Network Using Multi-objective Optimization

Aamir Ali, M. U. Keerio, and J. A. Laghari

Abstract—Distributed generation (DG) allocation in the distribution network is generally a multi-objective optimization problem. The maximum benefits of DG injection in the distribution system highly depend on the selection of an appropriate number of DGs and their capacity along with the best location. In this paper, the improved decomposition based evolutionary algorithm (I-DBEA) is used for the selection of optimal number, capacity and site of DG in order to minimize real power losses and voltage deviation, and to maximize the voltage stability index. The proposed I-DBEA technique has the ability to incorporate non-linear, nonconvex and mixed-integer variable problems and it is independent of local extrema trappings. In order to validate the effectiveness of the proposed technique, IEEE 33-bus, 69-bus, and 119-bus standard radial distribution networks are considered. Furthermore, the choice of optimal number of DGs in the distribution system is also investigated. The simulation results of the proposed method are compared with the existing methods. The comparison shows that the proposed method has the ability to get the multi-objective optimization of different conflicting objective functions with global optimal values along with the smallest size of DG.

Index Terms—Distribution system, distributed generation, multi-objective optimization, active power loss, improved decomposition based evolutionary algorithm (I-DBEA).

I. INTRODUCTION

At present, decentralized power generation is able to encounter the continuously increasing demand of energy efficiently. Approximately 16% of the total population globally survive without electricity [1]. The interest in the distributed generation (DG) allocation across the radial distribution network (RDN) is due to several facts, i.e., the evolution of DG technologies, the limitation on the construction of a new transmission line, the increase in customer demand, economic electric market, and the involvement of climate change. Hence, DGs are located near the load center and should be optimally allocated to minimize power losses, operation cost, and pollution, and to improve the voltage stability and the re-

liability of distribution system. On the contrary, inappropriate position and the capacity of DGs may have opposite effects, i.e., power losses due to reverse power flow, complication of protective relay coordination, rise in voltage, voltage stability, and power quality issues [2]. Furthermore, the latest advancement in the small-sized and power electronic based renewable generation technology has efficiently controlled the injection of large-scale output power of DGs. Hence, the optimal number, site and size of DGs have been considered as the global challenge for both the industry and academic sector. Numerous researches have been done to optimize the DG allocation problem to improve the counter effects of DG integration including the reduction of active power losses [3]–[12], voltage profile enhancement [3]–[7], [12]–[15], voltage stability index (VSI) [3], [6], [7], [16]–[18], transient stability [8], reliability [8], [14], [19], DG capacity [8], [14], [19], and greenhouse gas emission [14], [19].

In the vision of the above discussion, the optimal DG allocation problem is generally a multi-objective optimization problem and the objective functions are contradictory in nature. Hence, the objective functions are conflicting and a precise multi-objective formulation is required. Multi-objective optimization is classified into two core approaches. In the first approach, a preference-based weight vector w is chosen, thereafter it is multiplied with the associated objective functions to construct the composite function. Then, a composite function is optimized by using single-objective optimization. Weight methods for multi-objective problem formulation are discussed in [3], [7], [17], whereas the techniques based on penalty function are discussed in [16], and ε -constrained techniques are presented in [20]. The limitations of these techniques are that the weighted sum approach depends on the selected weights, and slave and master objectives are required in ε -constrained techniques. In the second approach, a set of potential solutions (also called Pareto optimal solutions) is given at the end of calculation by optimization algorithms and the number of solutions is non-dominated. Nevertheless, some of the above-discussed limitations are overcome by nondominated sorting genetic algorithm II (NSGA-II) along with differential evolution (DE) for mutation and recombination [5]. For the best Pareto optimal solution, fuzzy set theory with ε -constraint technique is applied in

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[21], min-max approach in [10] and genetic algorithm (GA) with addition of fuzzy goal programming (FGP) in [22]. But this combined technique is not able to deliver evenly the dispersed Pareto front (PF). For the evenly-dispersed PF, a normal boundary intersection method is suggested in [23].

Basically, most of the methods mentioned above need to produce the set of evenly-dispersed Pareto optimal solutions in order to choose the best solution. Further, in most of the literature, penalty function approach is considered to check the constraint violation. The limitation of this approach is the selection of penalty coefficient. A small penalty coefficient over-explores the infeasible region which delays the process of finding feasible solutions, and may pre-maturely converge to an infeasible solution. However, a large penalty coefficient may not explore the infeasible region, thereby resulting in an ultimate convergence. To avoid such difficulties, a penalty less constrained handling technique must be integrated with the evolutionary algorithm in order to search efficiently in the feasible region.

Recently, an improved optimization method called improved decomposition-based evolutionary algorithm (I-DBEA) has been introduced [24], which has the ability to search multi-objective optimization problem for DG site and size allocation. Compared with other nature-inspired algorithms, I-DBEA may have the ability to explore appropriate site and position of DG allocation. The usefulness of the proposed I-DBEA has not been explored for the DG allocation problem in distribution system. This is the first work which systematically searches the best site and capacity of DG allocation using I-DBEA. The application of I-DBEA has been done on IEEE 33-bus, 69-bus, and 119-bus standard RDNs in order to validate its effectiveness. The simulation results of the proposed I-DBEA are compared with those of other available methods. The contributions of this paper can be described as follows.

- 1) A fast and efficient direct search-based load flow approach is used for the computation of objective functions.
- 2) The integration of ε -constrained technique with the multi-objective I-DBEA handles various constraints while optimizing the objective functions.
- 3) Various DG sources (solar photovoltaic (PV) and wind turbine) are optimally injected into the distribution system to minimize the active power loss, voltage deviation (VD) and VSI.
- 4) In order to show the effectiveness and performance of I-DBEA, small-scale to large-scale radial distribution networks (33-bus, 69-bus and 119-bus) are considered.
- 5) The simulation results of the proposed method are compared with those of recent available methods with similar experimental setup.

The rest of this paper is organized as follows. Section II describes the mathematical formulation of the problem and objective functions. Section III describes the proposed multi-objective optimization method and Section IV presents the simulation results. The discussion and conclusion of this paper are presented in Section V and Section VI, respectively.

II. PROBLEM FORMULATION

Generally, load varies with time at distribution side in power system, whereas the optimal site and size of DG allocation with varying load is not appropriate. Therefore, the planning problem of optimal DG allocation is considered by the following assumptions [25]: ① RDNs are considered to be balanced; ② active and reactive power of the load is constant.

In this paper, DGs are considered as negative loads which do not regulate the bus voltage. The best site and size of DG allocation should be achieved without violating any constraints, and these constraints are to be checked through load flow analysis at each iteration. Fundamental objective functions such as line losses, voltage profile enhancement and VSI are examined. In subsequent sub-sections, power flow technique, objective functions and constraints are described.

