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A Multi-objective Optimum Distributed Generation Placement Using Firefly Algorithm

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Abstract

Nowadays, the power systems face several environmental and economic challenges and Distributed Generations (DGs) will be an effectual solution for them. The integration of DGs may result in power system volatility and losses. The optimal allocation of DGs will resolve the aforesaid issues. This study aims to implement multi-objective firefly algorithm for siting and sizing of DGs by optimizing six dissimilar objective functions such as minimization of power losses, improvement of voltage profile, enhancement of Voltage Stability Index, reduction of pollutant emission and elimination of average voltage Total Harmonic Distortion. Besides, fuzzy decision-making methodology has been deployed to choose one of the Pareto-optimal solutions as the Best Compromise Solution. The studies have been conducted on standard IEEE 33-bus system and a practical 62 bus Indian Utility System namely Tamil Nadu Generation and Distribution Corporation Limited as a real-world distribution network. The outcomes of the proposed work have been compared with related past studies and prominent improvement has been experienced.

Keywords Distributed generations · Optimal placement · Firefly algorithm · Power losses minimization · Voltage profile improvement · Pollutant minimization · Total harmonic distortion minimization · IEEE33-bus system · TANGEDCO

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1 Introduction

In recent times, DGs have gained more consideration in power systems for handling the environmental and financial challenges instigated by fossil fuel based power plants. DGs are known as the electric power generations that can be directly connected to loads or DS [1]. The DGs such as wind turbines, solar photovoltaic (PV), full-cells, biomass can mitigate the emission of greenhouse gases (GHG) and climate changes. Moreover, the DS are facing several defies due to the increasing electricity consumption and operational constraints [2]. The DS have been enforced to deliver power to the customer continuity. Owing to low voltage level and high currents, DS have been suffered from severe power losses and voltage volatility. Consequently, the incorporation of DGs have been considered to overwhelm the aforesaid problems [3, 4]. So as to preserve the high efficiency and to enhance the performance of the DS, the placement of DGs should be optimal. Furthermore, the optimal allocation and sizing of DGs will minimize the power losses, energy cost, pollutant emission and THD_v. Similarly, it increases the voltage profile and VSI. These concerns have stimulated the research effort towards the development of accurate and

fast techniques for optimal DG placement and sizing to prevent voltage collapse and reduce the system's power losses. In this context, several optimization techniques have been applied to solve optimal sizing and placement problem of DGs [5–8]. Detailed reviews on several optimal DG allocation algorithms and their implementation have been presented [9–12].

In recent years, several researches have been conducted to reduce the power loss and to increase the voltage profile in DS while optimizing optimal allocation problem of DGs and shunt capacitors [13]. Previously, analytical methods [14] and evolutionary algorithms like Generic Algorithm (GA) [15], Particle Swarm Optimization (PSO) [16, 17], hybrid PSO [18], hybrid Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) [19] have been applied for solving optimal allocation problem of single and multiple types of DGs. A logical methodology to optimally size and site both capacitors and DGs on DS has been presented [20] and PSO [21] has been implemented to improve the results. The meta-heuristic techniques for instance hybrid Harmony Search Algorithm (HSA) and Particle ABC (PABC) [22], Intersect Mutation Differential Evolution (IMDE) [23] and Backtracking Search Algorithm (BSA) [24] have all been employed to design and site both DGs and shunt capacitors. Most of these literatures have solved the problem with single objective namely real power loss minimization.

Most recently, Grey Wolf Optimizer (GWO) has been proposed to solve multiple objectives such as minimization of power loss and improvement of voltage profile [25]. A Multi Objective Shuffled Bat (Mo-SB) algorithm has been applied to select optimal placement of DGs by considering power loss and energy cost minimization [26]. Mo-SB algorithm has been proposed by hybrid Shuffled Frog Leaping Algorithm (SFLA) and Bat algorithm. Discrete Artificial Bee Colony (D-ABC) algorithm has been implemented to site DGs by considering the objectives such as maximization of system loadability and reduction of power losses [27]. Multiple objectives such as energy cost reduction, reliability enhancement, losses minimization and voltage deviation reduction have been considered while solving DGs optimization problem using Ant Lion Optimizer (ALO) [28] and Whale Optimization Algorithm (WOA) [29]. Lately, the improved chicken swarm optimization has been employed to place the charging stations optimally in the IEEE 33 bus system. The impact of Electric Vehicle load demand on the DS, in terms of per unit voltage profile, voltage stability index, average voltage deviation index and power loss has been discovered [30].