A. Power Flow Problem

Distribution networks are mostly radial and have low reactance to resistance ratio. Traditional load flow solutions such as Gauss-Seidel (GS) and Newton Raphson (NR) methods are not appropriate. Therefore, in this paper, power flow is done by using a direct search-based load flow approach [26]. In the proposed power flow techniques, three matrices are established namely bus injection to branch current (BIBC), branch current to bus voltage (BCBV) and distribution load flow (DLF). Simple matrix multiplication of these matrices is used to obtain load flow solutions, objective functions and constraints for the optimization process. A typical 6-bus RDN is shown in Fig. 1 [26], where B_1 - B_5 are branch currents and Z_{12} - Z_{56} are their associated branch impedances.

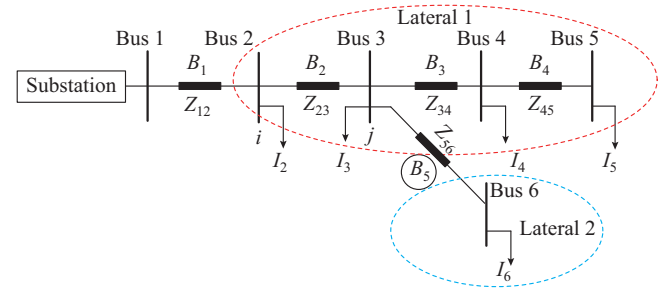


Fig. 1. Typical 6-bus RDN for load flow.

The current injection at bus i can be calculated as:

$$I_i = \left(\frac{P_i + jQ_i}{V_i} \right)^* \quad (1)$$

where V_i , I_i , P_i and Q_i are the voltage, current, active and reactive power at bus i , respectively; and the symbol $*$ is the complex conjugate. Further, the current I_i is decomposed into its real and imaginary parts.

$$\begin{cases} \text{Re}(I_i) = \frac{P_i \cos \theta_i + Q_i \sin \theta_i}{|V_i|} \\ \text{Im}(I_i) = \frac{P_i \sin \theta_i - Q_i \cos \theta_i}{|V_i|} \end{cases} \quad (2)$$

where θ_i is the bus voltage angle. As shown in Fig. 1, B is

the branch current matrix and Kirchhoff's current law (KCL) is used to calculate matrix $\mathbf{B}$ using (3).

$$\underbrace{\begin{bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \\ B_5 \end{bmatrix}}_{\mathbf{B}} = \underbrace{\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{\mathbf{BIBC}} \underbrace{\begin{bmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \\ I_5 \end{bmatrix}}_{\mathbf{I}} \quad (3)$$

However, the voltage drop at each bus with respect to reference bus is calculated by using Kirchhoff's voltage law (KVL) as:

$$\underbrace{\begin{bmatrix} V_1 \\ V_1 \\ V_1 \\ V_1 \\ V_1 \end{bmatrix}}_{\Delta \mathbf{V}} - \underbrace{\begin{bmatrix} V_2 \\ V_3 \\ V_4 \\ V_5 \\ V_6 \end{bmatrix}}_{\mathbf{BCBV}} = \underbrace{\begin{bmatrix} Z_{12} & 0 & 0 & 0 & 0 \\ Z_{12} & Z_{23} & 0 & 0 & 0 \\ Z_{12} & Z_{23} & Z_{34} & 0 & 0 \\ Z_{12} & Z_{23} & Z_{34} & Z_{45} & 0 \\ Z_{12} & Z_{23} & 0 & 0 & Z_{36} \end{bmatrix}}_{\mathbf{BCBV}} \underbrace{\begin{bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \\ B_5 \end{bmatrix}}_{\mathbf{B}} \quad (4)$$

Substituting the value of matrix $\mathbf{B}$ from (3) in (4), we obtain:

$$\Delta \mathbf{V} = \underbrace{\mathbf{BCBV} \cdot \mathbf{BIBC}}_{\mathbf{DLF}} \cdot \mathbf{I} = \mathbf{DLF} \cdot \mathbf{I} \quad (5)$$

where $\mathbf{DLF}$ is the distribution load flow matrix that helps calculate voltage drop at each bus with regard to the reference bus. $\mathbf{DLF}$ is simply calculated by using the following two steps.

Step 1: set branch impedance vector $\mathbf{Z}_b$ from the branch data.

Step 2: convert branch impedance vector into diagonal matrix, in which all the upper and lower elements are set as zero except the main diagonal, i.e., $\mathbf{Z} = \text{diag}(\mathbf{Z}_b)$, and multiply with matrix $\mathbf{I}$ for $\Delta \mathbf{V}$.

B. Multi-objective Optimization Functions

As suggested in the literature, the best value of DG position and capacity can be achieved by formulating various conflicting objective functions. Some of the fundamental problems such as active power losses, VD and VSI are considered as objective functions and can be defined as:

$$\begin{cases} \min(f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x})) & \mathbf{x} \in \Omega \\ \text{s.t. } g_i(\mathbf{x}) = 0 & i = 1, 2, \dots, p \\ h_k(\mathbf{x}) \leq 0 & k = 1, 2, \dots, q \\ \mathbf{x}^L \leq \mathbf{x} \leq \mathbf{x}^U \end{cases} \quad (6)$$

where $g_i(\mathbf{x})$ and $h_k(\mathbf{x})$ are the equality and inequality constraints, respectively; p and q are the numbers of equality and inequality constraints, respectively; $\mathbf{x}^L$ and $\mathbf{x}^U$ are the variable bounds of decision vectors; and Ω is the space of decision vector. Usually, the maximum power loss in a power system appears across the distribution network that affects the annual revenue. Therefore, the reduction of real line losses across distribution side is the primary objective. The power loss after the load flow analysis is calculated by (7) and it is the function of bus current injection [27].

$$L_p = \sum_{i=1}^N |B_i|^2 R_i = \mathbf{R}^T \mathbf{BIBC} \cdot \mathbf{I}^2 \quad (7)$$

where B_i and R_i are the branch current and resistance, respectively; and $\mathbf{R}$ is the branch resistance matrix containing the resistances of all the branches. Decomposing the current into its real and imaginary parts, (7) becomes:

$$L_p = \mathbf{R}^T \left[(\mathbf{BIBC} \cdot \text{Re}(\mathbf{I}))^2 + (\mathbf{BIBC} \cdot \text{Im}(\mathbf{I}))^2 \right] \quad (8)$$

Substituting the current from (2) in (7), the total active losses can be calculated as:

$$\min f_1 = \mathbf{R}^T \left(\mathbf{BIBC} \frac{P \sin \theta + Q \cos \theta}{|V|} \right)^2 + \mathbf{R}^T \left(\mathbf{BIBC} \frac{P \cos \theta + Q \sin \theta}{|V|} \right)^2 \quad (9)$$