Firefly Algorithm (FA) has been proposed to increase the speed of exploration and exploitation, the sporadic patterns and activities of fireflies have been adapted [31]. FA outperforms PSO on continuous constrained optimization problems [32]. Owing to the benefits of the FA, it has been extensively employed in several engineering applications. The typical power system optimization problems such as economic dispatch and load forecasting problems have been solved using FA [33, 34]. This study contributes.

- To solve the objectives such as minimization of power losses, minimization the voltage deviation, enhancement of VSI, reduction of pollutant emission and elimination of THDv simultaneously on a real-world power system.
- To apply the new meta-heuristic optimization algorithm namely MOFA for DG placement in DS.
- To test the proposed method on IEEE 33-bus and a practical 62 bus IUS by considering multiple objectives with different cases.

2 Mathematical Formulation

Six OFs for instance reduction of power losses, minimization of the voltage deviation, improvement of VSI, reduction of costs, reduction of pollutant emission, and elimination of average THDv for optimum DGs placement problem are selected.

2.1 Reduction of Power Losses

OF_1 intends to minimalize the power losses and it is stated as [35]

$$OF_1 = \min \sum_{i=1}^{nL} R_i |I_i|^2 \tag{1}$$

where, nL no. of branches, R_i the resistance of the i-th branch, I_i current magnitude of i-th branch.

2.2 Minimization the Voltage Deviation

OF_2 intends to minimize the voltage deviation by following Eq. (2).

$$OF_2 = \min \sum_{i=0}^{N} \left(\frac{v_i - v_i^{spec}}{v_i^{max} - v_i^{min}} \right)^2 \tag{2}$$

where. v_i bus voltage magnitude, v_i^{spec} specified voltage magnitude (1.0 p.u.)

2.3 Improvement of VSI

OF_3 intends to enhance VSI.

$$OF_3 = \min \left(\frac{1}{VSI(m_2)} \right) \tag{3}$$

$$VSI(m_2) = |V(m_1)|^4 - 4[P(m_2)X_{ij} - Q(m_2)R_{ij}]^2 \\ -4[P(m_2)R_{ij} + Q(m_2)X_{ij}]|V(m_1)|^2 \tag{4}$$

where, m_1 slack bus, $m_2, m_3, ..., m_n$ bus no. (2, 3,..., $n$bus), Vbus voltage (p.u), P and Qactive power (MW) and reactive power (MVar), R_{ij} and X_{ij} resistance (Ω) and reactance (Ω) of branch ij,

2.4 Reduction of Cost

The cost is minimized by optimizing OF_4.

$$OF_4 = \min \sum_{i=1}^{N_{DG}} (C_{DG_i}) \tag{5}$$

Where

$$C_{DG_i} = a + b \times PG_i \tag{6}$$

$$a = \frac{Capital\,cos\,t(\$/kW) \times Capacity(kW) \times Gr}{Lifetime(year) \times 8760 \times LF} \tag{7}$$

$$b = O\&M\,cos\,t(\$/kWh) + Fuel\,cos\,t(\$/kWh) \tag{8}$$

where, N_{DG} number of DGs, C_{DG_i} generation cost of i-th DG (\$/kWh), a, bfixed and variable generation cost constants, PG_i active power at i-th DG unit (kW), $Gr$the annual rate of profit (5%), $LF$the load factor of DGs (0.47), $O \& M\,cost$-operation and maintenance cost (\$/kWh).

2.5 Reduction of Pollutant Emissions

OF_5 has been modeled to reduce CO_2, SO_2, and NO_x emissions [36].

$$OF_5 = Min(f) = \sum_{i=1}^{N_{DG}} E_{DG_i} + E_{Grid} \tag{9}$$

$$E_{DG_i} = (CO_2^{DG} + NO_x^{DG} + SO_2^{DG}) \times PG_i \tag{10}$$

$$E_{Grid} = (CO_2^{Grid} + NO_x^{Grid} + SO_2^{Grid}) \times Pg_{Grid} \tag{11}$$

where, CO_2, SO_2, and NO_xcarbon dioxide, sulfur dioxide, and nitrogen oxides; E_{Grid} and E_{DG_i} emissions generated by the grid and i-th DG unit.

2.6 Elimination of THDV

OF_6 intends to eliminate the THD_v by using Eq. (12).

$$OF_6 = Min(THD_V) = \frac{\sum_{i-1}^{m} THD_{V_i}}{m} \tag{12}$$

where m is the no. of buses.
  and

$$THD_{vi}(\%) \leq THD_{v_{max}} \tag{13}$$

where, $THD_{v_{max}}$ is the maximum permissible bound at every bus (5%).

2.7 Restraints

The equality and inequality restraints are deliberated while solving the problem.

The restraints for power balance requirements are pondered as

$$\sum_{i=1}^{NG} PG_i - P_L = P_d \tag{14}$$

$$\sum_{i=1}^{NG} QG_i - Q_L = Q_d \tag{15}$$

The extreme power produced by DGs must not exceed the allowable bounds of DS.

  (a) Generator bounds

$$PG_i^{min} \leq PG_i \leq PG_i^{max} \tag{16}$$

$$QG_i^{min} \leq QG_i \leq QG_i^{max} \tag{17}$$

  (b) Bus voltage bounds

$$0.95 \leq V_i \leq 1.05, i = 1, 2, ..., nbus \tag{18}$$

  (c) DG Power factor bound

$$0.9 \leq PF \tag{19}$$

where, P_L and Q_L active power losses (MW) and reactive power losses (MVar); P_d and Q_d active power load demand (MW) and reactive power load demand (MVar).

3 FA for Multi-Objective Optimization (MOO)

The description and the implementation procedure have been adopted from [8, 10, 35, 39]. Table 1 offers the data of the DGs.

The MOO problem aims to optimize multiple and competing objective functions. It results with a non-dominated set of solutions namely Pareto solutions, rather than a single

Table 1 Data of the DGs [35]

DG	Size (MW)	Life span (year)	Capital cost ($/kW)	O&M cost ($/kWh)	Fuel cost ($/kWh)	Emission (lb/MWh)		
						NO_x	SO_2	CO_2
Grid	–	–	–	–	–	5.01	11.3	2042
PV	1	25	3976	0.0120	–	–	–	–
WT	5	25	1851	0.0092	–	–	–	–
GT	3	15	1226	0.0647	0.0658	0.28	0.95	1242.8

optimal solution. The formulation for a MOO problem can be expressed as follows

$$MinF(x) = \left[f_1(x), f_2(x), ..., f_p(x) \right]^T \qquad (20)$$

$$h(x) = 0$$

$$g(x) \leq 0$$

where $f_1, f_2, ..., f_p$ are the objective functions and x is the set of decision variables and $h(x)$ and $g(x)$ are the equality and inequality constraints of the problem.

FA is an optimization algorithm that imitates the behavior of fireflies [37–40]. The initial population of fireflies has been expressed based on Eq. (21).

$$c_{i,d} = c_{d,\min} + rand \cdot \left(c_{d,\max} - c_{d,\min} \right) i \in \left[1, N_F \right], d \in [1, D] \qquad (21)$$

where, N_F Number of fireflies; D Dimension of the problem; $rand$ random number between 0 to 1.

The position vector $c_i = \left(c_{i1}, c_{i2}, ..., c_{iD} \right)$ of the firefly i, which has been deliberated as a Pareto optimal solution. The modernized tactic of FA has been provided in the Eq. (22).

$$c_i^{new} = c_i^{old} + \beta_0 \exp \left(-\gamma r_{ij}^2 \right) \left(c_j^{old} - c_i^{old} \right) + \alpha \xi_i \qquad (22)$$

where, γ light absorption coefficient; β_0 attractiveness at $r_{ij}=0$; α randomization parameter; ξ_i vector of random numbers with Gaussian or uniform distributions.

The distance between any two fireflies r_{ij} can be calculated by Eq. (23).

$$r_{ij} = \left\| c_i - c_j \right\| = \sqrt{\sum_{k=1}^{D} \left(c_{i,k} - c_{j,k} \right)^2} \qquad (23)$$

where $c_{i,k}$ is the k-th dimension of independent variable c_i of the firefly i, $c_{j,k}$ is the k-th component of the independent variable c_j of the firefly j.