Bus VD is the degree of voltage quality. Therefore, in order to deliver better regulated bus voltage profile across the RDN, it is essential to minimize bus VD. In the proposed optimal DG allocation, bus VD is taken into account as objective function and is defined as [6]:

$$\min f_2 = \sum_{i=1}^N (V_i - 1)^2 \quad (10)$$

The security level of the distribution system is not sufficient considering the VD alone. Hence for the better voltage profile, VSI is suggested as one of the objective functions in this effort. The maximum VSI of the distribution system means that the bus has the ability to preserve its voltage profile within satisfactory limit over variable loading conditions. For the secure operation of distribution system, the utility tries to maintain VSI of distribution system near-unity of all buses. The circuit VSI shown in Fig. 1 connecting buses i and j is expressed as:

$$VSI_{ij} = V_i^4 - 4(P_{Lj}r_{ij} + Q_{Lj}x_{ij})V_i^2 - 4(P_{Lj}x_{ij} - Q_{Lj}r_{ij})^2 \quad (11)$$

where P_{Lj} , Q_{Lj} , r_{ij} , x_{ij} are the active power load, reactive power load, line resistance and inductive reactance linking between buses i and j , respectively. During the operation, a bus with the lowest value of VSI needs to be maximized to enhance the voltage level of the entire network. Thus, for the maximization of VSI, its objective function is given by [1]:

$$\max f_3 = \frac{1}{\min(VSI_{ij})} \quad \forall i, j \quad (12)$$

C. Constraints

The proposed objective functions defined in (9), (10) and (12) are subject to the following constraints:

$$P_i = V_i \sum_{j=1}^N V_j Y_{ij} \cos(\theta_{ij} + \delta_j - \delta_i) \quad \forall i \quad (13)$$

$$Q_i = -V_i \sum_{j=1}^N V_j Y_{ij} \sin(\theta_{ij} + \delta_j - \delta_i) \quad \forall i \quad (14)$$

$$S_{DER_i} \leq S_{DER}^{\max} \quad \forall i \quad (15)$$

$$\sum_{i=1}^N S_{DER_i} \leq S_{Peak} \quad \forall i \quad (16)$$

$$V_{\min} \leq V_i \leq V_{\max} \quad \forall i \quad (17)$$

$$I_{ij} \leq I_{ij}^{\max} \quad \forall i, j \quad (18)$$

where Y_{ij} is the element of bus admittance matrix connected to buses i and j ; θ_{ij} is the impedance angle of branch ij ; I_{ij} and $I_{ij}^{\max}$ are the branch current and the limit of maximum current between buses i and j , respectively; $S_{DG}^{\max}$ is the maximum allowable size of DG injected; S_{Peak} is the peak load of network; and $V_{\min}$ and $V_{\max}$ are the minimum and maximum voltage limits at all buses, respectively.

III. OPTIMIZATION METHOD

In this paper, multi-objective I-DBEA is used to optimize the objective functions [24]. The flowchart of the proposed optimization I-DBEA technique is shown in Fig. 2. The principal steps of I-DBEA technique are discussed in the following subsections.

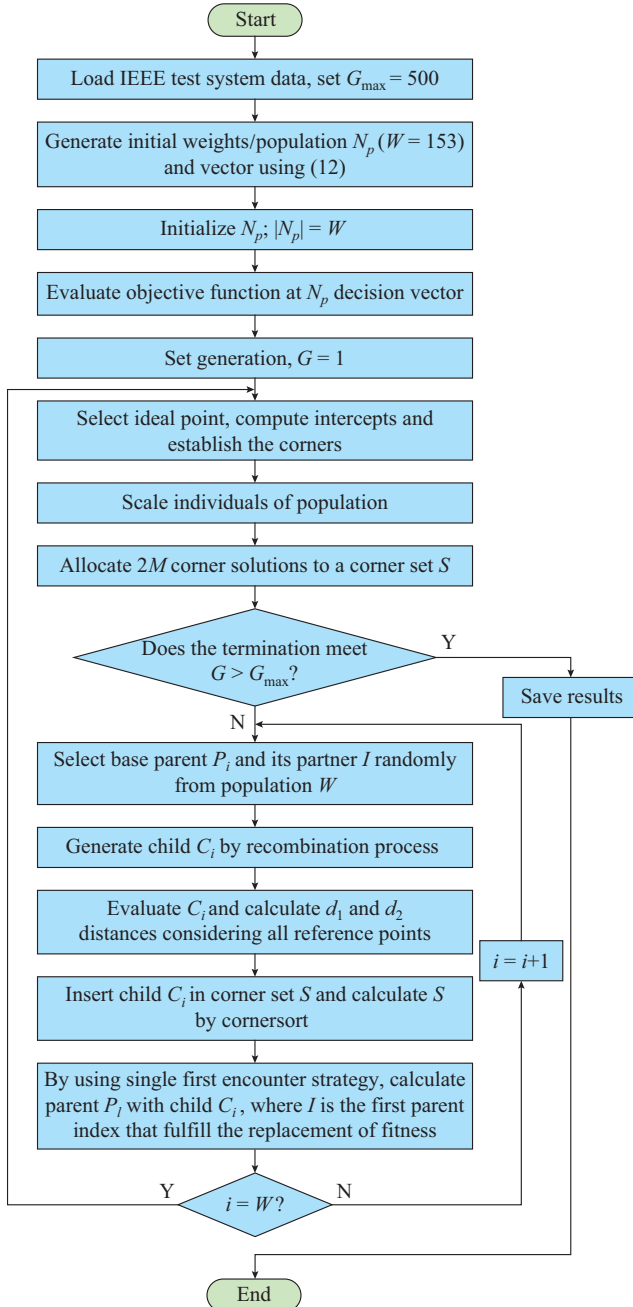


Fig. 2. Flowchart of I-DBEA optimization method.

A. Generation of Reference Points

At first, W sets of reference points are produced using normal boundary intersection (NBI) method [28]. These reference points collectively control the trade-off between the exploration and exploitation. A total number of 153 reference points are generated by (12) and the directions of reference points are molded by building straight line from the origin.

$$W = {}^{M+s-1}C_s \quad (19)$$

where $M+s-1$ is the constant number depends upon the number of objectives M and spacing between the points s in the search space.

Hyperplane for the objective functions using NBI method with an even space of $\delta=0.0625$ is calculated by using $\delta=1/s$ where $s=16$. Distribution of reference points for the three objective functions using 3-D normalized hyper plane is shown in Fig. 3. Initial randomly generated population size of the proposed method is equal to the number of reference points and are generated randomly within the range of decision vectors.

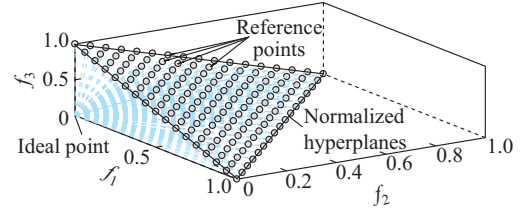


Fig. 3. Set of reference vectors generated using NBI method for three objective functions.

B. Computation and Normalization of Distances

Usually, in a decomposition-based approach, the fitness of objective functions with regard to the given directions is determined by using two distance measurements d_1 and d_2 , which are shown in Fig. 4 and computed as:

$$d_1 = \mathbf{w}^T \mathbf{f}'(\mathbf{x}) \quad (20)$$

$$d_2 = \|\mathbf{f}'(\mathbf{x}) - \mathbf{w}^T \mathbf{f}(\mathbf{x}) \mathbf{w}\| \quad (21)$$

where $\mathbf{w}$ is the unit vector showing direction along given reference point; d_1 is the Euclidian distance among origin and foot note; and d_2 is the normal length to the reference path.