3.1 Evaluation of Pareto optimal solution

While optimizing multiple objectives, it is tough to choose a single optimal solution. So as to choose the "most

appropriate" solution, the concept of optimality has been swapped by Pareto optimality. The Pareto optimal solution cannot be recognized with a single objective, and because of this, it has been determined without abating the enactment with more than one objective. A fuzzy approach has been employed to find the Pareto optimal solution. The fuzzy membership functions have been expressed by Eq. (24).

$$\mu_{Fi}(X) = \begin{cases} 1, & F_i(X) \leq F_i^{\min} \\ 0, & F_i(X) \geq F_i^{\max} \quad i = 1, 2 \\ \frac{F_i^{\max} - F_i(X)}{F_i^{\max} - F_i^{\min}}, & F_i^{\min} \leq F_i(X) \leq F_i^{\max} \end{cases} \qquad (24)$$

The values of $F^{\min}$ and $F^{\max}$ have been obtained through the payoff table. The singular optima of the objective functions have been estimated to make the payoff table for the competing objective functions p. Then the objective functions F_i, $i =1,...,$ p (F_i^* signifies the optimum value of F_i) has been resolved. The balance objective functions F_1, ..., F_{i-1}, F_{i+1}, ..., F_p have been estimated and signified as $F_i^i, ..., F_{i-1}^i, F_{i+1}^i, ..., F_p^i$. The i-th row of the payoff table has $F_i^i, ..., F_{i-1}^i, F_i^*, F_{i+1}^i, ..., F_p^i$. Similarly, all rows of the payoff table have been assessed. The j-th column of the payoff table has the estimated values for the objective function F_j among which the minimum and maximum values specify the bound of the objective function F_j for the implemented fuzzy method. The incessant and monotonic functions have been employed as membership functions. MOFA forms a population and searches in an objective space to select the optimal solution. While optimizing MOO, a set of non-dominated solutions has been saved in the origin. The solution X_1 dominates X_2 when the subsequent conditions have been satisfied:

$$\begin{aligned} &\forall j \in \{1, 2, ..., n\}, F_j(X_1) \leq F_j(X_2), \\ &\exists m \in \{1, 2, ..., n\}, F_m(X_1) < F_m(X_2), \end{aligned} \qquad (25)$$

The normalized membership function has been calculated for each individual using Eq. (26).

$$N_\mu(j) = \frac{\sum_{i=1}^{N_F} w_i \times \mu_{Fi}(X_j)}{\sum_{j=1}^{N_{rep}} w_i \sum_{i=1}^{N_F} w_i \times \mu_{Fi}(X_j)} \qquad (26)$$

This membership function has been executed to rank the non-dominated solutions consistent with the importance

Table 2 Results of MOF$_1$ for IEEE 33 bus system

DG	Site (Bus No.)	Capacity (kW)	Power loss (kW)	Voltage deviation (%)	VSI
PV	28	467.20	79.2450	0.0007	0.0140
WT	32	501.67			
GT	15	445.18			

Table 3 Results of MOF$_2$ for IEEE 33 bus system

DG	Site (Bus No.)	Size (kW)	Power loss (kW)	Energy cost ($/MWh)	Pollutant emission (lb/h)
PV	14	539.71	77.5412	25.0454	3124.8
WT	25	387.62			
GT	9	401.47			

Table 4 Results of MOF$_3$ for IEEE 33 bus system

DG	Site (Bus No.)	Size (kW)	Voltage deviation (%)	Energy cost ($/MWh)	THD$_v$ (%)
PV	31	506.30	0.0006	25.1424	1.6251
WT	28	379.35			
GT	07	242.23			

Table 5 Comparison of results for IEEE 33 bus system

Condition	Power loss (kW)	Energy cost ($/MWh)	Pollutant emission (lb/h)
Before integrating DGs	210.98	27.1624	7879.9
After integrating DGs	77.5412	25.0454	3124.8
Accelerated PSO [41]	151.40	–	–
PSO [16]	115.29	–	–

given over the objective functions and it has been signified as w$_i$ in Eq. (26).

4 Simulation Results

Two DS such as the IEEE 33-bus system [21] and the TANGEDCO 62-bus IUS [13] have been considered [25].

Three different cases are considered as follow.

Case 1 The position and size of DGs are estimated by considering three objectives (OF$_1$, OF$_2$, and OF$_3$).

$$MOF_1 = \min\left(OF_1, \ OF_2, \ OF_3\right) \tag{27}$$

Case 2 The objectives for instance OF$_1$, OF$_4$, and OF$_5$, have been optimized. MOF$_2$ has been expressed as:

$$MOF_2 = \min\left(OF_1, \ OF_4, \ OF_5\right) \tag{28}$$

Case 3 Multiple DGs are placed by optimizing the objectives, such as OF$_2$, OF$_4$, and OF$_6$. MOF$_3$ has been framed as:

$$MOF_3 = \min\left(OF_2, \ OF_4, \ OF_6\right) \tag{29}$$

4.1 Results of 33-Bus System

The results of case 1 have been offered in Table 2. It evidently infers that the optimal location and capacity of DGs make an optimistic effect to minimalize energy loss, increase voltage profile and boost VSI. Table 3 provides the technical, financial, and environmental benefits by solving MOF$_2$. Table 4 presents the minimized values of voltage deviation,

Table 6 Results of MOF$_1$ for 62 bus IUS

DG	Size (kW)	Site (Bus No.)	Power loss (MW)	Voltage deviation (%)	VSI
PV	845.34	17	35.3542	0.0035	0.0248
WT	4215.25	30			
GT	2412.04	48			

energy cost and THD$_v$ by optimizing MOF$_3$. Table 5 indicates that power loss, overall energy cost and pollutant emission have been minimized by 133.4388 kW, 2.117$/MWh, 4755.1 lb/h respectively after integrating DGs into the system.

4.2 Results of TANGEDCO 62-Bus IUS

The results of TANGEDCO 62-bus IUS indicate that a substantial minimization in power losses of 35.7842 MW is attained while optimizing MOF$_1$. Table 6 specifies that the minimized voltage deviation of 0.0035 p.u has been achieved. The outcomes of MOF$_2$ and MOF$_3$ have been presented in Tables 7 and 8. The PV and WT type DGs are vital in the minimization of emission, power loss and energy cost. A noticeable minimization in a power loss has been achieved from 40.4512 to 37.5452 MW. The energy cost has been minimized from 36.8121 $/MWh to 35.445 $/MWh. The pollutant emission has been decreased from 117,564.25 lb/h to 84,215.30 lb/h.

The voltage profile of the IEEE 33 bus and TANGEDCO 62 bus IUS are shown in Figs. 1 and 2 respectively. The

Table 7 Results of MOF$_2$ for 62 bus IUS

DG	Size (kW)	Site (Bus No.)	Power loss (MW)	Cost ($/MWh)	Pollutant emission (lb/h)
PV	845.36	20	37.5452	35.4457	84.215.30
WT	4246.30	35			
GT	2668.25	60			

Table 8 Results of MOF$_3$ for 62 bus IUS

DG	Size (kW)	Site (Bus No.)	Voltage deviation (%)	Energy cost ($/MWh)	THD$_v$ (%)
PV	941.25	31	0.0009	33.5412	1.1251
WT	4651.4	28			
GT	2457.9	07			

Fig. 2 Voltage profile for 62 bus IUS

Fig. 1 Voltage profile for IEEE 33 bus system

Fig. 3 Comparative results for IEEE 33 bus system on optimal placement problem

voltage profile values have been plotted before and after the integration of DGs. The illustrative comparisons of the power losses, energy cost and pollution emission for before and after integrating DGs have been shown in Figs. 3 and 4 for IEEE 33 bus system and 62 bus IUS respectively.