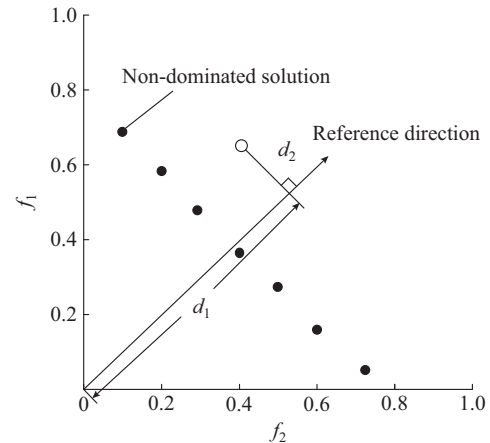


Fig. 4. Distance measurements with regard to reference direction.

The convergence and diversity of the suggested technique can be controlled by adjusting the values of d_1 and d_2 . If $d_2 = 0$, it shows perfect diversity which means the solutions are ideally aligned throughout the length of the required reference route; whereas a less value of d_1 gives superior convergence. In the proposed algorithm, $2M$ results are recognized by means of corner sort rank method suggested in [29]. Top-most M solutions are the smallest in all three objectives, whereas the next M solutions are founded by using L_2 -norm of all but one objective. From these solutions, the maximum value in each objective is recognized and the corresponding solution is nominated and referred to the extreme point which is equal to z^e . These points are used to produce hypervolume and calculate the extreme value of the objective function that is intercepted. On the other hand, the population at which the objective functions are minimum are called ideal points represented by $z = (f_1^{\min}, f_2^{\min}, \dots, f_M^{\min})$. The general equation of the plane through ideal points can be given as:

$$C_1 f_1 + C_2 f_2 + \dots + C_M f_M = 1 \quad (22)$$

where C_i ($i = 1, 2, \dots, M$) is the unit normal of plane and can be defined as $C_i = 1/a_i$, a_i is the intercept of hypervolumes along the objective function axes. Every optimized value of the objective functions can be scaled by:

$$f'_j(x) = \frac{f_j(x) - z_j}{a_j - z_j} \quad \forall j = 1, 2, \dots, M \quad (23)$$

C. Recombination Method

In this process, a simulated binary crossover (SBX) technique in [30] and polynomial mutation are used to create two child solutions. From these solutions, the first solution is measured as the individual trying to substitute any parent in the population.

D. Replacement and Selection

In the form of a steady state, the child solution is going to enter into the population through replacement if it is a non-dominated individual. The solution for child contests with all the parent population is arbitrary until it successfully replaces all the individuals. The value of distances $\{d_1, d_2\}$ represents the r^{th} solution in a randomly selected population and $\{d_{1_c}, d_{2_c}\}$ represents the child solutions in the r^{th} reference direction. If $d_{2_c} < d_{2_r}$, a child is considered as the winner or $d_{2_c} = d_{2_r}$ and $d_{1_c} < d_{1_r}$, elsewhere d_{1_r} and d_{2_r} remain selected. The preference of d_2 over d_1 removes the necessity of complex ε -based arrangement.

E. Handling of Constraints

The constraint handling technique is based on ε -level comparison [31]. The acceptable constraint violation (CV) can be calculated as:

$$CV = \sum_{i=1}^p \max(|g_i - \varepsilon|, 0) + \sum_{k=1}^q \max(h_k, 0) \quad (24)$$

$$CV_{\text{mean}} = \frac{1}{W} \sum_{j=1}^W CV_j \quad (25)$$

The allowable violation is given by:

$$\varepsilon_{CV} = CV_{\text{mean}} \cdot FR \quad (26)$$

where FR is the feasibility ratio between the feasible solutions to the population size W .

IV. SIMULATION RESULTS

In this paper, the best placement and capacity of DG allocation is considered by I-DBEA and is validated on IEEE 33-bus, 69-bus, and 119-bus standard RDNs. The technical details of IEEE test systems are taken from MATPOWER [32]. With the purpose of showing the effectiveness of the preferred scheme and comparison with other well-established algorithms in the previous work, the following suggested study cases are shown in Table I.

TABLE I
SUMMARY OF STUDY CASES

Test system	Study case	Explanation of case	No. of DGs
33-bus	1	Effect of number of DG placement	1-7
	2a	DGs operating at unity power factor (UPF)	3
	2b	DGs operating at UPF	4
	3	DGs operating at 0.85 lagging power factor (LPF)	3
69-bus	1	Effect of number of DG placement	1-7
	2	DGs operating at UPF	3
	3	DGs operating at 0.85 LPF	3
119-bus	1	Effect of number of DG placement	1-7
	2	DGs operating at UPF	7
	3	DGs operating at 0.85 LPF	7

In the subsequent section, first, the effect of placement of optimal DG numbers in 33-bus, 69-bus and 119-bus standard RDNs is analyzed. Thereafter, from an economical point of view, the number of DGs and site and size allocation in RDN are considered. The control parameters used in the proposed I-DBEA are given as follows: the maximum generation $Gen_{\max} = 500$, the size of population $N_p = W = 153$, the probability of crossover $p_c = 1$ and the probability of mutation $p_m = 1/D$, D is the dimension of the decision vector. For the problem formulation, MATLAB environment and Intel Core i3 3.50 MHz processor of CPU with RAM of 4 GB system are used for simulation.

A. Case 1: Effect of Number of DG Placement in IEEE Test Systems

In this case, the effect of DG injection in distribution network considering the minimum real power losses (RPLs), VD and the maximum VSI is examined by the increase of the quantity of DGs as shown in Fig. 5(a). It is clearly observed from Fig. 5(a) that RPL can be reduced by increasing the number and capacity of DGs for IEEE 33-bus and 69-bus standard RDNs. Figure 5(b) shows the reduction of real loss by increasing the number and size of DGs for IEEE 119-bus standard RDN. Furthermore, it can be observed from Fig. 5(a) that by optimally increasing the maximum amount of DG size and the number of DGs in 33-bus and 69-bus standard RDNs from 3 to 4, the fourth DG impact is small to optimize objective functions. Therefore, the economical placement of 3 DGs is optimal for IEEE 33-bus and 69-

bus standard RDNs. For IEEE 119-bus standard RDN, 7 DGs are optimal and economical, which can be observed from Fig. 5(b).

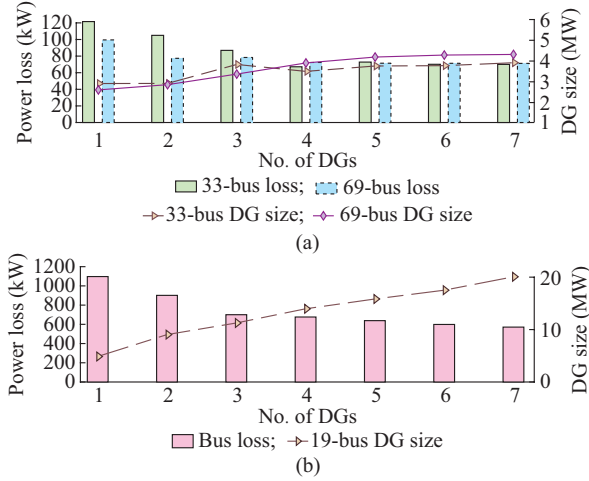


Fig. 5. Impact of capacity and number of DGs to optimize objective functions. (a) 33-bus and 69-bus. (b) 119-bus.

By increasing the number and size of DGs, the minimum VD and maximum VSI can be clearly observed from Fig. 6. It can be determined from Fig. 6(b) that the optimal values of VSI and VD have appeared when 7 DGs are used and are saturated when the quantity of DGs is increased to above 7.

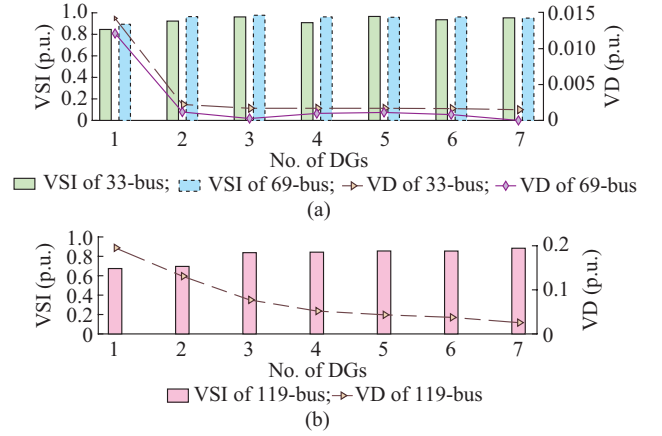


Fig. 6. Impact of number of DGs on VD and VSI. (a) 33-bus and 69-bus. (b) 119-bus.

B. Cases 2 and 3 of IEEE 33-bus Standard RDN

In these cases, the IEEE 33-bus standard RDN is considered. In order to show the effectiveness of the nominated method and comparison with other well-established optimization algorithms in the literature, the following suggested cases are studied.

1) Case 2a: Effect of 3 DGs Operating at UPF

Table II summarizes the simulation results of the suggested technique in comparison with current optimization method.

TABLE II
CASE 2 OF IEEE 33-BUS STANDARD RDN WITH 3 DGs OPERATING AT UPF

Technique	Location (bus No.)	DG size (MW)	Total DG size (MW)	RPL (kW)	P_L reduction (%)	VD (p.u.)	VSI (p.u.)
Base case				202.6670	0.00	0.1171	0.6988
CTLBO ε -method [1]	13, 25, 30	1.1926, 0.8706, 1.6296	3.6928	96.1732	52.54	0.0009	0.9638
CTLBO [1]	13, 24, 30	1.0364, 1.1630, 1.5217	3.7211	85.9595	57.59	0.0026	0.9481
TLBO [6]	12, 28, 30	1.1826, 1.1913, 1.1863	3.5602	124.6950	38.47	0.0011	0.9503
QOTLBO [6]	13, 26, 30	1.0834, 1.1876, 1.1992	3.4702	103.4030	48.97	0.0011	0.9530
GA [7]	11, 29, 30	1.5000, 0.4230, 1.0710	2.9940	106.3000	47.56	0.0407	0.9497
PSO [7]	8, 14, 32	1.1770, 0.9820, 0.8300	2.9890	105.3000	48.05	0.0335	0.9256
GA/PSO [7]	11, 16, 32	0.9250, 0.8630, 1.2000	2.9980	103.4000	48.99	0.0124	0.9508
IMOEOH [33]	14, 24, 30	1.0570, 1.0540, 1.7410	3.8520	95.0000	53.13	0.0008	0.9673
I-DBEA	13, 24, 30	1.0980, 1.0970, 1.7150	3.9131	94.8514	53.21	0.0007	0.9650

From Table II, it can be examined that the proposed method delivers the most cooperating results for the multi-objective optimal size and site of DG allocation problem at possible DG injection as a contrast to the available methods. The proposed method offers somewhat more line loss reduction and VD in contrast to the methods in [1], [6], [7], [33]. It is also clear from Table II that teaching learning based optimization (TLBO) [6], GA, particle swarm optimization (PSO), and hybrid GA and PSO [13] are incapable of injecting the required amount of DG power to acquire the same goal. Furthermore, the proposed method gives remarkable enhancement in all the objective functions, i.e., RPL, VD, and VSI. The I-DBEA method has reduced the line losses from 202.6670 kW to 94.8514 kW (53.21% reduction) and VD from 0.1171 p.u. to 0.0007 p.u., while the maximization of

VSI is from 0.6988 p.u. to 0.9650 p.u..

2) Case 2b: Effect of 4 DGs Operating at UPF

Table III summarizes the simulation results of the proposed technique for IEEE 33-bus standard RDN, considering simultaneously 4 DGs operating at UPF at different buses in comparison with existing methods.

It is observed from Table III that the I-DBEA delivers the most compromising results for the multi-objective optimal size and site of DG allocation problem at possible DG injection as a contrast to the available methods. Also, the suggested method offers somewhat more reduction in I^2R loss and VD along with maximizing VSI in contrast to the methods in [7] and [25]. It is also clear from Table III that GA/PSO and hybrid GA and PSO in [7] are incapable of injecting the

required amount of DG power to acquire the same goal, whereas hybrid GA/PSO [7] and improved multi-objective harmony search (IMOHS) [25] inject a large amount of DG power as associated to the proposed method. The I-DBEA has reduced the real power losses from 202.6670 kW to

66.1182 kW (67.43% reduction) and VD from 0.1171 p.u. to 0.0101 p.u., while the maximization of VSI is from 0.6988 p.u. to 0.9161 p.u.. Thus, the proposed method offers remarkable enhancement in all objective functions.

TABLE III
CASE 2 OF IEEE 33-BUS STANDARD RDN WITH 4 DGs OPERATING AT UPF

Technique	Location (bus No.)	DG size (MW)	Total DG size (MW)	RPL (kW)	P_L reduction (%)	VD (p.u.)	VSI (p.u.)
Base case				202.6670	0.00	0.1171	0.6988
GA [7]	6, 13, 24, 30	0.643, 0.857, 0.857, 0.738	3.0950	70.1000	65.42	0.0115	0.8776
PSO [7]	6, 15, 25, 31	0.830, 0.833, 0.541, 0.648	2.8520	71.3000	65.86	0.0109	0.8776
GA/PSO [7]	14, 24, 26, 32	0.663, 1.023, 0.867, 0.664	3.2170	68.2000	66.35	0.0130	0.8903
IMOHS [25]	6, 14, 24, 31	0.937, 0.667, 1.012, 0.731	3.3470	67.8000	66.55	0.0111	0.8891
IMOHO [33]	7, 14, 25, 31	0.930, 0.696, 0.729, 0.821	3.1760	67.3000	66.80	0.0076	0.9110
I-DBEA	24, 14, 31, 6	0.939, 0.576, 0.745, 0.922	3.1820	66.1182	67.43	0.0101	0.9161

3) Case 3: Effect of 3 DGs Operating at LPF

DGs are inadmissible to inject reactive power to the distribution network in the preceding study cases (Case 2) for the optimization of considered objective functions. In the presented case, the proposed technique is applied to obtain the best site and capacity of 3 DGs operating at 0.85 LPF. The simulation results of the proposed technique for IEEE 33-bus standard RDN, in which 3 DGs operating simultaneously at 0.85 LPF at different buses associated with present approaches in the literature are summarized in Table IV.