The values of VSI are less than 1 for the system, hence the system is stable. The values shows VSI close to 1 infers that the system is impending its load limit and is nearly unstable. Else, the more VSI is close to zero the more the node is stable. In reality, the optimal DG placement is selected based on which node has the highest VSI value. Figures 5 and 6 show the Pareto front of IEEE 33 bus system and 62 bus IUS respectively using MOFA. The BCS for all the cases have been identified from the
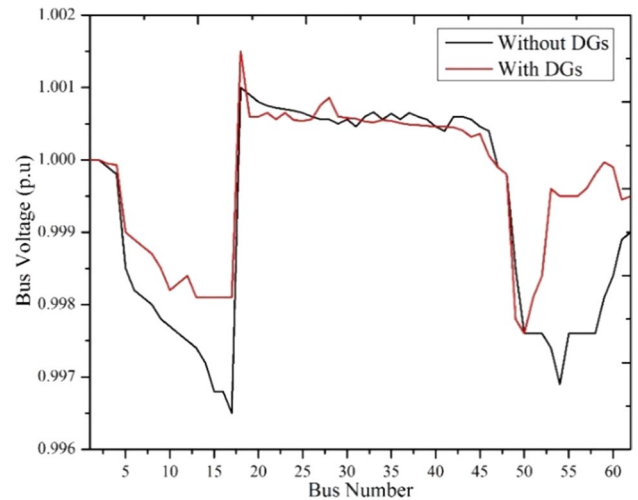
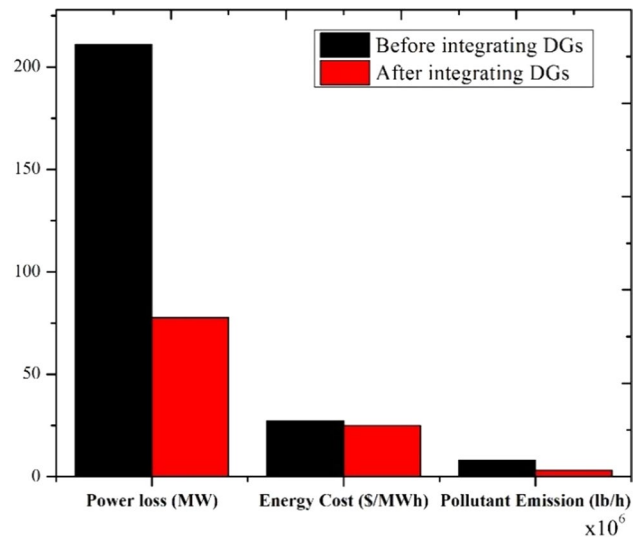three-dimensional Pareto optimal set attained by optimizing the MOO. It has been noted that every Pareto optimal solution is an alternate choice for a decision-maker.

The power system planner can espouse one of them for the individual system depends on its preferences over the objective functions. After applying the MOFA to generate Pareto sets, the BCS among them has been selected using fuzzy decision-making according to the Eq. (24). For instance, the performance analysis for the results of MOF$_3$ for 62 bus IUS is given in Tables 9. The best, worst, mean, variance and standard deviation (SD) [42] values are estimated and given in Table 10.
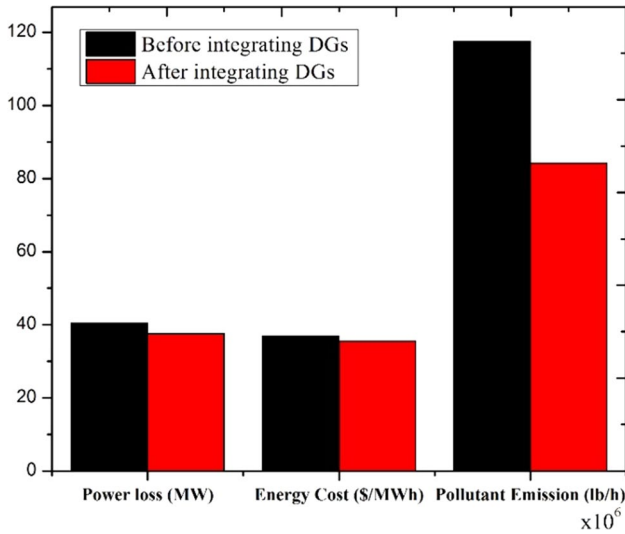
Fig. 4 Comparative results for 62 bus IUS on optimal placement problem

The consistency of the MOFA has been validated from the parameter variance and it has been estimated as 0.00245. The merits of MOFA is that it typically has good efficacy
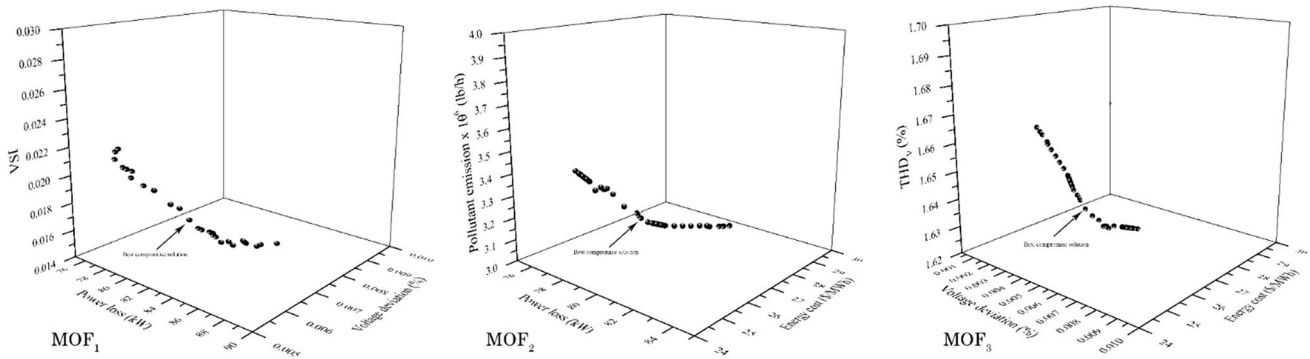
Table 9 Comparison of results before and after incorporating DGs for 62 bus IUS

Condition	Power loss (MW)	Energy cost ($/MWh)	Pollutant emission (lb/h)
Before integrating DGs	40.4512	36.8121	117,564.25
After integrating DGs	37.5452	35.4457	84,215.30

Table 10 Estimation of performance analysis the results of MOF$_3$ for 62 bus IUS

Statistic	Energy cost using MOFA
Best	33.5142 ($/MWh)
Worst	36.4025 ($/MWh)
Mean	35.2754 ($/MWh)
Variance	0.00245
SD	0.04949

Fig. 5 Three-dimensional Pareto optimal set attained by optimizing multiple objectives on IEEE 33 bus system
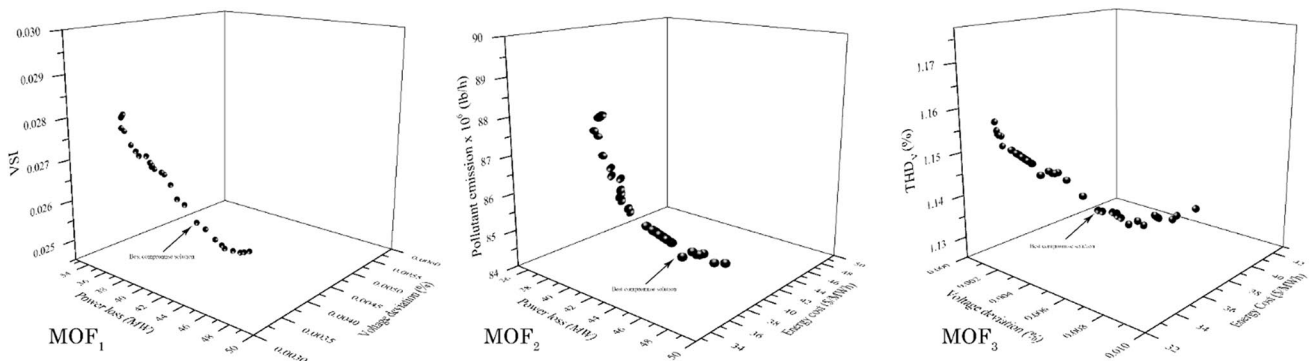

Fig. 6 Three-dimensional Pareto optimal set attained by optimizing multiple objectives on 62 bus IUS

for certain problems and necessitate only a minimum number of iterations. Though, one of its limitations is the high possibility of being stuck in local optima since it is a local search algorithm.

5 Conclusion

In this study, the MOFA is executed to estimate the numbers, placements and capacities of the DGs for IEEE 33-bus system and 62-bus IUS. The formulations of the objectives for instance minimization of power loss, reduction of voltage deviation, improvement of VSI, reduction of cost, mitigation of emission and elimination of THDv are modeled. A systematic and exhaustive investigation has been performed. The implementation of MOFA for optimal placement of DGs on DS reveals its efficiency. The execution of MOFA on IEEE 33-bus system and 62-bus IUS demonstrates that with DGs penetration, the power losses, energy cost, and pollutant emission can be reduced remarkably. Moreover, the overall voltage quality has been improved considerably. It has been experienced that the DG units operating in voltage control mode and having reactive power regulation capability efficiently improve the voltage stability margin regardless of the system size. The MOFA offers a modest and precise solution and do not needed extensive computations. Lastly, the MOFA is based on naive algorithm through simple mathematical formulations. Hence, it can be simply protracted to deliberate the load variation and erratic characteristics of renewable based DGs. In future, the economic, environmental, social, and technical impacts of the renewable energy sources would be investigated. The power loss estimation has been performed under both leading and lagging power factors while sizing of DGs.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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