From Table IV, it can be observed that I-DBEA offers bet-

ter results for optimal size and site of DG allocation problem at possible DG injection as a contrast to the available methods. I-DBEA offers somewhat more line loss minimization and VD reduction along with maximizing VSI in contrast to the methods in [4], [9], [11], [33]. It is also clear from Table IV that improved analytical (IA) method [4] and loss sensitivity factor simulated annealing (LSFSA) [9] are incapable of injecting the required amount of DG power to acquire the same goal, whereas improved multi-objective elephant herding optimization (IMOHO) [33] methods inject large value of DG power in contrast to I-DBEA method.

TABLE IV
CASE 3 OF IEEE 33-BUS STANDARD RDN WITH 3 DGs OPERATING AT 0.85 LPF

Technique	Location (bus No.)	DG size (MW)	Total DG size (MW)	RPL (kW)	P_L reduction (%)	VD (p.u.)	VSI (p.u.)
Base case				202.667	0.0000	0.1171	0.6988
IMOHO [33]	13, 24, 30	0.9290, 1.1810, 1.4730	3.5830	14.900	92.6000	0.0003	0.9814
Analytical [11]	6, 25, 31	1.8100, 0.8400, 0.9300	3.5800	26.100	87.1200	0.0086	0.8678
LSFSA [9]	6, 18, 30	1.3830, 0.5520, 1.0630	2.9980	26.700	86.8300	0.0013	0.9323
IA [4]	6, 14, 30	1.0590, 0.7410, 1.0590	2.8590	23.100	88.6000		
I-DBEA	13, 24, 30	0.7491, 1.0420, 1.2395	3.0307	14.570	92.8081	0.0002	0.9733

Furthermore, the proposed method gives remarkable enhancement in all the objective functions, i.e., RPL, VD, and VSI. The suggested technique has to optimize the real power losses from 202.6670 kW to 14.5757 kW (92.8081% reduction) and VD from 0.1171 p.u. to 0.0002 p.u., while the maximization of VSI is from 0.6988 p.u. to 0.9733 p.u.. It is clear from Tables II-IV that Case 3 gives the best results as associated to Cases 2a and 2b.

DGs operating at LPF add both active and reactive power to the distribution system, which enhances the efficiency of distribution network significantly compared with DGs operating at UPF. The enhancement of voltage profile for all cases of IEEE 33-bus distribution systems is shown in Fig. 7. The voltage waveform is near to unity in Case 2a and Case 3. Conversely, in Case 2b, the voltage profile is somewhat less because of small value of DG power injection.

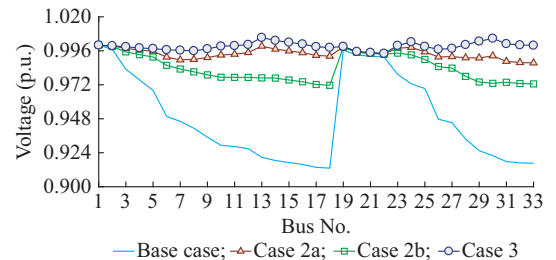


Fig. 7. Bus voltage profile of Cases 2 and 3.

Figure 8 shows the effectiveness of the proposed method to produce Pareto optimal solution considering multi-objective functions, which clearly shows that the I-DBEA method has the ability to find a widely-distributed set of non-dominated points.

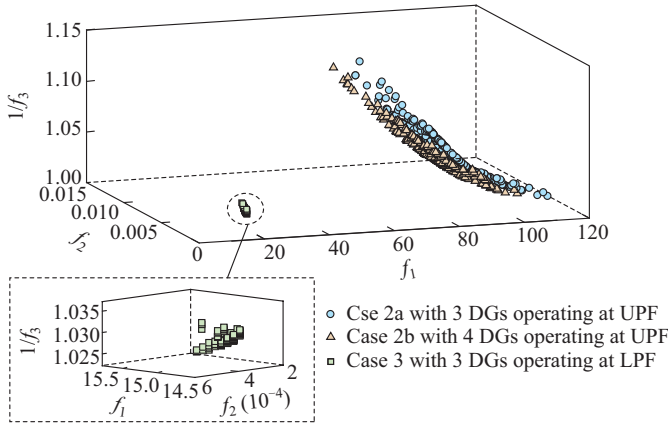


Fig. 8. Final Pareto front of all cases in IEEE 33-bus standard RDN.

C. Cases 2 and 3 of IEEE 69-bus Standard RDN

The implementation of the proposed method for the effective validation on IEEE 69-bus test system is presented in this case. Subsequently, due to the economic basis suggested in the literature, only 3 DGs operating at UPF and at 0.85 LPF are considered.

1) Case 2: Effect of 3 DGs Operating at UPF

The simulation results of the proposed method for IEEE 69-bus standard RDN, in which 3 DGs operating simultaneously at UPF at different buses are summarized in Table V. Table V shows that the proposed method achieves the maximum cooperating results to find the best size and site of DG allocation problem. The proposed method injects a small DG power value and finds the minimum power loss compared with the recent CTLBO ε -method [1]. The proposed method offers somewhat more P_L loss reduction and VD along with VSI enhancement in contrast to the methods presented by GA/PSO and hybrid GA/PSO [7], TLBO and quasi-oppositional TLBO (QOTLBO) [6], and comprehensive TLBO (CTLBO) ε -method [1]. It is also clear from Table V that GA, PSO, hybrid GA/PSO, TLBO, and QOTLBO are incapable of injecting required amount of DG injection to acquire the same goal, whereas CTLBO ε -method injects more DG power compared to I-DBEA. The proposed method has reduced the real power losses from 224.9 kW to 78.347 kW (65.17% reduction) and VD from 0.0993 p.u. to 0.0002 p.u., while the maximum VSI is from 0.6833 p.u. to 0.9772 p.u..

TABLE V
SIMULATION RESULTS OF IEEE 69-BUS STANDARD RDN WITH 3 DGs OPERATING AT UPF

Technique	Location (bus No.)	DG size (MW)	Total DG size (MW)	RPL (kW)	P_L reduction (%)	VD (p.u.)	VSI (p.u.)
Base case				224.900	0.00	0.0993	0.6833
GA [7]	21, 62, 64	0.9297, 1.0752, 0.9848	2.9897	89.000	60.42	0.0012	0.9706
PSO [7]	61, 63, 17	1.1998, 0.7956, 0.9925	2.9879	83.200	63.01	0.0049	0.9676
GA/PSO [7]	63, 61, 21	0.8849, 1.1926, 0.9105	2.9880	81.100	63.90	0.0031	0.9768
TLBO [6]	13, 61, 62	1.0134, 0.9901, 1.1601	3.1636	82.172	63.46	0.0008	0.9745
QOTLBO [6]	15, 61, 63	0.8114, 1.1470, 1.0022	2.9606	80.585	64.17	0.0007	0.9769
CTLBO [1]	11, 18, 61	0.5603, 0.4274, 2.1534	3.1411	76.372	66.04	0.0008	0.9770
CTLBO ε -method [1]	12, 25, 61	0.9658, 0.2307, 2.1336	3.3301	79.660	64.57	0.0003	0.9770
I-DBEA	61, 19, 11	2.1487, 0.4717, 0.7126	3.3200	78.347	65.17	0.0002	0.9772

2) Case 3: Effect of 3 DGs Operating at LPF

This case is presented in order to find the best position and capacity of 3 DGs operating at 0.85 LPF. The simulation results of the proposed method for IEEE 69-bus standard RDN compared with the techniques in the literature are shown in Table VI. From Table VI, it can be seen that I-DBEA attains the most cooperating results for optimal size and site of DG allocation problem at possible DG power injection as a contrast to the available methods. The proposed

method offers somewhat more RPL reduction and VD along with higher VSI in comparison to the method presented in IMOHS [25], LSFSA [9] and PSO [34]. It is also clear from Table VI that IMOHS, LSFSA, and PSO are incapable of injecting the required amount of DG power to acquire the same goal. The suggested technique has minimize the real power losses from 224.9 kW to 7.9660 kW (96.45% reduction) and VD from 0.099300 p.u. to 0.000266 p.u., while the maximum VSI is from 0.6833 p.u. to 0.9774 p.u..

TABLE VI
SIMULATION RESULTS OF IEEE 69-BUS STANDARD RDN WITH 3 DGs OPERATING AT 0.85 LPF

Technique	Location (bus No.)	DG size (MW)	Total DG size (MW)	RPL (kW)	P_L reduction (%)	VD (p.u.)	VSI (p.u.)
Base case				224.9000	0.00	0.099300	0.6833
IMOHS [25]	61, 11, 21	1.4552, 0.4769, 0.3124	2.2445	10.5000	95.33	0.001800	0.9468
LSFSA [9]	18, 60, 65	0.5498, 1.1954, 0.3122	2.0574	16.2600	92.77	0.002300	0.9678
PSO [34]	61, 64, 21	1.2780, 0.3010, 0.3240	1.9030	12.8000	94.30	0.003600	0.9541
I-DBEA	61, 59, 16	1.5000, 0.3700, 0.5750	2.4459	7.9660	96.45	0.000266	0.9774

It can be observed from Tables V and VI that Case 3 gives the best results since DGs operating at LPF add both active and reactive power to the network, which enhances the system performance significantly. The enhancement of the voltage profile for the all cases in IEEE 69-bus standard RDN is shown in Fig. 9. It can be observed from Fig. 9 that bus voltage is near to unity in Cases 2 and 3. In order to show the effectiveness of I-DBEA to produce optimal solution for multi-objective functions, the distribution of Pareto optimal solution set is presented in Fig. 10. It can be seen that the proposed method has the ability to find a widely-distributed set of non-dominated points for the three objective functions.

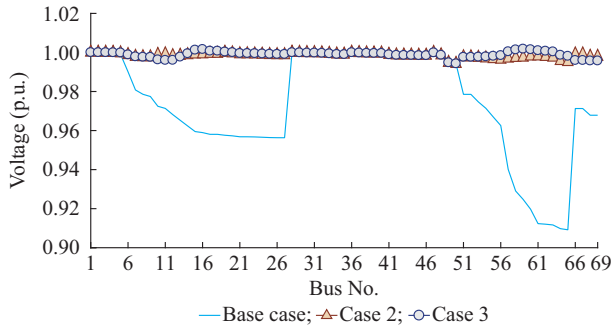


Fig. 9. Bus voltage profile of Cases 2 and 3 in IEEE 69-bus standard RDN.

D. Cases 2 and 3 of IEEE 119-bus Standard RDN

The simulation results of the proposed method for IEEE 119-bus standard RDN are discussed, where 7 DGs operate simultaneously at UPF and 0.85 LPF for different buses compared with the methods in the literature.

TABLE VII
IEEE 119-BUS STANDARD RDN WITH 7 DGs OPERATING AT UPF

Technique	Location (bus No.)	DG size (MW)	Total DG size (MW)	RPL (kW)	P_L reduction (%)	VD (p.u.)	VSI (p.u.)
Base case				1298.1	0.00	0.3576	0.5697
SA [9]	36, 48, 56, 75, 88, 103, 116	7.4670, 0.7110, 3.6740, 2.8250, 2.2980, 5.0800, 0.4610	22.5160	900.1	30.66	0.1022	0.7626
TLBO [6]	35, 48, 65, 72, 86, 99, 111	3.2460, 2.8860, 2.4310, 3.3060, 1.9920, 1.6040, 3.5980	19.0590	705.8	45.63	0.0430	0.8548
QOTLBO [6]	43, 49, 54, 74, 80, 94, 111	1.5880, 3.8460, 0.9850, 3.1900, 3.1630, 1.9530, 3.6010	18.3260	677.6	47.80	0.0353	0.8794
CTLBO ϵ -method [1]	22, 44, 51, 77, 81, 93, 115	2.0515, 1.1333, 4.4872, 2.6457, 4.6408, 3.7585, 3.2820	21.9990	655.8	49.48	0.0228	0.8948
CTLBO [1]	43, 51, 61, 76, 84, 100, 115	3.2693, 5.9000, 1.3302, 3.4981, 3.0069, 2.4184, 4.0690	23.4916	781.8	39.77	0.0110	0.8838
IMOEOH [33]	20, 42, 50, 74, 80, 97, 110	2.2330, 1.7540, 3.7120, 2.9060, 3.0270, 2.0750, 3.5130	19.2200	572.2	55.92	0.0257	0.8918
I-DBEA	96, 21, 73, 80, 50, 41, 109	2.1980, 1.9980, 3.1320, 2.9490, 3.4980, 2.4900, 3.7940	20.0710	571.1	56.01	0.0256	0.8917

2) Case 3: Effect of 7 DGs Operating at LPF

The simulation results of a proposed technique for IEEE 119-bus standard RDN, in which 7 DGs simultaneously operating at 0.85 LPF at different buses compared with current methods in the literature are concise in Table VIII. From Ta-

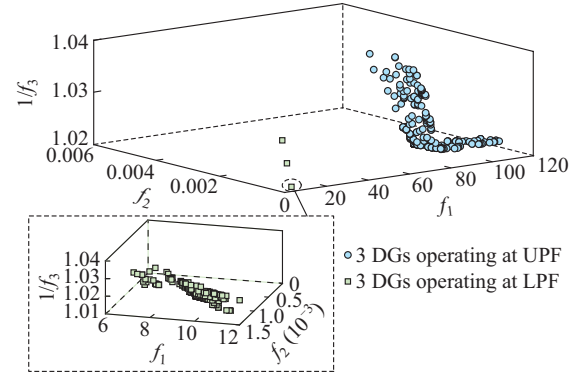


Fig. 10. Final Pareto front of Cases 2 and 3 in IEEE 69-bus standard RDN.

1) Case 2: Effect of 7 DGs Operating at UPF

The simulation results of the proposed method for 119-bus test system where 7 DGs inject power simultaneously at different buses are compared with methods in Table VII.

It is observed that I-DBEA method offers the compromising results for optimal size and site of DG allocation problem at possible DG injection as a contrast to the available methods. The proposed method offers somewhat more real power loss reduction and VD along with maximum voltage stability enhancement in contrast to the methods presented such as LSFSA, TLBO, QOTLBO, and CTLBO ϵ -method.

It can be observed from Table VII that TLBO, QOTLBO and IMOEOH are incapable of injecting the required amount of DG power to acquire the same goal. Whereas SA, CTLBO and CTLBO ϵ -method inject a higher amount of DG power than I-DBEA. The proposed method has reduced the real power losses from 1298.1 kW to 571.143 kW (56.01% reduction) and VD from 0.3576 p.u. to 0.0256 p.u., while the maximization of VSI is from 0.5697 p.u. to 0.8917 p.u..

ble VIII, it can be observed that I-DBEA achieves the most compromising results for the multi-objective optimal size and site of DG allocation problem at possible DG injection as a contrast to the available methods. The proposed method offers somewhat more real power loss reduction and VD

along with maximum VSI in contrast to the method presented in LSFSa [9]. It can be observed from Table VIII that IMOEOH and LSFSa inject more DG power to acquire the same goal. Furthermore, the proposed method gives remarkable enhancement in all the objective functions, i. e., I^2R

losses, VD, and VSI. The proposed method has reduced the real power losses from 1298.100 kW to 143.355 kW (88.95% reduction) and VD from 0.0993 p.u. to 0.0083 p.u., while the maximization of VSI is from 0.5697 p.u. to 0.9123 p.u..

TABLE VIII
IEEE 119-BUS 7 STANDARD RDN WITH DGs OPERATING AT 0.85 LPF

Technique	Optimal location (bus No.)	DG size (MW)	Total DG size (MW)	RPL (kW)	P_L reduction (%)	VD (p.u.)	VSI (p.u.)
Base case				1298.100	0.00	0.3576	0.5697
IMOEOH [33]	22, 41, 50, 74, 79, 91, 110	2.0600, 2.3390, 3.9670, 2.7870, 3.1070, 2.0870, 3.7130	20.0600	147.800	88.61	0.0059	0.8918
LSFSa [9]	36, 48, 56, 75, 88, 103, 116	7.0560, 2.5150, 4.9800, 3.1810, 0.7230, 6.1610, 0.5860	25.2020	634.800	51.09	0.0562	0.8918
I-DBEA	80, 41, 110, 20, 74, 96, 50	1.7940, 1.9980, 3.0317, 2.1473, 2.3310, 1.5827, 3.1997	16.0845	143.355	88.95	0.0083	0.9123

It can be observed from Tables VII and VIII that Case 3 gives the best results compared with Case 2. That is because DGs worked at LPF add both active and reactive power to the distribution system, which enhances the system performance compared with DGs operating at UPF. The enhancement of the voltage profile for all the cases in IEEE 119-bus standard RDN compared with the base case is shown in Fig. 11. It can be observed from Fig. 11 that bus voltage is near to unity in Cases 2 and 3. To show the efficiency of I-DBEA to produce an optimal solution for multi-objective functions, the distribution of Pareto optimal solution set is shown in Fig. 12. The set of Pareto optimal solution clearly shows that the proposed method has the ability to find a widely-distributed set of non-dominated points for three objective functions.

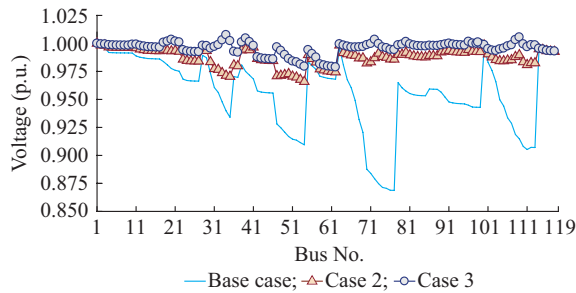


Fig. 11. Bus voltage profile of Cases 2 and 3 in IEEE 119-bus standard RDN.

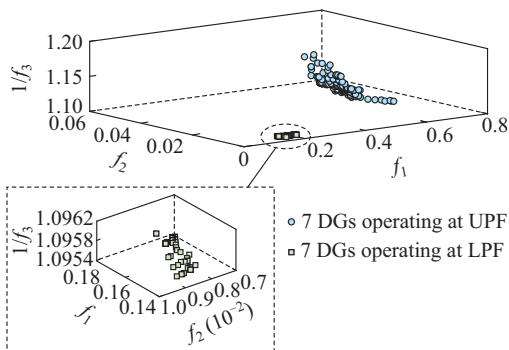


Fig. 12. Final Pareto front of Cases 2 and 3 in IEEE 119-bus standard RDN.

V. DISCUSSION

From the above simulation results of all standard IEEE radial networks, it can be observed that the minimum bus voltage has been improved beyond the smallest restriction limit following the optimal DG allocation. Furthermore, it can be observed that DG capable of injecting both real and reactive power significantly minimizes more line losses and VD along with the high value of VSI compared with the DGs only injecting active power. This is because of the availability of its reactive power capacity.

The simulation results have exposed that the applied methodology is not only efficient to find the best site and capacity of multiple DGs, but also effective for the selection of optimal number of DG (single as well as multiple) installations. The assessment of the performance of the proposed method with various other existing methods has shown that the proposed method has the lowest losses and smallest DG size in DGs of both category 1 (only inject active power) and category 2 (inject active and reactive power) types for single- as well as multi-DG allocation. Hence, the multi-objective optimization of conflicting objective functions, i. e., minimization of active power losses, VD, and maximization of VSI, has been achieved by allocating optimal number, site, and size of DG using the proposed method.

VI. CONCLUSION

The multi-objective optimization I-DBEA method for the optimal number, size, and position of DG allocation in the RDN is presented in this paper. The suggested method is applied in various test systems, i.e., IEEE 33-bus, 69-bus, and 119-bus standard RDNs, to validate its effectiveness. Most compromising and effective results are obtained compared with other similar work. From the simulation results, it can be observed that the I-DBEA method can effectively solve the non-linear and mixed-integer type of multi-objective problems. It is independent of parameter tuning, and is not trapped into local optima. It has also been proven from the simulation results that appropriate location and position of DG is effectively solved by the proposed I-DBEA method. The suggested method is independent of penalty factor, which results in better enhancement in voltage profile, VSI

and reduced real power losses in contrast to the methods available in the literature. Therefore, the proposed method can be implemented to solve any type of complex multi-objective problems and challenges in industry practice.

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